



**HAL**  
open science

# On the simplicity to produce falsified deep learning results

Adrien Chan-Hon-Tong

► **To cite this version:**

Adrien Chan-Hon-Tong. On the simplicity to produce falsified deep learning results. 2018. hal-01676691v1

**HAL Id: hal-01676691**

**<https://hal.science/hal-01676691v1>**

Preprint submitted on 5 Jan 2018 (v1), last revised 19 Nov 2019 (v7)

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

# On the simplicity to produce falsified deep learning results

Adrien CHAN-HON-TONG

January 5, 2018

## Abstract

Built on the top of works on adversarial examples, I show the existence of smuggling examples: alterations of training examples (precomputed from test set) which then lead the training toward unfairly good weights.

If from computer vision point of view this contribution is rather incremental, it is not from a social point of view. It is a clear warning message that falsification of the train/test paradigm is not just possible but easy with classic deep learning.

## 1 Introduction

Deep learning [10] results can be distorted even by unconscious/common bad practices like to tune few parameters on the test set, or more generally, to use little feed back from test evaluations [3]. So, one can imagine how it could be distorted by voluntary misconduct.

This statement is an issue considering the technological breakthrough of deep learning. Today, it seems that deep learning may lead to a major industrial revolution. Applications already goes much further than social network (automatic tagging of social network picture [16]) or web indexation (search into picture). Applications includes autonomous driving, security, financial management and health [6]. And, yet, this statement holds.

In research, one watchdog is the peer review process. Indeed, if a paper pretends to have reached very large level of quality with something almost not new, reviewer will be suspicious. But, *plausible but false* results are hardly detectable (except by doing the experiment) even if the reviewer is an expert from the field. This statement goes beyond the question about replicability vs reproducibility<sup>1</sup>: it is about the training/testing paradigm.

The real watchdog in research is benchmarking on guidance datasets. In such competition like IMAGENET [2] or MSCOCO, a leader team publishes only training data and provides a strict evaluation process<sup>2</sup>. This way, participants can not tune too much the algorithms on the test set, allowing a quite fair evaluation of the algorithms.

---

<sup>1</sup>see *Replicability is not reproducibility: nor is it good science* from Drummond 2009

<sup>2</sup>see <http://www.image-net.org/challenges/LSVRC/announcement-June-2-2015>

Now, such watchdog does not exist outside research. Sharing data and/or benchmarking himself with outsiders can not be imposed to companies. The main watchdog for companies is self certification. Self certification is very common on aerospace industry<sup>3</sup> and medical system and may become common for deep learning components in autonomous driving or computer assisted medical decision. Indeed, self certification can be a fair enough way to evaluate an algorithm. This is the case for example if algorithm, training and testing datasets are designed by unrelated teams/companies plus evaluation is done only after algorithm is completely frozen. Now, imposing such high standard self certification process seems hard. Especially, because a large part of deep learning companies are just too small to have unconnected teams to enforce such process. And, as the main problem with deep learning is the correctness of the output and not of the code correctness, formal verification (see [7] for an example) and other mathematics tool for verification are useless.

Off course, the question about *what should be the level of self certification required for deep learning module taking critical decision* is well too beyond the scope of this paper.

However, the goal of this paper is to remind the legislators and the community that falsification is not just possible but easy with deep learning. The contribution of this paper is inspired by adversarial examples<sup>4</sup> [13]. Adversarial example (presented with related work in next section) refers to the possibility to produce very large change in the output of a network with imperceptible input noise. In the section 3 of this paper, I present smuggling examples: the possibility to compute imperceptible noise of training examples in order to bias natural training toward any model, and especially, the model trained on the test set. Conclusion more detailed in final section is that with such smuggling examples, one could pretend to reach high result with highly reproducible experiment, while, being in a complete falsification of the training/testing paradigm.

## 2 Related works

Today, deep learning is overwhelmingly the state of the art of computer vision [10]. On static datasets, deep learning provides much higher accuracy than prior computer vision systems. For this reason, deep learning could be quickly use on real life applications including medical images and autonomous driving.

However, when applied to real life application deep learning system could have to face hacking behaviour from the users. Unfortunately, deep learning raises at least two hacking issues: privacy [14] and robustness[13].

