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# Adversarial Training against Systematic Uncertainty

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## Abstract

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## 1 Introduction

[GL: Distinction between statistical and systematic uncertainty.] [GL: Define nuisance parameters.] [GL: We want to build an accurate classifier whose output remains invariant with respect to systematic uncertainties.] [GL: Motivate the criterion (which may not be obvious for the ML crowd). See pivotal quantity motivation.]

## 2 Problem statement

Let assume a probability space  $(\Omega, \mathcal{F}, P)$ , where  $\Omega$  is a sample space,  $\mathcal{F}$  is a set of events and  $P$  is a probability measure. Let consider the multivariate random variables  $X_z : \Omega \mapsto \mathbb{R}^p$  and  $Y : \Omega \mapsto \mathcal{Y}$ , where  $X_z$  denotes a dependence on a nuisance parameter  $Z$  whose values  $z \in \mathcal{Z}$  define a parameterized family of its systematic uncertainties. That is,  $X_z$  and  $Y$  induce together a joint probability distribution  $p(X, Y|z)$ , where the conditional on  $z$  denotes  $X_z$ . For training, let further assume a finite set  $\{x_i, y_i, z_i\}_{i=1}^N$  of realizations  $X_{z_i}(\omega_i), Y(\omega_i)$ , for  $\omega_i \in \Omega$  and known values  $z_i$  of the nuisance parameter. Our goal is to learn a function  $f(\cdot; \theta_f) : \mathbb{R}^p \mapsto \mathcal{Y}$  of parameters  $\theta_f$  (e.g., a neural network-based classifier if  $\mathcal{Y}$  is a finite set of classes) and minimizing a loss  $\mathcal{L}_f(\theta_f)$ . In addition, we require that  $f(X_z; \theta_f)$  should be robust to the value  $z$  of the nuisance parameter – which remains unknown at test time. More specifically, we aim at building  $f$  such that in the ideal case

$$f(X_z(\omega); \theta_f) = f(X_{z'}(\omega); \theta_f) \quad (1)$$

for all samples  $\omega \in \Omega$  and all  $z, z'$  pairs of values of the nuisance parameter.

Since we do not have training tuples  $(X_z(\omega), X_{z'}(\omega))$  (for the same unknown  $\omega$ ), we propose instead to solve the closely related problem of finding a predictive function  $f$  such that

$$P(\{\omega | f(X_z(\omega); \theta_f) = y\}) = P(\{\omega' | f(X_{z'}(\omega'); \theta_f) = y\}) \text{ for all } y \in \mathcal{Y}. \quad (2)$$

In words, we are looking for a predictive function  $f$  which is a pivotal quantity [1] with respect to the nuisance parameter. That is, such that the distribution of  $f(X_z; \theta_f)$  is invariant with respect to the value  $z$  of the nuisance. Note that a function  $f$  for which Eqn. 1 is true necessarily satisfies Eqn. 2. The converse is however in general not true, since the sets of samples  $\{\omega | f(X_z(\omega); \theta_f) = y\}$  and  $\{\omega' | f(X_{z'}(\omega'); \theta_f) = y\}$  do not need to be the same for the equality to hold. In order to simplify

notations, and as only Eqn. 2 is of direct interest in this work, we denote from here on the pivotal quantity criterion as

$$p(f(X; \theta_f)|z) = p(f(X; \theta_f)|z') \text{ for all } z, z' \in \mathcal{Z}. \quad (3)$$

### 3 Method

Adversarial training was first proposed by [2] as a way to build a generative model capable of producing samples from random noise  $z \sim p_Z$ . More specifically, the authors pit a generative model  $g : \mathbb{R} \mapsto \mathbb{R}^p$  against an adversary classifier  $d : \mathbb{R}^p \mapsto \{0, 1\}$  whose antagonistic objective is to recognize real data  $X$  from generated data  $g(Z)$ . Both models  $g$  and  $d$  are trained simultaneously, in such a way that  $g$  learns to produce samples that are difficult to identify by  $d$ , while  $d$  incrementally adapts to changes in  $g$ . At the equilibrium,  $g$  models a distribution whose samples can be identified by  $d$  only by chance. That is, assuming enough capacity in  $d$  and  $g$ , the distribution  $p_{g(Z)}$  eventually converges towards the real distribution  $p_X$ .

In this work, we repurpose adversarial training as a means to constraint the predictive model  $f$  in order to satisfy Eqn. 3. In particular, we pit  $f$  against an adversary classifier  $r(\cdot; \theta_r) : \mathbb{R} \mapsto \mathcal{Z}$  of parameters  $\theta_r$  and associated loss  $\mathcal{L}_r(\theta_f, \theta_r)$ . Assuming that  $\mathcal{Z}$  defines a finite family of nuisance values  $z_l$  (for  $l = 1, \dots, |\mathcal{Z}|$ ), this classifier takes as input realizations of  $f(X; \theta_f)$ , for the current value  $\theta_f$  of  $f$  parameters, and produces as output probability estimates  $r(f(X; \theta_f); \theta_r)_l = \hat{p}(z_l|f(X; \theta_f))$  that  $f(X; \theta_f)$  is generated from the nuisance value  $z_l$ . If  $p(f(X; \theta_f)|z)$  varies with  $z$ , then the corresponding correlation can be captured by  $r$ . By contrast, if  $p(f(X; \theta_f)|z)$  is invariant with  $z$ , as we require, then  $r$  should perform poorly and be close to random guessing. Training  $f$  such that it additionally minimizes the performance of  $r$  therefore acts as a regularization towards Eqn. 3.

