

STOPPING GAN VIOLENCE: GENERATIVE UNADVERSARIAL NETWORKS

Samuel Albanie*

Institute of Deep Statistical Harmony
Shelfanger, UK

Sébastien Ehrhardt*

French Foreign Legion
Location Redacted

João F. Henriques*

Centre for Discrete Peace, Love and Understanding
Coimbra, Portugal

ABSTRACT

While the costs of human violence have attracted a great deal of attention from the research community, the effects of the network-on-network (NoN) violence popularised by Generative Adversarial Networks have yet to be addressed. In this work, we quantify the financial, social, spiritual, cultural, grammatical and dermatological impact of this aggression and address the issue by proposing a more peaceful approach which we term *Generative Unadversarial Networks* (GUNs). Under this framework, we simultaneously train two models: a generator G that does its best to capture whichever data distribution it feels it can manage, and a motivator M that helps G to achieve its dream. Fighting is strictly *verboten* and both models evolve by learning to respect their differences. The framework is both theoretically and electrically grounded in game theory, and can be viewed as a *winner-shares-all* two-player game in which both players work as a team to achieve the best score. Experiments show that by working in harmony, the proposed model is able to claim both the moral and log-likelihood high ground. Our work builds on a rich history of carefully argued position-papers, published as anonymous YouTube comments, which prove that the optimal solution to NoN violence is more GUNs.

Takes skill to be real, time to heal each other

Tupac Shakur, Changes, 1998

1 INTRODUCTION

Deep generative modelling is probably important (see e.g. Bengio et al. (2013a), Bengio et al. (2013b), Bengio et al. (2007a), Bengio et al. (2015) Bengio et al. (2007b) and (Schmidhuber et al., circa 3114 BC)). Justifications recently overheard in the nightclubs of Cowley¹ include the ability to accurately approximate data distributions without prohibitively expensive label acquisition, and computationally feasible approaches to beating human infants at chess². Deep generative modelling

* Authors are listed according to the degree to which their home nation underperformed at the 2016 European football championships

¹The nightclubs of Cowley are renowned for their longstanding philosophical support for Dubstep, Grime and Connectionism, and should not be confused with the central Oxford nightclub collective which leans more towards Dubstep, Grime and Computationalism - speak to *Old Man Bridge* at 3am on a Friday morning under the stairs of the smoking area for a more nuanced clarification of the metaphysical differences of opinion.

²Infants of other species (fox cubs, for example) remain an adorable open question in the field.

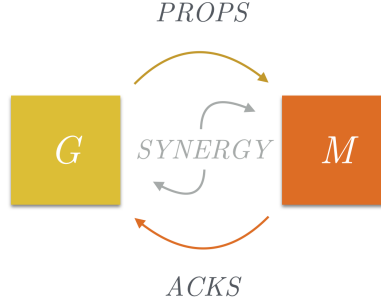


Figure 1: The proposed unadversarial training protocol. The generator G proposes samples, *PROPS*, and in return receives acknowledgements and praise, *ACKS* from the motivator M . As a direct consequence of the sense of teamwork fostered by our optimisation scheme, *synergy* abounds. Note: this figure best viewed at a distance, preferably at low resolution.

was broadly considered intractable, until recent groundbreaking research by Goodfellow et al. (2014) employed machiavellian adversarial tactics to demonstrate that metaphorical tractors could in fact be driven directly through the goddamn centre of this previously unploughed research field (subject to EU agricultural safety and set-aside regulations).

The key insight behind Generative Adversarial Networks (commonly referred to as GANs, GANGs or CAPONEs depending on sources of counterfeit currency) is to pit one model against another in a gladiatorial quest for dominance. However, as ably illustrated by respected human actor and philanthropist Russell Crowe in the documentary *Gladiator*, being an *actual gladiator* isn’t all sunshine and rainbows—although it’s possible to get a great tan, one still has to wear sandals.

Even though we are only in the introduction, we now bravely leap into a series of back-of-the-envelope calculations to compute a lower bound on the cost of that violence for the case of middle aged, median-income Generative Adversarial Networks living in comfortable, but affordable accommodation in the leafy suburbs of an appropriate class of functions.

