TRUST-LAPSE: An Explainable & Actionable Mistrust Scoring Framework for Model Monitoring

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Abstract—Continuous monitoring of trained ML models to determine when their predictions should and should not be trusted is essential for their safe deployment. Such a framework ought to be high-performing, explainable, post-hoc and actionable. We propose TRUST-LAPSE, a “mistrust” scoring framework for continuous model monitoring. We assess the trustworthiness of each input sample’s model prediction using a sequence of latent-space embeddings. Specifically, (a) our latent-space mistrust score estimates mistrust using distance metrics (Mahalanobis distance) and similarity metrics (cosine similarity) in the latent-space and (b) our sequential mistrust score determines deviations in correlations over the sequence of past input representations in a non-parametric, sliding-window based algorithm for actionable continuous monitoring. We evaluate TRUST-LAPSE via two downstream tasks: (1) distributionally shifted input detection and (2) drift detection, across diverse domains—audio & vision using public datasets and further benchmark our approach on challenging, real-world electroencephalograms (EEG) datasets for seizure detection. Our latent-space mistrust scores achieve state-of-the-art results with AUROCs of 84.1 (vision), 73.9 (audio), 77.1 (clinical EEGs), outperforming baselines by over 10 points. We expose critical failures in popular baselines that remain insensitive to input semantic content, rendering them unfit for real-world model monitoring. We show that our sequential mistrust scores achieve high drift detection rates: over 90% of the streams show < 20% error for all domains. Through extensive qualitative and quantitative evaluations, we show that our mistrust scores are more robust and provide explainability for easy adoption into practice.

Impact Statement—ML models show impressive performance across different domains. However, in the real-world, they fail silently & catastrophically, limiting their utility. With mistrust scores from TRUST-LAPSE, these failures can be automatically identified (model monitoring) and escalated to a human operator to mitigate. Our latent-space mistrust score outperforms standard baselines by over 10 points on existing benchmarks. We expose critical failures in top baselines with semantic content. In realistic settings, where data drifts over time, our sequential mistrust scores achieve very high drift detection rates and pinpoint when the model needs to be fine-tuned or retrained. As a prime example of practical impact, we’re currently assessing these methods for EEG seizure detection and radiology tasks in clinical settings. This could pave the way for effective clinical model deployment and human-AI partnership.

Index Terms—Mistrust Scores, Latent-Space, Model monitoring, Trustworthy AI, Explainable AI, Semantic-guided AI.

I. INTRODUCTION

MODERN machine learning (ML) has seen tremendous success in various tasks across multiple domains, surpassing human performance in many benchmarks [1]–[3]. However, despite their impressive accuracies on test sets even after rigorous validation and testing, black-box deep learning models fail silently and catastrophically with highly confident predictions [4]–[6]. Such silent failures have severe consequences in mission-critical domains like healthcare and autonomous driving, where errors are costly, resulting in injury and death [7]. In the wake of changing data and concept drifts in the real world, where incoming samples can come from shifted distributions or completely new distributions [8], it is imperative that we continuously monitor models after deployment to assess when their predictions should not be trusted.

While the concept of trust can be nuanced and context-driven [9], a (mis)trust scoring framework for continuous model monitoring must satisfy the following desiderata— it must be: post-hoc - use the trained, deployed model; explainable - help us understand why a prediction should or should not be trusted; and actionable - allow us to take an automated, concrete action for every prediction, e.g. accept or reject prediction, flag, alert a human, relabel data point or adaptively retrain the model. Most importantly, the framework must perform well to avoid algorithm aversion [10]. It must (1) assign high “mistrust” scores when the model is faced with large distributional shifts (out-of-distribution (OOD) data) such as noisy, corrupt data or new semantic content (semantic OOD data), and (2) assign low “mistrust” scores on learnt distributions yet unseen data (in-distribution or inD data), allowing for generalization.

To determine trust in model predictions, current works typically use (a) explainability methods (XAI) [11]–[13]; which, though explainable, post-hoc and suitable for providing qualitative insights, require humans to oversee the explanations and are not directly actionable for continuous and automated model monitoring; or (b) uncertainty estimation techniques [6], [14]–[18]; that are difficult to train or are computation-ally expensive. They are frequently non-post-hoc, requiring complicated modifications to training strategies and model architectures. Some even require exposure to labelled outlier data during training which are often unavailable while many do not scale well with input-dimensionality. And, as we’ll show later in this paper (Section VII-B), most of them are insensitive to input semantic content, failing to perform well as a trust scoring framework.

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In this paper, we propose TRUST-LAPSE (Fig. 1), a simple framework for mistrust scoring using sequences of latent-space embeddings for continuous model monitoring. It is based on two key insights. First, we leverage the fact that well-trained deep learning models can act as encoders by projecting noisy, high-dimensional inputs onto an induced hierarchical latent space. We observe that an encoder with enough inductive bias will map distributionally shifted inputs differently from other in-domain samples in the latent-space.

Second, unlike standard approaches that inspect test inputs purely in isolation, we can track the trajectory of latent-space embeddings across a set of samples to identify correlations. Most real-world scenarios (e.g., autonomous driving, electroencephalogram (EEG) seizure analysis, healthcare decision making, etc.) involve consecutive inputs to the model that are likely to be correlated sequentially e.g., an obstacle detector deployed in a self-driving car will see images correlated sequentially. A seizure detector installed in a neurology clinic will process hours of sequence-correlated EEG signals. Even low-risk models like image classifiers deployed over the cloud or Netflix recommendation systems will see correlations over sequential inputs when grouped by User ID or location. Thus, sequentially occurring samples share meaningful semantic correlations that can be leveraged for continuous model monitoring.

We evaluate TRUST-LAPSE via two real-world downstream tasks: (1) distributionally shifted (OOD) input detection and (2) data drift detection. Existing benchmarks are frequently limited to highly curated image datasets and do not extend to more diverse and realistic scenarios. Furthermore, most ML systems do not evaluate their ability to detect data drifts at all, presenting a gap between models performing well on test sets and models capable of being deployed in the wild. We perform extensive evaluations and experiments on diverse domains (audio, vision, clinical EEGs) and tasks, and show that TRUST-LAPSE is actionable, explainable and can be used with any trained model. Our main contributions are:

- We propose TRUST-LAPSE, a “mistrust” scoring framework using sequences of latent-space embeddings. To our knowledge, we are the first to use sequences of latent-space embeddings to quantify trustworthiness of model predictions for continuous model monitoring. We are also the first to use deep-learning based trust quantification techniques for EEG analyses.
- We achieve state-of-the-art (SOTA) on benchmarks across diverse domains and tasks: audio speech classification (73.9 AUROC), seizure detection using clinical EEGs (77.1 AUROC) and image classification (81.4 AUROC), outperforming baselines by ∼10 AUROC points.
- We benchmark TRUST-LAPSE and 6 other methods on their ability to flag semantically-shifted inputs as OOD while correctly identifying semantically-similar inputs (but from different datasets) as in-domain.
- We expose critical failures in popular baselines that remain insensitive to input semantic content, unlike TRUST-LAPSE.
- We achieve high detection rates when evaluating TRUST-LAPSE on data drift detection tasks, over 90% of streams show <20% error on all domains. We hope to set a precedent in using drift detection to evaluate model trust. We believe that this is essential for characterizing and monitoring ML performance in the wild.

