

# Proof of Azuma-Hoeffding Inequality

We upper bound  $E[e^{\alpha(X_t - X_0)}]$ .

Define  $Y_i = X_i - X_{i-1}$ ,  $i = 1, \dots, t$ .

Then,  $X_t - X_0 = \sum_{i=1}^t Y_i$ .

$|Y_i| \leq c$ , and since  $X_0, X_1, \dots$  is a martingale,

$$\begin{aligned} E[Y_i | X_0, X_1, \dots, X_{i-1}] &= E[X_i - X_{i-1} | X_0, X_1, \dots, X_{i-1}] \\ &= E[X_i | X_0, X_1, \dots, X_{i-1}] - X_{i-1} = 0. \end{aligned}$$

We consider  $E[e^{\alpha Y_i} | X_0, X_1, \dots, X_{i-1}]$ .

$$Y_i = -c_i \frac{1 - Y_i/c_i}{2} + c_i \frac{1 + Y_i}{2}$$

Since  $e^{\alpha Y_i}$  is convex for all  $\alpha > 0$ ,

$$\begin{aligned} e^{\alpha Y_i} &\leq e^{-\alpha c_i \frac{1 - Y_i/c_i}{2}} + e^{\alpha c_i \frac{1 + Y_i/c_i}{2}} \\ &= \frac{e^{\alpha c_i} + e^{-\alpha c_i}}{2} + \frac{Y_i}{2c_i} (e^{\alpha c_i} - e^{-\alpha c_i}). \end{aligned}$$

Hence,

$$\begin{aligned} & E[e^{\alpha Y_i} | X_0, X_1, \dots, X_{i-1}] \\ & \leq E\left[\frac{e^{\alpha c_i} + e^{-\alpha c_i}}{2} + \frac{Y_i}{2c_i}(e^{\alpha c_i} - e^{-\alpha c_i}) \mid X_0, X_1, \dots, X_{i-1}\right] \\ & \quad = \frac{e^{\alpha c_i} + e^{-\alpha c_i}}{2} \\ & \quad \leq e^{(\alpha c_i)^2/2}. \end{aligned}$$

$$E[e^{\alpha(X_t - X_0)}] = E[\prod_{i=1}^t e^{\alpha Y_i}]$$

$$E[E[\prod_{i=1}^t e^{\alpha Y_i} \mid X_0, X_1, \dots, X_{t-1}]]$$

$$= E[\prod_{i=1}^{t-1} e^{\alpha Y_i} E[e^{\alpha Y_t} \mid X_0, X_1, \dots, X_{t-1}]]$$

$$\begin{aligned} & \leq E[\prod_{i=1}^{t-1} e^{\alpha Y_i}] e^{(\alpha c_t)^2/2} \\ & \leq e^{\alpha^2 \sum_{k=1}^t c_k^2/2}. \end{aligned}$$

Thus,

$$\begin{aligned}\Pr(X_t - X_0 \geq \lambda) &= \Pr(e^{\alpha(X_t - X_0)} \geq e^{\alpha\lambda}) \\ &\leq \frac{E[e^{\alpha(X_t - X_0)}]}{e^{\alpha\lambda}} \\ &\leq e^{\alpha^2 \sum_{k=1}^t c_k^2 / 2 - \alpha\lambda} \\ &\leq e^{-\frac{\lambda^2}{2 \sum_{k=1}^t c_k^2}}\end{aligned}$$

by choosing  $\alpha = \frac{\lambda}{\sum_{k=1}^t c_k^2}$ .

A similar argument gives the bound for  $\Pr(X_t - X_0 \leq -\lambda)$ .

## Lipschitz condition

Let  $f : D_1 \times \dots \times D_n \rightarrow R$  be a real-valued function with  $n$  arguments from possibly distinct domains.

