

FTML practical session 13

13 juin 2025

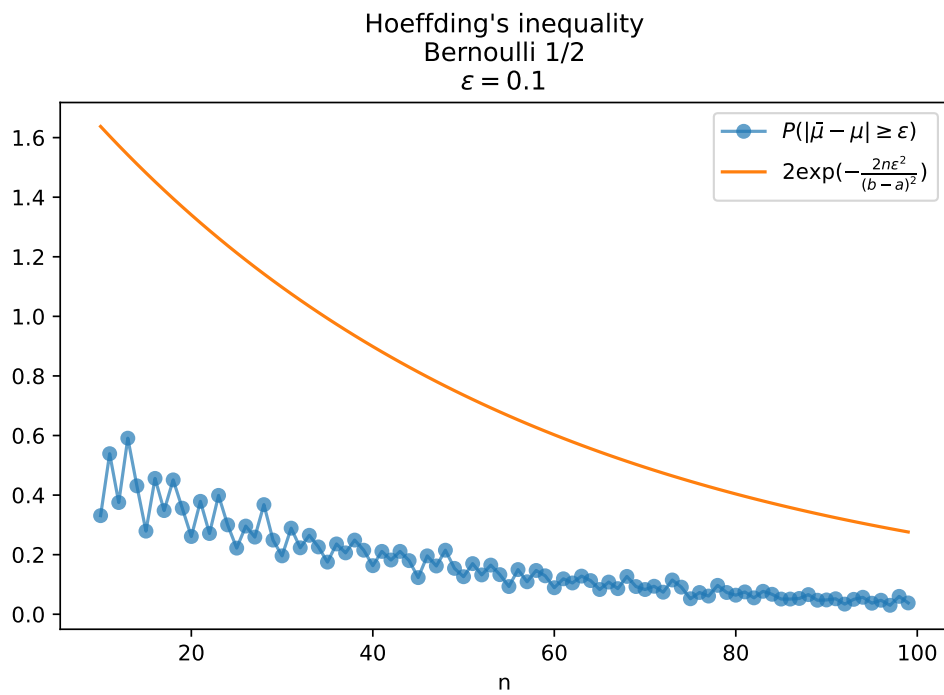


FIGURE 1 – Simulation of Hoeffding's inequality

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1 HOEFFDING'S INEQUALITY

The following result will be useful in order to prove the bound on the estimation error in section 2

Theorème 1. *Hoeffding's inequality*

Let $(X_i)_{1 \leq i \leq n}$ be n i.i.d real random variables such that $\forall i \in [1, n]$, $X_i \in [a, b]$ and $E(X_i) = \mu \in \mathbb{R}$. Let $\bar{\mu} = \frac{1}{n} \sum_{i=1}^n X_i$.
Then $\forall \epsilon > 0$,

$$P(|\bar{\mu} - \mu| \geq \epsilon) \leq 2 \exp\left(-\frac{2n\epsilon^2}{(b-a)^2}\right) \quad (1)$$

Run a simulation that allows to visualize Hoeffding's inequality, with a random variable of your choice, like in figures 2 and 3, where a Bernoulli variable of parameter $p = 1/2$ is used.

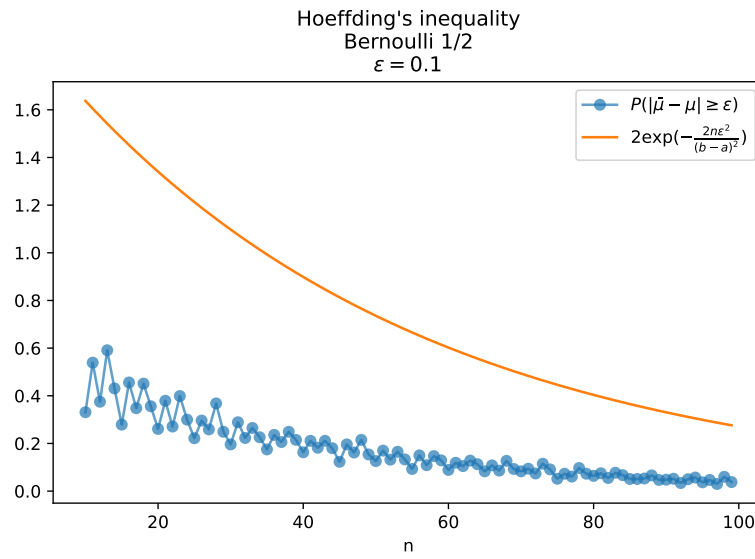


FIGURE 2 – Hoeffding's inequality with a Bernoulli variable of parameter $p = 1/2$ and $\epsilon = 0.1$