!! II. RELATED WORK

XAI methods provide complementary, post-hoc explanations to the predictions of black-box models to induce trust. They are usually sensitivity analyses, producing systematic perturbations of the inputs to see how predictions are affected [19]. They can either provide (i) feature importance explanations, that highlight top features responsible for a prediction, like LIME [12], SHAP [13], DeepLift [20], or (ii) example importance explanations, that highlight top training examples most responsible for a prediction, like Deep K-Nearest Neighbours [21].

Uncertainty estimation is a rich field with a long history. Classical techniques like density estimation [22], one-class SVMs [23], tree-isolation forests [24], etc., scale badly with input dimensionality [25]. [26] provides a “trust” score using level-set estimation and modified nearest neighbors search. However, it does not scale well to high dimensional datasets. Calibration is a frequentist notion of uncertainty [6], [27], [28], measured by proper scoring rules like log-loss or Brier scoring. Deep neural networks (NNs) typically use a Bayesian formalism to learn distributions over model weights [14], [16], [29]–[32] or approximate Bayesian inference such as Monte-Carlo Dropout [18] and Batch Normalization [33]. Reconstruction-based methods [34]–[38] use reconstruction loss as the uncertainty score. Quality of uncertainty estimates are commonly evaluated via OOD detection, a binary classification task. [15] uses maximum softmax probabilites (MSP) to detect OOD data. [39] introduces a temperature parameter to the softmax equation. [40] fits class-conditional Gaussians to intermediate activations and uses the Mahalanobis distance to identify OOD samples. Self-supervision helps get better representations that improves OOD detection [41]–[43]. Some consider (semi-)supervised
techniques for OOD detection with labelled outliers [44]–[49]. Others use generative techniques [50]–[52] including energy-based models [8], [53], [54] and likelihood ratios [55], but they can be overconfident on complex inputs [56]. Though many directly optimize for good performance on OOD detection, few are compatible to serve as trust scoring frameworks for continuous model monitoring. Our sequential mistrust scores build upon and shares similarity to change point detection (CP) methods in time-series data [57], [58], along with signal processing techniques such as Particle and Kalman filtering [59], [60]. However, traditional CP methods are limited to one (or low) dimensional data and fail in high dimensional settings [61].

[62] gives a complete overview of closely related topics of distributional shift detection including covariate shift, label shift and concept drift [63].

III. PRELIMINARIES & PROBLEM SETUP

Let $\mathcal{X}$ represent our high-dimensional input space, $\mathcal{X} \subseteq \mathbb{R}^n$. Let $\mathcal{Y} = \{0, 1, 2, ..., C - 1\}$ denote the label space where $C$ is the number of classes. A black-box classification model $f : \mathcal{X} \mapsto \mathcal{Y}$ is trained using a dataset $\mathcal{D}_{\text{train}}$ (assumed to be sampled from an underlying distribution $p^*$) such that $f(x) = p(Y = y|x)$, where $x \in \mathcal{X}$ and $y_i \in \mathcal{Y} \forall i$. The final prediction for an unseen input $x$ during inference is given by $\hat{y} = \arg \max_{y} p(y|x)$.

During deployment, a steady sequence of unseen inputs $\{..., x_{t-2}, x_{t-1}, x_t, x_{t+1}, x_{t+2}, \ldots\}$, where $t$ denotes time, is fed to the trained model $f$. For continuous model monitoring, our goal is to output mistrust scores $s_{\text{mis}}(x_t)$ for every input $x_t$ with threshold $th$ and a selective function $g(x_t)$ for every $x_t$ with threshold $th$ and a selective function $g(x_t)$ such that

$$\hat{y}_t = \arg \max_{y_t} p(y_t|x_t), \quad \text{if } s_{\text{mis}}(x_t) \leq \text{th}$$

$$\text{ABSTAIN or FLAG}, \quad \text{else}$$

$s_{\text{mis}}(x_t)$ is the associated mistrust in model prediction $\hat{y}_t$.

Assumption III.1 (Latent-Space Encoder). We assume that the trained black-box classifier $f : \mathcal{X} \mapsto \mathcal{Y}$ can be decomposed as $f = p \circ h$, where $h : \mathcal{X} \mapsto \mathcal{U}$ is the derived encoder that maps high-dimensional inputs $x \in \mathcal{X} \subseteq \mathbb{R}^n$ onto a latent-space $\mathcal{U} \subseteq \mathbb{R}^d$ through its embeddings, and $p : \mathcal{U} \mapsto \mathcal{Y}$ is the projection head that maps a latent-space embedding $u \in \mathcal{U}$ to an output label $y = p(u) \in \mathcal{Y}$.

Remark III.2. $h$ is inherently learnt when $f$ is trained using the InD training dataset $\mathcal{D}_{\text{train}}$. TRUST-LAPSE is agnostic to training strategy employed in training $f$, which can be supervised, transfer-learning, self-supervised or unsupervised depending on the label information present in $\mathcal{D}_{\text{train}}$.

We consider a classification setting here, though our framework can be extended to other scenarios such as regression, segmentation, etc.

IV. THE TRUST-LAPSE FRAMEWORK

A. Latent-Space Mistrust Scores

To extract the latent-space mistrust score of an input test sample’s prediction, we rely on two assumptions: (a) a well-trained encoder maps InD samples onto a region $\mathcal{D}$ in the latent-space but maps OOD inputs farther from this region under a distance metric, $d$, and (b) the OOD inputs that get mapped to the latent-space do not share similarity with InD inputs under a similarity metric, $sim$.

We first randomly sample a coreset from our InD training data $\mathcal{D}_{\text{train}}$ to model the extent of the InD region $\mathcal{D}$ within the fixed-dimensional latent-space.

$$\text{coreset} = \{h(x_i) \mid x_i \sim \mathcal{D}_{\text{train}}\}; \quad |\mathcal{D}_{\text{train}}| \geq |\text{coreset}|$$

We compute the distance score $s_{\text{dist}}$ and the similarity score $s_{\text{sim}}$ of the unseen test sample $x$ by comparing its latent-space embedding to those of samples in the coreset using a distance metric $d$ and a similarity metric $sim$ such that:

$$s_{\text{dist}}(x) = \min_{h(x_i) \in \text{coreset}} d(h(x_i), h(x))$$

$$s_{\text{sim}}(x) = \max_{h(x_i) \in \text{coreset}} sim(h(x_i), h(x))$$

Finally, the combined latent-space mistrust score is given by

$$s_{\text{LS}}(x) = s_{\text{dist}}(x) \cdot s_{\text{sim}}(x)$$

The distance score and the similarity score capture inductive biases in the latent-space differently and their product functions as an ‘AND’ between the two. Empirically, these scores taken individually are insufficient to estimate mistrust (Section VIII-A). We note that TRUST-LAPSE will accept any $d$ and $sim$ that is most suited for the target domain. We empirically choose the distance metric $d$ to be the Mahalanobis distance (amongst distances like Euclidean, Manhattan, etc.), obtained using class-conditional Gaussians [40] without label-smoothing [42] where class-wise means $\mu_c$ and covariance matrices $\Sigma_c$ are estimated from the coreset.

