Understanding Black-box Predictions via Influence Functions

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Outline

Why do we need this method?

How does it work?

What can it be used for?

Summary

Why do we need this method?

- Authors views
- Existing approaches
- A new approach



Provide explanation

Improve models

Existing approaches

- Simplification
- Maximally activate neurons
- Find responsible parts
- See model as fixed



A new Approach -Model is learned





A new Approach

- Impact of training points

<u>Prediction</u>



A new Approach - Summary

How did the model come to its result?



What would happen if we change the weights?

Which training points where most influential?

How does it work?

- Approach
- Issues

Approach - Fundamentals

Training points:

$$z_1, \dots, z_n$$
 with $z_i = (x_i, y_i) \in X \times Y$

empirical risk minimizer:

$$\hat{\theta} = \operatorname{argmin}_{\theta \in \Theta} \frac{1}{N} \Sigma_i^N L(z_i, \theta)$$

Approach

- Formalizing the problem

$$\hat{\theta}_{\epsilon,z} = \arg\min_{\theta \in \Theta} \frac{1}{N} \Sigma_i^N L(z_i, \theta) + \epsilon L(z, \theta)$$
$$\Rightarrow \hat{\theta}_{\epsilon,z} - \hat{\theta}$$

• Problem: retraining expensive

Approach

- Influence Functions
- concept in robust statistics (Hampel, 1974)
- effect of a change in one observation on an estimator (Kahn, 2015)
- Based on Gâteaux derivative

Approach

- Influence of weight changes

 $I_{up,params}(z) = -H_{\widehat{\theta}}^{-1} \nabla_{\theta} L(z, \widehat{\theta})$

- Calculations for:
 - $I_{up,loss}$ using chain rule
 - $I_{pert,loss}$ analogous

Issues

- Efficiency
- We require $H_{\hat{\theta}}^{-1}$
- Training points: $n, \hat{\theta} \in \mathbb{R}^p \to O(np^2 + p^3)$



Issues - Efficiency



Issues

- Non-differentiable loss



Issues

- Non-differentiable loss



What can it be used for?

• Applications



Understanding

Debugging



Identifying mislabeled training data DOG DOG

Generating adversarial training examples

- Understanding model prediction



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- Understanding model prediction

examples Most helpful training



- Understanding model prediction

Further helpful example for ANN



Summary

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Measure upweighting



Many applications

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Sources - Literature

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Sources - Assets

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