Topological Uncertainty: Monitoring trained neural networks through persistence of activation graphs

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Abstract

Although neural networks are capable of reaching astonishing performances on a wide variety of contexts, properly training networks on complicated tasks requires expertise and can be expensive from a computational perspective. In industrial applications, data coming from an open-world setting might widely differ from the benchmark datasets on which a network was trained. Being able to monitor the presence of such variations without retraining the network is of crucial importance. In this article, we develop a method to monitor trained neural networks based on the topological properties of their activation graphs. To each new observation, we assign a Topological Uncertainty, a score that aims to assess the reliability of the predictions by investigating the whole network instead of its final layer only, as typically done by practitioners. Our approach entirely works at a post-training level and does not require any assumption on the network architecture, optimization scheme, nor the use of data augmentation or auxiliary datasets; and can be faithfully applied on a large range of network architectures and data types. We showcase experimentally the potential of Topological Uncertainty in the context of trained network selection, Out-Of-Distribution detection, and shift-detection, both on synthetic and real datasets of images and graphs.

1 Introduction

Over the last decade, Deep Learning (DL) has become the most popular approach to tackle complex machine learning tasks, opening the door to a broad range of industrial applications. Despite its undeniable strengths, monitoring the behavior of deep Neural Networks (NN) in real-life applications can be challenging. The more complex the architectures become, the stronger the predictive strengths of the networks, but the looser our grasp on their behaviors and weaknesses.

Training a neural network requires task-specific expertise, is time consuming, and requires the use of high-end expensive hardware. With the rise of companies providing model marketplaces (e.g., [Kumar et al., 2020, §, Table 1] or tensorflow-hub), it is now common that users only have access to fixed trained neural networks, with few information on the training process, and would rather avoid training the networks again.

In practice, a network can perform well on a given learning problem—in the sense that it can achieve high accuracy on the training and test sets—, but lack reliability when used in real-life applications thereafter. One can think of, among other examples, adversarial attacks, that are misinterpreted by neural networks with high confidence levels [Nguyen et al., 2015; Akhtar and Mian, 2018; Biggio and Roli, 2018], calibration issues leading to under- or over-confident predictions [Guo et al., 2017; Ovadia et al., 2019; Hein et al., 2019], lack of robustness to corruption or perturbation of the input data [Hendrycks and Dietterich, 2019].

Related work. Many techniques have been proposed to improve or monitor the behavior of NN deployed in real-life applications. Most require specific actions taken during the training phase of the network; for instance via data augmentation [Shorten and Khoshgoftaar, 2019]), the use of large auxiliary datasets\textsuperscript{1} [Hendrycks et al., 2019], mod-

\textsuperscript{1}In particular, the 80 million tiny images dataset [Torralba et al., 2008], used as an auxiliary dataset in state-of-the-art OOD detection techniques [Chen et al., 2020], has been withdrawn

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ulations of the network architecture [DeVries and Taylor, 2018] or its objective function [Atzmon et al., 2019; Van Amersfoort et al., 2020], or using several networks at once to produce predictions [Lakshminarayanan et al., 2017].

The approach we introduce in this article focuses on acting at a post-training level only, and since our goal is to benchmark it against the use of confidence alone in a similar setting, we use, in our experimental results, the baseline introduced in [Hendrycks and Gimpel, 2017], which proposes to monitor NNs based on their confidences and on the idea that low-confidence predictions may account for anomalies.

Using topological quantities to investigate NN properties has experienced a growth of interest recently (see for instance [Guss and Salakhutdinov, 2018; Carlsson and Gabrielsson, 2020]). In [Gebhart and Schrater, 2017; Gebhart et al., 2019], the authors introduce the notion of activation graphs and showcase their use in the context of adversarial attacks. We mix this idea with [Rieck et al., 2019], which proposes to investigate topological properties of NN layer-wise. A topological score based on an estimation of the NN decision boundary has been proposed in [Ramamurthy et al., 2019] to perform trained network selection, an idea we adapt in Subsection 4.1.

Contributions. In this work, we propose a new approach to monitor trained NNs by leveraging the topological properties of activation graphs. Our main goal is to showcase the potential benefits of investigating network predictions through the lens of the whole network instead of looking at its confidence encoded by its final layer only as usually done in practice.

To that aim, we introduce Topological Uncertainty (TU), a simple topological quantity that, for a given NN and a new observation, encodes how the network “reacts” to this observation, and whether this reaction is similar to the one on training data. Our approach does not require any assumption on the network training phase nor the type of input data, and can thus be deployed in a wide variety of settings. Furthermore, it only relies on computing maximum spanning trees (MST), leading to a simple and efficient implementation.

Experimentally, we show that TU can be used to monitor trained NNs and detect Out-of-Distribution (OOD) or shifted samples when deployed in real-life applications. Our results suggest that TU can drastically improve on a standard baseline based on the network confidence in different situations. Our implementation will be made publicly available.

