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Efficient Statistical Assessment of Neural Network Corruption Robustness

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Abstract

We quantify the robustness of a trained network to input uncertainties with a stochastic simulation inspired by the field of Statistical Reliability Engineering. The robustness assessment is cast as a statistical hypothesis test: the network is deemed as locally robust if the estimated probability of failure is lower than a critical level. The procedure is based on an Importance Splitting simulation generating samples of rare events. We derive theoretical guarantees that are non-asymptotic w.r.t. sample size. Experiments tackling large scale networks outline the efficiency of our method making a low number of calls to the network function.

1 Introduction

Despite state-of-the-art performances on many Computer Vision and NLP tasks, Deep Neural Networks (DNNs) have been shown to be sensitive to both adversarial and random perturbations [Gilmer et al., 2019, Franceschi et al., 2018]. Concerns about their safety and reliability have come forth as their applications move to critical fields, such as the defense sector or self-driving vehicles.

Certification A posteriori certification aims at verifying the correct behavior of a trained network $f : \mathbb{R}^n \rightarrow \mathbb{R}^m$. This expected property is usually defined locally (a.k.a. instance-wise property): the network performs correctly in the neighborhood $\mathcal{V}(\mathbf{x}_o) \subset \mathbb{R}^n$ of a particular input $\mathbf{x}_o \in \mathbb{R}^n$. Let us denote $\iota(\cdot|\mathbf{x}_o) : \mathbb{R}^n \rightarrow \{0, 1\}$ the function indicating a violation of the expected property. The network is locally correct if $\iota(\mathbf{x}|\mathbf{x}_o) = 0$ for any $\mathbf{x} \in \mathcal{V}(\mathbf{x}_o)$.

In classification, the property takes the name of *robustness* and reads as: the output of the network remains unchanged over the neighborhood $\mathcal{V}(\mathbf{x}_o)$. It certifies that the network is robust against inputs corrupted by uncertainties of limited support or adversarial perturbations of constrained distortion.

The certification mechanism has two desired features as defined in [Singh et al., 2018]:

- Soundness: it does not certify the network when the property does not hold.
- Completeness: it does certify the network whenever the property holds.

Corruption robustness assessment Adversarial robustness corresponds to a worst-case analysis whereas *corruption robustness* considers random perturbations of the inputs. The key ingredient is the introduction of a statistical model π_0 of epistemic uncertainties occurring along the acquisition chain of the input. For instance, Franceschi et al. [2018] take Gaussian and uniform distributions over the l_p ball $\mathcal{B}_{p,\epsilon}(\mathbf{x}_o)$ of radius ϵ centered on \mathbf{x}_o .

This recent trend goes with a *quantitative* assessment gauging to what extent a given property holds or does not hold. For instance, Webb et al. [2019] estimate the probability p that a property is violated under a given statistical model of the inputs. This approach makes no assumption about the network under scrutiny as it is used as a black box. This grants the scalability to tackle deep networks. The main difficulty lies in the efficiency, *i.e.* the computational power needed to estimate weak probabilities. Their lack of soundness stems from the inability to determine if the probability p of violation is exactly zero or too small to be estimated.

Section 2 presents a brief overview of robustness assessment procedures outlining the assumptions made about the network and their limitations.

This work presents a scalable and efficient procedure assessing corruption robustness under a large panel of statistical models. It provides completeness and theoretical guarantees on the lack of soundness.

2 Related work

This section reviews the state-of-the-art in certification and corruption robustness assessment.

Assessment by example Distortion constrained adversarial attacks, like PGD, look for property violations, a.k.a. adversarial examples, inside the ball $\mathcal{B}_{p,\epsilon}(\mathbf{x}_o)$. In the context of robustness, they take advantage of the fast computation of the gradient of the network function thanks to back-propagation. They are fast, complete but unsound a priori. The network is not certified if the attack succeeds, but a failure says nothing about the property: attacks are empirical processes without guarantees.

Formal certification Using a SMT solver, [Katz et al., 2017] provide a sound and complete certification method, called ReLUplex, designed for Neural Networks with ReLU activation functions. However the same paper shows that the problem of sound and complete certification of neural networks (even restricted to ReLU activations) is NP-complete. Scaling to large modern networks seems difficult. In addition, although these formal methods are complete in theory, in practice the procedure might give up, terminating undecided with a ‘timeout’ if the underlying solver is too slow.

Incomplete certification To gain scalability, researchers have proposed sound but by-design incomplete verification methods resorting to abstract domains which are usually convex approximations of the input domain. Singh et al. [2019] obtain significant speeding up compared to ReLUplex and other complete certifiers. They introduce a verification benchmark called ERAN (see Sect. 5). Weng et al. [2018] design another incomplete certification based on lower and upper linear functional bounds of Multi-Layer Perceptrons (MLPs) with ReLU activation. It is generalized to MLPs with general activation functions in [Zhang et al., 2018] and to Convolutions Neural Networks (CNNs) in [Boopathy et al., 2019, Weng et al., 2019]. All these certifications methods rely on lower bounds of the minimum distance of adversarial examples. They are thus pessimistic in the sense that they can reject many valid properties because the lower bound is not always tight enough. In order to be ‘more complete’, Salman et al. [2019] solve the optimal convex relaxation (only for specific problems on MNIST and CIFAR10 datasets) with extensive computational resources. They conclude that the tightness of the lower bounds cannot be improved, suggesting that this approach has found its limit.

Statistical assessment Corruption robustness assumes a statistical model π_0 of noisy inputs like Gaussian or uniform distributions over the l_p ball $\mathcal{B}_{p,\epsilon}(\mathbf{x}_o)$. Franceschi et al. [2018] study the robustness of both linear and deep neural networks. They obtain precise bounds for linear classifiers which they extend to non-linear classifiers with ‘locally approximately flat decision boundaries’. Webb et al. [2019] introduce a robustness metric (the lower, the more robust) is defined by:

$$p := \pi_0(\iota(\mathbf{X}|\mathbf{x}_o) = 1) = \int_{\mathbb{R}^n} \iota(\mathbf{x}|\mathbf{x}_o)\pi_0(d\mathbf{x}). \quad (1)$$

The quantitative assessment is in stark contrast with the adversarial robustness literature taking a worst-case analysis. A connection is established when π_0 is the uniform distribution over the ball $\mathcal{B}_{p,\epsilon}(\mathbf{x}_o)$: the volume of the set of adversarial examples equals $p \text{vol}(\mathcal{B}_{p,\epsilon}(\mathbf{x}_o))$. Baluta et al. [2021] name probability p the adversarial density.

The main difficulty lies in the estimation of this integral, in particular when the event $\{\iota(\mathbf{X}|\mathbf{x}_o) = 1\}$ is rare under distribution π_0 . Baluta et al. [2021] use a crude Monte Carlo simulation. Webb et al. [2019] use Importance Splitting (a.k.a. multi-level splitting) with a rejuvenative mechanism based on the Metropolis-Hastings algorithm. These two last works make no assumption about the network as their procedure uses it as a black box. This grants scalability (in the sense that it tackles deep networks). The efficiency of the statistical test/estimation procedure is measured by the runtime or the number of calls to the black-box model.

