

A Hoeffding-Azuma Type Inequality for Random Processes

Mahir Hasanov*

Department of Mathematics, Istanbul Beykent University, Türkiye

*Corresponding author: hasanov61@yahoo.com

Abstract. The subject of this paper is a Hoeffding-Azuma type estimation for the difference between an adapted random process and its conditional expectation given a related filtration.

1. Introduction

Hoeffding-Azuma type inequalities have very important applications in probability theory, statistics and different branches of science. In this section we give a brief history of Hoeffding-Azuma type inequalities.

1.1. Classical Hoeffding-Azuma type inequalities. Let (Ω, \mathcal{F}, P) be a probability triple, where Ω is a sample space, \mathcal{F} is a σ -algebra on Ω and P is a σ -additive probability measure on \mathcal{F} . Let us denote by \mathcal{B} the Borel algebra on \mathbb{R} . Note that $\mathcal{B} = \sigma(\tau_{|x-y|})$, the minimal σ -algebra containing the natural topology $\tau_{|x-y|}$ on \mathbb{R} .

Definition 1.1. A function $X : \Omega \rightarrow \mathbb{R}$ is called a random variable if X is \mathcal{F} -measurable function, i.e. $X^{-1}(\mathcal{B}) \subset \mathcal{F}$.

For definitions from the probability theory, used in this article see ([5], Sections 2.1, 6.1, 12.1 and 12.2).

The classical Hoeffding inequality is about finding upper bounds for the probability that the sum of n independent random variables exceeds its mean by a positive number nt . The pioneering work was by Hoeffding ([6], Theorem 2) who proved the following theorem.

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Theorem 1.1. (Hoeffding Inequality) If X_1, X_2, \dots, X_n are independent random variables and $a_i \leq X_i \leq b_i$, $i = 1, 2, \dots, n$. Then,

$$P(\bar{X} - \mu \geq t) \leq e^{-2n^2 t^2 / \sum_{i=1}^n (b_i - a_i)^2}$$

where,

$$\bar{X} = \frac{X_1 + X_2 + \dots + X_n}{n}, \quad \mu = E(\bar{X}).$$

Besides Hoeffding inequality there are two more classical fundamental results. These are Azuma inequality and Chernoff inequality. Let us give both inequalities in the form expressed by T. Tao ([9], Theorem 2.1.3 and Theorem 2.1.5).

Theorem 1.2. (Chernoff Inequality) Let X_1, X_2, \dots, X_n be independent scalar random variables with $|X_i| \leq K$ almost surely, with mean μ_i and variance σ_i^2 . Then for any $\lambda > 0$, one has

$$P(|S_n - \mu| \geq \lambda \sigma) \leq C \max(\exp(-c\lambda^2), \exp(-c\lambda\sigma/K)),$$

for some constants $C, c > 0$, where $\mu = \sum_{i=1}^n \mu_i$, $\sigma^2 = \sum_{i=1}^n \sigma_i^2$ and $S_n = X_1 + X_2 + \dots + X_n$.

Theorem 1.3. (Azuma Inequality) Let X_1, X_2, \dots, X_n be a sequence of scalar random variables with $|X_i| \leq 1$ almost surely. Assume also that we have martingale difference property

$$E(X_i | X_1, \dots, X_{i-1}) = 0$$

almost surely, for all $i = 1, \dots, n$. Then for any $\lambda > 0$ the sum $S_n = X_1 + X_2 + \dots + X_n$ obey the large deviation inequality

$$P(|S_n| \geq \lambda\sqrt{n}) \leq C \exp(-c\lambda^2)$$

for some constants $C, c > 0$.

1.2. Hoeffding-Azuma type inequalities for Martingale differences. Martingales and Markov chains are known to be widely used areas of Hoeffding-Azuma type inequalities.

Definition 1.2. (see [5], Section 12.1) A sequence of random variables $Y = \{Y_n : n \geq 0\}$ is martingale with respect to the sequence $X = \{X_n : n \geq 0\}$ if, for all $n \geq 0$

- a) $E(|Y_n|) < \infty$,
- b) $E(Y_{n+1} | X_0, X_1, \dots, X_n) = Y_n$

The Hoeffding inequality for martingale differences is of supreme importance in the theory of martingales (see [5], Section 12.2.)