2 Background

2.1 Neural networks

For the sake of clarity, we restrict our presentation to sequential neural networks, although our approach (detailed in Section 3) can be generalized to more general architectures, e.g., recurrent neural networks. We also restrict to classification tasks; let \( d \) denote the dimension of the input space and \( K \) be the number of classes. A (sequential) neural network

(NN) learns a function \( F: \mathbb{R}^d \rightarrow \mathbb{R}^K \) that can be written as

\[
F = f_L \circ \cdots \circ f_1,
\]

where \( \{f_\ell\}_{\ell=1}^L \) are elementary blocks defined for \( \ell = 1, \ldots, L \) as

\[
x_{\ell+1} = f_\ell(x_\ell) = \sigma_\ell(W_\ell \cdot x_\ell + b_\ell),
\]

with \( W_\ell \in \mathbb{R}^{d_\ell \times d_{\ell+1}}, b_\ell \in \mathbb{R}^{d_{\ell+1}}, \) and \( \{\sigma_\ell\} \) are activation maps, e.g., \( \sigma_\ell = \text{ReLU} : x \mapsto \max\{x, 0\} \). In classification tasks, the final activation \( f_L = \sigma_L \) is usually taken to be the soft-max function, so that the output \( x_L = F(x) \) can be understood as a probability distribution on \( \{1, \ldots, K\} \) whose entries \( \{F(x)_k\}_k \) indicate the likelihood that \( x \) belongs to class \( k \). The predicted class is thus \( \arg \max_k \{F(x)_k\} \), while the confidence that the network has in its prediction is \( \max_k \{F(x)_k\} \in [0, 1] \). Given a training set of observations and labels \( \{X^{\text{train}}, Y^{\text{train}}\} = (x_i, y_i)_{i=1}^{N_{\text{train}}} \) distributed according to some (unknown) joint law \( (X, Y) \), the network parameters \( W_\ell, b_\ell \) are optimized to minimize the loss \( \sum \mathcal{L}(F(x_i), y_i) \) for some loss function \( \mathcal{L} \) (e.g., the categori-cal cross-entropy). The training accuracy of \( F \) is defined as

\[
\frac{1}{N_{\text{train}}} \sum_{i=1}^{N_{\text{train}}} \mathbb{1}[\arg \max_{y} \mathcal{L}(F(x_i)) = y_i].
\]

2.2 Activation graphs and topological descriptors

Activation graphs. Let us consider a neural network \( F \) and two layers of size \( d_\ell \) and \( d_{\ell+1} \) respectively, connected by a matrix \( W_\ell \in \mathbb{R}^{d_\ell \times d_{\ell+1}} \). One can build a bipartite graph \( G_\ell \) whose vertex set is \( V_\ell \sqcup V_{\ell+1} \) with \( |V_\ell| = d_\ell \) and \( |V_{\ell+1}| = d_{\ell+1} \), and edge set is \( E_\ell = V_\ell \times V_{\ell+1} \). Following [Gebhart et al., 2019], given an instance \( x \in \mathbb{R}^d \), one can associate to each edge \( (i, j) \in E_\ell \) the weight \( |W_\ell(i, j) \cdot x_\ell(i)| \), where \( x_\ell(i) \) (resp. \( W_\ell(i, j) \)) denotes the \( i \)-th coordinate of \( x_\ell \in \mathbb{R}^d \) (resp. entry \( (i, j) \) of \( W_\ell \in \mathbb{R}^{d_\ell \times d_{\ell+1}} \)). Intuitively, the quantity \( |W_\ell(i, j) \cdot x_\ell(i)| \) encodes how much the observation \( x \) “activates” the connection between the \( \ell \)-th unit of the \( \ell \)-th layer and the \( j \)-th unit of the \((\ell + 1)\)-th layer of \( F \). In this way, we obtain a sequence of bipartite graphs \( (G_\ell(x, F))_\ell \) called the activation graphs of the pair \((x, F)\), whose vertices are \( V_\ell \sqcup V_{\ell+1} \) and edges weights are given by the aforementioned formula.

Maximum spanning trees and persistence diagrams. To summarize the information contained in these possibly large graphs in a quantiative way, we rely on topological descriptors called persistence diagrams, coming from the Topological Data Analysis (TDA) literature. A formal introduction to TDA is not required in this work (we refer to the appendix for a more general introduction): in our specific case, persistence diagrams can be directly defined as the distribution of weights of a maximum spanning tree (MST). We recall that given a connected graph \( G \) with \( N \) + 1 vertices, a MST is a connected acyclic sub-graph of \( G \) sharing the same set of vertices such that the sum of the \( N \) edge weights is maximal among such sub-graphs. MST can be computed efficiently, namely in quasi-linear time with respect to the number of edges in \( G \). Given the ordered weights \( w_1 \geq \cdots \geq w_N \) of a MST built on top of a graph \( G \), its persistence diagram is

\[3\]Note that this formalism encompasses both fully-connected and convolutional layers that are routinely used by practitioners.
the one-dimensional probability distribution
\[ \mu(G) := \frac{1}{N} \sum_{i=1}^{N} \delta_{w_i}, \]
where \( \delta_{w_i} \) denotes the Dirac mass at \( w_i \in \mathbb{R} \). See Figure 2 for an illustration.

Comparing and averaging persistence diagrams. The standard way to compare persistence diagrams relies on \textit{optimal partial matching metrics}. The choice of such metrics is motivated by stability theorems that, in our context, imply that the map \( x \mapsto \mu(G_r(x, F)) \) is Lipschitz with Lipschitz constant that only depends on the network architecture and weights\(^4\) (and not on properties of the distribution of \( x \sim X \) for instance). The computation of these metrics is in general challenging [Kerber \textit{et al.}, 2017]. However, in our specific setting, the distance \( \text{Dist}(\mu, \nu) \) between two diagrams \( \mu = \frac{1}{N} \sum_{i=1}^{N} \delta_{w_i} \) and \( \nu = \frac{1}{N} \sum_{i=1}^{N} \delta_{w_i'} \) can be simply obtained by computing a 1D-optimal matching\(^4\), which in turn only requires to match points in increasing order, leading to the simple formula
\[ \text{Dist}(\mu, \nu)^2 = \frac{1}{N} \sum_{i=1}^{N} |w_i - w_i'|^2, \]
where \( w_1 \geq w_2 \geq \cdots \geq w_N \) and \( w_1' \geq w_2' \geq \cdots \geq w_N' \).