The quantitative assessment falls back to certification by taking a final decision: the network is *deemed* reliable if the probability of violation is smaller than $p_c > 0$, a critical probability set by the user. It strikes the trade-off between the lack of soundness and the efficiency: a low p_c increases the soundness but requires estimating probabilities as low as p_c which is computationally demanding.

3 Our approach to corruption robustness assessment

Our approach uses statistical hypothesis testing as a certification *surrogate*. As in [Baluta et al., 2021], the user sets a low critical probability p_c and the test assesses whether p is lower or larger. However, rather than a testing approach powered by crude Monte Carlo simulations, our workhorse is a more efficient Sequential Monte Carlo algorithm [Naesseth et al., 2019]. This so-called ‘Last Particle’ simulation was invented by Guyader et al. [2011] and is a variant of the Adaptive Multi-Level Sampling employed by Webb et al. [2019]. We show that, with a carefully chosen termination condition, it is advantageous both in terms of computational efficiency and theoretical guarantees.

Sect. 3.1 presents the ‘Last particle’ simulation that Sect. 3.2 applies to statistical hypothesis testing in the framework of robustness assessment. Alg. 1 gives the pseudo-code of our procedure.

3.1 The Last Particle simulation

The goal of the Last Particle simulation is to efficiently generate samples drawn according to a reference probability distribution π_0 but in a region $\mathcal{R} := \{\mathbf{y} : h(\mathbf{y}) > 0\} \subset \mathbb{R}^n$ where $h : \mathbb{R}^n \rightarrow \mathbb{R}$, is the so-called the *score function*. Efficiency is the ability to perform this task using few calls to the score function, even when probability $\pi_0(\mathcal{R})$ is small.

The simulation manages a set of N particles (*i.e.* samples) which are initially i.i.d. with respect to π_0 . The name ‘Last Particle’ comes from the fact that the simulation ‘kills’ the sample with the lowest score at each step. The score of this last particle becomes the intermediate level L_k at iteration k (Alg. 1, line 6). Then, that particle is refreshed by sampling according to π_0 but conditioned on the event $\{h(\mathbf{X}) > L_k\}$. This sampling procedure is performed by $\text{Gen}(L_k, 1)$ in line 11 and is detailed in Sect. 4. $\text{Gen}(-\infty, N)$ then simply means sampling N random vectors according to π_0 (line 3).

The algorithm stops when the number of iterations reaches integer m or at any iteration k if the intermediate threshold L_k is positive which means the simulation has generated samples as required.

Consider the function $\Lambda : \mathbb{R} \rightarrow \mathbb{R}_+$ defined as

$$\Lambda(\ell) := -\log \pi_0(h(\mathbf{X}) > \ell). \quad (2)$$

This function is unknown in practice, but one can easily see that it is non decreasing.

During one run of Alg. 1, the intermediate levels are random variables following an increasing order by construction: $L_1 < L_2 < \dots < L_k$. We here copy the main result of the Last Particle simulation:

Theorem 1 ([Guyader et al., 2011]). *The variables $\Lambda(L_1), \Lambda(L_2), \dots$ are distributed as the successive arrival times of a Poisson process with rate N : $\Lambda(L_k) = 1/N \sum_{j=1}^k E_j$, where $E_j \stackrel{i.i.d.}{\sim} \mathcal{E}(1)$.*

As the sum of i.i.d. exponential random variables is distributed¹ as a Gamma random variable, this theorem states that $\Lambda(L_k) \sim \Gamma(k, N)$ (*i.e.* scale k and rate N).

¹Here and after, \sim denotes distributional equality between random variables.

Algorithm 1 Robustness assessment with Last Particle simulation

Require: Number of particles N , critical probability level p_c , confidence interval level α

Ensure: Cert

```

1: Initialize:  $p \leftarrow 1 - 1/N$ ,  $k \leftarrow 1$ , Cert  $\leftarrow False$ , Stop  $\leftarrow False$ 
2:  $m \leftarrow \text{Comp\_m}(p_c, \alpha, N)$  ▷ See Sect. 3.3
3:  $\{\mathbf{x}_i\}_{i=1}^N \leftarrow \text{Gen}(-\infty, N)$  ▷ See Sect. 4
4: while  $k \leq m$  & Stop = False do
5:    $i^* \leftarrow \arg \min_{i \in 1:N} h(\mathbf{x}_i)$ 
6:    $L_k \leftarrow h(\mathbf{x}_{i^*})$ 
7:   if  $L_k > 0$  then
8:     Stop  $\leftarrow True$ 
9:      $P_{est} \leftarrow p^{k-1}$ 
10:  end if
11:   $\mathbf{x}_{i^*} \leftarrow \text{Gen}(L_k, 1)$  ▷ See Sect. 4
12:   $k \leftarrow k + 1$ 
13: end while
14: if Stop = False then
15:   Cert  $\leftarrow True$ 
16:    $P_{est} \leftarrow p_c$ 
17: end if
18: return Cert,  $P_{est}$ 

```

3.2 Corruption robustness assessment as a statistical test

In the framework of robustness assessment of classifiers, the score function is related to the usual loss in the adversarial example literature:

$$h(\mathbf{x}) := \max_{k \neq c(\mathbf{x}_o)} f_k(\mathbf{x}) - f_{c(\mathbf{x}_o)}(\mathbf{x}), \quad (3)$$

where $f(\mathbf{x})$ represents the predicted probabilities (or logits) vector and $c(\mathbf{x}) := \arg \max_k f_k(\mathbf{x})$ is the predicted class for input \mathbf{x} . Note that $h(\mathbf{x}_o) < 0$ and that the violation indicator function of Sect. 1 is simply $\iota(\mathbf{x}|\mathbf{x}_o) = \mathbb{1}(h(\mathbf{x}) > 0)$. The input π_0 models the corruption distribution around \mathbf{x}_o . The probability of robustness violation defined in (1) writes as $p := \pi_0(h(\mathbf{X}) > 0)$.

Our approach establishes a hypothesis test parametrized by a low probability p_c given by the user.

- \mathcal{H}_0 : The probability of robustness violation $p > p_c$. The network should not be certified.
- \mathcal{H}_1 : The probability of robustness violation $p < p_c$. The network can be certified.

For a given true probability of violation p , we establish the following properties.