Theorem 1.4. (Hoeffding inequality for martingale differences) Let $Y = \{Y_n : n \geq 0\}$ be a martingale, and suppose that there exists a sequence K_1, K_2, \dots , of real numbers such that $P(|Y_n - Y_{n-1}| \leq K_n) = 1$ for all n . Then

$$P(|Y_n - Y_0| \geq x) \leq 2 \exp\left(-\frac{1}{2}x^2 / \sum_{i=1}^n K_i^2\right), \quad x > 0. \quad (1.1)$$

Inequality (1.1) means that if the martingale differences are bounded then the large deviation of Y_n from its initial value Y_0 is small.

There are many new results and their applications in the literature on these issues.

A generalization of Hoeffding inequality for dependent random variables was given in [10]. Optimal bounds for Hoeffding's inequalities were found in [8]. In [4] it was proved a Hoeffding type inequality to partial sums that are derived from a uniformly ergodic Markov chain. New type of inequalities were introduced in [2] (see also references therein). In [3] some inequalities were obtained for unbounded random variables.

[7] Significantly improved the well-known Bennett-Hoeffding bound for sums of independent random variables by using, instead of the class of all increasing exponential functions, a much larger class of generalized moment functions. The resulting bounds have certain optimality properties.

2. Inequalities for Adopted Random Precesses

A random process is a collection of random variables $\{X(t), t \in T\}$. Particularly, a sequence $X_0, X_1, X_2, \dots, X_n, \dots$ of random variables defined on the same probability triple (Ω, \mathcal{F}, P) is a random process.

Definition 2.1. Let $\{\mathcal{F}_n\}_{n=0}^{\infty}$ be a sequence of σ -sub-algebras of \mathcal{F} , such that $\mathcal{F}_0 \subseteq \mathcal{F}_1 \subseteq \dots \subseteq \mathcal{F}_n \subseteq \dots \subseteq \mathcal{F}$. Then $\{\mathcal{F}_n\}_{n=0}^{\infty}$ is called a filtration of (Ω, \mathcal{F}, P) and a sequence $\{X_n : n \geq 0\}$ of random variables is said to be adapted to the filtration $\{\mathcal{F}_n\}_{n=0}^{\infty}$ if X_n is \mathcal{F}_n measurable for all n .

We denote by $E(X_n | \mathcal{F}_{n-1})$ the condition expectation of X_n given \mathcal{F}_{n-1} for all $n \geq 1$.

As pointed out in the introduction the classical Hoeffding inequality is about finding upper bounds for the probability that the sum of n independent random variables exceeds its mean by nt .

Finding upper bounds for the probability that the sum of n terms of an adapted random process exceeds its conditional mean by x is also among the topics of interest.

As far as we know, no previous research has investigated $P\left(\left|\sum_{i=1}^n (X_i - E(X_i | \mathcal{F}_{i-1}))\right| \geq x\right)$ for general adopted random processes, which is the main subject of this paper.

The basic result is the following theorem.

Theorem 2.1. Let $\{X_n : n \geq 0\}$ be a sequence of random variables which is adapted to a filtration $\{\mathcal{F}_n\}_{n=0}^{\infty}$. If $|X_n - E(X_n | \mathcal{F}_{n-1})| \leq C_n$ almost surely, for $n \geq 0$ then

$$P\left(\left|\sum_{i=1}^n (X_i - E(X_i | \mathcal{F}_{i-1}))\right| \geq x\right) \leq 2e^{-\frac{x^2}{\sum_{i=1}^n C_i^2}} \quad (2.1)$$

Proof. Let us define the following sequence:

$$\begin{aligned}
Y_0 &= X_0; \\
Y_1 &= X_0 + (X_1 - E(X_1|\mathcal{F}_0)); \\
&\vdots \\
Y_n &= X_0 + (X_1 - E(X_1|\mathcal{F}_0)) + \dots + (X_n - E(X_n|\mathcal{F}_{n-1})).
\end{aligned}$$