As for generative adversarial networks, we propose to train  $f$  and  $r$  simultaneously, which we carry out by considering the value function

$$E(\theta_f, \theta_r) = \mathcal{L}_f(\theta_f) - \mathcal{L}_r(\theta_f, \theta_r) \quad (4)$$

that we optimize by finding the saddle point  $(\hat{\theta}_f, \hat{\theta}_r)$  such that

$$\hat{\theta}_f = \arg \min_{\theta_f} E(\theta_f, \hat{\theta}_r), \quad (5)$$

$$\hat{\theta}_r = \arg \max_{\theta_r} E(\hat{\theta}_f, \theta_r). \quad (6)$$

The adversarial training procedure to obtain  $(\hat{\theta}_f, \hat{\theta}_r)$  is formally presented in Algorithm 1 in the case of  $f$  being a classifier and of the cross-entropy loss for both  $\mathcal{L}_f$  and  $\mathcal{L}_r$ . The algorithm consists in using stochastic gradient descent alternatively to optimize Eqn. 5 and 6.

[GL: Extension to continuous nuisance parameters: have the adversary  $r$  models the conditional distribution  $p(z|f(X; \theta_f))$ , e.g. with a network whose 2 outputs are the parameters of a truncated gaussian and optimized such that  $p(z|f(X; \theta_f)) \approx N(\mu(f(X; \theta_f); \theta_r), \sigma(f(X; \theta_f); \theta_r))$ . The associated loss should be the negative log-likelihood (= cross-entropy), which is maximal when the approximation is perfect and minimal when the truncated gaussian degenerates to a uniform (when  $\sigma$  is large), in which case we should have the guarantee that  $f$  is pivotal.]

[GL: This section and theoretical results should be rewritten in such a way that categorical and continuous nuisance values are solved under the same principled approach.]

### 4 Theoretical results

In this section, we show that in the setting of Algorithm 1, the procedure converges to a classifier  $f$  which is a pivotal quantity in the sense of Eqn. 3. Results below are derived in a non-parametric setting, by assuming that both  $f$  and  $r$  have enough capacity. To simplify the presentation, we also assume the uniform prior  $p(z) = \frac{1}{|\mathcal{Z}|}$  for all  $z \in \mathcal{Z}$ , e.g. by having the same number of training samples for each modality  $z$  of the nuisance parameter.

**Proposition 1.** *Let  $\theta_f$  be fixed and  $\hat{\theta}_r = \arg \max_{\theta_r} E(\theta_f, \theta_r)$ . If  $r(f(X; \theta_f); \hat{\theta}_r)_l = \frac{1}{|\mathcal{Z}|}$  for all  $z_l$ , then  $f$  is a pivotal quantity.*

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**Algorithm 1** Adversarial training of a classifier  $f$  against an adversary  $r$ .

*Inputs:* training data  $\{x_i, y_i, z_i\}_{i=1}^N$

*Outputs:*  $\hat{\theta}_f, \hat{\theta}_r$

*Hyper-parameters:* Number  $T$  of training iterations, Number  $K$  of gradient steps to update  $r$ .

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1: for  $t = 1$  to  $T$  do
2:   for  $k = 1$  to  $K$  do ▷ Update  $r$ 
3:     Sample minibatch  $\{x_m, z_m\}_{m=1}^M$  of size  $M$ ;
4:     With  $\theta_f$  fixed, update  $r$  by ascending its stochastic gradient  $\nabla_{\theta_r} E(\theta_f, \theta_r) :=$ 

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$$\nabla_{\theta_r} \sum_{m=1}^M \left[ \sum_{z_l \in \mathcal{Z}} 1(z_m = z_l) \log r(f(x_m; \theta_f); \theta_r)_l \right];$$

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5:   end for
6:   Sample minibatch  $\{x_m, y_m, z_m\}_{m=1}^M$  of size  $M$ ; ▷ Update  $f$ 
7:   With  $\theta_r$  fixed, update  $f$  by descending its stochastic gradient  $\nabla_{\theta_f} E(\theta_f, \theta_r) :=$ 

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$$\nabla_{\theta_f} \sum_{m=1}^M \left[ - \sum_{y_c \in \mathcal{Y}} 1(y_m = y_c) \log f(x_m; \theta_f)_c + \sum_{z_l \in \mathcal{Z}} 1(z_m = z_l) \log r(f(x_m; \theta_f); \theta_r)_l \right];$$

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8: end for

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*Proof.* Let us first recall that the cross-entropy for distributions  $p$  and  $q$  is minimized when  $p = q$ . For  $\mathcal{L}_r$  defined as the cross-entropy between the true conditional distribution of the nuisance  $p_{Z|f(X; \theta_f)}$  and the approximate conditional distribution of the nuisance  $p_{r(f(X; \theta_f); \theta_r)|f(X)}$ , the optimal parameters  $\hat{\theta}_r = \arg \max_{\theta_r} E(\theta_f, \theta_r) = \arg \min_{\theta_r} L_r(\theta_f, \theta_r)$  are therefore such that  $p_{r(f(X; \theta_f); \hat{\theta}_r)|f(X)} = p_{Z|f(X; \theta_f)}$ .