$$d(h(x)) = \min_c (h(x) - \mu_c)^T \Sigma_c^{-1} (h(x) - \mu_c)$$

As similarity metric $sim$, we adopt the cosine similarity between the test input’s representation and the coreset.

$$sim(h(x), h(x_i)) = \frac{h(x) \cdot h(x_i)}{||h(x)|| \cdot ||h(x_i)||}; \quad h(x_i) \in \text{coreset}$$

B. Sequential Mistrust Scores

For continuous model monitoring, where the trained model is presented with a steady sequence of high-dimensional inputs (Fig 1), we begin with the assumption that there is value in evaluating samples in the context of other samples instead of viewing them in isolation. We use the representational capabilities of modern encoders (Remark III.1) and examine the sequence of latent-space mistrust scores, instead of directly modeling the incoming high-dimensional, multivariate data stream i.e., we detect when to mistrust model predictions by comparing the sequence of reduced-dimension, latent-space mistrust scores ($s_{\text{LS}}$) with those of coreset samples. By ensuring that $s_{\text{LS}}$ are scalar values, we reduce the problem to change-point (CP) detection for a one-dimensional sequence.

We put forth an unsupervised, non-parametric, sliding-window based algorithm that builds on the work done by [58] to generate our sequential mistrust scores $s_{\text{mis}}$. We consider a sequence of $r$ samples in the input data...
stream denoted by \( \{x_1, x_2, \ldots, x_t, \ldots, x_r\} \). We obtain the scalar latent-space mistrust scores for the \( r \) samples, \( \{s_{LSS}(x_1), s_{LSS}(x_2), \ldots, s_{LSS}(x_t), \ldots, s_{LSS}(x_r)\} \) from their representations \( \{h(x_1), h(x_2), \ldots, h(x_t), \ldots, h(x_r)\} \) as explained in Section IV-A.

Given two window sizes \( w_A \) and \( w_B \) \((w_A, w_B \ll r)\), we define a reference window \( R_W \) drawn using the coreset and a sliding window from the input data stream \( (S_W)_t \) to be

\[
R_W = [s_{LSS}(x_{c_1}), \ldots, s_{LSS}(x_{c_{w_A}})]
\]

\[
(S_W)_t = [s_{LSS}(x_t), \ldots, s_{LSS}(x_{t+w_B})]
\]

where \( t \in \{1, \ldots, (r-w_B)\} \) and \( x_{c_t} \in \{x \mid h(x) \in \text{coreset}\} \) as visualized in Fig. 1. On choosing an appropriate or distance measure \( F \) (e.g. probability odds ratio, Kolmogorov-Smirnov, Wilcoxon, Mann-Whitney, etc.), we compute the sequential mistrust score between reference window \( R_W \) and the \( t \)th sliding window \( (S_W)_t \) for the \( t \)th sample

\[
s_{\text{min}}(x_t) = F(R_W, (S_W)_t)
\]

For our empirical analysis, we choose the Mann-Whitney statistic [64] as our measure \( F \). The null hypothesis \( H_0 \) for our setting here is that the two windows (reference and sliding) come from the same distribution. We hope to reject \( H_0 \) in favour of the alternate hypothesis \( H_1 \) at a significance level of 0.05 whenever the inputs show large distribution shifts and hence the predictions should be mistrusted. This approach (as in [58]) assumes the data points are generated sequentially by some underlying probability distribution, but otherwise makes no assumptions on the nature of the generating distribution nor does it assume the samples are identically distributed.

**Remark IV.1.** Smaller window sizes allow changes in input distribution to reflect in the mistrust scores sooner. We observed that results were relatively robust to a large range of window sizes 15-30 (vision) and 40-60 (audio, EEGs), so we pick 25, 50 respectively to get a hyperparameter free setting.

**V. EXPERIMENTAL SETUP**

To evaluate TRUST-LAPSE, we perform experiments across multiple domains – vision, audio and clinical EEGs. We choose the task of image classification for the visual domain and spoken word classification from audio clips for the audio domain. We further take up the challenging, real-world task of seizure detection from clinical EEG signals, framed as an EEG clip binary classification task for the healthcare domain. Our code (currently given with supplementary material) will be made publicly available on GitHub.

**Audio.** We use raw audio from Google Speech Commands (GSC) dataset (labels: 0-9 + words) [65] and Free Spoken Digits Dataset (FSDD) (labels: 0-9) [66]. We train an M5 encoder [67] with raw audio data from GSC 0-9 and evaluate it on (a) unseen samples from GSC 0-9 (full semantic overlap), (b) FSDD 0-9 (full semantic overlap), and (c) samples from the non-digit words from GSC (no semantic overlap).

**EEG Signals.** We train a Dense-Inception encoder [68] on 19 channel, 200Hz sampling frequency, 60 second clips of EEG data from Stanford Health Care (SHC) (InD: patients 20-60 years) and evaluate it on unseen data from SHC (full semantic overlap), Lucile Packard Children’s Hospital (LPCH) (OOD partial semantic overlap: patients <20 years) and the public Temple University Hospital seizure corpus (TUH) [69], [70] (OOD lesser semantic overlap: different patient demographics, hardware).

**Vision.** We train a ResNet18 [71] encoder, trained on CIFAR10 (OOD) [72], evaluated on unseen data from CIFAR10 (full semantic overlap), CIFAR100 (partial semantic overlap) [72] and SVHN (no semantic overlap) [73]. We also train a LeNet encoder on MNIST (InD) [74], and evaluate it on MNIST-like data i.e., unseen data from MNIST (full semantic overlap), FashionMNIST (no semantic overlap) [75], eMNIST (partial semantic overlap) [76] and kMNIST (no semantic overlap) [77] (collectively referred to as \( x \)-MNIST) datasets for digit classification as is typically reported in literature [15], [55].

Details on data pre-processing, model training, embedding extraction and sequential framework settings in Appendix XI-A.

**Baselines.** We use the following baselines to compare against our framework. We don’t compare with methods that are not post-hoc, that require exposure to outliers, or are not actionable (most existing XAI methods) to match model monitoring settings.

1. MSP [15]: Lower maximum softmax probability (MSP) \( p(\hat{y}|x) = \max_k p(y = k|x) \) as the confidence or uncertainty score, indicating lower trust.
2. Predictive Entropy [55]: Higher entropy of the predicted class distribution – \( \sum_k p(y = k|x) \log p(y = k|x) \) indicates higher mistrust.
3. KL-divergence with Uniform distribution [44]: Lower the KL divergence of the softmax predictions to the uniform distribution \( U \), \( \text{KL}(U||p(y|x)) \), lower the trust.
4. ODIN [39]: use temperature-scaling and input perturbations to MSP to indicate trust. We fix \( T = 1000, \epsilon = 1.4e^{-3} \), following their common setting, instead of tuning the parameters with outlier exposure.
5. Vanilla Mahalanobis [40]: Use the Mahalanobis distance from the nearest class-conditional Gaussian with shared covariance as the trust score. This approach directly fits in with our latent-space distance scoring method (Section IV-A) though we use class-wise covariance matrices.
6. Test-time Dropout [18]: Use Monte Carlo (test-time) dropout to estimate the prediction distribution variance to indicate uncertainty and hence, mistrust. Note that it is computationally intensive requiring \( k \) forward passes of the classifier, with \( k \)-fold increase in runtime. We use \( k = 10 \).