We have

$$Y_n = Y_{n-1} + (X_n - E(X_n|\mathcal{F}_{n-1})). \quad (2.2)$$

Evidently, Y_n is \mathcal{F}_n measurable for all n and $E((X_n - E(X_n|\mathcal{F}_{n-1}))|\mathcal{F}_{n-1}) = 0$. Then it follows from (2.2) that $E(Y_n|\mathcal{F}_{n-1}) = Y_{n-1}$, i.e. $\{Y_n; n \geq 0\}$ is a martingale sequence. Note that,

$$\sum_{i=1}^n (X_i - E(X_i|\mathcal{F}_{i-1})) = Y_n - Y_0. \quad (2.3)$$

By (2.3)

$$P\left(\sum_{i=1}^n (X_i - E(X_i|\mathcal{F}_{i-1})) \geq x\right) = P(Y_n - Y_0 \geq x). \quad (2.4)$$

Let $\theta > 0$, then

$$E(e^{\theta(Y_n - Y_0)}) = \int_{\Omega} e^{\theta(Y_n - Y_0)} dP \geq \int_{Y_n - Y_0 \geq x} e^{\theta(Y_n - Y_0)} dP \geq e^{\theta x} \int_{Y_n - Y_0 \geq x} dP.$$

Hence,

$$E(e^{\theta(Y_n - Y_0)}) \geq e^{\theta x} \int_{Y_n - Y_0 \geq x} dP = e^{\theta x} P(Y_n - Y_0 \geq x)$$

and

$$P(Y_n - Y_0 \geq x) \leq e^{-\theta x} E(e^{\theta(Y_n - Y_0)}). \quad (2.5)$$

Next, we estimate $E(e^{\theta(Y_n - Y_0)})$. By the tower property we obtain that

$$E(e^{\theta(Y_n - Y_0)}) = E\left(E(e^{\theta(Y_n - Y_0)}|\mathcal{F}_{n-1})\right). \quad (2.6)$$

$$E(e^{\theta(Y_n - Y_0)}|\mathcal{F}_{n-1}) = e^{\theta(Y_{n-1} - Y_0)} E(e^{\theta(Y_n - Y_{n-1})}|\mathcal{F}_{n-1}).$$

We set $f(y) = e^{\theta y}$, $|y| \leq C_n$. The function $f(y) = e^{\theta y}$ is convex, whence it follows that

$$e^{\theta y} \leq \frac{1}{2}\left(1 - \frac{y}{C_n}\right)e^{-\theta C_n} + \frac{1}{2}\left(1 + \frac{y}{C_n}\right)e^{\theta C_n} = \left(\frac{1}{2}e^{-\theta C_n} + \frac{1}{2}e^{\theta C_n}\right) + \frac{y}{2C_n}(e^{\theta C_n} - e^{-\theta C_n}).$$

Thus,

$$e^{\theta y} \leq e^{\frac{1}{2}\theta^2 C_n^2} + \frac{y}{2C_n}(e^{\theta C_n} - e^{-\theta C_n}), \quad |y| \leq C_n. \quad (2.7)$$

$Y_n - Y_{n-1} = X_n - E(X_n|\mathcal{F}_{n-1})$ and by the condition of the theorem $|Y_n - Y_{n-1}| \leq C_n$. Then setting $y = Y_n - Y_{n-1}$ in (2.7) we obtain

$$e^{\theta(Y_n - Y_{n-1})} \leq e^{\frac{1}{2}\theta^2 C_n^2} + \frac{Y_n - Y_{n-1}}{2C_n}(e^{\theta C_n} - e^{-\theta C_n}), \quad |y| \leq C_n. \quad (2.8)$$

Taking the conditional expectation of (2.8) and using the fact that

$E(Y_n - Y_{n-1}|\mathcal{F}_{n-1}) = 0$ we get

$$E(e^{\theta(Y_n - Y_{n-1})} | \mathcal{F}_{n-1}) \leq e^{\frac{1}{2}\theta^2 C_n^2}.$$