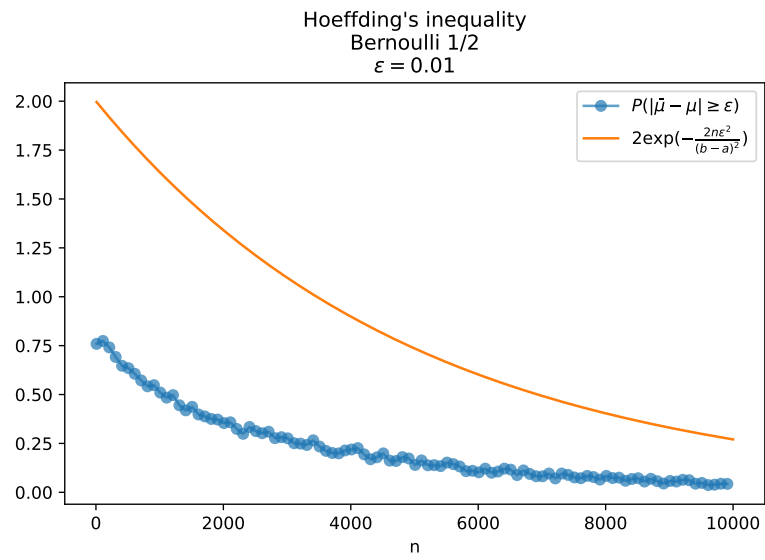


FIGURE 3 – Hoeffding's inequality with a Bernoulli variable of parameter $p = 1/2$ and $\epsilon = 0.01$

2 BOUND ON THE ESTIMATION ERROR

We consider a usual supervised learning setting, and the a space of functions F in which we choose our estimators. The dataset contains n samples, the empirical risk is noted R_n and the real risk R . If f_n is the empirical risk minimizer, and f_a the optimal estimator in F , we have seen this result during the lectures :

$$0 \leq R(f_n) - R(f_a) \leq 2 \sup_{h \in F} |R(h) - R_n(h)| \quad (2)$$

Our objective is to bound equation 2. We make the following additional hypotheses :

- F is finite, with $|F|$ elements.
- The loss l is uniformly bounded : $l(\hat{y}, y) \in [a, b]$ with a and b real numbers.

We will also use the following result :

Proposition 2. *Boole's inequality*

Let A_1, A_2, \dots , be a countable set of events of a probability space $\{\Omega, \mathcal{F}, P\}$. Then,

$$P\left(\bigcup_{i \geq 1} A_i\right) \leq \sum_{i \geq 1} P(A_i) \quad (3)$$

Step 1] Using 2, we have that :

$$P\left(R(f_n) - R(f_a) \geq t\right) \leq P\left(2 \sup_{h \in F} |R(h) - R_n(h)| \geq t\right) \quad (4)$$

Step 2]

Show that

$$P\left(2 \sup_{h \in F} |R(h) - R_n(h)| \geq t\right) \leq \sum_{h \in F} P(2|R(h) - R_n(h)| \geq t) \quad (5)$$

Step 3]

Show that

$$P\left(R(f_n) - R(f_a) \geq t\right) \leq 2|F| \exp\left(-\frac{nt^2}{2(b-a)^2}\right) \quad (6)$$

Step 4]

We write

$$\delta = 2|F| \exp\left(-\frac{nt^2}{2(b-a)^2}\right) \quad (7)$$

Show that with probability larger than $1 - \delta$,

$$R(f_n) \leq R(f_a) + \sqrt{\frac{2(b-a)^2 \left(\log\left(\frac{2}{\delta}\right) + \log(|F|)\right)}{n}} \quad (8)$$

In which situations do we have for instance that $a = 0$ and $b = 1$?

In `tp_02_ols`, we observed a rate in $\frac{\sigma^2 d}{n}$, hence faster than $\mathcal{O}\left(\frac{1}{\sqrt{n}}\right)$. How can we interpret this?/Users/nico/Desktop/enseignement/epita/slides/lecture 7 solution/lecture 7 solution.pdf