With this metric comes a notion of \textit{average persistence diagram}, called a \textit{Fréchet mean} [Turner \textit{et al.}, 2014]: a Fréchet mean \( \overline{\mu} \) of a set of \( M \) diagrams \( \mu_1, \ldots, \mu_M \) is a minimizer of \( \nu \mapsto \sum_{m=1}^{M} \text{Dist}(\mu_m, \nu)^2 \), which in our context simply reads
\[ \overline{\mu} := \frac{1}{M} \sum_{m=1}^{M} \delta_{\bar{w}_i}, \]
where \( \bar{w}_i = \frac{1}{M} \sum_{m=1}^{M} w_i^{(m)} \) and \( w_i^{(m)} \) denotes the \( i \)-th point of \( \mu_m \). The Fréchet mean provides a geometric way to concisely summarize the information contained in a set of persistence diagrams.

3 Topological Uncertainty (TU)

Building on the material introduced in Section 2, we propose the following pipeline, which is summarized in Figure 2. Given a trained network \( F : \mathbb{R}^d \rightarrow \mathbb{R}^K \) and an observation \( x \), we build a sequence of activation graphs \( G_1(x, F), \ldots, G_{L-1}(x, F) \). We then compute a MST of each \( G_\ell(x, F) \), which in turn induces a persistence diagram \( D_\ell(x, F) := \mu(G_\ell(x, F)) \).

\textbf{Topological Uncertainty.} Given a network \( F : \mathbb{R}^d \rightarrow \mathbb{R}^K \) trained on a set \( X^{\text{train}} \), one can store the corresponding sequence of diagrams \( (D_\ell(x^{\text{train}}, F)) \) for each \( x^{\text{train}} \in X^{\text{train}} \). These diagrams summarize how the network is activated by the training data. Thus, given a new observation \( x \) with \( \arg \max(F(x)) = k \), one can compute the sequence \( (D_\ell(x, F))_k \) and then the quantity
\[ \min_{x^{\text{train}} \in X^{\text{train}}} \text{Dist}(D_\ell(x, F), D_\ell(x^{\text{train}}, F)), \]
that is, comparing \( D_\ell(x, F) \) to the diagrams of training observations that share the same predicted label than \( x \). Figure 1 (right) shows how this quantity evolves over the plane, and how, contrary to the network confidence (left), it allows one to detect instances that are far away from the training distribution.

Since storing the whole set of training diagrams for each class and each layer \( \{D_\ell(x^{\text{train}}, F) : \arg \max(F(x^{\text{train}})) = k \} \) might be inefficient in practice, we propose to summarize these sets through their respective Fréchet means \( \overline{D_\ell}^{\text{train}} \).

For a new observation \( x \in \mathbb{R}^d \), let \( k(x) = \arg \max(F(x)) \) be its predicted class, and \( (D_\ell(x, F))_k \) the corresponding persistence diagrams. The \textbf{Topological Uncertainty} of \( x \) is defined to be
\[ TU(x, F) := \frac{1}{L} \sum_{\ell=1}^{L} \text{Dist}(D_\ell(x, F), \overline{D_\ell}^{\text{train}}), \]
which is the average distance over layers between the persistence diagrams of the activation graphs of \( (x, F) \) and the average diagrams stored from the training set. Having a low TU suggests that \( x \) activates the network \( F \) in a similar way to the points in \( X^{\text{train}} \) whose class predicted by \( F \) was the same as \( x \). Conversely, an observation with a high TU (although being possibly classified with a high confidence) is likely to account for an OOD sample as it activates the network in an unusual manner.

\textbf{Remarks.} Our definition of activation graphs differs from the one introduced in [Gebhart \textit{et al.}, 2019], as we build one activation graph for each layer, instead of a single, possibly very large, graph on the whole network. Note also that the definition of TU can be declined in a variety of ways. First, one does not necessarily need to work with all layers \( 1 \leq \ell \leq L \), but can only consider a subset of those. Similarly, one can estimate Fréchet means \( \overline{D_\ell}^{\text{train}} \) using only a subset of the training data. These techniques might be of interest when dealing with large datasets and deep networks. One could also replace the Fréchet mean \( \overline{D_\ell}^{\text{train}} \) by some other diagram of interest; in particular, using the empty diagram instead allows us to retrieve a quantity analogous to the \textit{Neural persistence} introduced in [Rieck \textit{et al.}, 2019]. On an other note, there are other methods to build persistence diagrams on top of activation graphs that may lead to richer topological descriptors, but our construction has the advantage of returning diagrams supported on the real line (instead of the plane as it usually occurs in TDA) with fixed number of points, which dramatically simplifies the computation of distances and Fréchet means, and makes the process efficient practically.

4 Experiments

This section showcases the use of TU in different contexts: trained network selection (§4.1), monitoring of trained networks that achieve large train and test accuracies but have not been tweaked to be robust to Out-Of-Distribution observations (§4.2) or distribution shift (§4.3).