**VI. TRUST-LAPSE EVALUATION FRAMEWORK**

Here, we describe our quantitative evaluation framework from three perspectives. In Section IX, we examine TRUST-LAPSE qualitatively from the lens of explainability.

**A. Evaluating Latent-Space Mistrust Scores**

For all experiments, we evaluate only using samples unseen during training. We empirically evaluate TRUST-LAPSE’s latent-space mistrust scores and all baselines in their ability to
(i) assign high mistrust (flag) when the model should not be trusted, i.e., inputs with large distributional shifts the model cannot generalize to, while (ii) producing low mistrust for trustworthy inputs, i.e., inputs that the model has generalized well to. For this task, our test sets include unseen samples drawn from the same distribution as the training data along with samples from unseen classes (new semantic content) and significantly different datasets (large distributional shifts). We evaluate performance using area under the receiver operating characteristic (AUROC↑), area under the precision-recall curve (AUPR↑) and the false positive rate at 80% true positive rate (FPR80↓). Higher AUROC, AUPR indicate better ability to differentiate between trustworthy and untrustworthy predictions. Higher FPR80 indicates most predictions are not being trusted, leading to algorithm aversion (See Section VII-A).

B. Evaluating Sensitivity to Semantic Content

Ideally, we want methods to flag new semantic content (irrespective of which dataset they belong to) since model predictions on such inputs cannot be trusted, while at the same time being able to identify and not flag semantically-similar inputs (even if they’re from different datasets) as inputs that the model has generalized to. We also follow the setting recommended by [78] to avoid dataset bias during training by holding out few classes from a dataset during training and using the held-out classes as new semantic content for evaluation (See Section VII-B).

C. Evaluating Sequential Mistrust Scores for Model Monitoring

To evaluate TRUST-LAPSE on data drift detection, we generate long sequences of test data by randomly sampling to emulate real-life data streams during continuous model monitoring setups. For each trial, we generate a stream of test data from our test sets of length 10,000 samples with change points inserted every $k$ samples in each trial. Distribution changes are simulated by first randomly choosing InD or OOD (Bernoulli random variable with probability $p \in \{0.2, 0.5, 0.7\}$) and then randomly drawing $k \in \{50, 100, 200, 500, 1000, 5000\}$ samples from the chosen distribution. This simulates various concentrations of OOD data. We evaluate performance metrics such as % error across trials and detection accuracy over $N = 1000$ trials. (See Section VII-C)

VII. RESULTS
A. SOTA Performance on Standard Benchmarks

TRUST-LAPSE’s latent-space mistrust scores achieve the state-of-the-art (SOTA) on distributionally shifted input detection on all metrics across all domains: audio (spoken digit classification), clinical EEG (seizure detection) and vision (image classification) compared to our baselines (Table 1). AUROC values for TRUST-LAPSE scores are 73.9%, 77.1%, and 81.4%, 9, 10 and 12 points higher than the strongest baseline, Test-time Dropout, for the tasks respectively. We further do an ablation in Section VIII-A to examine where the performance benefits are from.

B. Semantic Sensitivity: Exposing Critical Failures in Baselines

We investigate if methods can flag new semantic content even if they’re from the same dataset and not flag inputs with large semantic overlaps even if from different datasets.

Audio. In our audio experiments, we train our encoder only on GSC 0-9 (forming the InD classes) and find that it generalizes well to FSDD 0-9. The other 25 classes in GSC (Yes, No, Right, Left, Bird, etc: GSC-Words) have never been encountered by the model, have drastic semantic shifts in their content when compared to the InD classes 0-9 and predictions on these classes need to be flagged. During evaluation, we show the model unseen samples from each of the classes in GSC along with samples from FSDD 0-9 (same semantic content as InD data but different dataset) and measure which predictions are flagged as untrustworthy. We want methods to flag predictions on GSC-Words yet trust their predictions on GSC 0-9 and FSDD 0-9 (Table II, row Semantic-Split). For comparison, we consider the undesirable counterfactual setting where a method should only trust predictions on GSC 0-9, flagging everything else (even though the model has generalized to predict well over FSDD 0-9). For the counterfactual setting, we see that AUROC values for most baselines, notably Test-time Dropout and Predictive Entropy, increase significantly, whereas they drop for TRUST-LAPSE and vanilla Mahalanobis (Table II, row Dataset-Split). This shows popular baselines have narrow capabilities that assume only data belonging to InD classes and having the same dataset statistics as the training data will trusted, a critical failure. All other data will be flagged, leading to very high false positive rates (FPRs) and algorithm aversion in practice. In contrast, TRUST-LAPSE is able to identify true trustworthy samples despite dataset statistics, and flag new semantic content.

Vision (CIFAR10). For our CIFAR10 experiments, we train our encoder only on 7 classes of CIFAR10, leaving out classes Airplane, Bird and Dog. We study the effect of semantic overlap between the 100 classes from CIFAR100, along with the 3 left out classes from CIFAR10, on the 7 InD classes (Automobile, Cat, Deer, Frog, Horse, Ship, Truck). We analyse class-wise performance and we see that TRUST-LAPSE’s performance strongly correlates to semantic content overlap unlike other methods which seem to rely on dataset statistics. For example, we consider Class Pickup-Truck and Streetcar from CIFAR100. Though they are disjoint from the InD Classes Automobile and Truck in CIFAR10, they share a high degree of semantic overlap and should be considered InD, not flagged. Counterfactually requiring that they must flagged should result in lower performance (Table III, top two rows), performance on classes that don’t share any semantic overlap with the 7 InD classes should remain high (Table III, bottom two rows).

Vision (MNIST). We train two different encoders, one trained on all digits 0-9 while the other was trained on \{0, 1, 4, 6, 7, 8, 9\} leaving digits 2, 3 and 5. Only certain classes from the e-MNIST data share semantic overlap – letters ‘o’, ‘1’, ‘i’, ‘z’, ‘y’, ‘s’ and ‘q’ share structural similarity with classes 0, 1, 2, 4, 5 and 9 respectively. We show results for both encoders with (counterfactual, reduced AUROC) and without the above classes (increased AUROC) in counterfactual
TABLE I: Trust Scoring: Distributionally Shifted Input Detection Performance. Mean scores (standard deviations in parentheses) over 5 random runs are reported. Best scores in bold. TRUST-LAPSE achieves SOTA over all domains and tasks.

| Task (OOD Sets)        | Speech Classification (Other spoken words) | Seizure Detection (Other institutions) | Image Classification (SVHN) |
|------------------------|--------------------------------------------|-----------------------------------------|-----------------------------|
|                         | Audio                                      | EEG Data                                | Vision                      |
|                         | AUROC ↑                                   | AUROC ↓                                  | AUROC ↑                          |
| MSP                     | 62.6 (0.6)                                | 52.7 (0.5)                              | 51.5 (0.6)                  |
| Predictive Entropy      | 61.5 (0.6)                                | 51.5 (0.5)                              | 51.5 (0.9)                  |
| KL_\text{U}            | 55.3 (0.5)                                | 47.5 (0.2)                              | 57.9 (0.7)                  |
| ODIN                    | 46.6 (0.6)                                | 44.8 (1.1)                              | 71.2 (9.2)                  |
| Vanilla Mahalanobis     | 68.0 (1.4)                                | 63.6 (0.9)                              | 52.0 (1.7)                  |
| Test-Time Dropout       | 64.9 (0.3)                                | 61.9 (0.7)                              | 52.3 (0.3)                  |
| TRUST-LAPSE (ours)      | 73.9 (0.6)                                | 70.4 (0.8)                              | 43.9 (0.5)                  |

