Understanding Black-box Predictions via Influence Functions

ICML 2017 Best Paper

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Paper and Author Infos

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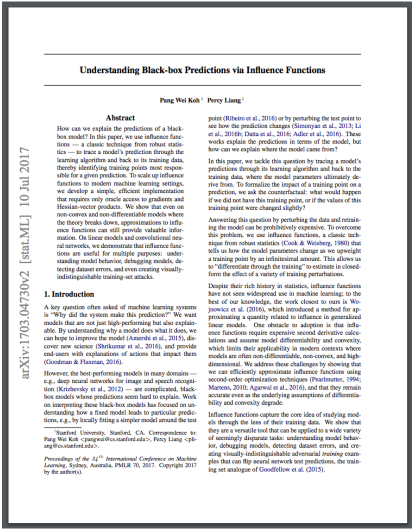

arXiv:1703.04730v2 [stat.ML] 10 Jul 2017

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Pang Wei Koh [1] **Percy Liang** [1]

Abstract

How can we explain the predictions of a black-box model? In this paper, we use influence functions — a classic technique from robust statistics — to trace a model's prediction through the learning algorithm and back to its training data, thereby identifying training points most responsible for a given prediction. To scale up influence functions to modern machine learning settings, we develop a simple, efficient implementation that requires only oracle access to gradients and Hessian-vector products. We show that even on non-convex and non-differentiable models where the theory breaks down, approximations to influence functions can still provide valuable information. On linear models and convolutional neural networks, we demonstrate that influence functions are useful for multiple purposes: understanding model behavior, debugging models, detecting dataset errors, and even creating visually-indistinguishable training-set attacks.

1. Introduction

A key question often asked of machine learning systems is "Why did the system make this prediction?" We want models that are not just high-performing but also explainable. By understanding why a model does what it does, we can hope to improve the model (Amershi et al., 2015), discover new science (Shrikumar et al., 2016), and provide end-users with explanations of actions that impact them (Goodman & Flaxman, 2016).

However, the best-performing models in many domains — e.g., deep neural networks for image and speech recognition (Krizhevsky et al., 2012) — are complicated, black-box models whose predictions seem hard to explain. Work on interpreting these black-box models has focused on understanding how a fixed model leads to particular predictions, e.g., by locally fitting a simpler model around the test point (Ribeiro et al., 2016) or by perturbing the test point to see how the prediction changes (Simonyan et al., 2013; Li et al., 2016b; Datta et al., 2016; Adler et al., 2016). These works explain the predictions in terms of the model, but how can we explain where the model came from?

In this paper, we tackle this question by tracing a model's predictions through its learning algorithm and back to the training data, where the model parameters ultimately derive from. To formalize the impact of a training point on a prediction, we ask the counterfactual: what would happen if we did not have this training point, or if the values of this training point were changed slightly?

Answering this question by perturbing the data and retraining the model can be prohibitively expensive. To overcome this problem, we use influence functions, a classic technique from robust statistics (Cook & Weisberg, 1980) that tells us how the model parameters change as we upweight a training point by an infinitesimal amount. This allows us to "differentiate through the training" to estimate in closed-form the effect of a variety of training perturbations.

Despite their rich history in statistics, influence functions have not seen widespread use in machine learning; to the best of our knowledge, the work closest to ours is Wojnowicz et al. (2016), which introduced a method for approximating a quantity related to influence in generalized linear models. One obstacle to adoption is that influence functions require expensive second derivative calculations and assume model differentiability and convexity, which limits their applicability in modern contexts where models are often non-differentiable, non-convex, and high-dimensional. We address these challenges by showing that we can efficiently approximate influence functions using second-order optimization techniques (Pearlmutter, 1994; Martens, 2010; Agarwal et al., 2016), and that they remain accurate even as the underlying assumptions of differentiability and convexity degrade.

Influence functions capture the core idea of studying models through the lens of their training data. We show that they are a versatile tool that can be applied to a wide variety of seemingly disparate tasks: understanding model behavior, debugging models, detecting dataset errors, and creating visually-indistinguishable adversarial *training* examples that can flip neural network test predictions, the training set analogue of Goodfellow et al. (2015).