Proposition 1. *The probability of false positive $P_{fp}(p)$ equals:*

$$P_{fp}(p) := \mathbb{P}(\text{Cert} = \text{True} | p > p_c) = \frac{\int_0^{-N \log p} t^m e^{-t} dt}{\int_0^{+\infty} t^m e^{-t} dt} = \frac{\gamma(m, -N \log p)}{\Gamma(m)}. \quad (4)$$

Proof. Certification means that, according the Alg. 1, even after m loops, the intermediate threshold L_m is still lower than 0. This happens with probability:

$$P_{fp}(p) = \mathbb{P}(L_m < 0) = \mathbb{P}(\Lambda(L_m) < \Lambda(0)) = \frac{\gamma(m, -N \log p)}{\Gamma(m)}, \quad (5)$$

since $\Lambda(L_m) \sim \Gamma(m, N)$ and $\Lambda(0) = -\log p$; $\gamma(s, x)$ being the lower incomplete gamma function. \square

Proposition 2. *The probability of false negative $P_{fn}(p)$ equals:*

$$P_{fn}(p) := \mathbb{P}(\text{Cert} = \text{False} | p < p_c) = \frac{\int_{-N \log p}^{+\infty} t^m e^{-t} dt}{\int_0^{+\infty} t^m e^{-t} dt} = \frac{\bar{\gamma}(m, -N \log p)}{\Gamma(m)}. \quad (6)$$

Proof. The certification failed because $L_K > 0$ for some $K \leq m$, or equivalently $\Lambda(L_K) > \Lambda(0)$. Note that this was not true at iteration $K - 1$ (otherwise the while loop would have been broken earlier). In other words, $K - 1 = \sup\{i : \sum_{j=1}^i E_j < -N \log p, E_j \stackrel{\text{i.i.d.}}{\sim} \mathcal{E}(1)\}$, so that $K - 1$ follows the Poisson distribution $\mathcal{P}(-N \log p)$. The probability of false negative is the c.d.f. of $K - 1$ at $m - 1$:

$$P_{\text{fn}}(p) = \mathbb{P}(K \leq m) = \mathbb{P}(K - 1 \leq m - 1) = \frac{\bar{\gamma}(m, -N \log p)}{\Gamma(m)}, \quad (7)$$

where $\bar{\gamma}(s, x)$ is the *upper* incomplete gamma function. \square

This shows that $P_{\text{fn}}(p)$ is an increasing function and the worst case happens when p converges to p_c :

$$\forall p < p_c, P_{\text{fn}}(p) \leq P_{\text{fn}}(p_c) = 1 - P_{\text{fp}}(p_c). \quad (8)$$

Remark that the trade-off between false positive and false negative probabilities is hard at $p = p_c$. Yet, Eq. (7) tells that $P_{\text{fn}}(p)$ is quickly vanishing as $p \rightarrow 0$, especially when N is large.

3.3 Corruption robustness assessment as a certification problem

In the context of certification, we show that i) our procedure is complete but not sound, ii) false positive probability drives the lack of soundness.

A false negative is not a bad event since it avoids us to certify when the probability p of violation is not zero. At the same time, our procedure always certifies whenever the property holds since $P_{\text{fn}}(0) = 0$. On the contrary, a false positive remains an error since we certify when $p > p_c > 0$. Let us quantify the lack of soundness by

$$P_{\text{ns}}(p) := \mathbb{P}(\text{Not Sound} | p) = \begin{cases} 1 - P_{\text{fn}}(p) & \text{if } p < p_c \\ P_{\text{fp}}(p) & \text{otherwise} \end{cases} \quad (9)$$

Let us recall that in our case it holds simply $1 - P_{\text{fn}}(p) = P_{\text{fp}}(p)$.

Proposition 3. *A suitable choice of the maximum number of iterations m in Alg. 1 can control the lack of soundness by the critical probability p_c and a required significance level $\alpha \in (0, 1)$ s.t.*

$$P_{\text{ns}}(p) \leq \alpha, \forall p \geq p_c. \quad (10)$$

Proof. This amounts to enforce that $P_{\text{fp}}(p) \leq \alpha, \forall p > p_c$. Since $-\log p$ is a decreasing function, the worst case occurs in (5) when $p \rightarrow p_c$. It is thus safe to ensure $P_{\text{fp}}(p_c) = \alpha$. This is done by carefully selecting m s.t. the α -quantile of the r.v. $\Gamma(m, N)$ equals $-\log p_c$. The routine `Comp_m` in Alg. 1 solves this numerically with a line search (see Appendix A for some approximations). \square

If we assume a Bayesian approach where the p.d.f. of p is denoted by $f_P : [0, 1] \rightarrow \mathbb{R}_+$, then the probability of not being sound is given by

$$\mathbb{P}(\text{Not Sound}) = \int_{0^+}^{p_c} (1 - P_{\text{fn}}(p)) f_P(p) dp + \int_{p_c}^1 P_{\text{fp}}(p) f_P(p) dp \quad (11)$$

$$\leq \int_{0^+}^{p_c} f_P(p) dp + \alpha \int_{p_c}^1 f_P(p) dp = \alpha + (1 - \alpha) \mathbb{P}(p < p_c). \quad (12)$$

The lack of soundness decreases if both α and p_c are small. This makes the point with the state-of-the-art. Baluta et al. [2021] are unable to set p_c to a low value because their simulation is based on a crude Monte Carlo, whereas Webb et al. [2019] do not give any guarantee similar to our level α .

Efficiency Appendix A proposes approximated closed forms outlining that m scales as $\log 1/p_c$. This is also visible in the typical values given in Table 1. A lower significance level moderately increases the number of iterations. Section 4 details how to sample a new particle at each iteration as needed in line 11, Alg. 1. This method consumes a fixed number of calls to the network. In total, the maximum number of calls scales as $O(\log 1/p_c)$. This is in stark contrast with [Baluta et al., 2021] where the number of calls is proportional to $1/p_c$. Note that this is a maximum: our procedure makes an early stop whenever $L_k > 0$ (line 8, Alg. 1) and outputs $\text{Cert} = \text{False}$ as well as failure probability estimate P_{est} .

Table 1: Maximum number of iterations m and its approximation \tilde{m}_1 (see App. A)

N	p_c	$\alpha = 0.1$		$\alpha = 0.01$		$\alpha = 0.001$	
		m	\tilde{m}_1	m	\tilde{m}_1	m	\tilde{m}_1
20	10^{-10}	489	489	512	514	529	532
20	10^{-30}	1430	1431	1470	1471	1499	1502
10	10^{-10}	251	251	267	269	280	283
10	10^{-30}	726	726	754	755	774	777
2	10^{-10}	56	56	64	65	69	73
2	10^{-30}	154	155	167	169	177	180

4 Sampling procedures

This section details the crucial ingredient of our procedure: sampling a new input \mathbf{X} whose score $h(\mathbf{X})$ is above a given level L . This random generator is called $\text{Gen}(L, 1)$ in line 11, Alg. 1. Appendix B considers a case where the statistical model π_0 and the network are so simple that this sampling is easy. This section details more general scenarios making no assumption about the score function. Our sampling is a rejection procedure relying on *reversible proposals* and *transformations*.