In other words, for all  $z_l \in \mathcal{Z}$ , we have  $r(f(X; \theta_f); \hat{\theta}_r)_l = p(z_l|f(X; \theta_f))$ . By assumption,  $r(f(X; \theta_f); \hat{\theta}_r)_l = \frac{1}{|\mathcal{Z}|}$ , and therefore  $p(z_l|f(X; \theta_f)) = \frac{1}{|\mathcal{Z}|}$ . Using the Bayes' rule, we write

$$\begin{aligned} p(f(X; \theta_f)|z_l) &= \frac{p(z_l|f(X; \theta_f))p(f(X; \theta_f))}{p(z_l)} \\ &= \frac{\frac{1}{|\mathcal{Z}|}p(f(X; \theta_f))}{\frac{1}{|\mathcal{Z}|}} \\ &= p(f(X; \theta_f)), \end{aligned}$$

which holds for all  $z_l \in \mathcal{Z}$  and implies that  $f$  is a pivotal quantity. □

**Proposition 2.** *If there exists a saddle point  $(\hat{\theta}_f, \hat{\theta}_r)$  for Eqn. 5 and 6 such that  $E(\hat{\theta}_f, \hat{\theta}_r) = H(p_{Y|X}) - \log |\mathcal{Z}|$ , then  $f(\cdot; \hat{\theta}_f)$  is both an optimal classifier and a pivotal quantity.*

*Proof.* For fixed  $\theta_f$ , the adversary  $r$  is optimal at  $\hat{\theta}_r = \arg \max_{\theta_r} E(\theta_f, \theta_r) = \arg \min_{\theta_r} L_r(\theta_f, \theta_r)$ , in which case  $p_{r(f(X; \theta_f); \hat{\theta}_r)|f(X)} = p_{Z|f(X; \theta_f)}$  and  $L_r$  reduces to the entropy  $H(p_{Z|f(X; \theta_f)})$  of the conditional distribution of the nuisance. The value function  $E$  can therefore be rewritten as

$$E'(\theta_f) = L_f(\theta_f) - H(p_{Z|f(X; \theta_f)}).$$

In particular, we have the lower bound  $H(p_{Y|X}) - \log |\mathcal{Z}| \leq L_f(\theta_f) - H(p_{Z|f(X; \theta_f)})$  where the equality holds at  $\hat{\theta}_f = \arg \min_{\theta_f} E'(\theta_f)$  only when

- $\hat{\theta}_f$  corresponds to the parameters of an optimal classifier, in which case the log-loss  $L_f$  reduces to its minimum value  $H(p_{Y|X})$ ,
- all outcomes of  $Z|f(X; \hat{\theta}_f)$  are equally likely, in which case  $p(z_l|f(X; \hat{\theta}_f)) = \frac{1}{|\mathcal{Z}|}$  for all  $z_l \in \mathcal{Z}$  and  $H(p_{Z|f(X; \hat{\theta}_f)}) = - \sum_{z_l \in \mathcal{Z}} p(z_l|f(X; \hat{\theta}_f)) \log p(z_l|f(X; \hat{\theta}_f)) = - \sum_{z_l \in \mathcal{Z}} \frac{1}{|\mathcal{Z}|} \log \frac{1}{|\mathcal{Z}|} = \log |\mathcal{Z}|$ .

Accordingly, the second condition implies that  $r(f(X; \hat{\theta}_f); \hat{\theta}_r)_l = \frac{1}{|\mathcal{Z}|}$  and therefore that at this point, because of Proposition 1, the optimal classifier  $f(\cdot; \hat{\theta}_f)$  is also a pivotal quantity.  $\square$

**Proposition 3.** *[GL: It remains to prove that the procedure of Algorithm 1 converges towards that saddle point. The proof should be similar to the proof of convergence in the GAN paper.]*

[GL: We should further discuss that in practice, the equality in Prop 2 may never hold. We should discuss in which circumstances. In such case, the pivotal quantity constraint can however be enforced by outweighing the  $L_r$  term, resulting in a trade-off between classifier optimality and pivotality.]

## 5 Experiments

## 6 Related work

[GL: Similar to domain adaptation, but with infinitely many domains, as parameterized by  $Z$ , also related to transfer learning.]

[GL: Other applications: removing implicit bias in data (e.g. gender bias).]

## 7 Conclusions

### Acknowledgments

### References

- [1] M. H. Degroot and M. J. Schervish, *Probability and statistics*. 4 ed., 2010.
- [2] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, “Generative adversarial nets,” in *Advances in Neural Information Processing Systems*, pp. 2672–2680, 2014.