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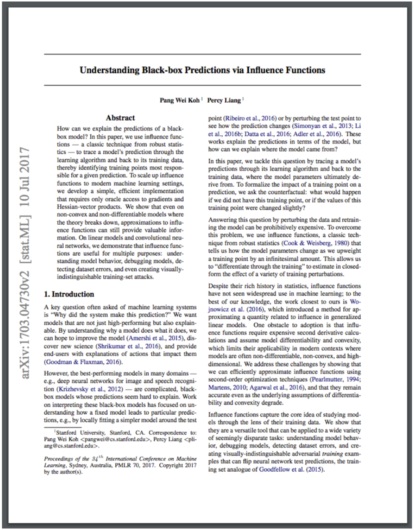

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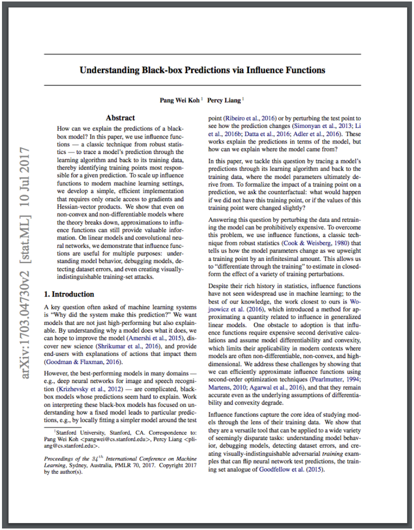

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Affiliations:

Computer Science, Stanford University

- Artificial Intelligence Lab
- Natural Language Processing Group
- Statistical Machine Learning Group

Overview

Introduction

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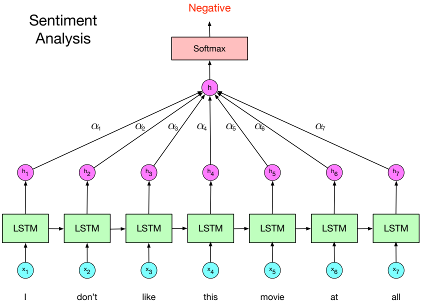

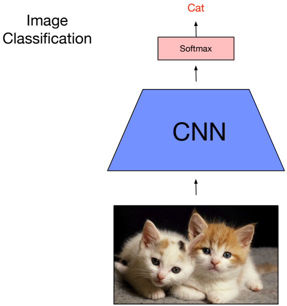

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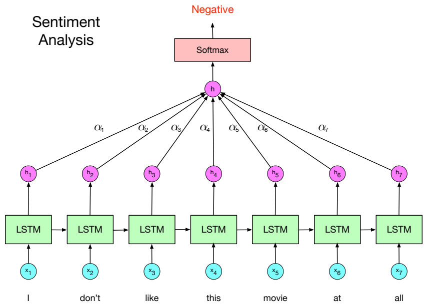

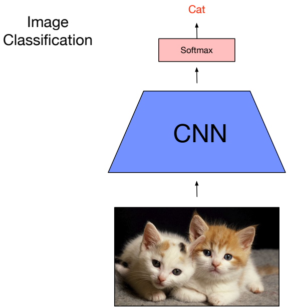

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- Where does the model come from?
- Can we explain predictions in terms of training points?

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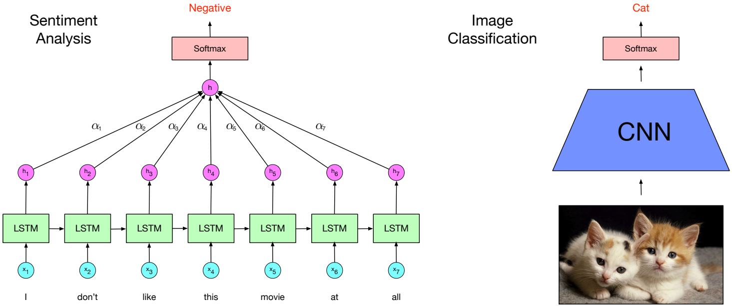

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Motivation

What's the influence of a training point to the prediction of test sample?

ML Background

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Empirical Risk Loss

Given a prediction problem: $\mathcal{X}$ (images) $\rightarrow$ $\mathcal{Y}$ (labels)

$$R(\theta) \stackrel{\text{def}}{=} \frac{1}{n}\sum_{i=1}^{n} L(z_i, \theta)$$

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- $z_i = (x_i, y_i) \in \mathcal{X} \times \mathcal{Y}$;
- $\theta \in \Theta$: parameter space;
- $L(z, \theta)$: loss function, *e.g.*, cross entropy.

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$$\textbf{Goal:} \quad \hat{\theta} \stackrel{\text{def}}{=} \arg\min_{\theta \in \Theta} \frac{1}{n}\sum_{i=1}^{n} L(z_i, \theta)$$

- Assumption: $R(\theta)$ is *twice-differentiable* and *strictly convex*.

Overview

Upweighting a training point

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Question 1:

How would predictions change if we did not have a specific training point?