Therefore,

$$E(e^{\theta(Y_n - Y_0)} | \mathcal{F}_{n-1}) \leq e^{\theta(Y_{n-1} - Y_0)} e^{\frac{1}{2}\theta^2 C_n^2}.$$

By using this inequality, (2.6) and iterations we get

$$E(e^{\theta(Y_n - Y_0)}) = E\left(E(e^{\theta(Y_n - Y_0)} | \mathcal{F}_{n-1})\right) \leq E(e^{\theta(Y_{n-1} - Y_0)}) e^{\frac{1}{2}\theta^2 C_n^2} \leq e^{\frac{1}{2}\theta^2 \sum_{i=1}^n C_i^2}.$$

It follows from (2.5) that

$$P\left(\sum_{i=1}^n (X_i - E(X_i | \mathcal{F}_{i-1})) \geq x\right) \leq e^{-\theta x + \frac{1}{2}\theta^2 \sum_{i=1}^n C_i^2}$$

Finally, minimizing the right side of this inequality in θ and replacing the terms under the sum we obtain the needed inequality (2.1).

$$P\left(\left|\sum_{i=1}^n (X_i - E(X_i | \mathcal{F}_{i-1}))\right| \geq x\right) \leq 2e^{(-\frac{x^2}{2} / \sum_{i=1}^n C_i^2)}.$$

Note. If $\{X_n : n \geq 0\}$ is a martingale sequence, then $\sum_{i=1}^n (X_i - E(X_i | \mathcal{F}_{i-1})) = X_n - X_0$ and in this case we get the martingale difference inequality (1.1).

3. Random Processes in the Hilbert Space $L^2(\Omega, \mathcal{F}, P)$

Let $X = \{X_i : i \geq 0\}$ be an adopted random process and $X_i \in L^2(\Omega, \mathcal{F}_i, P)$ for all i . As can be seen from the following theorem that if $X_i \in L^2(\Omega, \mathcal{F}_i, P)$ then the conditional expectation $E(X_i | \mathcal{F}_{i-1})$ is a version of orthogonal projection of X_i onto the subspace $L^2(\Omega, \mathcal{F}_{i-1}, P)$.

Theorem 3.1. (see [1]) Let (X, Z) be a bivariate random vector and $L_Z = \{g(Z) | g(Z) \in L_2(\Omega), g \text{ is a Borel function}\}$. Let $E[X^2] < \infty$. Then there exists a Borel function $g_0 : \mathbb{R} \rightarrow \mathbb{R}$ with $E[(g_0(Z))^2] < \infty$, such that $E[(X - g_0(Z))^2] = \inf\{E[(X - g(Z))^2] | g(Z) \in L_Z\}$. Moreover, $g_0(Z) = E[X|Z]$.

By a using a Hilbert space property we can write

$$X_i = E(X_i | \mathcal{F}_{i-1}) + Y_i, \tag{3.1}$$

where $Y_i \in (L^2(\Omega, \mathcal{F}_{i-1}, P))^\perp$ - the orthogonal complement of the subspace $L^2(\Omega, \mathcal{F}_{i-1}, P)$. By (3.1) we have Y_i is \mathcal{F}_i measurable and

$$Y_i = X_i - E(X_i | \mathcal{F}_{i-1}). \tag{3.2}$$

An immediate consequence of (3.2) is

Corollary 1. $E(Y_i | \mathcal{F}_{i-1}) = 0$.

The main conclusion of the above given arguments is given in the following theorem.

Theorem 2. Let Y_n be a version of orthogonal projection of X_n onto the subspace $L^2(\Omega, \mathcal{F}_{n-1}, P)^\perp$, $n \geq 0$.

If $|Y_n| \leq C_n$ almost surely, for $n \geq 0$ then

$$P\left(\left|\sum_{i=1}^n Y_i\right| \geq x\right) \leq 2e^{\left(-\frac{x^2}{2/\sum_{i=1}^n C_i^2}\right)}.$$

Conflicts of Interest: The author declares that there are no conflicts of interest regarding the publication of this paper.

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