The function  $f$  is said to satisfy the **Lipschitz condition** with bound  $c$ , if for any  $x_1 \in D_1, \dots, x_n \in D_n$ , any  $i \in \{1, \dots, n\}$ , and any  $y_i \in D_i$ ,

$$|f(x_1, \dots, x_{i-1}, x_i, x_{i+1}, \dots, x_n) - f(x_1, \dots, x_{i-1}, y_i, x_{i+1}, \dots, x_n)| \leq c$$

That is, changing the value of any single coordinate can change the function value by at most  $c$ .

# A General Framework for Applying Azuma's Inequality

**Theorem 1.** *Suppose we have a sequence of random variables  $X_1, \dots, X_n$  and a function  $f(\hat{X}) = f(X_1, \dots, X_n)$  which satisfies Lipschitz condition.*

*Consider the Doob martingale:*

$$Z_0 = E[f(X_1, \dots, X_n)] \text{ and}$$

$$Z_k = E[f(X_1, \dots, X_n) | X_1, \dots, X_k], \quad 1 \leq k \leq n.$$

*If  $X_1, \dots, X_n$  are independent random variables, then  $|Z_k - Z_{k-1}| \leq c$ .*

We can thus use Azuma to get a concentration bound for  $f$ .

## Proof

We will show for discrete random variables that only take a finite number of values.

Let  $S_k$  stand for  $X_1, X_2, \dots, X_k$ .

And  $f_k(\hat{X}, x) = f(X_1, \dots, X_{k-1}, x, X_{k+1}, \dots, X_n)$ .

and  $f_k(\hat{z}, x) = f(z_1, \dots, z_{k-1}, x, z_{k+1}, \dots, z_n)$ .

$$Z_k - Z_{k-1} = E[f(\hat{X})|S_k] - E[f(\hat{X})|S_{k-1}]$$

$$Z_k - Z_{k-1} \leq \max_x E[f(\hat{X})|S_{k-1}, X_k = x] - E[f(\hat{X})|S_{k-1}]$$

$$Z_k - Z_{k-1} \geq \min_y E[f(\hat{X})|S_{k-1}, X_k = y] - E[f(\hat{X})|S_{k-1}]$$

We bound:

$$\begin{aligned} & \max_x E[f(\hat{X})|S_{k-1}, X_k = x] - \min_y E[f(\hat{X})|S_{k-1}, X_k = y] \\ &= \max_{x,y} (E[f(\hat{X})|S_{k-1}, X_k = x] - E[f(\hat{X})|S_{k-1}, X_k = y]) \\ &= \max_{x,y} (E[f_k(\hat{X}, x) - f_k(\hat{X}, y)|S_{k-1}]) \end{aligned}$$

For any values  $x, y, z_1, \dots, z_{k-1}$ ,

$$\begin{aligned} & E[f_k(\hat{X}, x) - f_k(\hat{X}, y)|X_1 = z_1, \dots, X_{k-1} = z_{k-1}] \\ &= \sum_{z_{k+1}, \dots, z_n} \Pr((X_{k+1} = z_{k+1}) \cap \dots \cap (X_n = z_n)) \cdot (f_k(\hat{z}, x) - f_k(\hat{z}, y)). \\ &\leq c. \end{aligned}$$

Hence  $E[f_k(\hat{X}, x) - f_k(\hat{X}, y)|S_{k-1}] \leq c$ .

## Balls and Bins

Suppose  $m$  balls are thrown independently and uniformly into  $n$  bins.

Let  $Z$  be the number of empty bins.

$$\mu = E[Z] = n\left(1 - \frac{1}{n}\right)^m \sim ne^{m/n}.$$

We want to show a concentration result for  $Z$ .

Let  $X_t$  represent the bin into which the  $t$ th ball falls.

The sequence  $Z_t = E[Z|X_1, \dots, X_t]$  is a Doob martingale.

$Z = F(X_1, \dots, X_n)$  satisfies the Lipschitz condition.

Hence,  $|Z_t - Z_{t-1}| \leq 1$ .

Thus,  $\Pr(|Z - E[Z]| \geq \lambda) \leq 2e^{-\lambda^2/2m}$ .