\textbf{Datasets and experimental setting.} We use standard, publicly available, datasets of graphs and images. MNIST,
Figure 2: Pipeline presented in this article: Each observation activates the network with a weight \(|W_{\ell}(i, j) \cdot x_{\ell}(i)|\) on the edge connecting the \(i\)-th unit in the \(\ell\)-th layer to the \(j\)-th unit of the \((\ell + 1)\)-th layer. A maximum spanning tree is then computed for each layer \(\ell\) of the network, whose distribution of weights provides a corresponding persistence diagram. On this example, the network used is a simple network with two hidden-layers of 64 units each with ReLU activation, each layer is fully-connected (dense matrix).

Figure 3: Score and accuracies obtained on 45 models trained on the MNIST dataset when fed with a set \(X_{1,0}\) of images representing 0 and 1 digits. The point annotations refer to the values \((i, j)\) on which the network was initially trained. For instance, a network trained on 7 and 4 has a score of 0.49 and an accuracy of \(\sim 75\%\) on \(X_{1,0}\).

Fashion-MNIST, CIFAR-10, SVHN, DTD are datasets of images, while MUTAG and COX2 are datasets of graphs coming from a chemical framework. We also build two OOD image datasets, Gaussian and Uniform, by randomly sampling pixel values following a Gaussian distribution (resp. uniform on the unit cube). A detailed report of datasets and experimental settings (data preprocessing, network architectures and training parameters, etc.) can be found in the appendix.

4.1 Trained network selection for unlabeled data

In this subsection, we showcase our method in the context of trained network selection through an experiment proposed in [Ramamurthy et al., 2019, §4.3.2]. Given a dataset with 10 classes (here, MNIST or Fashion-MNIST), we train 45 NNs on the binary classification problems \(i\) vs. \(j\) for each pair of classes \((i, j)\) with \(i > j\), and store the average persistence diagrams of the activation graphs for the different layers and classes as explained in Section 3. These networks are denoted by \(F_{i,j}\) in the following, and consistently reach high accuracies on their respective training and test sets given the simplicity of the considered tasks. Then, for each pair of classes \(k_1 > k_2\), we sample a set of new observations \(X_{k_1,k_2}\) made of 200 instances sampled from the test set of the initial dataset (in particular, these observations have not been seen during the training of any of the \((F_{i,j})_{i,j}\) whose labels are \(k_1\) and \(k_2\). Assume now that \(k_1, k_2\) and the labels of our new observations are unknown. The goal is to select a network that is likely to perform well on \(X_{k_1,k_2}\) among the \((F_{i,j})_{i,j}\). To that aim, we compute a score for each pairing \((k_1, k_2) \leftrightarrow (i, j)\), which is defined as the average TU (see Eq. (1)) when feeding \(F_{i,j}\) with \(X_{k_1,k_2}\). A low score between \((i, j)\) and \((k_1, k_2)\) suggests that \(X_{k_1,k_2}\) activates \(F_{i,j}\) in a "known" way, thus that \(F_{i,j}\) is likely to be a relevant classifier for \(X_{k_1,k_2}\), while a high score suggests that the data in \(X_{k_1,k_2}\) is likely to be different from the one on which \(F_{i,j}\) was trained, making it a less relevant choice. Figure 3 plots the couple (scores, accuracies) obtained on MNIST when taking \((k_1, k_2) = (1, 0)\), that is, we feed networks that have been trained to classify between \(i\) and \(j\) handwritten digits with images representing 0 and 1 digits. Not surprisingly, \(F_{1,0}\) achieves both a small TU (thus would be selected by our method) and a high accuracy. On the other hand, using the model \(F_{7,6}\) on \(X_{1,0}\) leads to the highest score and a low accuracy.

To quantitatively evaluate the benefit of using our score to select a model, we use the the metric proposed by [Ramamurthy et al., 2019]: the difference between the mean accuracy obtained using the 5 models that have the lowest scores and the 5 models that have the highest scores. We obtain a \(+14.8\%\)-increase on MNIST and a \(+12.6\%\)-increase on Fashion-MNIST. These positive values indicate that, on average, using low TU as a criterion helps to select a better model to classify our new set of observations. As a comparison, using the average network confidence as a score leads
to +6.6% on MNIST and +4.7% on Fashion-MNIST, indicating that using (high) confidence to select a model would be less relevant than using TU, on average. See the appendix for a complementary discussion.

Remark. Our setting differs from the one of [Ramamurthy et al., 2019]: in the latter work, the method requires to have access to true labels on the set of new observations \(x_{k_1,k_2}\) (which we do not), but do not need to evaluate \(F_{ij}(x)\), \(x \in X_{k_1,k_2}\) on each model \(F_{ij}\) (which we do). To that respect, we stress the complementary aspect of both methods.

### 4.2 Detection of Out-Of-Distribution samples

The following experiment illustrates the behavior of TU when a trained network faces Out-Of-Distribution (OOD) observations, that is, observations that are not distributed according to the training distribution. To demonstrate the flexibility of our approach, we present the experiment in the context of graph classification, relying on the COX2 and the MUTAG graph datasets. Complementary results on image datasets can be found in Table 1 and in the appendix. Working with these datasets is motivated by the possibility of using simple networks while achieving reasonably high accuracies which are near state-of-the-art on these sets. To train and evaluate our networks, we extract 40 spectral features from graphs—thus representing a graph by a vector in \(\mathbb{R}^{10}\)—following a procedure proposed in [Carrière et al., 2020]. See the appendix for details.