4.1 Reversible proposals

We call a (parametric) proposal any a random function $K : \mathbb{R}^n \times \mathbb{R}_+ \rightarrow \mathbb{R}^n$. Iterations of i.i.d. proposal generate a Markov chain which is said to be *reversible (detailed balance)* with respect to the distribution π_0 if the following assertion holds:

$$\forall s > 0, \mathbf{X} \sim \pi_0 \Rightarrow (\mathbf{X}, K(\mathbf{X}, s)) \sim (K(\mathbf{X}, s), \mathbf{X}). \quad (13)$$

A simple example for $\pi_0 = \mathcal{N}(\mathbf{0}_n; \sigma^2 \mathbf{I}_n)$ is given in [Guyader et al., 2011]:

$$K(\mathbf{X}, s) := \frac{\mathbf{X} + s\mathbf{N}}{\sqrt{1 + s^2}} \quad \text{with } \mathbf{N} \sim \mathcal{N}(\mathbf{0}_n; \sigma^2 \mathbf{I}_n). \quad (14)$$

The rejection method described in Alg. 2 takes as input a set \mathcal{X} of particles whose score is larger than L . It randomly picks one particle in \mathcal{X} and applies t times a fresh proposal, followed by a rejection based on the score. If the selected sample is a realization of the distribution π_0 conditioned by a score larger than L , then one application of the proposal keeps π_0 invariant while the rejection ensures that the score remains above L . By induction, iterating maintains these two properties, and in fact leaves invariant the conditional distribution thanks to reversibility (see [Guyader et al., 2011] and App. E).

Alg. 1 uses the procedure of Alg. 2 as follows. At iteration k , L is indeed L_k , *i.e.* the score of the ‘last’ particle \mathbf{x}_{i^*} , and $\mathcal{X} = \{\mathbf{x}_i\}_{i \neq i^*}$ which contains $(N - 1)$ particles whose score is larger than L . The output is one ‘fresh’ particle and the number of particles equals N from one iteration to another.

The parameter s plays the role of *strength*: $s = 0$ implies that the proposal just copies the input, while $s \rightarrow +\infty$ means that $K(\mathbf{x}, s)$ does not depend on \mathbf{x} . The proposal strength s is thus important. With a small value, the proposal makes small moves. A large value explores faster but leads to higher rejection rate. Appendix D presents a strategy to automatically control its value depending on the past behavior of the algorithm in order to maintain a given rejection rate.

Theoretically, under some irreducibility assumption, an infinity of iterations in Alg. 2 provides a fresh particle statistically independent of the particles in \mathcal{X} as needed in Alg. 1:

Proposition 4. *Assume that, the proposal $K(\mathbf{x}, s)$ has a density bounded from below uniformly in \mathbf{x} and $s \geq s_0$. Then the distribution of $\Lambda(L_m)$ converges towards the Gamma distribution $\Gamma(N, m)$ exponentially fast with the number t of proposal applications.*

Proof and Remarks. The proof is given in Appendix E and uses a classical probabilistic coupling argument. It requires the lower bound assumption which is a form of strong irreducibility of the proposal. This is compliant with the proposals used in this work. In particular all the formulas given in Prop. 1 and after hold true asymptotically for large t . \square

Algorithm 2 Sampling one particle $\text{Gen}(L, 1)$

Require: threshold L , finite set \mathcal{X} of particles whose score is larger than L

Ensure: new particle \mathbf{X}

```
1:  $\mathbf{X} \leftarrow \mathcal{U}(\mathcal{X})$  ▷ Draw uniformly a particle in  $\mathcal{X}$ 
2: for  $k = 1 : t$  do
3:    $\mathbf{Z} \leftarrow K(\mathbf{X}, s)$  ▷  $\pi_0$  reversible proposal. See Sect. 4.1
4:   if  $h(\mathbf{Z}) > L$  then ▷ Rejection
5:      $\mathbf{X} \leftarrow \mathbf{Z}$ 
6:   end if
7: end for
8: return  $\mathbf{X}$ 
```

In practice, we choose the number t of iterations approximately proportional to the inverse of rejection rate, maintained approximately constant by tuning the proposal strength s (see App. D).

Refreshing a particle consumes t calls to the score function. This is done *once* per iteration of Alg. 1. Therefore, our method globally consumes $O(t \log 1/p_c)$ calls. This means that the figures in Table 1 are to be multiplied by t . Webb et al. [2019] also manage a sample of size N , but *all* the particles are separately refreshed at *each* iteration by applying t Metropolis-Hasting transitions. Their number of calls per iteration is N times larger than our. Moreover, their typical setup is $N \approx 1000$ and $t \approx 1000$, while ours is $N \approx 2$ and $t \approx 50$. Our complexity is thus smaller by 4 orders of magnitude.

4.2 Isoprobabilistic transformation

The proposal (14) is simple but reversible only w.r.t. the normal distribution. The transformation method is well known in the field of Statistical Reliability Engineering [Melchers and Beck, 2018]. It amounts to work with a latent random vector $\mathbf{G} \sim \mathcal{N}(\mathbf{0}_d; \mathbf{I}_d)$ and to apply the transformation $\mathbf{X} = T(\mathbf{G}, \mathbf{x}_o)$ mapping the normal distribution to the reference model π_0 . Some well known examples are:

- $\mathbf{X} \sim \mathcal{N}(\mathbf{x}_o, \sigma^2 \mathbf{I}_n)$: $d = n$ and $T(\mathbf{G}, \mathbf{x}_o) = \mathbf{x}_o + \sigma \mathbf{G}$
- $\mathbf{X} \sim \mathcal{U}(\mathcal{B}_{+\infty, \epsilon}(\mathbf{x}_o))$: $d = n$ and $T(\mathbf{G}, \mathbf{x}_o) = \mathbf{x}_o + \epsilon(2\Phi^{-1}(\mathbf{G}) - 1)$ (component-wise)
- $\mathbf{X} \sim \mathcal{U}(\mathcal{B}_{2, \epsilon}(\mathbf{x}_o))$: $d = n + 2$ and $T(\mathbf{G}, \mathbf{x}_o) = \mathbf{x}_o + \epsilon \mathbf{G}(1 : n) / \|\mathbf{G}\|_2$

More complex examples are inverse Rosenblatt or Nataf transformations [Melchers and Beck, 2018].

This transformation is composed with h to redefine the score function $h_G = h \circ T$ that applies on latent vector \mathbf{G} , *i.e.* random vectors suitable for the proposal (14). This amounts to use Alg. 1 directly on the latent variable with score function h_G and in conjunction with Alg. 2 and proposal (14).

5 Experimental evaluation

This section presents experimental results on ACAS Xu, MNIST, and ImageNet datasets with some trained classifications networks listed in App. F.3 together with implementation details. Experiences were run on a laptop PC (CPU=Intel(R) Core(TM) i7-9750H, GPU=GeForce RTX 2070) except for experiences on ImageNet which were run on a Nvidia V100 GPU.

5.1 Idealized case

This section considers a setup where $\pi_0 = \mathcal{N}(\mathbf{x}_o; \sigma^2 \mathbf{I}_n)$ and score function h is linear. This setup is ideal because sampling a fresh particle is straightforward (*i.e.* without Alg. 2) as shown in App. B.

Fig. 1 shows the impact of N . In terms of hypothesis testing (see Sect. 3.2), a larger N yields steeper functions: $P_{\text{fp}}(p)$ (resp. $P_{\text{fn}}(p)$) quickly vanishes to zero as p gets larger (resp. smaller) than p_c . In terms of certification (see Sect. 3.3), a small N is not a bad choice: the probability $P_{\text{ns}}(p)$ of not being sound takes lower values in the range $p < p_c$. For $p > p_c$, $P_{\text{ns}}(p)$ is lower than α (as stated by Prop. 3) but converges to 0 more slowly. Last but not least, the procedure makes only 167 calls to the score function for $N = 2$, instead of 1470 for $N = 20$.