Following the literature, we define the adversaries as two models, a discriminator D and a generator G . However, since we don’t agree with the literature or wish to condone its violent actions in any form, we immediately redefine the models as follows:

$$D, G := G, D \quad (1)$$

Note that the equation above is valid and above board, since the current version of mathematics (v42.1 at the time of writing) supports simultaneous assignment³. Therefore, in the following exposition, D represents the generator and G represents the discriminator. Next, we define a cost function, $C : \mathcal{V} \rightarrow \$$, mapping the space of model violence \mathcal{V} into the space $\$$ spanned by all mattresses stuffed with U.S. dollars, as follows:

$$C(V) = \alpha \int \beta_V(G) \quad (2)$$

in which β_V is a violent and discriminatory mapping from the discriminator G to the closest mathematical structure which appears to be a human brain and α is a constant representing the cost of human violence, to be determined by trawling through posts on social media. Note that β_V may be a violent function, but not crazy-violent (i.e. it must be *Khinchin-integrable*)⁴.

³We caution readers not to rely on this assumption in future versions. Mathematics has not supported backwards compatibility since Kurt “*Tab-Liebehaber*” Gödel re-implemented the entire axiomatic foundations of the language rather than be constrained to four-space equation indentation (see Gödel (1931) for the details).

⁴Since Neuroscience tells us that human brains are AlexVGGIncepResNets *almost-everywhere*, in practice we found that these functions need not be overly belligerent.

To evaluate this cost, we first compute α with a melancholy search of Twitter, uniquely determining the cost of violence globally as \$1876 for every person in the world (Twitter, 2016). Integrating over all discriminators and cases of probable discrimination, we arrive at a conservative value of 3.2 gigamattresses of cost. By any reasonable measure of humanity (financial, social, spiritual, cultural, grammatical or indeed dermatological), this is too many gigamattresses.

Having made the compelling case for GUNs, we now turn to the highly anticipated *related work* section, in which we adopt a petty approach to resolving disagreements with other researchers by purposefully avoiding references to their relevant work.

2 RELATED WORK

These violent delights have violent ends

Geoff Hinton, date unknown

Our work is connected to a range of adversarial work in both the machine learning and the machine forgetting communities. To the best of our knowledge Smith & Wesson (1852) were the first to apply GUNs to the problem of generative modelling, although similar ideas have been explored in the context of discriminative modelling as far back as the sixteenth century by Fabbrica d’Armi Pietro Beretta in an early demonstration of one-shot learning. Unfortunately, since neither work evaluated their approach on public benchmarks (not even on MNIST), the significance of their ideas remains under appreciated by the machine learning community.

Building on the approach of Fouhey & Maturana (2012)⁵, we next summarise the adversarial literature most closely related to ours, ordered by Levenshtein edit distance: GAN (Goodfellow et al., 2014), WGAN (Arjovsky et al., 2017), DCGAN (Radford et al., 2015), LAPGAN (Denton et al., 2015), InfoGAN (Chen et al., 2016), StackedGAN (Huang et al., 2016) and UnrolledGAN (Metz et al., 2016)⁶.

Unadversarial approaches to training have also received some attention, primarily for models used in other domains such as fashion (Crawford, 1992) and bodybuilding (Schwarzenegger, 2012)). Some promising results have also been demonstrated in the generative modelling domain, most notably through the use of *Variational Generative Stochastic Networks with Collaborative Shaping* (Bachman & Precup, 2015). Our work makes a fundamental contribution in this area by dramatically reducing the complexity of the paper title.

3 GENERATIVE UNADVERSARIAL NETWORKS

Under the Generative Unadversarial Network framework, we simultaneously train two models: a generator G that does its best to capture whichever data distribution it feels it can manage and a motivator M that helps G to achieve its dream. The generator is trained by learning a function $G(\vec{z}; \theta_g)$ which transforms samples from a uniform prior distribution $p_z(\vec{z})$ into the space graciously accommodating the data⁷. The motivator is defined as a function $M(\vec{x}; \theta_M)$ which uses gentle gradients and persuasive language to encourage G to improve its game. In particular, we train G to maximise $\log(M(G(\vec{z})))$ and we simultaneously train M to maximise $\log(M(G(\vec{z})))$. Thus, we see that the objectives of both parties are aligned, reducing conflict and promoting teamwork.