The privacy issue is that, with classical network, one can infer information about the dataset from the network weight learnt on this dataset. Air gap deep networks have been proposed [14] as bypass. It consists in trying to learn a public network from privates networks having seen the training data.

---

<sup>3</sup>see [https://ec.europa.eu/transport/modes/air/safety/safety-rules\\_en](https://ec.europa.eu/transport/modes/air/safety/safety-rules_en)

<sup>4</sup>first appear on arxiv in *Intriguing properties of neural networks*

The robustness issue is that classical networks admit adversarial examples. It is possible to design a specific imperceptible noise that will make the network producing dumb output [12, 19]. The easy way to generate such example is to look into the root algorithm to train networks: the back propagation of the gradient[11]. Back propagation allows to compute derivative according to each weight given a loss from the last layer. This relies on the computation of derivative according to each *neuron*. Thus, by a nature, back propagation allows to compute derivative according to the input data itself (this can be done easily with PYTORCH for example, just asking the internal variable to store gradient). If these derivative are high, then, it means that with a very little change in the input data, one can get a very different output from the network. And, this is the case for classical deep learning network.

From a scientific point of view, the importance of this lack of robustness is ambiguous. From one hand, regularity is often thought to be a matter of algorithm (a lot of literature is interested by the theoretical property of machine learning algorithms see [1, 17] for examples). And so, changing the network output just by applying an imperceptible noise raises questions about what is really learnt by the network. But, on the other hand, [18] shows that, in the finite case, all algorithm are equally bad when averaged over all possible problems. Thus, if we hope to learnt something with an algorithm it means that regularity is somehow a matter of targeted data[20]. This way, one should not expect the algorithm to handle samples from outside the target data, like for examples adversarial samples.

But, from a social point of view, this is a problem because if network are deployed in real word, people will interact with them. And so, networks may have to deal with adversarial examples. Especially, [9] shows that these examples can be produced in real physical word.

Now, I present in this paper an other hacking weakness. But, here, the hacking does not come from the user but from the seller. Based on adversarial examples, I show the existence of smuggling examples i.e. examples that allows to hack the train/test paradigm. Indeed, in the next section, I show how one can pre compute a specific noise to the training images (knowing the test set) in order to produce an unfairly high efficient algorithm on the test set.

## 3 Smuggling examples

### 3.1 Targeted pipeline

In order to stress the possibility to falsify the train/test paradigm while being reproducible, I target a 0 meta parameter deep learning pipeline.

The pipeline is a convolutional neural network (CNN) with IMAGENET weight as feature extractor plus SVM [17] as classifier. All images (training images and testing images) are forwarded into the CNN network and transformed into a vector. Then, a SVM is trained on the training vector (with LIBLINEAR default parameter [4]).

Given the training/testing images, this pipeline (inspired from [5]) is

completely straightforward and reproducing (code will be posted in an appropriated github).

### 3.2 Computing smuggling example

Now, the question is to know if one could use the test set to compute a little perturbation of each **training** images in order to get an unfairly high result on the test set.

Mathematically, let  $x_1, \dots, x_N$  be some vectors in  $\mathbb{R}^{D+1}$  (value into the last dimension is 1 for all vectors) and  $y_1, \dots, y_N$  the corresponding -1/+1 label in the binary case. Given a vector  $w$  in  $\mathbb{R}^{D+1}$ , the smoothed error of  $w$  on the data  $x, y$  is  $e(w, x, y) = w|w + C \sum_n \text{relu}(1 - y_n x_n |w)$  with  $\text{relu}$  be the function 0 for negative and identity for positive and  $|$  the scalar product. The SVM optimisation<sup>5</sup> consists to solve  $\min_w e(w, x, y)$ .

Here, I will use  $C = 1$  (the default LIBLINEAR parameter). Let notice that, in the linearly separable hard margin SVM case ( $C \gg 1$ ), final hyperplane is only influenced by support vectors. But in the most common case, vectors are not separable and soft margin ( $C \approx 1$ ) is used instead, and so, all vectors can influence somehow on  $w$ .