Table 2: ACAS Xu – Confusion matrix comparing ERAN [DeepPoly+MILP] and Last Particle [$N = 2, p_c = 10^{-50}, t = 40$]

		ERAN			
		Certified	Uncertified	Infeasible	TimeOut
Last Particle	Certified	107	9	1	1
	Uncertified	0	103	4	0

5.2 ACAS Xu

We evaluate our method on the ACAS Xu (Airborne Collision Avoidance System X for unmanned aircrafts) case study [Owen et al., 2019]. It consists in 45 neural networks used to approximately compress a large lookup table (2GB) containing discrete decisions (‘Clear-of-conflicts’, ‘weak right’, ‘strong right’, ‘weak left’, or ‘strong left’) as well as 5 input/output properties. This makes $45 * 5 = 225$ cases. We compare our method with the complete certification based on DeepPoly [Singh et al., 2019] and Mixed-Integer Programming from the ERAN benchmark.

Table 2 contains the confusion matrix taking into account the cases for which the ERAN complete certification fails because the Gurobi optimizer either outputs an ‘infeasible’ status or reaches a timeout (set to 600 seconds). Unsurprisingly, our method is complete in the sense that it certifies all cases certified by ERAN. It is not sound as it admits 9 false positives. This is due to the critical probability p_c which is not low enough (the decisions were exactly the same over 10 runs). Yet, our method takes a decision on the 6 unsolved cases by ERAN. In addition our method is faster for all ACAS Xu properties except for the property 4, confer figure 2.

5.3 MNIST

We compare our procedure with with the DeepPoly *incomplete* certification on MNIST [LeCun et al., 1990] with 4 neural networks from the ERAN benchmark (see App. F.3). We focus on L_∞ uniform robustness since the implementation provided for DeepPoly cannot deal with L_2 norms. We run our algorithm with $N = 2, p_c = 10^{-35}$ and $t = 40$. As in ACAS Xu experiment, our method runs faster than the ERAN method as shown in table 3. Interestingly, the average runtime of our method decreases with larger ϵ since the probability p of violation is bigger, whereas DeepPoly computation time increases with the size of the input space tested. On the one hand DeepPoly provides an efficient lower bound to both corruption and adversarial robustness, on the other hand our method provides a fast upper bound. 10 independent LP simulations (runs) on the same image always give the same output and the standard deviation is thus empirically negligible in our setting.

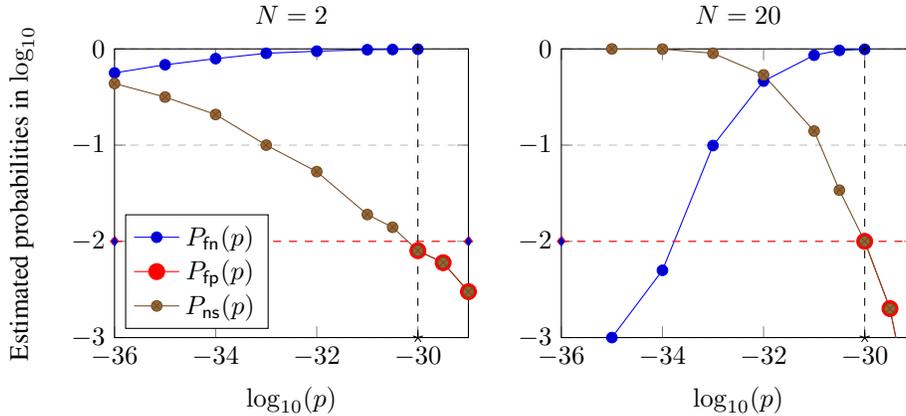


Figure 1: Estimated probabilities of false positive, false negative, and not sound certification, vs. true violation probability p in the ideal setup where $p_c = 10^{-30}, \alpha = 0.01$. Estimation over 1000 runs.

Table 3: MNIST – Comparison ERAN [DeepPoly] and Last Particle [$N = 2, p_c = 10^{-35}, t = 40$]

ϵ	ERAN		Last Particle	
	Certified (%)	runtime (sec.)	Certified (%)	runtime (sec.)
0.015	82	5.69	99	1.04 ± 0.005
0.03	62	5.92	97	1.03 ± 0.01
0.06	28	8.13	93	1.00 ± 0.01
0.1	22	8.84	85	0.96 ± 0.02

Table 4: ImageNet - Last Particle [$N = 2, p_c = 10^{-15}, t = 20$]

Network	ϵ	Avg. runtime (in sec. $\pm std$)	Avg. number of calls	Certified (%)
MobileNet	0.02	20.78 ± 0.74	1388	71
	0.03	18.74 ± 0.18	1274	64
	0.06	14.5 ± 0.11	1037	50
ResNet50	0.02	33.86 ± 1.14	1537	81
	0.03	31.38 ± 0.48	1434	71
	0.06	25.51 ± 0.67	1160	59

5.4 ImageNet

For the last experiment, our method analyses 2 neural networks (ResNet50 et MobileNet) with 100 test images from ImageNet dataset [Deng et al., 2009] correctly classified by each network. These experiments were run on a Nvidia V100 GPU. The average number of calls reported is rounded up and the average runtime is for a pass over one image. The robustness is again defined against noise uniformly distributed over L_∞ of radius ϵ . As one can notice, the compute time increases reasonably the input space dimension and network size.

6 Conclusion

The paper proposes a statistical simulation to make assessment on corruption robustness. It looks at this problem from a hypothesis testing (false positive/ false negative) and from a certification (completeness / soundness) points of view. The procedure is scalable, efficient, complete and comes with guarantees on the lack of soundness. There are two limitations: 1) The Last Particle simulation is sequential, which is not GPU friendly. Yet, we provide a code processing several inputs \mathbf{x}_o in parallel. 2) Our procedure is general as it uses the network as a black-box classifier. But, it does not exploit its gradient easily computed thanks to backpropagation. More sophisticated mixing kernels using gradients information (e.g. Langevin Monte Carlo, Hamiltonian MC) can accelerate convergence.

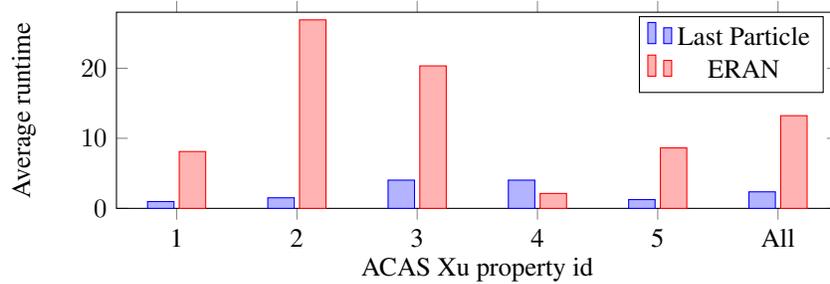


Figure 2: ACAS Xu – runtimes in sec. of ERAN (Deep Zonotope) and Last Particle algorithm [$N = 2, p_c = 10^{-50}, t = 40$]

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Broader Impact

As deep learning applications move to the physical world it is crucial to understand to what extent and in which situations their predictions can be trusted. Both adversarial and corruption robustness assessment methods are a key step towards building trustworthy deep-learning based cyber-physical systems. At the same time limits of such methods should always be clearly established and their dependence on data explicit.