The core components of our framework are illustrated in Figure 1. The GUN training scheme was inspired largely by Clint Eastwood’s memorable performance in *Dirty Harry* but also in part by the Transmission Control Protocol (TCP) three-way handshake (Postel et al., 1981), which was among the first protocols to build harmony through synergy, acknowledgements and the simple act of

⁵This innovative work was the first to introduce the concept of an alphabetically-related, rather than scientifically-related literature review.

⁶In the interest of an unadversarial literature review, we note that Bishop (2006) and Murphy (2012) make *equally good* (up to $\epsilon = 10^{-6}$) references for further exploration of this area.

⁷The choice of the uniform prior prevents discrimination against prior samples that lie far from the mean. It’s a small thing, but it speaks volumes about our inclusive approach.

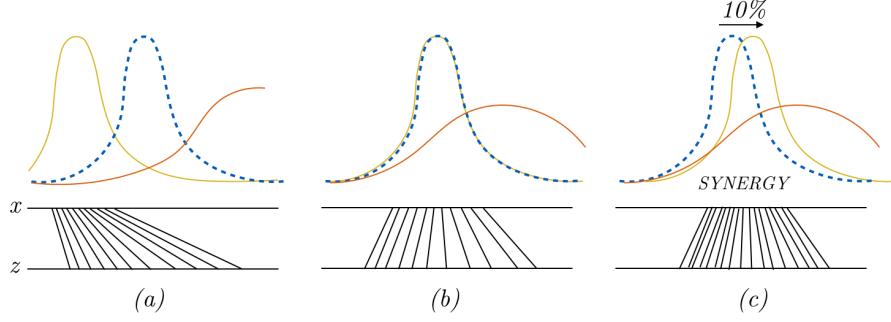


Figure 2: (a) GUNs are trained by updating the generator distribution G (yellow line) with the help and support of the motivator (red line) to reach its dream of the data distribution (blue dashed). (b) With a concerted effort, the generator reaches its goal. (c) Unlike previous generators which were content with simply reaching this goal, our generator is more motivated and gives it ‘110%’ moving it a further 10% past the data distribution. While this isn’t terribly helpful from a modelling perspective, we think it shows the right kind of attitude.

Algorithm 1 Training algorithm for Generative Unadversarial Networks

- 1: **procedure** TRAIN
 - 2: **for** #iterations **do**
 - 3: Sample n noise samples from prior $p_z(\vec{z})$ and compute $G(\vec{z}^{(1)}; \theta_g), \dots, G(\vec{z}^{(n)}; \theta_g)$.
 - 4: Sample n data samples $\vec{x}^{(1)}, \dots, \vec{x}^{(n)}$, from the data distribution.
 - 5: Let G show pairs $(\vec{x}^{(i)}, G(\vec{z}^{(i)}; \theta_g))$ to M as slides of a powerpoint presentation⁸.
 - 6: Sample constructive criticism and motivational comments from M .
 - 7: Update the powerpoint slides and incorporate suggestions into θ_g .
-

shaking hands. A description of the training procedure used to train G and M is given in Algorithm 1.

Algorithm 1 can be efficiently implemented by combining a spare meeting room (which must have a working projector) and a top notch deep learning framework such as MatConvNet (Vedaldi & Lenc, 2015) or Soumith Chintala (Chintala, 2012-present). We note that we can further improve training efficiency by trivially rewriting our motivator objective as follows⁹:

$$\theta_M^* = \min_{\theta_M} \oint_{S(G)} \log(R) + \log(1 - \zeta) \quad (3)$$

Equation 3 describes the flow of reward and personal well-being on the generator network surface. ζ is a constant which improves the appearance of the equation. In all our experiments, we fixed the value of ζ to zero.

⁸To guarantee polynomial runtime, it is important to ensure that the generator is equipped with the appropriate dongle and works through any issues with the projector *before* the presentation begins.

⁹If this result does not jump out at you immediately, read the odd numbered pages of (Amari & Nagaoka, 2000). This book should be read in Japanese. The even-numbered pages can be ripped out to construct beautiful *orizuru*.

