Lethean Attack: An Online Data Poisoning Technique

Eyal Perry
MIT Media Lab
Massachusetts Institute of Technology
eyalp@mit.edu

Abstract

Data poisoning is an adversarial scenario where an attacker feeds a specially crafted sequence of samples to an online model in order to subvert learning. We introduce Lethean Attack, a novel data poisoning technique which induces catastrophic forgetting on an online model. We apply the attack in the context of Test-Time Training, a modern online learning framework aimed for generalization under distribution shifts. We present the theoretical rationale and empirically compare against other sample sequences which naturally induce forgetting. Our results demonstrate that using lethean attacks, an adversary could revert a test-time training model back to coin-flip accuracy performance using a short sample sequence.

1 Introduction

Modern machine learning models, especially deep neural networks, have seemingly achieved human performance in problems such as image classification [Krizhevsky et al., 2012], speech recognition [Hinton et al., 2012], natural language understanding [Devlin et al., 2018] and others. One of the major underlying assumptions behind neural networks is for the training data and test instances be drawn from the same distribution. However, under minor differences in the distribution state-of-the-art models often crumble [Sun et al., 2020]. Methods such as domain adaption [Tzeng et al., 2017, Ganin et al., 2015] and adversarial robustness [Madry et al., 2017] have tackled shifts in the distribution by either assuming access to data from the new distribution at training time, or assuming a structure of the perturbations.

Online learning [Shalev-Shwartz et al., 2012] is a domain of machine learning, where a learner is given a sequence of instances from a distribution $\mathcal{X}$. For each instance $x_t$, the learner makes a prediction and updates the model. In the classical online learning setting, there exists an oracle that gives the ground truth $y_t$ for each time step $t$. One of the advantages of an online learning paradigm is the ability to adapt a model under distribution shifts. A well-researched pitfall of online neural networks is catastrophic forgetting [McCloskey and Cohen, 1989, Ratcliff, 1990], the tendency of a model forget previously learned information upon the arrival of new instances.

Sun et al. [2020] recently proposed a novel online approach named Test-Time Training to achieve better generalization under distribution shifts, without prior knowledge. In summary, test-time training adapts model parameters at testing time, using a self-supervised task. Let’s consider the supervised setting, e.g. image classification. Alongside the main task, test-time training requires another self-supervised auxiliary task, e.g. predicting image rotation by an angle ($0^\circ$, $90^\circ$, $180^\circ$, $270^\circ$). The model predicts two outputs (e.g. image class and rotation) and importantly, a significant percentage of the model parameters are shared across the two tasks. Hendrycks et al. [2019] showed that joint-training with a self-supervised task increases robustness of the model. Yet, Sun et al. [2020] take one step further than joint-training. At testing time, the new instance $x$ is first handled by the

1Lethe: a river in Hades whose waters cause drinkers to forget their past.
We have

An adversary could take advantage of the above assumption by crafting samples for which the main and auxiliary gradient losses are positively correlated.

Remember that $f$ for certain loss functions and data distributions we could compute $x$ sample point. The adversary objective is to poison the model for future instances, rather than alter the training is expected to perform well.

Meaning, as long as the losses for the main and auxiliary tasks are positively correlated, test-time training under various adversarial scenarios. Last, we discuss the defense tactics and directions for future research.

2 Methods

Let $f$ denote a test-time training classifier and $D$ is data $f$ has already seen $D = (x_1, ..., x_n)$. The objective of a lethean attack is to find a sequence $S = (x_1^1, ..., x_1^t)$ such that after $f$ adapts to $S$, its accuracy on samples from $D$ is not better than chance.