TABLE II: Semantic Sensitivity - exposing critical failures in baselines. Audio: In audio digit classification, spoken digits from different datasets (full semantic overlap) should result in AUROC ↑. Counterfactually, flagging them (dataset-split) should result in AUROC ↓. Mean over 5 random runs. Best scores in bold. Only TRUST-LAPSE achieves this with competitive performance.

| AUROC                  | Audio                                      | Predictive Entropy | KL_\text{U} | ODIN | Vanilla Mahalanobis | Test-Time Dropout | TRUST-LAPSE (ours) |
|------------------------|--------------------------------------------|--------------------|-------------|------|---------------------|-------------------|--------------------|
| Higher is better ↑     | Semantic-Split                             | 62.1 (0.6)         | 61.1 (0.6)  | 55.0 (0.6) | 46.6 (0.7)         | 67.6 (1.6)        | 64.4 (0.5)         | 73.9 (0.6)         |
| Lower is better ↓      | Dataset-Split                              | 81.8 (0.5)         | 82.1 (0.5)  | 80.6 (0.6) | 67.5 (0.6)         | 49.5 (0.8)        | 82.1 (0.2)         | 50.6 (0.7)         |

evaluations (Table IV).

Clinical EEGs. While discussions on semantic issues on clinical EEGs may be out of scope for this paper, we do observe interesting semantic effects in this case as well. For instance, seizure types unseen by the network will generate higher mistrust scores.

C. Drift Detection with Sequential Mistrust Scores

To evaluate the performance of TRUST-LAPSE on drift detection, we simulate 1000 data streams of 10,000 data points each for each domain, with injected change points as explained in Section VI-C. We then calculate the sequential mistrust scores using the two-sided Mann-Whitney test [64] at a significance level of 0.05 for each sample’s latent-space mistrust score in the stream and run it throughout our sequential detector with window sizes \(w_A = w_B = 25\) for vision experiments and \(w_A = w_B = 50\) for audio and EEG experiments (Remark IV.1). We perform a 2-cluster KMeans [79] on the generated Mann-Whitney scores to assign trust and flag (mistrust) actions. We define the detector to have erred if it wrongly concludes that an incoming test sample’s prediction is to be flagged (assigned high mistrust) when it was actually supposed to be trusted or vice-versa. If the framework detects the change point within its fixed window size, we do not consider it as an error. For each data stream, we then add the errors of all samples to calculate detection error. We repeat this for all \(N = 1000\) streams to estimate the detector’s error distribution across streams. Fig. 3 shows the error distribution over EEG data streams. Over 73% of the streams have less than 10% error and over 93% have less than 20% error. For our audio domain, over 85% of the streams have less than 10% error and over 97% have less than 20% error. For our vision tasks, the error distribution is much tighter and we are able to get near 99% detection accuracy for over 95% of the streams. We show plots of generated trust scores from TRUST-LAPSE and other baselines for parts of audio data streams as examples in Figs. 2, 4 (more plots in Appendix, Figs. 8-9).

VIII. ANALYSES AND ABLATIONS

We perform extensive ablations on TRUST-LAPSE to study the effects of (i) individual components in our mistrust scores (Section VIII-A), (ii) coreset size (Section VIII-B), and (iii) encoder capacity (Section VIII-C) on its performance.

A. Importance of individual components in TRUST-LAPSE

Where do the performance gains of TRUST-LAPSE come from? We study the effect of each individual component in TRUST-LAPSE to answer this question.

Distance Metric. We empirically observed that Mahalanobis distance (M. Dist) outperformed Euclidean (also reported in [40]), Manhattan, and Chebyshev distances. Unlike [42], who use M. Dist with label-smoothing and [40], with shared covariance, we observed M. Dist to perform best with class-wise covariance matrices and without label-smoothing. We found the shared covariance assumption more restrictive and did not fit different types of data. From Table V, we see that it performs worse across all tasks and domains compared to our M. Dist formulation (Section IV-A). We also see that using only our M. Dist follows the same trend as TRUST-LAPSE regarding semantic sensitivity, i.e., it is more sensitive to semantic content than dataset statistics, but its performance is not high enough to be competitive.

Similarity Metric. We see that cosine similarity (C. Sim) is is sensitive to both dataset-statistics and semantic-content. But just using C. Sim can be dangerous since it can be overly sensitive to dataset statistics even if there is no semantic overlap (Table V, audio). In combination with M. Dist, however, TRUST-LAPSE is able to reap the best of both metrics across all tasks and domains (Table V).

Latent-space mistrust (s_{\text{LS}}) vs Sequential mistrust (s_{\text{min}}). Visualizing the scores for a datastore (Fig. 2) shows that...
TABLE III: CIFAR100 Pickup Truck & Street Car share high semantic overlap with InD classes Truck & Automobile. Counterfactually requiring them to be flagged should result in AUROC↓ / AUPR↑ (top set). Airplane & Fish do not show any semantic overlap with InD classes, and should simultaneously result in AUROC↑ / AUPR↑ (bottom set). Vanilla Mahalanobis and Test-Time Dropout achieve high performance in one set (blue) but not the other. KL_U and TRUST-LAPSE achieve peak performance simultaneously in both sets (bold). Mean over 5 random runs.

| (AUROC / AUPR) | CIFAR | MSP | Predictive Entropy | KL_U | ODIN | Vanilla Mahalanobis | Test-Time Dropout | TRUST-LAPSE (ours) |
|----------------|-------|-----|---------------------|------|------|----------------------|-------------------|--------------------|
| Lower is better | Pickup Truck | 79.4 / 29.2 | 79.1 / 27.6 | 69.8 / 18.1 | 81.5 / 18.2 | 69.1 / 20.7 | 94.2 / 50.6 | 68.8 / 18.3 |
| Higher is better | Airplane | 89.1 / 48.8 | 89.4 / 51.9 | 91.3 / 57.1 | 89.3 / 54.9 | 65.8 / 19.2 | 95.5 / 54.7 | 90.2 / 57.5 |

TABLE IV: MNIST. 0to9 denotes encoder trained on 0-9 digits. M235 indicates encoder trained on digits \{0 to 9\} - \{2,3,5\}, i.e., \{0,1,4,6,7,8,9\}. “Semantic” indicates that e-MNIST classes with ambiguous semantic overlap on InD classes, i.e., \{1,i,o,...\} are removed from evaluation. Mean over 5 random runs. Best scores in bold.