Now, let consider a desired output. Typically, let note  $w_{test}^*$  the result of a SVM optimization on the test set. Everybody hope to optimize on the train set but to get  $w_{test}^*$  (or something close). Now, let notice that if each  $x_n$  is transformed into  $x'_n = x_n + \delta_n w^* + \lambda_n$  with  $\lambda_n |w_{test}^* = 0$  and  $\delta_n > 0$ , then it is trivial that  $e(w_{test}^*, x', y) \leq e(w_{test}^*, x, y)$  because  $\forall n, \text{relu}(1 - y_n x'_n |w_{test}^*) = \text{relu}(1 - y_n x_n |w_{test}^* - \delta y_n^2 w_{test}^* |w_{test}^*) \leq \text{relu}(1 - y_n x_n |w_{test}^*)$  ( $\text{relu}$  is an increasing function).

So, if one add a little transformation on each image in order to increase the scalar product between  $x_n$  (CNN features from the image) and the desired vector  $w_{test}^*$ , it unfairly decreases the distance with  $w_{train}^*$  (the vector which will result from the optimization on the modified training data). Let notice that decreasing the error is decreasing the distance to the minimum as this is a convex problem.

So one can easily produce smuggling examples by:

- take network CNN initialized from IMAGENET
- add a fully connected layer initialized with the desired SVM weight (typically the weight that one get by optimizing the SVM on the test set)
- for each training image, optimize a noise added on the image in order to increase the network classification - this can be easily done by gradient descent using the derivatives that are computed by back propagation
- learning a SVM on the modified training images will produce weights biased to be close to the desired SVM weights

Let notice that the optimal additive perturbation to bias weight toward a target can be formalized and computed at least by replacing  $w|w$

---

<sup>5</sup>Here, I will write optimization and not training as I will apply this optimization on original train data, test data and modified train data.

per  $\|w\|_1$ . Because, the problem of computing  $\min_w$  can be converted into an inequality problem on  $w$  using primal-dual theory. Then, these set of inequality can become a set of constraint into new formulation with perturbations as variable and where objective function is  $L_1$  distance between  $w$  and the target. This is a classical optimisation trick and could be more detailed into an appendix. But, here, vector are derived from application of CNN to image, and, this is the image that should be perturbed. So there is no room for this kind of formal optimisation.

Now, the possibility to create smuggling examples is kind of trivial (and if not, a way is just presented bellow). But, the question is how smuggling are these examples. In other words, how these smuggling examples have to be far from the original examples to produce a real bias.

Indeed, I show in the next subsection that smuggling attack could be dramatic with classical deep learning. This statement is currently base on partial result on CIFAR10 (a well know dataset of computer vision) and should off course be extended. But, yet, it prove a point.

### 3.3 Experiment on CIFAR10

For this preliminary experiment, I just use one very classical network VGG<sup>6</sup>. Other networks should be considered (e.g. alexnet, googlenet, resnet see [15] for a brief review).

I also use only CIFAR10 [8] but other datasets would be considered.

Images (32x32) are forwarded into VGG until conv4\_1 and transformed into 2048 vectors.

Honest performances of the pipeline are 69% of accuracy (train on raw train images, test on raw test images). Desired performances (train on raw test images, test on the same) are 99%. There is thus a room for smuggling examples.

With only few gradient step (with lr = 1, momentum = 0.5, cross entropy), the unfair performance (train on modified train image, test on test) reaches 77% with a noise no more than 5 over 256 (in color intensity).

This preliminary results have off course to be strengthen but show that smuggling examples are easy to implement.

## 4 social implication

I have show that, knowing the test set, one can add a small noise to training data in order to increase the performance on the test set. Off course, such misconduct is not possible if test set is hidden until algorithm is frozen.

Now, inversely, if a test set is made public. Then, one could collect relevant training data, and modify these training data with this smuggling examples to reach unfair performance on the test set. This person could even make the modified data public and claim to have resolved the problem with a 0 meta parameter pipeline completely reproducible. Worse,

---

<sup>6</sup><https://github.com/jcjohnson/pytorch-vgg>

if transformation are small enough, it could be impossible to detect that these are transformed data.

One can argue that nobody will organize a benchmark with a public testing set. I hope so. But, what about if testing set is just collected by a team from a same company or even by the only team of the company. Again, let think about a public organization with non deep learning expert who want to do a tender including minimal performance on a test set by the end of the project. Could legislation really allow the test set to be hidden ? How could a company answer a tender with penalty based on exigence on an hidden dataset ? How could a judge decide about a complain from the company that the problem comes from the data and no the produced algorithm ?