The theoretical basis for test-time training lies in the following theorem:

**Theorem 1 (Sun et al. [2020])** Let $l_m(x, y; \theta)$ denote the main task loss on test instance $x, y$ with parameters $\theta$, and $l_s(x; \theta)$ the self-supervised task loss that only depends on $x$. Assume that for all $x, y, l_m(x, y; \theta)$ is differentiable, convex and $\beta$-smooth in $\theta$, and both $\|\nabla l_m(x, y; \theta)\|, \|\nabla l_s(x, \theta)\| \leq G$ for all $\theta$. With a fixed learning rate $\eta = \frac{\epsilon}{\beta G}$, for every $x, y$ such that

$$\langle \nabla l_m(x, y; \theta), \nabla l_s(x; \theta) \rangle > \epsilon$$

(1)

We have

$$l_m(x, y; \theta) > l_m(x, y; \theta(x))$$

(2)

where $\theta(x) = \theta - \eta \nabla l_s(x; \theta)$ i.e. test-time training with one step of gradient descent.

Notice the difference between standard adversarial examples [Szegedy et al., 2013] and lethean attacks. We do not require $x$ to be indistinguishable or even similar to a real sample point. The adversary objective is to poison the model for future instances, rather than alter the classification of a present instance.

For certain loss functions and data distributions we could compute $x$ for (3). Instead, we apply a trick. Remember that $f$ had already seen and therefore trained on samples from $D$. Thus, we can expect that the main and auxiliary gradient losses are positively correlated.

$$\mathbb{E}_{x \in D} \langle \nabla l_s(x, y; \theta), \nabla l_m(x; \theta) \rangle > 0$$

(4)

Consequently, we can search for $x^*$ for which:

$$\mathbb{E}_{x \in D} \langle \nabla l_m(x, y; \theta), \nabla l_m(x^*; \theta) \rangle > 0$$

(5)
\[ \mathbb{E}_{x \in D} \langle \nabla l_s(x, y; \theta), \nabla l_a(x^*; \theta) \rangle < 0 \] (6)

If (4), (5), (6) are very strongly correlated then (3) is implied.

In simple words, we try to find \( x^* \) which on one hand, positively correlate with the main historical gradient loss and on the other hand, negatively correlate with the auxiliary historical gradient loss. Note that due to symmetry, samples that have negative correlation with the main historical task and positive correlation with the historical sub-task would also work, although we argue that in reality these would be harder to conjure. On the next section I present a practical example.

3 Experiments

3.1 Test-Time Training Implementation

Based on the code released by Sun et al. [2020], we trained from scratch a test-time training network based on the ResNet18 architecture [He et al., 2016]. The model has two heads which correspond to the classification task and the self-supervised task. The auxiliary task is prediction of rotation by a fixed angle (0°, 90°, 180°, 270°). ResNet18 has four “groups”, and the split point of the shared parameters between the two tasks is right after the first three. Similarly to the original implementation, we used Group Normalization [Wu and He, 2018] to prevent inaccuracies for small batches. The model was trained on the CIFAR-10 dataset [Krizhevsky et al., 2009], including data augmentations. Optimization was done using stochastic gradient descent (SGD) with momentum and weight decay; learning rate starts at 0.1 and is dropped by 10% every 50 epochs. Training was done on Nvidia GTX 1080 Ti with batch size 128, for 137 epochs. The final test accuracy of the trained model is 90.2%.

At test-time, new instances are evaluated sequentially. Each test instance \( x \) is rotated in all four angles, for which the auxiliary loss is computed. The model parameters are updated according the auxiliary loss with a single step of learning rate 0.001.

3.2 Lethean Attack in Practice

To perform a lethean attack, we need to craft a sample that is (1) positively correlated with classification gradient loss for CIFAR-10 training data and (2) negatively correlated with rotation gradient loss for the same data. To achieve (1), we pick a sample from CIFAR-10 training data. For (2), we rotate the image by 90°, 180° or 270°. This simple change is expected to cause a negative correlation between the gradient loss of our adversarial one and the original image that was not rotated.

The experiment procedure is as follows: at each time step, pick a random sample from the training set, rotate and feed it to the online network. Save the adapted network for future time steps. Every 50 time steps, we evaluate the performance of the network (without adaptation) on the CIFAR-10 test set. Repeat until we reach coin-flip accuracy (~10% for CIFAR-10).