| MNIST (AUROC ↓ / AUPR ↑) | MSP | Predictive Entropy | KL_U | ODIN | Vanilla Mahalanobis | Test-Time Dropout | TRUST-LAPSE (ours) |
|---------------------------|-----|--------------------|------|------|----------------------|-------------------|--------------------|
| 0to9                      | 89.5 / 96.8 | 89.9 / 97.1 | 90.3 / 97.2 | 89.6 / 96.9 | 90.3 / 97.3 | 96.3 / 97.3 | 96.1 / 99.0 |
| 0to9 Semantic             | 92.1 / 97.0 | 92.6 / 97.3 | 92.8 / 97.5 | 92.2 / 97.1 | 93.7 / 97.6 | 97.6 / 97.0 | 98.6 / 99.5 |
| M235                      | 90.7 / 98.2 | 91.0 / 98.3 | 90.9 / 98.3 | 90.6 / 98.2 | 91.9 / 98.5 | 97.6 / 98.6 | 97.5 / 99.6 |
| M235 Semantic             | 92.6 / 98.3 | 92.9 / 98.4 | 92.5 / 98.3 | 92.5 / 98.3 | 94.1 / 98.6 | 98.4 / 98.6 | 99.0 / 99.8 |

despite high AUROCs, 9r,s5 (and baselines) show small margins between low mistrust and high mistrust scores and are more sensitive to possible threshold changes. Adding \(s_{\text{min}}\) makes it more robust and easy to interpret.

**Only sequential mistrust scores.** Conceptually, we can use our sequential windowing approach (Section IV-B) directly on the (non-scalar) latent-space embeddings, skipping latent-space mistrust scoring (Section IV-A) entirely. However, [61] shows that hypothesis-based tests such do not scale well to the multivariate case. Hence, we do not consider it a viable option.

TABLE V: Contributions from individual components of TRUST-LAPSE. Details on Semantic- and Dataset-Splits in Section VII-B.

| Score | Audio | CIFAR | MNIST |
|-------|-------|-------|-------|
| Semantic Split AUROC ↑ | Only distance (M. Dist [40]) | 65.8 | 96.2 | 95.1 |
| Only distance (Our M. Dist) | 72.8 | 98.0 | 96.2 |
| Only similarity (ours) | 65.8 | 98.4 | 98.9 |
| Latent-Space Mistrust (ours) | 73.9 | 98.9 | 99.0 |
| Dataset Split AUROC ↓ | Only distance (M. Dist [40]) | 48.0 | 69.4 | 91.9 |
| Only distance (Our M. Dist) | 50.2 | 83.2 | 94.8 |
| Only similarity (ours) | 81.7 | 88.0 | 97.0 |
| Latent-Space Mistrust (ours) | 50.6 | 87.5 | 97.4 |

B. Coreset size

Our latent-space mistrust score uses cosine similarity for pairwise comparison of a test sample’s latent-space embedding with those of training data. This could be computationally intensive, especially for large datasets. We reduce computation costs, memory overhead and latency by using a subset of training data (coreset) instead of the full trainset. The coreset is extracted simply by randomly sampling a fraction from every class in the trainset, unlike complicated strategies used in other works [41]. We see from Table VI that just 2% of the trainset is sufficient to achieve performance similar to the full trainset. In fact, for our clinical EEG task, we use just 2% of the training samples for all experiments and reach the SOTA.

TABLE VI: Coreset Ablations. AUROC for various coreset sizes (% of training samples). Even 2% of training data gives good results.

| Coreset (%) | Audio | CIFAR | MNIST | EEG |
|-------------|-------|-------|-------|-----|
| 1%          | 73.60 | 85.43 | 96.90 | -   |
| 2%          | 73.85 | 85.81 | 97.02 | 77.10 |
| 10%         | 73.90 | 86.20 | 97.10 | -   |
| 100%        | 73.99 | 86.63 | 97.21 | -   |

C. Encoder capacity

**Performance depends on encoder capacity.** We compare two different encoder architectures for our audio task, trained and evaluated identically: (i) a lower capacity encoder, Kymatio [80], InD testset accuracy: 0.75 and (ii) the higher capacity M5 encoder (Section V), InD test set accuracy: 0.85. We observe that TRUST-LAPSE performs worse with Kymatio. It is not able to flag OOD examples (GSC-Words) based on TRUST-LAPSE scores (Fig. 5, top). On the other hand, TRUST-LAPSE performs really well with the M5 encoder (Table VII-A) and is able to correctly separate out semantic InD samples from semantic OOD samples (Appendix Fig. 21, right). Thus, the success of TRUST-LAPSE is highly dependent on the capacity of the trained encoder.

**TRUST-LAPSE detects lack of generalization.** To simulate the setting where a model doesn’t generalize well beyond the test set, we train Kymatio for the same task (i.e., same InD semantic classes 0-9) but with the much smaller FSDD dataset. We see that it reaches 0.97 classification accuracy on the FSDD test set. On evaluation with GSC 0-9, it only gets 0.42 accuracy, showing it does not generalize well. **If we didn’t have access to labelled GSC 0-9 examples (as is common**
in real-world settings), can TRUST-LAPSE identify this lack of generalization? Indeed, we find that TRUST-LAPSE scores for this encoder flag GSC 0-9 examples (Fig. 5, bottom), indicating that the model overfit to FSDD and would not have generalized to GSC 0-9.

IX. Qualitative Explainability Evaluations

TRUST-LAPSE indicates when the model’s prediction should be trusted and when it shouldn’t be. Along with it, TRUST-LAPSE also provides insight about the model’s behaviour when provided with a new input, guiding future actions (accept, reject, flag, abstain, etc) on its prediction. As we saw in Section VIII-C, TRUST-LAPSE informs model generalizability and model error: it can indicate when the model can no longer generalize to incoming data. As such, at a meta-level, TRUST-LAPSE itself needs to be explainable to be of practical value - we need to know why a model’s prediction is to be trusted or not to follow the recommended action. In this section, we will see how to explain scores generated from TRUST-LAPSE. Since TRUST-LAPSE bases its decision on the model’s own latent-space, understanding explanations behind the scores from TRUST-LAPSE inform explanations on the model prediction itself. Note that this is complementary to typical post-hoc explainability methods which typically perform sensitivity analyses [19] on the model directly, with systematic perturbations and observations of performance changes to produce “explanations”.

Explaining Mistrust Scores from TRUST-LAPSE: A recipe for practitioners

Nearest coreset samples in latent-space. To compute latent-space mistrust scores \( s_{LSS} \), TRUST-LAPSE uses coreset samples that are “closest” according to a distance metric \( d \) and similarity metric \( \text{sim} \). Thus, when a new sample is flagged, a practitioner can easily compare it with the closest instances to explain TRUST-LAPSE’s recommendation. By identifying ways in which the new sample is different, both in the input space and in the latent-space, the practitioner can then mitigate in ways specific to the domain.

Samples from the sliding window. Often in real-world applications, as time passes, samples start to drift away from the original expected distribution (especially important in clinical settings) [63]. To compute sequential mistrust scores, TRUST-LAPSE utilizes a sliding window of a fixed window size over the last few samples and compares it with reference window sampled from the coreset. Thus, when TRUST-LAPSE raises an alert, a practitioner can look at the sliding window as a whole and compare it with the reference window to identify drifts that are only visible by looking at many samples at once.

