# Second Order PAC-Bayesian Bounds for the Weighted Majority Vote

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## Introduction

Weighted majority vote is a fundamental technique in machine learning for combining predictions of multiple classifiers.

#### **Our Contributions**:

- Second order PAC-Bayesian bound for the weighted majority vote.
- Minimization of the bound does not deteriorate the test error.

## Standard first order analysis

**Observation**: If p-weighted majority vote makes an error, then at least a p-weighted half of the classifiers make an error. Thus, we have that

 $\mathbb{E}_{\rho}[\mathbb{1}(h(X) \neq Y)]$  $L(MV_{\rho})$ ρ-weighted mass Expected loss of ρ-weighted majority vote

First order bound: Applying Markov's inequality  $(\mathbb{P}(X \ge \varepsilon) \le \frac{1}{\varepsilon}\mathbb{E}[X])$ 

 $2 \mathbb{E}_{D}[\mathbb{E}_{\rho}[\mathbb{1}(h(X) \neq Y)]]$  $2 \mathbb{E}_{\rho}[L(h)]$ Expected loss of  $\rho$ -weighted randomized classifier

of errors

Issues with the first-order bound:

- Ignores correlation of errors among ensemble members.
- Minimization degrades the test error (Lorenzen et al., 2019).

# **Prior second order analysis**

The C-bounds (Lacasse et al., 2007, Germain et al., 2015, Laviolette et al., 2017): Based on Chebyshev-Cantelli inequality

$$\mathbb{P}(X \ge \varepsilon) \le \frac{\mathbb{E}[X^2] - \mathbb{E}[X]^2}{\mathbb{E}[X^2] - \mathbb{E}[X] + \varepsilon^2}$$

Issues with prior second order bounds:

- $\mathbb{E}[X^2]$  and  $\mathbb{E}[X]$  in the denominator make estimation hard.
- Empirically weaker than the first order bound.
- Impossible to optimize except in very restrictive cases.

#### A novel second order oracle bound

 $\geq$  0.5 )

 $L(MV_{\rho})$  $\leq$ Expected loss of ρ-weighted majority vote

ρ-weighted mass of errors

#### **Second-order Markov's inequality** $\mathbb{P}(X \ge \varepsilon) \le \frac{1}{\varepsilon^2} \mathbb{E}[X^2]$ :

\_\_\_\_

 $4 \mathbb{E}_{D}[\mathbb{E}_{\rho}[\mathbb{1}(h(X) \neq Y)]^{2}]$  $\leq$ \_\_\_\_

 $4 \mathbb{E}_{o^2}[L(h, h')]$ 

Key Points:

- **Tandem loss** counts an error if both h and h' err on a sample.
- Tandem loss is small when the two hypotheses h and h' both have low expected errors and their errors are anticorrelated.
- Second order oracle bound:

 $L(MV_{\rho}) \leq 4 \mathbb{E}_{\rho^2}[L(h, h')]$ 

### Second order PAC-Bayesian bound

By applying PAC-Bayes- $\lambda$  (Thiemann et al., 2017) to  $\mathbb{E}_{o^2}[L(h, h')]$ For  $\pi$  independent of S, with probability at least  $1 - \delta$  for all  $\rho$  and  $\lambda \in (0,2)$ 

$$L(MV_{\rho}) \leq 4 \mathbb{E}_{\rho^2}[L(h, h')]$$

Empirical **Tandem loss**  $\mathbb{E}_{0^2}[\widehat{L}(h, h', S)]$  $\leq 4$  $-\lambda/2$ 

Key Points:

- Takes correlation of errors into account.
- We can easily find the  $\rho$  distribution minimizing the bound. • The minimization of the bound does not degrade the test error

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## **Empirical evaluation**

- $\mathbb{P}(\mathbb{E}_{\rho}[\mathbb{1}(h(X) \neq Y)] \geq 0.5)$
- $4 \mathbb{E}_{\rho^2}[\mathbb{E}_{D}[\mathbb{1}(h(X) \neq Y \land h'(X) \neq Y)]]$ Expected **Tandem Loss**: L(h, h')

- $2 \operatorname{KL}(\rho \| \pi) + \ln \frac{2\sqrt{n}}{\delta}$  $n\lambda(1-\lambda/2)$ PAC-Bayes upper bound on  $\mathbb{E}_{0^2}[L(h, h')]$

(the lower the better)



• Optimized weights  $\rho^*$  generated by the first order [FO] and the new second order [TND] bound.



### Summary

- Minimizing first order bounds deteriorates the test error. Existing second order bounds are looser and can not be optimized.
- Novel second order oracle and PAC-Bayesian bounds for the weighted majority vote based on second order Markov's inequality.
- Minimization of the bound does not deteriorate the test error.



#### • Test error of optimized majority vote over uniformly weighted baseline for first order [FO] and new second order [TND] bound