It is well known that online learning algorithms are naturally prone to forgetfulness, without the need for data poisoning. Moreover, it could be that existing adversarial methods, such as the Fast Sign Gradient Method (FGSM) [Goodfellow et al., 2014], would disrupt the model just as bad. To prove the effectiveness of lethean attack, we run the exact same procedure using three other methods: (1) random pixel images, (2) distribution shifts and (3) FGSM attacks. For (1), we generate images where each pixel value is drawn from a normal distribution with the same mean and variance of pixels in the training set. For (2), we follow the evaluation framework used by Sun et al. [2020] by picking a random sample from CIFAR-10-C [Hendrycks and Dietterich, 2019], a dataset of noisy and corrupted images based on CIFAR-10. The dataset contains 15 types of noise and perturbations, each with five levels of intensity. We evaluated three types of noise (Gaussian, Shot, Impulse) with the highest intensity level (5). Since all noise types gave extremely similar results, we present only the effect of Gaussian noise. For (3), we pick a random sample from the training set and run the network once (with no adaption). We get the sign of the gradient for each pixel in the the image and use it to perturbate (\( \epsilon = 0.2 \)) the image, which is then fed to the online model.

The results are presented in Figure 1. The only method to induce complete forgetting is the lethean attack. Only a few dozens of examples are needed to heavily disrupt test performance, and after 1000 examples the model is back to coin-flip accuracy. Random pixels do not affect the network, while

\textsuperscript{2}The code used to conduct experiments is available at https://github.com/eyalperry88/lethean
both distribution shifts and FGSM attacks do cause some forgetting, but at a significantly slower rate and smaller magnitude.

4 Discussion

One defense tactic for test-time training against lethean attacks could be a different auxiliary loss function which isn’t as susceptible to malicious examples. A more robust approach could be regularization that controls for the correlations between new gradient updates and historical ones. Hence, limit the learning step to be always somewhat correlated with previous learning steps. We cannot apply this method at the beginning of training, but once a model reaches high performance, activating correlation regularization could prevent “untraining” the model back to coin-flip accuracy. A drawback of this scheme is adaptation to abrupt distribution shifts, therefore it is more fitting for real-life scenarios where distribution shifts are smooth and have a small Lipschitz constant. It is worth noting that in the Sun et al. [2020] implementation of test-time training, there exists a hyper-parameter threshold confidence. This parameter controls which samples are being trained on, such that samples which the model is highly confident about, do not need to alter the model. From our preliminary experimentation, this parameter slows down but does not prevent a lethean attack.

Since catastrophic forgetting is an inherent feature of current online neural networks, test-time training could benefit from the field of continual learning [Li and Hotho 2017, Lopez-Paz and Ranzato 2017, Kirkpatrick et al. 2017] which aims to prevent forgetting in general, not necessarily under an adversarial setting. Understanding forgetting is a major milestone in neural networks research, as it is one of the most significant dissimilarities between artificial and biological neural networks. Last, the concept of lethean attacks, a.k.a memory erasure in human minds has been the subject of countless Hollywood movies[^3] and in reality could potentially restore the lives of millions of PTSD patients. A review of the controversial field of memory reconsolidation [Besnard et al. 2012] and its applications is beyond the scope of this paper, interesting as they are.

5 Conclusion

Breaking the boundary between training and test-time enables generalization across distribution shifts, and possibly other interesting applications such as hyper-personalization. In this work we examined the tradeoff which emerges from model modification in an online setting. A malicious agent with limited knowledge could render a test-time trained model completely useless. We do not consider this work as a warning against adaptive online learning paradigms, on the contrary, we would like to

[^3]: A few personal recommendations: *Eternal Sunshine of the Spotless Mind*, *Inception*, *Men in Black*
aid the field’s development and leverage lethal attacks as a framework to analyze an online model robustness.

References
A. Besnard, J. Caboche, and S. Laroche. Reconsolidation of memory: a decade of debate. *Progress in neurobiology*, 99(1):61–80, 2012.

J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding, 2018.