For both datasets, we build a set of 100 fake graphs in the following way. Let \(N\) and \(M\) be the distributions of number of vertices and number of edges respectively in a given dataset (e.g., graphs in MUTAG have on average 17.9 ± 4.6 vertices and 19.8 ± 5.7 edges). Fake graphs are sampled as Erdős-Rényi graphs of parameters \((n, m/n^2)\), with \(n \sim N\), \(m \sim M\), thus by construction fake graphs have (on average) the same number of vertices and edges as graphs from the training dataset. These sets are referred to as Fake-MUTAG and Fake-COX2, respectively.

Now, given a network \(F_{\text{MUTAG}}\) trained on MUTAG (resp. \(F_{\text{COX2}}\) trained on COX2), we store the average persistence diagrams of each classes. It allows us to compute the corresponding distribution of TUs \(T_{\text{train}} = \{T(U(x, F_{\text{MUTAG}})) : x \in \text{MUTAG}\}\) (resp. \(T(U(x, F_{\text{COX2}}))\)). Similarly, we evaluate the TUs of graphs from the Fake-MUTAG (resp. Fake-COX2) and from COX2 (resp. MUTAG). These distributions are shown on Figure 4 (second and fourth plots, respectively). As expected, the TUs of training inputs \(T_{\text{train}}\) are concentrated around low values. Conversely, the TUs of OOD graphs (both from the Fake dataset and the second graph dataset) are significantly higher. Despite these important differences in terms of TU, the network still shows confidence near 100% (first and third plots) over all the OOD datasets, making this quantity impractical for detecting OOD samples.

To quantify this intuition, we propose a simple OOD detector. Let \(F\) be a network trained on MUTAG or COX2, with distribution of training TUs \(T_{\text{train}}\). A new observation \(x\) is classified as an OOD sample if \(T(U(x, F))\) is larger than the \(q\)-th quantile of \(T_{\text{train}}\). This classifier can be evaluated with standard metrics used in OOD detection experiments: the False Positive Rate at 95% of True Positive Rate (FPR at 95%TPR), and the Area Under the ROC Curve (AUC). We compare our approach with the baseline introduced in [Hendrycks and Gimpel, 2017] based on confidence only: a point is classified as an OOD sample if its confidence is lower than the \(q\)-th quantile of the distribution of confidences of training samples. As recorded in Table 1, this baseline performs poorly on these graph datasets, which is explained by the fact that (perhaps surprisingly) the assumption of loc. cit. that training samples tend to be assigned a larger confidence than OOD-ones is not satisfied in this experiment. In the third row of this Table, we provide similar results for a network trained on CIFAR-10 using other image datasets as OOD sets. Although in this setting TU is not as efficient as it is on graph datasets, it still improves on the baseline reliably.

### 4.3 Sensitivity to shifts in sample distribution

This last experimental subsection is dedicated to distribution shift. Distribution shifts share similar ideas with OOD-detection, in the sense that the network will be confronted to samples that are not following the training distribution. However, the difference lies in the fact that these new observations are shifted instances of observations that would be sampled with respect to the training distribution. In particular, shifted instances still have an underlying label that one may hope to recover. Formally, given a training distribution \(\mathcal{X}\) and a parametric family of shifts \((s_\gamma)\) with the convention that \(s_0 = \text{id}\), a shifted sample with level of shift \(\gamma\) is a sample \(s_\gamma(x_1), \ldots, s_\gamma(x_N)\), where \(x_1, \ldots, x_N \sim \mathcal{X}\) with underlying labels \(y_1, \ldots, y_N\). For instance, given an image, one can apply a corruption shift of parameter \(\gamma = n \in \mathbb{N}\) where \(s_\gamma(x)\) consists of randomly switching \(n\) pixels of the image \(x(x_{ij} \mapsto 1 - x_{ij})\). See the top row of Figure 5 for an illustration.

Ideally, one would hope a trained network \(F\) to be robust to shifts, that is \(\arg \max(F(x)) = \arg \max(F(s_\gamma(x)))\). However, since the map \(x \mapsto s_\gamma(x)\) cannot be inverted in general, one cannot realistically expect robustness to hold for high levels of shift. Here, we illustrate how TU can be used as a way to monitor the presence of shifts that would lead to a dramatic diminution of the network accuracy in situations where the network confidence would be helpless.

For this, we train a network on MNIST and, following the methodology presented in Section 3, store the corresponding average persistence diagrams for the 10 classes appearing in the training set. We then expose a batch of 1000 obser-
general will be the focus of further works.

Studying (see the appendix for complementary experiments involving Topological Uncertainty, and more generally activation graphs, when it comes to understand and monitor changes in the network’s confidence. These changes are likely to reflect a shift in the distribution of observations (that is, the proportion of observations that are still correctly classified). (right) The confidence of the network in its predictions. Although the accuracy is dropping significantly, the network remains overall extremely confident in its predictions.

5 Conclusion and perspectives

Monitoring trained neural networks deployed in practical applications is of major importance and is challenging when facing samples coming from a distribution that differs from the training one. While previous works focus on improving the behavior of the network confidence, in this article we propose to investigate the whole network instead of restricting it to its final layer. By considering a network as a sequence of bipartite graphs on top of which we extract topological features, we introduce the Topological Uncertainty, a tool to compactly quantify if a new observation activates the network in the same way as training samples did. This notion can be adapted to a wide range of networks and is entirely independent from the way the network was trained. We illustrate numerically how it can be used to monitor networks and how it turns out to be a strong alternative to network confidence on these tasks. We will make our implementation publicly available.

