### Neural Network Learning: Theoretical Foundations

Speaker : Semin Choi

Department of Statistics, Seoul National University, South Korea

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### Comparing the Different Approaches

Bounding with the Fat-Shattering Dimension

• Theorem 12.8.

$$\mathcal{N}_1(\epsilon, F, m) \le \mathcal{N}_\infty(\epsilon, F, m) \le \left(\frac{\sqrt{m}}{\epsilon}\right)^{\operatorname{fat}_F(\epsilon/4)\log_2(m/(\epsilon\operatorname{fat}_F(\epsilon/4)))}$$

Theorem 18.2.

$$\mathcal{N}_1(\epsilon, F, m) \le \left(\frac{1}{\epsilon}\right)^{\operatorname{fat}_F(\epsilon/8) \log_2(m/(\epsilon \operatorname{fat}_F(\epsilon/8)))}$$

Bounding with the Pseudo-Dimension

• Theorem 12.2.

$$\mathcal{N}_1(\epsilon, F, m) \leq \mathcal{N}_{\infty}(\epsilon, F, m) \leq \left(\frac{m}{\epsilon}\right)^{\operatorname{Pdim}(F)}$$

• Theorem 18.4.

$$\mathcal{N}_1(\epsilon, F, m) \le \left(\frac{1}{\epsilon}\right)^{\operatorname{Pdim}(F)}$$

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### Uniform Convergence Results

Part 2 (Classification with Real-valued Functions)

• 
$$\operatorname{er}_P(f) = P\{\operatorname{sgn}(f(x) - 1/2) \neq y\}$$

•  $\operatorname{er}_P^{\gamma}(f) = P\{\operatorname{margin}(f(x), y) < \gamma\}$ 

 $P^{m}\{\operatorname{er}_{P}(f) \ge \widehat{\operatorname{er}}_{z}^{\gamma}(f) + \epsilon \text{ for some } f \text{ in } F\} \le 2\mathcal{N}_{\infty}(\gamma/2, F, 2m) \exp\left(-\frac{\epsilon^{2}m}{8}\right).$ 

Part 3 (Regression)

• 
$$\operatorname{er}_P(f) = \mathbb{E}(f(x) - y)^2 = \mathbb{E}l_f$$

 $P^{m}\{|\mathbf{er}_{P}(f) - \hat{\mathbf{er}}_{z}(f)| \ge \epsilon \text{ for some } f \text{ in } F\} \le 4\mathcal{N}_{1}(\epsilon/16, F, 2m) \exp\left(-\frac{\epsilon^{2}m}{32}\right).$ 

# Proof

#### Part 2

### Lemma 1.

$$\max_{z \in \mathbb{Z}^{2m}} \Pr(\sigma z \in R) \le \mathcal{N}_{\infty}(\gamma/2, F, 2m) \exp\left(-\frac{\epsilon^2 m}{8}\right)$$

where

$$R = \{(r,s) \in Z^m \times Z^m : \text{ some } f \text{ in } F \text{ has } \hat{\mathrm{er}}_s(f) \ge \hat{\mathrm{er}}_r^\gamma(f) + \epsilon/2\}$$

If  $\sigma z \in R$ , then there is some  $\hat{f} \in T$  such that

$$\hat{\mathrm{er}}_{s}^{\gamma/2}(\hat{f}) \geq \hat{\mathrm{er}}_{r}^{\gamma/2}(\hat{f}) + \epsilon/2$$

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# Proof

#### Part 3

Lemma 2.

$$\max_{z \in Z^{2m}} \Pr(\sigma z \in R) \le 2\mathcal{N}_1(\epsilon/16, F, 2m) \exp\left(-\frac{\epsilon^2 m}{32}\right)$$

where

$$R = \{(r,s) \in Z^m \times Z^m : \text{ some } f \text{ in } F \text{ has } |\hat{\mathrm{er}}_r(f) - \hat{\mathrm{er}}_s(f)| \ge \epsilon/2\}$$

If  $\sigma z \in R$ , then there is some  $\hat{f} \in T$  such that

$$\left| \hat{\operatorname{er}}_r(\hat{f}) - \hat{\operatorname{er}}_s(\hat{f}) \right| \ge \epsilon/4.$$

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