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Influence Function Approximation

$$\hat{\theta}_{\epsilon,z} \stackrel{\text{def}}{=} \arg\min_{\theta \in \Theta} \frac{1}{n} \sum_{i=1}^{n} L(z_i, \theta) + \epsilon L(z, \theta)$$

$$\mathcal{I}_{\text{up, params}}(z) \stackrel{\text{def}}{=} \left. \frac{d\hat{\theta}_{\epsilon,z}}{d_\epsilon} \right|_{\epsilon=0} = -H_{\hat{\theta}}^{-1} \nabla_\theta L(z, \hat{\theta})$$

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Influence of training point z to z_{test}

$$\mathcal{I}_{\text{up,loss}}(z, z_{\text{test}}) \stackrel{\text{def}}{=} \left.\frac{dL(z_{\text{test}},\hat{\theta}_{\epsilon,z})}{d\epsilon}\right|_{\epsilon=0} = \nabla_\theta L(z_{\text{test}},\hat{\theta})^\top \left.\frac{d\hat{\theta}_{\epsilon,z}}{d\epsilon}\right|_{\epsilon=0}$$

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$$\left. \frac{d\hat{\theta}_{\epsilon, z_\delta, -z}}{d\epsilon} \right|_{\epsilon=0} = -H_{\hat{\theta}}^{-1} (\nabla_\theta L(z_\delta, \hat{\theta}) - \nabla_\theta L(z, \hat{\theta}))$$

$$\approx -H_{\hat{\theta}}^{-1} [\nabla_x \nabla_\theta L(z, \hat{\theta})] \delta$$

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Influence to z_{test} with z replaced by z_δ

$$\mathcal{I}_{\text{pert,loss}}(z, z_{\text{test}}) \stackrel{\text{def}}{=} -\nabla_\theta L(z_{\text{test}}, \hat{\theta})^\top H_{\hat{\theta}}^{-1} \nabla_x \nabla_\theta L(z, \hat{\theta})$$

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Efficiently Calculating Influence

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Challenges

$$\mathcal{I}_{\text{up,loss}}(z, z_{\text{test}}) = -\nabla_\theta L(z_{\text{test}}, \hat{\theta})^\top H_{\hat{\theta}}^{-1} \nabla_\theta L(z, \hat{\theta})$$

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- $H_{\hat{\theta}} = \frac{1}{n}\sum_{i=1}^{n} \nabla_\theta^2 L(z_i, \hat{\theta}), \theta \in R^p$: inversion takes $O(np^2 + p^3)$;
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Solving s_{test}

- Conjugate Gradients (CG): $\arg\min_t \{\frac{1}{2} t^\top H_{\hat{\theta}} t - s_{\text{test}}^\top t\}$;
- Stochastic estimation: speed up CG;

Overview

Validation and Extensions

Validation and Extensions

Validity of Influence Function

$$-\frac{1}{n}\mathcal{I}_{\text{up,loss}}(z, z_{\text{test}}) \quad \text{vs.} \quad L(z_{\text{test}}, \hat{\theta}_{-z}) - L(z_{\text{test}}, \hat{\theta})$$

- Influence function vs. leave-one-out retraining

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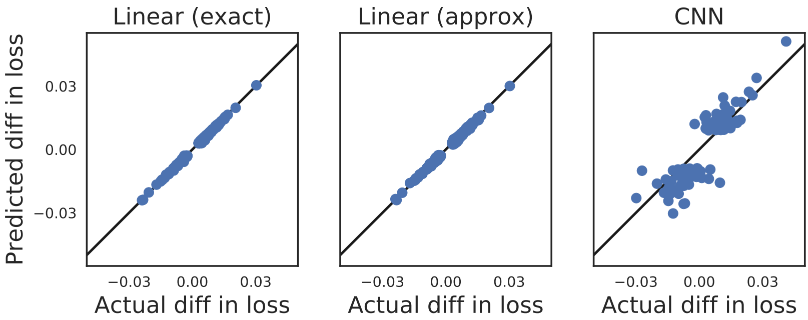

Validation and Extensions

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Extensions

- Non-convexity and non-convergence: quadratic approximation
  - $\widetilde{L}(z,\theta) = L(z,\widetilde{\theta}) + \nabla L(z,\widetilde{\theta})^\top(\theta - \widetilde{\theta}) + \frac{1}{2}(\theta - \widetilde{\theta})^\top(H_{\widetilde{\theta}} + \lambda I)(\theta - \widetilde{\theta})$
- Non-differentiable loss: replaced with smoothing version
  - $\mathrm{Hinge}(s) = \max(0, 1-s) \rightarrow \mathrm{SmoothHinge}(s,t) = t\log(1+\exp(\frac{1-s}{t}))$