We believe that this work will motivate further developments involving Topological Uncertainty, and more generally activation graphs, when it comes to understand and monitor neural networks. In particular, most techniques introduced in recent years to improve confidence-based descriptors may be declined to be used with Topological Uncertainty. These trails of research will be investigated in future work.
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A Elements of Topological Data Analysis and theoretical considerations

A.1 Construction of persistence diagrams for activation graphs.

In this section, we provide a brief introduction to Topological Data Analysis (TDA) and refer to [Edelsbrunner and Harer, 2010; Oudot, 2015; Chazal and Michel, 2017] for a more complete description of this field.

Let $X$ be a topological space and $f: X \to \mathbb{R}$ be a real-valued continuous function. The sublevel set of parameter $t$ of $(X,f)$ is the set $F_t := \{ x \in X : f(x) \leq t \} \subseteq X$. As $t$ increases from $-\infty$ to $+\infty$, one gets an increasing sequence (i.e., nested with respect to the inclusion) of topological spaces called the filtration of $X$ by $f$. Given such a filtration, persistent homology tracks the times $t$ of appearance and disappearance of topological features (such as connected components, loops, cavities, etc.). For instance, a new connected component may appear at time $t_1$ in the sublevel set $F_{t_1}$, and may disappear—that is, it may get merged with an already present, other connected component—at time $t_2 \geq t_1$. We say that this connected component persists over the interval $[t_1, t_2]$ and we store the pairs $(t_1, t_2)$ as a point cloud in the Euclidean plane called the persistence diagram of the sublevel sets of $(X,f)$. Persistence diagrams of the sublevel sets are defined similarly. We refer to Figure 6 for an illustration.

Now, given a graph $G = (V,E)$ and a weight function $w: E \to \mathbb{R}$, we build a superlevel set persistence diagram as follows: at $t = +\infty$ (i.e., at the very beginning), we add all the nodes $V$. Then, we build a sequence of subgraphs $G_t = \{ (V,E_t) \}$ with $E_t = \{ e \in E : w(e) \geq t \}$, that is, we add edges in decreasing order with respect to their weights. In this process, no new connected component can be created (we never add new vertices), and each new edge inserted at time $t$ either connects two previously independent components leading to a point with coordinates $(+\infty, t)$ in the persistence diagram, or creates a new loop in the graph. In our construction, we propose to only keep track of connected components (0-dimensional topological features). Since all points in the persistence diagram have $+\infty$ as first coordinate, we simply discard it and end up with a distribution of real numbers $t_1 \geq \cdots \geq t_N$, where $N = |V| - 1$, which exactly corresponds to the weights of a maximum spanning tree built on top of $G$, see for instance [Doraiswamy et al., 2020, Proof of Lemma 2] for a proof.

Therefore, in our setting, we can compute the persistence diagram of an activation graph $G_t(x,F)$ connecting two layers, using the weight function $w: e \mapsto \|W_l(i,j)x_l(i)\|$, where $e$ is the edge connecting the $i$-th unit of the input layer to the $j$-th unit of the output layer.

A comparison with Neural persistence. Given a bipartite graph, the construction we propose is exactly the one introduced in [Rieck et al., 2019]. The difference between the two approaches is that loc. cit. works with the network weights $\|W_l(i,j)\|$ directly, obtaining one graph for each layer of the network $F$, while we use activation graphs $G_t(x,F)$ with weights $\|W_l(i,j)x_l(i)\|$, so that we obtain one graph per ob-
Persistence x for each layer of the network. Then, both approaches compute a persistence diagram (MST) on top of their respective graphs. The second difference is that, in order to make use of their persistence diagrams in a quantitative way, [Rieck et al., 2019] proposes to compute their total persistence, which is exactly the distance between a given diagram and the empty one (forcing to match all the points of the given diagram onto the diagonal Δ). Taking advantage of the fact that our diagrams always have the same number of points (determined by the in- and out-layers sizes), we instead propose to compute distances to a reference diagram, namely the Fréchet mean of diagrams obtained on the training set. This allows us to compactly summarize information contained in the training set and use it to monitor the network behavior when facing new observations.

A.2 Metrics and Stability results.

Diagram metrics in our setting. Let Δ = {(t, t) ∈ R^2} denote the diagonal of the Euclidean plane. Let μ, ν be two diagrams with points X := \{x_1, ..., x_n\} ⊆ R^2 and Y := \{y_1, ..., y_m\} ⊆ R^2, respectively. Persistence diagrams are compared using optimal partial matching metrics. Namely, given a parameter 1 ≤ p ≤ +∞, the p-th diagram metric is defined by

\[ d_p(\mu, \nu) = \left( \inf_{s} \sum_{x \in X \cup \Delta} \| x - \gamma(x) \|^p dx \right)^{1/p}, \]

where γ ranges over bijections between X ∪ Δ and Y ∪ Δ. Intuitively, it means that one can either match points in X to points in Y, or match points in X (resp. in Y) to their orthogonal projections onto the diagonal Δ. Among all the possible bijections, the optimal one is selected and used for computing the distance.

