

M2R: Mathematics of Machine Learning

Theorem (Hoeffding-Azuma inequality)

Let $(X_t)_{t \in \mathbb{N}^*}$ be a $(\mathcal{F}_t)_{t \geq 1}$ -adapted real-valued process in L^1 . Assume that for all $t \geq 1$, there exists a \mathcal{F}_{t-1} -measurable r.v. A_t and a positive constant c_t such that $X_t \in [A_t; A_t + c_t]$ a.s.

Then, the martingale $(S_t)_{t \geq 1}$ defined by $S_t := \sum_{s=1}^t (X_s - \mathbb{E}[X_s | \mathcal{F}_{s-1}])$ satisfies:

$$\forall t \geq 1, \forall \lambda \in \mathbb{R}, \mathbb{E}[e^{\lambda S_t}] \leq \exp\left(\frac{\lambda^2}{8} \sum_{s=1}^t c_s^2\right) \quad (1)$$

In other words, S_t is subgaussian with variance factor $\frac{1}{4} \sum_{s=1}^t c_s^2$. As a consequence,

$$\forall x > 0, \mathbb{P}\left(\max_{1 \leq t \leq T} S_t \geq x\right) \leq \exp\left(-\frac{2x^2}{\sum_{s=1}^T c_s^2}\right) \quad (2)$$

Proof:

• We first prove (1). Note that, for all $t \geq 1$ and $\lambda \in \mathbb{R}$,

$$\mathbb{E}[e^{\lambda S_t}] = \mathbb{E}\left[\mathbb{E}\left[e^{\lambda S_{t-1}} \cdot e^{\lambda \underbrace{(X_t - \mathbb{E}[X_t | \mathcal{F}_{t-1}])}_{=: Y_t}} \middle| \mathcal{F}_{t-1}\right]\right]$$

$$= \mathbb{E}\left[e^{\lambda S_{t-1}} \cdot \underbrace{\mathbb{E}\left[e^{\lambda Y_t} \middle| \mathcal{F}_{t-1}\right]}_{\leq e^{\frac{\lambda^2 c_t^2}{4}} \text{ a.s. by the Hoeffding lemma (conditionally on } \mathcal{F}_{t-1}, Y_t \text{ lies in a fixed interval of width } c_t)}\right]$$

$$\leq e^{\frac{\lambda^2 c_t^2}{8}} \cdot \mathbb{E}[e^{\lambda S_{t-1}}]$$



By induction, we get $\mathbb{E}[e^{\lambda S_t}] \leq e^{\frac{\lambda^2}{8} \sum_{s=1}^t c_s^2}$. $\mathbb{E}[e^{\lambda \cdot S_0}] = e^{\frac{\lambda^2}{8} \sum_{s=1}^0 c_s^2} = 1$, which proves (1).

- To derive (2), first note that $(e^{\lambda S_t})_{t \geq 1}$ is a nonnegative submartingale ($e^{\lambda S_t}$ is a non-decreasing and convex function of S_t , and $(S_t)_{t \geq 1}$ is a martingale). We can thus use the following result:

Lemma (Doob's inequality for nonnegative submartingales)

Let $(Z_t)_{t \geq 1}$ be a nonnegative submartingale. Then, for all $u > 0$,

$$\mathbb{P}\left(\max_{1 \leq t' \leq t} Z_{t'} \geq u\right) \leq \frac{\mathbb{E}[Z_t]}{u}$$

Proof: cf. Williams, Probability with Martingales.

Now we use the above lemma with $Z_t = e^{\lambda S_t}$. It yields:

$$\begin{aligned} \mathbb{P}\left(\max_{1 \leq t' \leq t} S_{t'} \geq x\right) &= \mathbb{P}\left(\max_{1 \leq t' \leq t} e^{\lambda S_{t'}} \geq e^{\lambda x}\right) \leq \frac{\mathbb{E}[e^{\lambda S_t}]}{e^{\lambda x}} \\ &\leq e^{-\left(\lambda x - \frac{\lambda^2}{8} \sum_{s=1}^t c_s^2\right)} \quad \text{by (1)} \end{aligned}$$

Optimizing in λ ($\lambda^* = \frac{4x}{\sum_{s=1}^t c_s^2}$) we get:

$$\mathbb{P}\left(\max_{1 \leq t' \leq t} S_{t'} \geq x\right) \leq \exp\left(-\frac{2x^2}{\sum_{s=1}^t c_s^2}\right),$$

which concludes the proof. ■