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A Approximations for the computation of m

Providing a very low critical probability p_c means that certification occurs when the simulation ends after a large number of iterations m . $\Lambda(L_m)$ follows a Gamma distribution $\Gamma(m, N)$ which can be then approximated by the Gaussian law $\mathcal{N}(m/N; m/N^2)$ (application of the Central Limit Theorem). We introduce ℓ_c the threshold associated to p_c s.t. $p_c = \mathbb{P}(h(\mathbf{X}) > \ell_c)$, and $m_c = \log(p_c)/\log(1 - 1/N)$.

Under this assumption:

$$\mathbb{P}(\Lambda(L_m) < \Lambda(\ell_c)) = \alpha \rightarrow \Lambda(\ell_c) = \frac{m}{N} - z_\alpha \frac{\sqrt{m}}{N} \quad (15)$$

with $z_\alpha = \Phi^{-1}(1 - \alpha) > 0$ for $\alpha < 1/2$ and $\Lambda(\ell_c) = -\log(p_c)$. We find a first approximation of m by solving this second order polynomial in \sqrt{m} :

$$m \approx \tilde{m}_1 = \left\lceil \frac{1}{4} \left(z_\alpha + \sqrt{z_\alpha^2 - 4N \log(p_c)} \right)^2 \right\rceil. \quad (16)$$

This clearly shows that the dependence on p_c is approximately logarithmic. Table 1 shows that this approximation is excellent even for large p_c .

Moreover, if N is large enough, then $N \log(p_c) = Nm_c \log(1 - 1/N) \approx m_c$ and m approximately satisfies

$$m - z_\alpha \sqrt{m} - m_c = 0, \quad (17)$$

producing

$$m \approx \tilde{m}_2 = \left\lceil \frac{1}{4} \left(z_\alpha + \sqrt{z_\alpha^2 + 4m_c} \right)^2 \right\rceil = \left\lceil m_c \left(\sqrt{1 + z_\alpha^2/4m_c} + \frac{z_\alpha}{2\sqrt{m_c}} \right)^2 \right\rceil. \quad (18)$$

This shows that m is a little larger than $m_c = \log(p_c)/\log(1 - 1/N)$.

B Experiments in the idealized case

This appendix details the experimental results of Sect. 5.1. This section assumes that $\mathbf{X} = \mathbf{x}_o + \sigma \tilde{\mathbf{X}}$ with $\tilde{\mathbf{X}} \sim \mathcal{N}(\mathbf{0}_n; \mathbf{I}_n)$ and that $h(\mathbf{x}) = \mathbf{x}^\top \mathbf{g} - \tau$ with $\mathbf{g} \in \mathbb{R}^n$ and $\|\mathbf{g}\| = 1$ (w.l.o.g.). In this textbook case, the true probability $p = \pi_0(h(X) > 0)$ depends on τ by

$$p = 1 - \Phi\left(\frac{\tau - \mathbf{x}_o^\top \mathbf{g}}{\sigma}\right). \quad (19)$$

We now explain how to ‘directly’ sample a new particle as required by line 11, Alg. 1 for this particular case, without resorting to Alg. 2.

The projection of $\tilde{\mathbf{X}}$ onto \mathbf{g} is Gaussian distributed. By linearity of the score function, conditioning on the event $\mathcal{E} := \{h(\mathbf{X}) > L\}$ means that the c.d.f of $Z := \tilde{\mathbf{X}}^\top \mathbf{g}$ equals:

$$F_Z(z) = \mathbb{1}(z > L_0) \cdot \frac{\Phi(z) - \Phi(L_0)}{1 - \Phi(L_0)} \quad \text{with } L_0 := (L - \mathbf{x}_o^\top \mathbf{g})/\sigma. \quad (20)$$

On the other hand, the projection of $\tilde{\mathbf{X}}$ onto any other direction orthogonal to \mathbf{g} remains normal distributed. This justifies the following construction:

$$Z = F_Z^{-1}(U) = \sigma \Phi^{-1}((1 - \Phi(L_0/\sigma))U + \Phi(L_0/\sigma)) \quad \text{with } U \sim \mathcal{U}_{[0,1]} \quad (21)$$

$$\mathbf{X} = \mathbf{x}_o + \sigma (Z\mathbf{g} + (\mathbf{I}_n - \mathbf{g}\mathbf{g}^\top)\mathbf{N}) \quad \text{with } \mathbf{N} \sim \mathcal{N}(\mathbf{0}_n; \mathbf{I}_n), \quad (22)$$

In a nutshell, $(\mathbf{I}_n - \mathbf{g}\mathbf{g}^\top)$ is the projection onto the $(n - 1)$ -dimension subspace orthogonal to \mathbf{g} . This operator resets the projection of \mathbf{N} onto \mathbf{g} , which is then set to Z . Section 5.1 uses this toy example to illustrate our procedure in the idealized case.

C Choice of N and T

Most experiences are run with $N = 2$ which is counter-intuitive. In this section we elaborate on the choice of N and T using experiments in case of linear decision function and X follows a Gaussian law. More precisely we take $X \sim \mathcal{N}(0, I_d)$ and the score function $s : \mathbb{R}^d \ni x \mapsto x^T n$ with $n \in \mathbb{R}^d$ defining the normal vector of the decision hyperplane. For simplicity, we take $n = e_1$ i.e. the first vector of the canonical basis of \mathbb{R}^d . With this toy model the probability of failure for a threshold level L is given by,

$$p = \mathbb{P}(s(X) > L) = \mathbb{P}(X_1 > L) = 1 - \Phi(L) \quad (23)$$

We now apply the last particle algorithm 1 to the statistical test with null hypothesis $\mathcal{H}_0 : p \geq p_c$ and alternative hypothesis $\mathcal{H}_1 : p < p_c$. For numerical experiments below, we take $p = p_c$ and $\alpha = 0.05$. We let vary the number of particles N in the range $\{2, 20, 100\}$ and the parameter T in the range $\{25, 50, 100, 150, 200\}$. For each couple of parameters (N, T) we make 1000 runs and count the number of false positive (i.e. the number of times the algorithm wrongfully asserted that $p < p_c$). The results are presented in the table 5 below.

