# Neural Network Inspired Data Feature Extraction (DO-14)

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## Problem

Outcome of this project: D.Zou, R. Balan, M. Singh, *On Lipschitz Bounds of General Convolutional Neural Networks*, IEEE Trans. Info. Theory, to appear in 2020.

Problem: Estimate the Lipschitz constant of a Deep Convolutive Network.

**Types of Lipschitz Constants (LC)** for a M-layer Deep Network  $\Phi$ ,  $y = \Phi(x)$ :

$$L^{2} = \sup_{x_{1} \neq x_{2}} \frac{\|y_{2} - y_{1}\|_{2}^{2}}{\|x_{2} - x_{1}\|_{2}^{2}}$$

Analytical estimate using a Linear Program:

$$L_c^2 \approx \prod_{k=1}^M \sigma_{max}^2(A_k)$$

3 Local LC:

$$Lip(x)^{2} = \lim_{r \to 0} \sup_{x_{2}: ||x_{2}-x||_{2} < r} \frac{||y_{2}-y||_{2}^{2}}{||x_{2}-x||_{2}^{2}}$$

Impirical LC:

$$L_{emp} = \sup_{x_1 \neq x_2; \ x_1, x_2 \in DataBase} \frac{\|y_2 - y_1\|_2^2}{\|x_2 - x_1\|_2^2}$$

Lipschitz Analysis of Deep Networks

### Results Findings - 1

• Computation of Local Lipschitz bound and relationship with the global bound, for DNN with ReLU activation map:

$$Lip(x) = \sigma_{max} \left( \prod_{k=1}^{M} D_k(x) T_k \right) \quad L = \max_{\|x\| \le R} Lip(x)$$

Q Numerical values for AlexNet on ImageNet database:

Method	Lip const
Analytical estimate <i>L<sub>c</sub></i> : compute Bessel bounds and solve a linear program	$2.51  imes 10^3$
Empirical bound <i>L<sub>emp</sub></i> : take quotient from pairs of samples	$7.32\times10^{-3}$
Numerical approximation <i>L</i> : compute local Lipschitz constants and take the maximum	1.44

Lipschitz Analysis of Deep Networks

#### Results Findings - 2

Obscrepancy between L and L<sub>emp</sub> We introduce and compute an effective Jacobian J<sub>eff</sub> that accounts for mid-range interactions:

$$J(x) = P_M D_M T_M \cdots P_2 D_2 T_2 P_1 D_1 T_1$$
$$J_{eff} = \mathbb{E}[P_M] \mathbb{E}[D_M] T_M \cdots \mathbb{E}[P_1] \mathbb{E}[D_1] T_1 = \frac{p_1 \cdots p_M}{\tau^m} A_M \cdots A_1$$
Then:  $L_{eff} = \sigma_{max}(J_{eff})$ . For AlexNet, the number of layers  $M = 5$ , the Pool Tile Size  $\tau = 9$  and the number of Pooling Layers  $m = 3$ .  
Experimentally over 10,000 pairs we obtained:

 $p_1 = 0.4115$ ,  $p_2 = 0.3184$ ,  $p_3 = 0.3587$ ,  $p_4 = 0.2733$ ,  $p_5 = 0.1943$ The estimated effective Lipschitz constant:

$$L_{eff} = 1.78 \cdot 10^{-2}$$

which is about twice the emprirical constant  $7.32 \cdot 10^{-3}$ .

## Next Steps

Open questions and future steps:

- How to speed up the computation of the effective Jacobian?
- 2 Adaptive/On-line algorithm for tunable deep networks
- Observation How to use this estimate as a constraint or a penalty in learning deep networks?
- Onnections with the Fisher Information Matrix and the mean-field theory.