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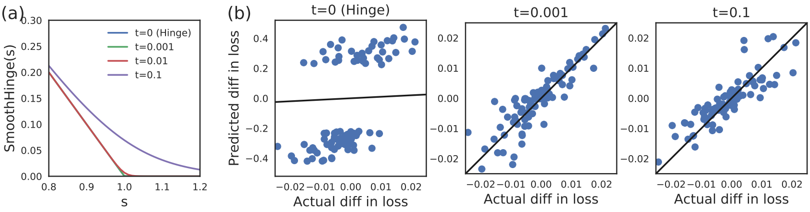

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Use Cases of Influence Functions

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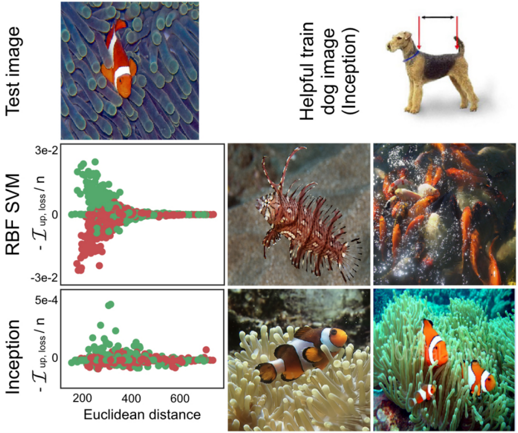

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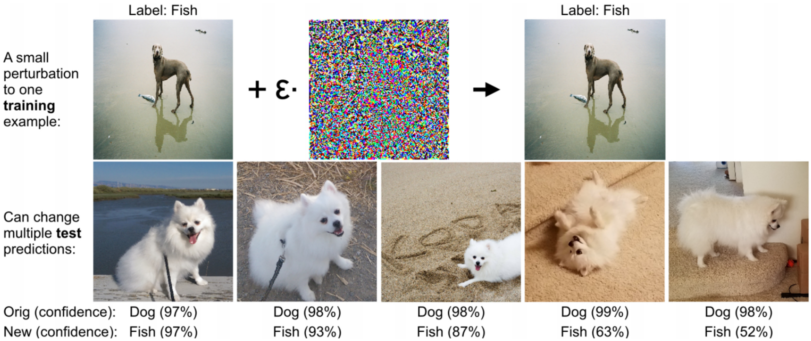

Use Cases of Influence Functions

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- Debugging domain mismatch: $-\mathcal{I}_{\text{up,loss}}(z_i, z_{\text{test}})$

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children re-admitted: $3/24$ changed to $3/4$

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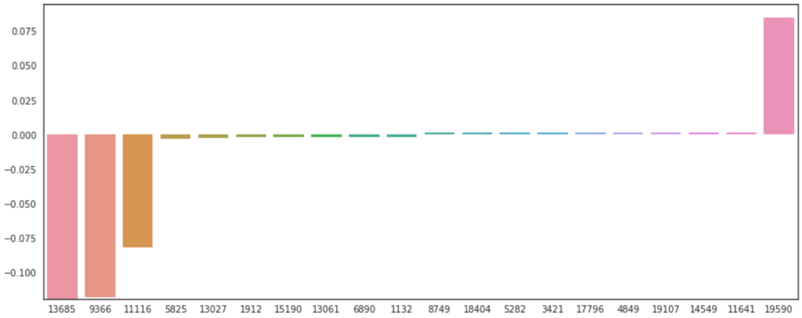

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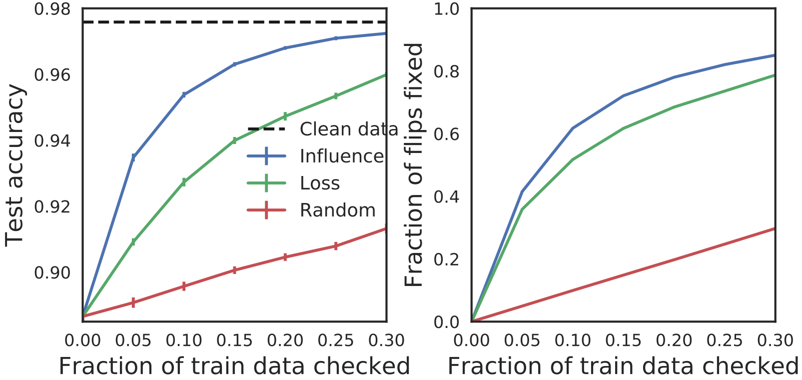

Overview

1. Introduction
2. Approach
   - Upweighting a training point
   - Perturbing a training point
3. Influence Calculation
4. Validation and Extensions
5. Applications

Questions?