Table 5: Estimation of false positive rates and number of calls in function of T and N for a toy model

N	T	Estimated false positive rate	Avg. number of calls
2	25	0.038	1.05e+03
2	50	0.041	2.08e+03
2	100	0.033	4.14e+03
2	150	0.026	6.19e+03
2	200	0.040	8.28e+03
20	25	0.034	1.04e+04
20	50	0.050	2.07e+04
20	100	0.048	4.15e+04
20	150	0.043	6.20e+04
20	200	0.043	8.29e+04
100	25	0.036	5.19e+04
100	50	0.052	1.04e+05
100	100	0.049	2.07e+05
100	150	0.033	3.11e+05
100	200	0.050	4.15e+05

D Automatic control of kernel strength

In practice the strength parameter s of the kernel is adapted at each iteration using an heuristic. More precisely we choose a acceptance ratio threshold $a_* \in [0, 1]$ and at iteration k , after the line 11 of Algorithm 1, decrease the s by a decay rate $0 < \gamma < 1$. Conversely if the acceptance ratio is high but progress, as measured by the relative gain between the old and the new level, is too slow we increase s by the same parameter γ . This tuning mechanism is further outlined in algorithm 3. Experimentally we find that, with well chosen parameters (a_*, g_*, γ) this adaptive tuning speeds up the algorithm drastically keeping both acceptance ratio and level-wise progress under control.

E Proof of proposition 4

π_0 denotes the reference probability distribution. The proof applies to the last particle algorithm describes in Alg.1 in the case where the refreshed particle state $\text{Gen}(l, 1)$ is given for each $l \in \mathbb{R}$ by Alg.2. We recall that in Alg.2, $\text{Gen}(l, 1)$ is obtained by t iterations of a proposal K with score-based accept /reject; starting from a uniformly chosen other (surviving) particle with score strictly greater than l .

The proof is based on a (instructive and explicit) probabilistic coupling between this last particle algorithm and the 'idealized algorithm' counterpart. The latter is obtained by taking for $\text{Gen}(l, 1)$ the

Algorithm 3 Adaptive Sampling for one particle AdaptGen($L, 1$)

Require: threshold L , finite set \mathcal{X} of particles whose score is larger than L , input strength parameter s_{in} , scaling parameter $\gamma < 1$, acceptance ratio threshold a_* , gain threshold g_*

Ensure: new particle \mathbf{X} , new strength parameter s_{out}

```

1: Initialize Count  $\leftarrow 0$ ,  $s_{out} \leftarrow s_{in}$ ,  $\mathbf{X} \leftarrow \mathcal{U}(\mathcal{X})$  ▷ Draw uniformly a particle in  $\mathcal{X}$ 
2: for  $k = 1 : t$  do
3:    $\mathbf{Z} \leftarrow K(\mathbf{X}, s_{in})$  ▷  $\pi_0$  reversible proposal. See Sect. 4.1
4:   if  $h(\mathbf{Z}) > L$  then ▷ Rejection
5:      $\mathbf{X} \leftarrow \mathbf{Z}$ 
6:     Count  $\leftarrow$  Count + 1
7:   end if
8: end for
9: if Count  $< t \times a_*$  then
10:   $s_{out} \leftarrow \gamma \times s_{in}$  ▷ Decrease  $s$  if acceptance rate is too low
11: else
12:   $L_* \leftarrow \min(h(\mathbf{X}), \min_{x \in \mathcal{X}} h(x))$ 
13:  Gain  $\leftarrow \frac{L_* - L}{|L|}$ 
14:  if Gain  $< g_*$  then
15:     $s_{out} \leftarrow \frac{s_{in}}{\gamma}$  ▷ Increase  $s$  if the progress is too low
16:  end if
17: end if
18: return  $\mathbf{X}, s_{out}$ 

```

exact conditional distribution $\pi_0(d\mathbf{x}|h(\mathbf{x}) > l)$. The underlying idea (see Guyader et al. [2011]) is that the Markov chain generated by Gen($l, 1$) in Alg.2 leaves invariant the distribution $\pi_0(d\mathbf{x}|h(\mathbf{x}) > l)$, so that the idealized algorithm is formally the limit of the simulated algorithm when $t \rightarrow +\infty$.

Step 0: Checking the lower bound assumption

The lower bound assumption can be rewritten as follows:

$$\exists p_* > 0, s_0 > 0, \forall \mathbf{x}, s \geq s_0, \quad \text{Law}(K(\mathbf{x}, s)) \geq p_* \pi_0 \quad (\text{Doebelin})$$

where inequality between two measures simply means that their difference is a non-negative measure. (Doebelin) is a well-known irreducibility condition coined 'Doebelin condition' in the probabilistic literature on Markov chain.

Let us check that the lower bound condition is compliant with some very minor variants of the transformation method detailed in Sect. 4.2.

Consider for instance the transformation: $\mathbf{X} \sim \mathcal{U}(\mathcal{B}_{2,\epsilon}(\mathbf{x}_o))$, $T(\mathbf{U}, \mathbf{x}_o) = \mathbf{x}_o + \epsilon \mathbf{U}(1 : n)$ where \mathbf{U} is $n + 2$ -dimensional with uniform distribution on the unit sphere of \mathbb{R}^{n+2} .

On the other hand, consider the proposal on the unit sphere of \mathbb{R}^{n+2} obtained by composing the Gaussian proposal (14) in \mathbb{R}^{n+2} with an additional orthogonal projection. This proposal on the sphere has the following two properties: i) it is reversible with respect to the uniform distribution on the sphere (by a symmetry argument), ii) its density satisfies (Doebelin) (by lower bounding (14) with initial condition on the unit sphere by a centered Gaussian distribution).

Combining the latter proposal with T we obtain again a proposal reversible w.r.t. $\mathcal{U}(\mathcal{B}_{2,\epsilon}(\mathbf{x}_o))$ and satisfying (Doebelin). See below for possible (slight but technical) generalizations to proposals satisfying weaker versions of (Doebelin).

Step 1: Uniform rejection rate

The acceptance rate of a proposal satisfying (Doebelin) with accept rule given by score $h(\mathbf{x}) > l$ is bounded from below by:

$$p_* \mathbb{P}(h(\mathbf{X}) > l),$$

which is, in turn, uniformly bounded from below if $l \leq l_0$ with $\mathbb{P}(h(\mathbf{X}) > l_0) > 0$.

Note that the proof is thus compliant with the tuning of the proposal strength s w.r.t. a constant rejection rate (App. D), since that latter can be carried out while ensuring (Doebelin).

Step 2: Coupling of proposals

Let us define the ‘local’ coupling between proposals that will enable the coupling between algorithms. Let \mathbf{x}, \mathbf{x}' be given, as well as a proposal satisfying (Doebelin). A *coupled proposal* $K((\mathbf{x}, s), K(\mathbf{x}, s))$ is generated as follows: i) with probability p_* , generate a successful coupling $K(\mathbf{x}, s) = K'(\mathbf{x}', s)$ with distribution π_0 ; ii) else, generate independent proposals $K(\mathbf{x}, s)$ and $K'(\mathbf{x}', s)$ with respective distributions $\text{Law}(K(\mathbf{x}, s)) - p_*\pi_0$ and $\text{Law}(K'(\mathbf{x}', s)) - p_*\pi_0$.

Clearly, the associated two marginal distributions of $K(\mathbf{x}, s)$ and $K'(\mathbf{x}', s)$ are respectively $\text{Law}(K(\mathbf{x}, s))$ and $\text{Law}(K'(\mathbf{x}', s))$.