Curating coresets & reference windows. In case the practitioner finds that a model would have performed well on certain samples (trustworthy predictions) but they are being flagged incorrectly by TRUST-LAPSE, the mitigation is easy. The practitioner can simply examine the coreset, add few more
representative samples into it or remove bad samples from it. In the same manner, the practitioner can also update samples in the reference window to improve the sequential mistrust scores. They can choose to observe the scores with several reference windows to see patterns and differences between the flagged samples and the reference samples. Thus, now the practitioner can not only explain TRUST-LAPSE, but very easily improve it as well.

**Qualitative Analysis through Visualizations.** TRUST-LAPSE comes with several visualizations options that make the above explanations and debugging more human-understandable and easy to interpret.

Since the model’s learnt latent-space is key for TRUST-LAPSE performance, we visualize the latent-space embeddings of the coreset and incoming samples using the UMAP [81] tool.

As an example, we take our audio dataset and plot the UMAP embeddings of our raw InD coreset data and their extracted latent-space representations from the trained encoders in Fig. 6, left (UMAP plots for other domains in Appendix, Figs. 15, 16, 17). We see that the raw data are too high-dimensional to be captured according to their class labels by UMAP. On the other hand, the extracted representations arrange themselves in well-separable clusters (Fig. 6, middle) showing the representational capacity of the trained encoder. To a certain extent, the distance score and the similarity score can be visualized in the UMAP embeddings as well for first level debugging, but it is important to note that it is not necessarily distance preserving; it is just a 2D projection of a much higher dimensional latent-space and is bound to be noisy.

The most useful visualization comes from tracking various components of TRUST-LAPSE (i.e the distance and similarity scores, the latent-space mistrust score and the sequential mistrust score) across the datastream on a plot. A practitioner, having access to such plots on their dashboard updated over real-time, can easily explain TRUST-LAPSE scores at a high level. In Figs. 2, 4, we can see, at a glance, how the input data distributions are changing just by looking at the sequential mistrust score plots.

Another useful set of visualizations that can help interpret the scores and explain TRUST-LAPSE’s recommendations is to plot the distribution of scores across different datasets (if in real-time, sets or windows of data sampled from the stream). Fig. 7 shows such a TRUST-SCORE distribution for our EEG domain. TRUST-LAPSE correctly will flag samples from both LPCH (blue) and TUH (green) since the model is trained on SHC (Orange scores: Stan-InD) and hasn’t been fine-tuned. However, on examining Fig. 7, we can infer that LPCH scores are “closer” to SHC scores while TUH scores are much farther out, suggesting that LPCH data distributions to be closer to SHC. This is indeed the case: SHC and LPCH share similar hardware infrastructure, located in the same area, etc. They differ only in the ages of the patient population they serve. TUH, on the other hand, has lot of dissimilarities in hardware, patient populations, age group, etc.
X. Discussion

Corest & Training Data TRUST-LAPSE requires access to trained models along with a small fraction of training data (Section VIII-B). However, in most real settings, training data may not be available easily. In such cases, some known data samples that the model is known to perform well can act as the coreset. Our coreset ablations also paves the way for choosing different data sampling strategies that can ensure more “representational” samples (based on domain knowledge).

Generalization Ideally, high-performing models that are well-trained, rigorously tested and validated ought to generalize well to new environments, populations, and scenarios. However, in reality, they may not do so without needing fine-tuning or retraining. Our preliminary experiments (Section VIII-C) suggest that accurate mistrust scoring from TRUST-LAPSE can pinpoint when the model needs to be fine-tuned or retrained.

Flexibility TRUST-LAPSE can accept any type of distance and similarity metrics as well as sequential mistrust scoring measure. We investigated several classical metrics (Section VIII-A) and verified that our sequential mistrust and latent-space mistrust are complementary. This suggests that there may be more metrics, even learnt ones, which can be easily incorporated into TRUST-LAPSE. Moreover, our sequential formulation provides an opportunity to leverage contextual information present in a set or sequence of inputs which cannot be harnessed by standard approaches that look at samples in isolation. It is independent of latent-score mistrust and can be applied on any score sequence.

XI. Conclusions & Future Work

We develop a mistrust scoring framework, TRUST-LAPSE, that can quantify trustworthiness of model predictions during inference and perform continuous model monitoring. We use the model’s own latent-space representations along with a robust sequential, sliding window test to inform trust in model predictions. Our framework is explainable (each metric and score is human interpretable), post-hoc (can work with any trained model), actionable (automated, fast and provides concrete decisions) and high-performing. We achieve SOTA on distributionally shifted input detection with our approach on three diverse domains – vision, audio and clinical EEGs. Furthermore, we achieve high drift detection rates, crucial for continuous model monitoring. Through our extensive experiments and analyses, we expose critical flaws in current works, provide an explainability workflow and understand where performance benefits come from. We hope TRUST-LAPSE will be adopted for routinely characterizing model trust and model performance in the wild. We will investigate (i) developing alternative, learnt metrics for our latent-space mistrust, (ii) using our sequential windowing approach on other scores apart from latent-space mistrust, and (iii) using our mistrust scores for active learning in future work.

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CODE & DATA AVAILABILITY

All our code for TRUST-LAPSE, baselines and all the experiments presented in the paper will be made publicly available on GitHub. All audio, vision and the TUH datasets are publicly available (Section V). SHC and LPCH data contain patient sensitive information and cannot be shared publicly. Details on data preprocessing steps, experimental settings provided in Appendix XI-A.

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APPENDIX

A. Detailed Experimental Setup

Image Encoders & Pre-processing We carry out our vision experiments using CNN-based classifiers, i.e. the LeNet architecture [74] when working with x-MNIST data and the ResNet18 architecture [71] when working with CIFAR10/100/SVHN data. With the x-MNIST data, we normalize the inputs using the mean and standard deviation calculated from the training set for both training and inference, as is standard. With the CIFAR10/100/SVHN data, we apply the normalization transform along with augmentation strategies (random crop and horizontal flips) during training and only normalization during inference. x-MNIST data have dimensionality $28 \times 28 = 784$ while CIFAR-like data have dimensionality $32 \times 32 \times 3 = 3072$.

Audio Encoders & Pre-processing For our audio experiments, we use the M5 classifier [67] as our encoder. We also train a simple two-layer network – a static, normalized, log-scattering layer that extracts scattering coefficients from audio signals [80] followed by a log-softmax layer that generates output probabilities to compare encoder capabilities (Section VIII-C). Both models are trained only on classes 0-9 from the GSC dataset with the rest of the classes as OOD inputs. In all cases, we learn embeddings directly from raw, one second audio clips (resampled to 8kHz) without making use of any spectrogram features like MFCC [82]. Raw audio data have dimensionality of $1 \times 8000 = 8000$, much larger than the vision datasets.

EEG Encoders & Pre-processing For our seizure detection task, we use the Dense-Inception based models [68] as encoders. We use the same data pre-processing strategy as given by [68]. The models are trained on 19 channel, 12 second or 60 second raw EEG clips from InD datasets, resampled to 200Hz. EEG clips have dimensionality of $60 \times 200 \times 19 = 228,000$, much larger than audio or vision datasets.