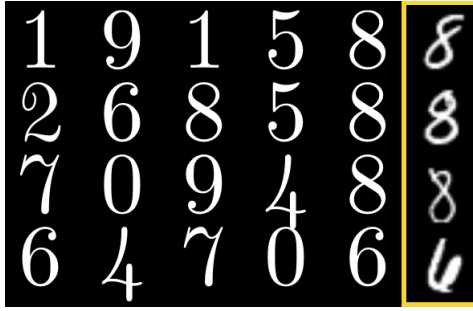


Figure 3: Visualised samples from the GUN model trained on MNIST¹¹ (the nearest training examples are shown in the right hand column). Note that these samples have been carefully cherry picked for their attractive appearance. Note how the GUN samples are much clearer and easier to read than the original MNIST digits.

4 EXPERIMENTS

Give the people what they want (MNIST)

Yann LeCun, date unknown

In this section we subject the GUN framework to a rigorous qualitative experimental evaluation by training unadversarial networks on MNIST. Rather than evaluating the model *error-rate* or probability on *withheld test data*, we adopt a less confrontational metric, *opportunities for improvement*. We also assess samples generated by the trained model by *gut feeling*, enabling a direct comparison with a range of competing generative approaches. Following academic best practices, key implementation details can be found in our private code repository¹⁰.

We *warm-start* the network with toy data taken from the latest Lego catalog. To nurture the right kind of learning environment, we let the network find its own learning rate and proceed by making ϵ -greedy updates with an ϵ value of 1. We consider hard-negative mining to be a gratuitously harsh training procedure, and instead perform *easy-positive mining* for gentler data digestion.

We now turn to the results of the experiment. Inspired by the Finnish education system, we do not test our models during the first formative epochs of development. A quantitative comparison with two other popular generative approaches has been withheld from publication to respect the privacy of the models involved. However, we are able to reveal that GUN had by far the most *opportunities for improvement*. We observed a sharp increase in performance once we all agreed that the network was doing well. By contrast, the adversarial nature of standard GAN methodologies usually elicits a fight-or-flight behavior, which can result in vanishing gradients and runaway losses. Samples drawn from the trained network are shown in Figure 3.

5 CONCLUSION

In this work, we have shown that network-on-network violence is not only unethical, it is also unnecessary. Our experiments demonstrate that happy networks are productive networks, laying the groundwork for advances in motivational machine learning. Indeed, unadversarial learning is an area rife with opportunities for further development. In future work, we plan to give an expanded treatment of important related subjects including nurtural gradients and k-dearest neighbours¹².

¹⁰We also make available a public copy of this repository which *almost* compiles. For the sake of brevity, all code comments, variables and function calls have been helpfully removed and replaced cross-platform, universally compatible ascii art. The code can be found at <http://github.com/albanie/SIGBOVIK17-GUNs>.

¹¹For ease of visualisation, the GUN samples were lightly post-processed with L^AT_EX.

¹²While we have exhaustively explored the topic of *machine learning GUNs*, we leave the more controversial topic of *machine GUN learning* to braver researchers.

ACKNOWLEDGEMENTS

The authors would like to acknowledge the quality of Karel Lenc’s homemade pancakes. This work was supported by the NRA (National Research Association).