This combinatorial problem is computationally expensive to solve (a fortiori, so is the one of computing Fréchet means for this metric). Fortunately, in our setting, where diagrams are actually one-dimensional, that is, supported on the real line, and have the same number of points N = d_t + d_{t+1} − 1, computing the optimal bijection becomes trivial. Indeed, one can observe first that, since we use ∥·∥_1 as our ground metric on the plane, it is never optimal to match a point x ∈ X (resp. y ∈ Y) to the diagonal, since ∥x − y∥_1 ≤ ∥x − s(x)∥_1 + ∥y − s(y)∥_1, where s denotes the orthogonal projection of a point onto the diagonal, see Figure 7. Since the persistence diagrams (that have to be compared) always have the same number of points in our setting, we can simply ignore the diagonal. In this way, we end up with an optimal matching problem between 1D measures. In that case, it is well-known that the optimal matching is given by matching points in increasing order, see for instance [Santambrogio, 2015, §2.1]. Thus, the distance Dist introduced in the article is equal to the distance d_1 up to a normalization term 1/N. This normalization is meant to prevent large layers from artificially increasing the distance between diagrams (and thus the Topological Uncertainty) and helps making distances over layers more comparable. The same normalization appears in [Rieck et al., 2019].

Stability. Let G = (V, E) be a graph, and w, w' : E → R be two weight functions on its edges. In this context, the stability theorem (see for instance [Chazal et al., 2016]) in TDA states that

\[ d_∞(\text{Dgm}(G, w), \text{Dgm}(G, w')) ≤ \sup_{e ∈ E} |w(e) − w'(e)|. \]

3In general, two persistence diagrams μ and ν can have different numbers of points.
Now, let us consider a (sequential) neural network $F$ with $L$ layers and assume that all activations map $\sigma_{\ell}$ for $1 \leq \ell \leq L - 1$ are 1-Lipschitz. We now introduce the notation

$$A_{\ell} = \sup_{i_{\ell},i_{\ell+1}} \sum_{i_{\ell+1}} |W_{\ell}(i_{\ell}, i_{\ell+1})|.$$ 

Then, the map $x_{\ell} \mapsto \sigma_{\ell}(W_{\ell}(x_{\ell} + b_{\ell}))$ is an $A_{\ell}$-Lipschitz transformation (for the $\| \cdot \|_{\infty}$ norm). Indeed, one has:

$$\sup_{1 \leq \ell+1 \leq d_{\ell+1}} \left\| \sigma_{\ell} \left( \sum_{i_{\ell+1}} W_{\ell}(i_{\ell}, i_{\ell+1})x_{\ell}(i_{\ell}) + b_{\ell}(i_{\ell}) \right) \right\|
\leq \sup_{1 \leq \ell \leq d_{\ell+1}} \left( d_{\ell} \sum_{i_{\ell+1}} |W_{\ell}(i_{\ell}, i_{\ell+1})||x_{\ell}(i_{\ell}) - y_{\ell}(i_{\ell})| \right)
\leq A_{\ell} \| x_{\ell} - y_{\ell} \|_{\infty}.$$ 

Therefore, the map $x \mapsto x_{\ell}$ is Lipschitz with Lipschitz constant $A_{\ell} := \prod_{\ell' \leq \ell} A_{\ell'}$. Now, using the stability theorem, we know that for $x, y$ two observations, one has

$$d_{\infty}(D_{\ell}(x, F), D_{\ell}(y, F)) \leq A_{\ell} \| x - y \|_{\infty}.$$ 

Finally, observe that $\frac{1}{N} d_1 \leq d_{\infty}$, so that the same result holds using the metric Dist introduced in the main paper.

We end this subsection by highlighting that, contrary to most applications of TDA, having a low Lipschitz constant in our stability result is not crucial as we actually want to be able to separate observations based on their Topological Uncertainties. Nevertheless, studying and proving results in this vein is of great importance in order to understand the theoretical properties of Topological Uncertainty, a project that we left for further work.

## B Complementary experimental details and results

### Implementation

Our implementation relies on tensorflow 2 [Abadi et al., 2016] for neural network training and on Gudhi [Maria et al., 2014] for persistence diagrams (MST) computation. Note that instantiating the SimplexTree (representation of the activation of the graph in Gudhi) from the matrix $([W_{\ell}(i, j)x_{\ell}(i)])_{ij}$ is the limiting factor in terms of running time in our current implementation, taking up to 0.9 second on a 784 $\times$ 512 dense matrix for instance. Using a more suited framework to turn a matrix into a MST may drastically improve the computational efficiency of our approach. As a comparison, extracting a MST of a graph using Gudhi only takes about 0.03 second.

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### B.1 Datasets

#### Datasets description

The MNIST and FMNIST datasets [LeCun and Cortes, 2010; Xiao et al., 2017] both consist of training data and 10,000 test data that are grey-scaled images of shape $28 \times 28$, separated in 10 classes, representing handwritten digits and fashion articles, respectively.

The CIFAR10 dataset [Krizhevsky, 2009] is a set of RGB images of shape $32 \times 32 \times 3$, separated in 10 classes, representing natural images (airplanes, horses, etc.).

The SVHN dataset (Street View House Number) [Netzer et al., 2011] is a dataset of RGB images of shape $32 \times 32 \times 3$, separated in 10 classes, representing digits taken from natural images.