I argue that there will be pressure to allow low control standard on deep learning module (e.g. data sharing between evaluator and designer). But accepting such data sharing makes smuggling attack possible.

## References

- [1] Thomas Cover and Peter Hart. Nearest neighbor pattern classification. *IEEE transactions on information theory*, 13(1):21–27, 1967.
- [2] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In *Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on*, pages 248–255. IEEE, 2009.
- [3] Cynthia Dwork, Vitaly Feldman, Moritz Hardt, Toniann Pitassi, Omer Reingold, and Aaron Roth. The reusable holdout: Preserving validity in adaptive data analysis. *Science*, 349(6248):636–638, 2015.
- [4] Rong-En Fan, Kai-Wei Chang, Cho-Jui Hsieh, Xiang-Rui Wang, and Chih-Jen Lin. LIBLINEAR: A library for large linear classification. *Journal of Machine Learning Research*, 9:1871–1874, 2008.
- [5] Ross Girshick, Jeff Donahue, Trevor Darrell, and Jitendra Malik. Rich feature hierarchies for accurate object detection and semantic segmentation. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2014.
- [6] Hayit Greenspan, Bram van Ginneken, and Ronald M Summers. Guest editorial deep learning in medical imaging: Overview and future promise of an exciting new technique. *IEEE Transactions on Medical Imaging*, 35(5):1153–1159, 2016.
- [7] Gerwin Klein, Kevin Elphinstone, Gernot Heiser, June Andronick, David Cock, Philip Derrin, Dhammika Elkaduwe, Kai Engelhardt, Rafal Kolanski, Michael Norrish, et al. sel4: Formal verification of an os kernel. In *Proceedings of the ACM SIGOPS 22nd symposium on Operating systems principles*, pages 207–220. ACM, 2009.
- [8] Alex Krizhevsky and Geoffrey Hinton. Learning multiple layers of features from tiny images. 2009.

- [9] Alexey Kurakin, Ian J. Goodfellow, and Samy Bengio. Adversarial examples in the physical world. In *International Conference on Learning Representations (ICLR)*, 2017.
- [10] Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. Deep learning. *Nature*, 521(7553):436–444, 2015.
- [11] Yann LeCun, Bernhard E Boser, John S Denker, Donnie Henderson, Richard E Howard, Wayne E Hubbard, and Lawrence D Jackel. Handwritten digit recognition with a back-propagation network. In *Advances in neural information processing systems*, pages 396–404, 1990.
- [12] Seyed Mohsen Moosavi DeZfooli, Alhussein Fawzi, Omar Fawzi, and Pascal Frossard. Universal adversarial perturbations. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, July 2017.
- [13] Anh Nguyen, Jason Yosinski, and Jeff Clune. Deep neural networks are easily fooled: High confidence predictions for unrecognizable images. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 427–436, 2015.
- [14] Reza Shokri and Vitaly Shmatikov. Privacy-preserving deep learning. In *Proceedings of the 22nd ACM SIGSAC conference on computer and communications security*, pages 1310–1321. ACM, 2015.
- [15] Christian Szegedy, Sergey Ioffe, Vincent Vanhoucke, and Alexander A Alemi. Inception-v4, inception-resnet and the impact of residual connections on learning. In *AAAI*, pages 4278–4284, 2017.
- [16] Yaniv Taigman, Ming Yang, Marc’Aurelio Ranzato, and Lior Wolf. Deepface: Closing the gap to human-level performance in face verification. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1701–1708, 2014.
- [17] Vladimir Naumovich Vapnik and Vladimir Vapnik. *Statistical learning theory*, volume 1. Wiley New York, 1998.
- [18] David H Wolpert. The lack of a priori distinctions between learning algorithms. *Neural computation*, 8(7):1341–1390, 1996.
- [19] Cihang Xie, Jianyu Wang, Zhishuai Zhang, Yuyin Zhou, Lingxi Xie, and Alan Yuille. Adversarial examples for semantic segmentation and object detection. In *The IEEE International Conference on Computer Vision (ICCV)*, Oct 2017.
- [20] Chiyuan Zhang, Samy Bengio, Moritz Hardt, Benjamin Recht, and Oriol Vinyals. Understanding deep learning requires rethinking generalization. In *International Conference on Learning Representations (ICLR)*, 2017.