REFERENCES

- Amari, Shun-ichi and Nagaoka, Hiroshi. Methods of information geometry, volume 191 of translations of mathematical monographs. *American Mathematical Society*, pp. 13, 2000.
- Arjovsky, Martin, Chintala, Soumith, and Bottou, Léon. Wasserstein gan. *arXiv preprint arXiv:1701.07875*, 2017.
- Bachman, Philip and Precup, Doina. Variational generative stochastic networks with collaborative shaping. In *ICML*, pp. 1964–1972, 2015.
- Bengio, Yoshua, Lamblin, Pascal, Popovici, Dan, Larochelle, Hugo, et al. Greedy layer-wise training of deep networks. *Advances in neural information processing systems*, 19:153, 2007a.
- Bengio, Yoshua, LeCun, Yann, et al. Scaling learning algorithms towards ai. *Large-scale kernel machines*, 34(5):1–41, 2007b.
- Bengio, Yoshua, Courville, Aaron, and Vincent, Pascal. Representation learning: A review and new perspectives. *IEEE transactions on pattern analysis and machine intelligence*, 35(8):1798–1828, 2013a.
- Bengio, Yoshua, Yao, Li, Alain, Guillaume, and Vincent, Pascal. Generalized denoising auto-encoders as generative models. In *Advances in Neural Information Processing Systems*, pp. 899–907, 2013b.
- Bengio, Yoshua, Goodfellow, Ian J, and Courville, Aaron. Deep learning. *Nature*, 521:436–444, 2015.
- Bishop, Christopher M. Pattern recognition. *Machine Learning*, 128:1–58, 2006.
- Chen, Xi, Duan, Yan, Houthoofd, Rein, Schulman, John, Sutskever, Ilya, and Abbeel, Pieter. Info-gan: Interpretable representation learning by information maximizing generative adversarial nets. In *Advances in Neural Information Processing Systems*, pp. 2172–2180, 2016.
- Crawford, Cindy. Shape your body workout, 1992.
- Denton, Emily L, Chintala, Soumith, Fergus, Rob, et al. Deep generative image models using a laplacian pyramid of adversarial networks. In *Advances in neural information processing systems*, pp. 1486–1494, 2015.
- Fouhey, David F and Maturana, Daniel. The kardashian kernel, 2012.
- Gödel, Kurt. Über formal unentscheidbare sätze der principia mathematica und verwandter systeme i. *Monatshefte für mathematik und physik*, 38(1):173–198, 1931.
- Goodfellow, Ian, Pouget-Abadie, Jean, Mirza, Mehdi, Xu, Bing, Warde-Farley, David, Ozair, Sherjil, Courville, Aaron, and Bengio, Yoshua. Generative adversarial nets. In *Advances in neural information processing systems*, pp. 2672–2680, 2014.
- Huang, Xun, Li, Yixuan, Poursaeed, Omid, Hopcroft, John, and Belongie, Serge. Stacked generative adversarial networks. *arXiv preprint arXiv:1612.04357*, 2016.
- Metz, Luke, Poole, Ben, Pfau, David, and Sohl-Dickstein, Jascha. Unrolled generative adversarial networks. *arXiv preprint arXiv:1611.02163*, 2016.
- Murphy, Kevin P. *Machine learning: a probabilistic perspective*. MIT press, 2012.
- Postel, Jon et al. Transmission control protocol rfc 793, 1981.

Radford, Alec, Metz, Luke, and Chintala, Soumith. Unsupervised representation learning with deep convolutional generative adversarial networks. *arXiv preprint arXiv:1511.06434*, 2015.

Schwarzenegger, Arnold. *Arnold: The education of a bodybuilder*. Simon and Schuster, 2012.

Twitter. Erik solheim: Cost of violence globally = \$1876 for every person in the world. global peace index here: <http://ow.ly/WouI3014Czf>, 2016.

Vedaldi, Andrea and Lenc, Karel. Matconvnet: Convolutional neural networks for matlab. In *Proceedings of the 23rd ACM international conference on Multimedia*, pp. 689–692. ACM, 2015.

AUTHORS’ BIOGRAPHIES

SAMUEL

Samuel started writing biographies at the tender age of 24, when he penned his first short story “Ouch that seriously hurt, keep your **** cat away from me” about the life of Jack Johnson, his brother’s lovable albino cat with anger management issues. His career as a biographer has gone from strength to strength ever since, flourishing in several other phyla of the animal kingdom. He is a noted expert on the much beloved native English Panda and is a self-award winning author on the challenges of hunting them.

SEBASTIEN

Sebastien holds a self-taught liberal arts degree, and passed his driver’s license exam with highest honours. Secretly a [REDACTED] national, he then joined the French Foreign Legion and was deployed

[REDACTED]
[REDACTED]
[REDACTED] in Nicaragua, [REDACTED] of [REDACTED], [REDACTED].
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[REDACTED]

JOÃO

João *El Tracko* F. Henriques holds a joint bachelors degree in guerilla warfare tactics and cakemaking from the University of Coimbra, where he has been tracking down the ~~vietims~~ subjects of his critically acclaimed biographies for over five years. Little did they know that his visual object tracking skills extend to real-life. Though some (all) of his subjects have since passed away, their legend lives on his thoughtfully written monograph, “How to most effectively interview someone who is trying desperately to escape from you”.