Additional Details We train all encoders on InD training data using standard weight initializations, SGD/Adam optimizer and ReLU non-linearities. We train and tune hyperparameters for our encoders using only InD data samples. We don’t expose any outlier data to our encoders. We extract activations from a fully connected (FC) hidden layer before the logits layer to form latent-space representations. We normalize our distance scores and similarity scores before forming the latent-space mistrust scores in cases where one of them is tightly bound while the other is not (for instance, cosine similarity is bound to $[-1, 1]$). For our sequential mistrust scoring, we set window sizes $w_A, w_B = 25$ for vision tasks and $w_A, w_B = 50$ for audio and EEG tasks (Remark IV.1). We choose the reference window by sampling randomly from the training set (or coreset) and using its latent-space mistrust scores in any order. For generating the data streams for drift detection, we randomly shuffle the evaluation set and choose in data points sequentially. We first obtain the latent-space mistrust scores for the evaluation set forming a 1D evaluation sequence, on which we form the sliding window analysis sequentially.

B. Supplementary Tables

Table VII shows performance on CIFAR100 and x-MNIST datasets which have partial semantic overlap between train distribution and test distributions, scores are over 5 random runs. In our MNIST experiments, we see TRUST-LAPSE performs comparably with Test-Time Dropout. It has the best AUPR and comparable AUROC and FPR80 values. When CIFAR100 classes are added (naively considered disjoint from CIFAR10 as in standard benchmarks) to the evaluation, TRUST-LAPSE shows the best AUPR score and the second best AUROC and FPR80.

C. Additional Figures and Visualizations

Drift Detection Some examples of data streams generated from sampling EEG, audio and vision datasets are shown in Figs. 8, 9, 10, 11, 12, 13, and 14). The X axis indicates the time sequence. The Y axis gives the scores (Mann Whitney Scores are the same as mistrust scores). Using a two cluster KMeans algorithm, change points are detected and predictions on individual samples are trusted or flagged.

Latent-Space Visualizations Additional UMAP plots are in Figs. 15, 16, 17.

Distribution Plots of latent-space mistrust scores from TRUST-LAPSE for EEG are shown in Fig. 18 and for GSC (audio) in Fig. 19. For comparison, test-time dropout score distributions are shown in Fig. 20. We see that InD and semantic OOD scores are much more separable for TRUST-LAPSE than Test-Time Dropout.
TABLE VII: OOD performance: CIFAR10 image classification on $x$-MNIST and CIFAR100 which have partial semantic overlap. Mean and standard deviations over five random runs. Best scores indicated in bold.

|               | $x$-MNIST | CIFAR100 |
|---------------|-----------|----------|
|               | AUROC ↑   | AUPR ↑   | FPR80 ↓ | AUROC ↑ | AUPR ↑ | FPR80 ↓ |
| MSP           | 0.899 ± 0.006 | 0.979 ± 0.002 | 0.148 ± 0.012 | 0.852 ± 0.014 | 0.986 ± 0.001 | 0.231 ± 0.018 |
| Predictive Entropy | 0.902 ± 0.006 | 0.981 ± 0.002 | 0.147 ± 0.011 | 0.854 ± 0.014 | 0.986 ± 0.001 | 0.230 ± 0.017 |
| KL-U          | 0.899 ± 0.007 | 0.980 ± 0.002 | 0.164 ± 0.012 | 0.860 ± 0.015 | 0.987 ± 0.001 | 0.223 ± 0.023 |
| ODIN          | 0.898 ± 0.006 | 0.979 ± 0.002 | 0.148 ± 0.015 | 0.845 ± 0.018 | 0.986 ± 0.001 | 0.251 ± 0.031 |
| Vanilla Mahalanobis | 0.918 ± 0.006 | 0.984 ± 0.001 | 0.118 ± 0.015 | 0.679 ± 0.012 | 0.967 ± 0.001 | 0.558 ± 0.025 |
| Test-Time Dropout | **0.976 ± 0.002** | **0.986 ± 0.001** | **0.016 ± 0.001** | **0.925 ± 0.004** | 0.986 ± 0.000 | **0.049 ± 0.003** |
| TRUST-LAPSE (ours) | **0.972 ± 0.002** | **0.995 ± 0.000** | 0.037 ± 0.038 | 0.866 ± 0.008 | **0.988 ± 0.001** | 0.239 ± 0.028 |

Fig. 8: (left) Snapshot of the TRUST-LAPSE mistrust scores. Within a window of 15 samples, it is able to detect the change point for the seizure detection task. (right) % Error distribution over 1000 trials.

Fig. 9: Drift Detection (MNIST): Data stream with distribution shifts occurring every 500 steps. The orange lines indicate true change points. Blue plot represents the sequential mistrust scores.
Sequential Mistrust Score shows the most separability between trustworthy (blue low segment) and to be flagged (blue high segment) points.

Fig. 10: Trust scores from Baselines and TRUST-LAPSE (CIFAR).

Fig. 11: Trust scores from Baselines and TRUST-LAPSE (MNIST). Sequential Mistrust Score shows the most separability between trustworthy (blue low segment) and to be flagged (blue high segment) points.
Fig. 12: Drift Detection: Data stream with distribution shifts occurring every 500 steps. The orange lines indicate true change points. Blue plot represents the sequential mistrust scores.

Fig. 13: Drift Detection: Data stream with distribution shifts occurring every 100 steps. The orange lines indicate true change points. Blue plot represents the sequential mistrust scores.

Fig. 14: Drift Detection (CIFAR): Data stream with distribution shifts occurring every 500 steps. The orange lines indicate true change points. Blue plot represents the sequential mistrust scores.
Fig. 15: UMAP embeddings of CIFAR data (left) raw InD data (middle) representations from the trained encoder, i.e. a 2D projection of the latent-space (c) Semantic OOD samples added to the mix (only few classes are shown for visualization purposes).

Fig. 16: UMAP embeddings of MNIST data (left) raw InD data (middle) representations from the trained encoder, i.e. a 2D projection of the latent-space (c) Semantic OOD samples added to the mix (only few classes are shown for visualization purposes).
Fig. 17: UMAP embeddings of EEG data: Representations from the trained encoder, i.e. a 2D projection of the latent-space are visualized here.
Fig. 18: TRUST-LAPSE scores distribution on EEG data

Fig. 19: TRUST-LAPSE scores distribution on GSC (audio). InD and OOD classes are more separable.

Fig. 20: Test-time Dropout scores distribution on GSC (audio). InD and OOD classes are less separable.
Fig. 21: Distribution of TRUST-LAPSE scores across semantic InD (GSC 0-9, FSDD 0-9) and OOD classes with (left) Kymatio encoder, (right) M5 encoder, class-wise OOD scores are shown. GSC 0-9 and FSDD 0-9 are merged here and only part of the full list of OOD classes shown. All GSC OOD classes are merged together as green in the left figure.

Fig. 22: Distribution of TRUST-LAPSE scores with trained Kymatio encoder. (left) Kymatio encoder trained with GSC 0-9 data, achieving 0.75 classification accuracy. The InD scores from the two datasets (blue and orange) are indistinguishable (right) Kymatio encoder trained with FSDD 0-9 data, achieving 0.97 classification accuracy. The InD scores between the two datasets are separable, showing that it has overfit to the dataset statistics.