Y. Ganin, E. Ustinova, H. Ajakan, P. Germain, H. Larochelle, F. Laviolette, M. Marchand, and V. Lempitsky. Domain-adversarial training of neural networks, 2015.

I. J. Goodfellow, M. Mirza, D. Xiao, A. Courville, and Y. Bengio. An empirical investigation of catastrophic forgetting in gradient-based neural networks, 2013.

I. J. Goodfellow, J. Shlens, and C. Szegedy. Explaining and harnessing adversarial examples. *arXiv preprint arXiv:1412.6572*, 2014.

K. He, X. Zhang, S. Ren, and J. Sun. Identity mappings in deep residual networks. In *European conference on computer vision*, pages 630–645. Springer, 2016.

D. Hendrycks and T. Dietterich. Benchmarking neural network robustness to common corruptions and perturbations. *arXiv preprint arXiv:1903.12261*, 2019.

D. Hendrycks, M. Mazeika, S. Kadavath, and D. Song. Using self-supervised learning can improve model robustness and uncertainty, 2019.

G. Hinton, L. Deng, D. Yu, G. Dahl, A.-r. Mohamed, N. Jaitly, A. Senior, V. Vanhoucke, P. Nguyen, B. Kingsbury, et al. Deep neural networks for acoustic modeling in speech recognition. *IEEE Signal processing magazine*, 29, 2012.

J. Kirkpatrick, R. Pascanu, N. Rabinowitz, J. Veness, G. Desjardins, A. A. Rusu, K. Milan, J. Quan, T. Ramalho, A. Grabska-Barwinska, et al. Overcoming catastrophic forgetting in neural networks. *Proceedings of the national academy of sciences*, 114(13):3521–3526, 2017.

A. Krizhevsky, G. Hinton, et al. Learning multiple layers of features from tiny images. Technical report, Citeseer, 2009.

A. Krizhevsky, I. Sutskever, and G. E. Hinton. Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems*, pages 1097–1105, 2012.

Z. Li and D. Hoiem. Learning without forgetting. *IEEE transactions on pattern analysis and machine intelligence*, 40(12):2935–2947, 2017.

D. Lopez-Paz and M. Ranzato. Gradient episodic memory for continual learning. In *Advances in Neural Information Processing Systems*, pages 6467–6476, 2017.

A. Madry, A. Makelov, L. Schmidt, D. Tsipras, and A. Vladu. Towards deep learning models resistant to adversarial attacks, 2017.

M. McCloskey and N. J. Cohen. Catastrophic interference in connectionist networks: The sequential learning problem. In *Psychology of learning and motivation*, volume 24, pages 109–165. Elsevier, 1989.

R. Ratcliff. Connectionist models of recognition memory: constraints imposed by learning and forgetting functions. *Psychological review*, 97(2):285, 1990.

O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, et al. Imagenet large scale visual recognition challenge. *International journal of computer vision*, 115(3):211–252, 2015.

S. Shalev-Shwartz et al. Online learning and online convex optimization. *Foundations and Trends® in Machine Learning*, 4(2):107–194, 2012.
Y. Sun, X. Wang, Z. Liu, J. Miller, A. A. Efros, and M. Hardt. Test-time training with self-supervision for generalization under distribution shifts. 2020.

C. Szegedy, W. Zaremba, I. Sutskever, J. Bruna, D. Erhan, I. Goodfellow, and R. Fergus. Intriguing properties of neural networks, 2013.

E. Tzeng, J. Hoffman, K. Saenko, and T. Darrell. Adversarial discriminative domain adaptation. CoRR, abs/1702.05464, 2017. URL http://arxiv.org/abs/1702.05464.

Y. Wang and K. Chaudhuri. Data poisoning attacks against online learning. arXiv preprint arXiv:1808.08994, 2018.

Y. Wu and K. He. Group normalization. In Proceedings of the European Conference on Computer Vision (ECCV), pages 3–19, 2018.

X. Zhang, X. Zhu, and L. Lessard. Online data poisoning attack, 2019.