The DTD dataset (Describable Texture Dataset) [Cimpoi et al., 2014] is a set of RGB images whose shape can vary between $300 \times 300 \times 3$ and $640 \times 640 \times 3$, separated in 47 classes.

Finally, Gaussian and Uniform refers to synthetic dataset of images of shape $32 \times 32 \times 3$ where pixels are sampled i.i.d following a normal distribution $N(0.5, 0.1)$ and a uniform distribution on $[0, 1]$, respectively.

The MUTAG dataset is a small set of graphs (188 graphs) coming from chemistry, separated in 2 classes. Graphs have on average 17.9 vertices and 19.8 edges. They do not contain nodes or edges attributes and are undirected.

The COX2 dataset is a small set of graphs (467 graphs) coming from chemistry, separated in 2 classes. Graphs have on average 41.2 vertices and 43.7 edges. They do not contain nodes or edges attributes and are undirected.

#### Preprocessing

All natural images datasets are rescaled to have coordinates in $[0, 1]$ (from $[0, 255]$). The coordinates of images belonging to the Gaussian dataset are thresholded to $[0, 1]$. When feeding a network trained on CIFAR10 with smaller grey-scaled images (from MNIST and FMNIST), we pad the smaller images with zeros (by adding two columns (resp. rows) on the left and on the right of the image) and repeat the grey-scale matrix along the three channels. Conversely, we randomly sub-sample $32 \times 32 \times 3$ patches for images coming from the DTD dataset, as typically done in similar experiments.

The preprocessing of graphs datasets is slightly more subtle. In order to describe graphs as Euclidean vectors, we follow a procedure described in [Carrière et al., 2020]. We compute the first 30 eigenvalues of their normalized Laplacian (or pad with 0s if there is less than 30 eigenvalues). Additionally, we compute the quantile of the Heat Kernel Signature of the graphs with parameter $t = 10$ as suggested in [Carrière et al., 2020]. This processing was observed to be sufficient to reach fairly good accuracies on both MUTAG and COX2, namely $\sim 88\%$ on MUTAG and $\sim 78\%$ on COX2, about $2 \sim 3\%$ below the state-of-the-art results reported in [Carrière et al., 2020, Table 2].

### B.2 Networks architectures and training

Depending on the type of data and the dataset difficulty, we tried our approach on different architectures.
• For MUTAG and COX2, we used a simple network with one-hidden layer with 32 units and ReLU activation. The input and the hidden layer are followed by Batch normalization operations.

• For networks trained on MNIST and FMNIST, we used the reference architecture described at https://github.com/pytorch/examples/tree/master/mnist (although reproduced in tensorflow 2). When computing TU on top of this architecture, we only take the two final fully-connected layers into account (see the paragraph Remarks in the main paper).

• For networks trained on CIFAR-10, we used the architecture in https://www.tensorflow.org/tutorials/images/cnn.

All networks are trained using the ADAM optimizer [Kingma and Ba, 2015] (from tensorflow) with its defaults parameters, except for graph datasets where the learning rate is taken to be 0.01.

### B.3 Complementary experimental results.

We provide in this subsection some complementary experimental results and discussions that aim at putting some perspective on our work.

**About trained network selection.** First, we stress that the results we obtain using either the TU or the confidence can probably be improved by a large margin⁹: if the method was perfectly reliable, one would expect a ~ +50% increase between the accuracy obtained by a network with low TU (resp. high confidence) and the accuracy obtained by a network with high TU (resp. low confidence). Indeed, this would indicate that the score clearly separates networks that perfectly split the input dataset (leading to an accuracy of ~ 100%) and those which classify all the points in a similar way (accuracy of 50%).

**OOD detection: complementary illustrations.** Figure 8 shows the distribution of the TU for a network trained on the CIFAR-10 dataset (from which we store average persistence diagrams used to compute the TU) and a series of OOD datasets. Although the results are less conclusive that those obtained on graph datasets, the distribution of TUs on training data remains well concentrated around low values while being more spread for OOD datasets (with the exception of the DTD dataset, on which our approach indeed performs poorly), still allowing for a decent detection rate. Figure 9 provides a similar illustration for a network trained on MNIST using FMNIST as an OOD dataset. On this example, interestingly, the confidence baseline [Hendrycks and Gimpel, 2017] achieves a perfect FPR at 95% TPR of 0% and an AUC of 64, while our TU baseline achieves a FPR at 95% of 5% (slightly worse than the confidence baseline) but an overall good AUC of 98.

**Sensitivity to shift under Gaussian blur.** Figure 10 illustrates the behavior of TU, accuracy, and network confidence

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⁹Our scores are however in the same range as those reported by [Ramamurthy et al., 2019], namely +10.5% on MNIST and +23% on Fashion-MNIST in their experimental setting.
Figure 10: (Top row) A 0 digit from the MNIST dataset exposed to increasing level of shift (Gaussian blur). (Bottom row), (Left). The TU (with 0.1 and 0.9 quantiles) of corrupted inputs in the MNIST dataset with respect to the corruption level $\sigma$. (Middle) The accuracy of the network on these data (that is, the proportion of observations that are still correctly classified). (Right) The confidence of the network in its predictions.

when data from the MNIST are exposed to Gaussian blur of variance $\sigma \in [0, 5]$ (see the top row for an illustration). The increase in TU accounts for the shift in the distribution in a convincing way. Interestingly, on this example, the confidence reflects the shift (and the drop in accuracy) in a satisfactory way, contrary to what happens when using a corruption shift.