Step 3: Coupling of the two algorithms

Let us denote by L_k and L'_k the two levels of the last particle at iteration k in Alg. 1 for the *real and idealized algorithms, respectively*. If $L_k = L'_k$, we sample independently \mathbf{X}'_k , the new, refreshed particle of the idealized algorithm, according to the exact conditional distribution $\pi_0(d\mathbf{x}|h(\mathbf{x}) > L_k)$ (this replaces line 1 in Alg. 2). \mathbf{X}'_k is then modified in parallel with the new particle of the real algorithm according to Alg. 2 by iterating t times the coupled proposal transition of Step 2; K being used for the real and idealized algorithms, respectively.

After t iterations one has thus obtained a successful coupling with probability (conditional on L_k) $1 - (1 - p_*\mathbb{P}(h(\mathbf{X}) > L_k))^t \xrightarrow[t \rightarrow +\infty]{} 1$.

Moreover, since Alg. 2 leaves invariant the conditional distribution $\pi_0(d\mathbf{x}|h(\mathbf{x}) > L_k)$, it does not modify the distribution of the refreshed particle in the idealized algorithm.

Step 4: Conclusion by induction

Let l_0 be any critical level such that $\pi_0(h(\mathbf{X}) > l_0) > 0$. We consider the following induction hypothesis at iteration k :

H_k On the event, $L_k \leq l_0$, The probability that the two particle systems are equal tends exponentially fast to 1 when $t \rightarrow +\infty$.

Assume H_k is true. The probability that the two particle systems are equal at iteration $k + 1$ is the probability conditioned by equality at iteration k multiplied by probability of equality at iteration k . If the score level is below l_0 , the former conditioned probability is bounded below by $1 - (1 - p_*\mathbb{P}(h(\mathbf{X}) > l_0))^t$ by Step 3 so that using H_k the induction on H_{k+1} is complete.

We deduce that $\mathbb{P}(L_m \leq l_0)$ converges exponentially fast with t large towards $\mathbb{P}(L'_m \leq l_0)$ for each l_0 . Using in addition Theorem 1 on the idealized algorithm, we conclude the proof.

Possible Generalizations: It is possible to relax the irreducibility condition (Doebelin) so that it is verified by most practical proposals, see Sec. 4.2. This requires using so-called Lyapounov functions, as well as an extra (but mild) assumption on the shape of h ‘at infinity’.

For instance, consider the Gaussian proposal (14) in \mathbb{R}^{n+2} . It satisfies the Doebelin condition (Doebelin), but only locally, for all \mathbf{x} in a ball, p_* depending now of the size of the ball.

The extra assumption on the shape of the score function h at infinity is then necessary to check that the rejection rate is again uniformly bounded from below.

Finally, one can remark that the following so-called Lyapounov condition $\mathbb{E}[|K(\mathbf{x}, s)|^2] \leq \rho|x|^2 + c$ holds true (with $\rho = \frac{1}{1+s^2} < 1$ and $c = \frac{s^2}{1+s^2} < +\infty$). It ensures that the proposal cannot be stuck at infinity, in areas where the ‘local’ Doebelin condition is poor.

One can then couple proposals using (Doebelin) as above, but only when the coupled initial states are in a given ball, and use the Lyapounov condition (see Hairer and Mattingly [2011]) to nonetheless obtain a successful coupling with a lower bounded success rate.

The proof then works as above.

Final remarks: Note that the exponential convergence rate obtained in the proof of Proposition 4 is too sub-optimal to be suitable for practical purpose. Practical estimation of this rate is left for future work although estimating the mixing rate of such Markov chain is known to be difficult and widely dependent on the geometry of h .

F Implementation details of the experiments

This section gives further details on the implementation available at

<https://github.com/karimtito/efficient-statistical>

The source code provided can be used to re-run experiments or run different experiments (see README file for more information).

F.1 ACAS Xu

In the experiments on the ACAS Xu DNN compression case study we used the 45 neural networks from the VNNLIB website (in ONNX format), which do not require normalizing the inputs. We only tested the 5 first properties since they apply to all networks. We use an adaptive procedure to tune the strength parameter s as explained in D. Experiments main parameters are set to: $N = 2$, $p_c = 10^{-50}$, $T = 40$, $\alpha = 10^{-3}$. We initialize the strength s at 1.5 and use the adaptive sampling procedure of section D with $\gamma = 0.99$, $a_* = 0.90$, $g_* = 0.01$. In addition we ran experiments with the ERAN complete certification method using DeepPoly and Mixed Integer programming on the same benchmark.

F.2 MNIST

We selected 4 neural networks from the ERAN benchmark: 3 architectures of varying complexity trained with pytorch named 'convMedGReLU_PGDK_w_0.1', 'ffnnReLU_PGDK_w_0.1_6_500' & 'ffnnReLU_Point_6_500' and a simpler model trained with tensorflow 'mnist_relu_9_200'. We use batched version of the Last Particle algorithm where we test the local robustness around 100 images in parallel. For each image we create a system of $N (= 2)$ particles and we call the score at each iteration (line 6 in Algorithm 1) with a batch consisting of all lower-scored particles. This trick accelerates the computations by taking advantage of the GPU. We also used the adaptive tuning of the strength, initializing s at 1.5 and with $\gamma = 0.999$, $a_* = 0.90$, $g_* = 0.01$.

F.3 ImageNet

Similarly to MNIST we used a batched version of the Last Particle algorithm presented in section 3. Again we also used a automatic control mechanism (see section D, initializing s at 1 and taking $\gamma = 0.999$, $a_* = 0.90$, $g_* = 0.01$). For ImageNet we could not run the ERAN certification methods unfortunately since these methods barely scale to such high input dimension and management of ImageNet is not implemented for now on the ERAN GitHub repository.

Checklist

1. For all authors...
 - (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes] Efficiency and scalability are experimentally demonstrated in Sect. 5. Non-asymptotic guarantees are proven in Prop. 1 to 4.
 - (b) Did you describe the limitations of your work? [Yes] We did in the conclusion
 - (c) Did you discuss any potential negative societal impacts of your work? [Yes] We did in the 'Broader Impact' Section.
 - (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes] Yes, we had.
2. If you are including theoretical results...
 - (a) Did you state the full set of assumptions of all theoretical results? [Yes] Especially for Prop. 4.
 - (b) Did you include complete proofs of all theoretical results? [Yes] In particular, proof of Prop. 4 is in App. E
3. If you ran experiments...
 - (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] App. F.3 gives

the implementation details to reproduce the experimental results. The code is available on github: <https://github.com/karimtito/efficient-statistical>

- (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] In App. F.3.
 - (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes] For run-times of the Last Particle algorithm, since the method is stochastic.
 - (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes]
4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
- (a) If your work uses existing assets, did you cite the creators? [Yes] Datasets and benchmark suite.
 - (b) Did you mention the license of the assets? [Yes]
 - (c) Did you include any new assets either in the supplemental material or as a URL? [No]
 - (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [N/A]
 - (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [N/A]
5. If you used crowdsourcing or conducted research with human subjects...
- (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]
 - (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]
 - (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]