Donsker's Theorem: A brief review

Abhilash Singh Avik Biswas Sanket Agrawal

Department of Mathematics & Statistics Indian Institute of Technology Kanpur

February 13, 2021



Outline

- Introduction
- 2 Donsker's Theorem
 - Heuristic approach
 - Donsker's result
 - Generalization
- Simulation

Let $Z_1, \ldots Z_n \sim F$ be a random sample taking values in \mathcal{X} . Define the *Empirical measure* as,

$$F_n = \frac{1}{n} \sum_{i=1}^n \delta_{Z_i}.$$
 (1)

Let $Z_1, \ldots Z_n \sim F$ be a random sample taking values in \mathcal{X} . Define the *Empirical measure* as,

$$F_n = \frac{1}{n} \sum_{i=1}^n \delta_{Z_i}.$$
 (1)

Then the *Empirical Process* is defined as,

$$X_n = \sqrt{n}(F_n - F) \tag{2}$$

Let $Z_1, \ldots Z_n \sim F$ be a random sample taking values in \mathcal{X} . Define the *Empirical measure* as,

$$F_n = \frac{1}{n} \sum_{i=1}^n \delta_{Z_i}.$$
 (1)

Then the Empirical Process is defined as,

$$X_n = \sqrt{n}(F_n - F) \tag{2}$$

For any measurable function g, define

$$F_ng := \int gdF_n, \, \forall n; \quad Fg := \int gdF$$

Consider $\mathcal{G} = \{g \text{ defined on } \mathcal{X}, g \text{ measurable}\}$. Then, the collection of random elements $\{X_ng : g \in \mathcal{G}\}$ is called an *empirical* process indexed by \mathcal{G} .

Consider
$$\mathcal{X} = \mathbb{R}$$
 and $\mathcal{G} = \{I_{(-\infty,t]}(\cdot) : t \in \mathbb{R}\}$. Then,

Consider
$$\mathcal{X}=\mathbb{R}$$
 and $\mathcal{G}=\{\mathit{I}_{(-\infty,t]}(\cdot):t\in\mathbb{R}\}.$ Then,

$$\hat{F}_n(t) := F_n I_{(-\infty,t]} = \frac{1}{n} \sum_{i=1}^n I_{(-\infty,t]}(Z_i); \quad t \in \mathbb{R}$$

$$X_n(t) := X_n I_{(-\infty,t]} = \sqrt{n}(\hat{F}_n(t) - F(t)); \quad t \in \mathbb{R}$$

Motivations

- Glivenko-Cantelli Theorem
- By Central Limit Theorem (CLT),

$$X_n(t) \stackrel{d}{ o} N\left(0, F(t)(1-F(t))\right), \;\; ext{for each } t \in \mathbb{R}.$$

What happens for collective t?

Ans:

Motivations

- Glivenko-Cantelli Theorem
- By Central Limit Theorem (CLT),

$$X_n(t) \stackrel{d}{ o} N\left(0, F(t)(1-F(t))\right), \;\; ext{for each } t \in \mathbb{R}.$$

What happens for collective t?

Ans:

Donsker's Theorem

(uniform CLT, functional CLT, Invariance principle, and what not...)

Doob's Heuristic approach

Let
$$F = U[0,1]$$
. For any $k \in \mathbb{N}$ and $0 \le t_1 < t_2 < \cdots < t_k \le 1$,

$$(X_n(t_1),\ldots,X_n(t_k))\stackrel{CLT}{\rightarrow} N_k(0,\Sigma),$$

where $E(i,j) = \min\{t_i, t_j\} - t_i \cdot t_j$. Following is from Doob (1949).

Doob's Heuristic approach

Let F = U[0,1]. For any $k \in \mathbb{N}$ and $0 \le t_1 < t_2 < \cdots < t_k \le 1$,

$$(X_n(t_1),\ldots,X_n(t_k))\stackrel{CLT}{\to} N_k(0,\Sigma),$$

where $E(i,j) = \min\{t_i, t_j\} - t_i \cdot t_j$. Following is from Doob (1949).

We shall assume, until a contradiction frustrates our devotion to heuristic reasoning, that in calculating asymptotic $x_n(t)$ process distributions when $n \to \infty$ we may simply replace the $x_n(t)$ processes by the x(t) process. It is clear that this cannot be done in all possible situations, but let the reader who has never used this sort of reasoning exhibit the first counter example.

Doob's Heuristic approach

Let F = U[0,1]. For any $k \in \mathbb{N}$ and $0 \le t_1 < t_2 < \cdots < t_k \le 1$,

$$(X_n(t_1),\ldots,X_n(t_k))\stackrel{CLT}{\rightarrow} N_k(0,\Sigma),$$

where $E(i,j) = \min\{t_i, t_j\} - t_i \cdot t_j$. Following is from Doob (1949).

Hence,

$$X_n(t) \stackrel{??}{\to} X(t)$$

such that finite dimensional distribution of X(t) for any k is $N_k(0, \Sigma)$.

Theorem (Donsker, 1952)

$$X_n \stackrel{d}{\to} X$$
 in $D([0,1], \|\cdot\|_{\infty})$

where X is the standard Brownian Bridge process on [0,1].

Theorem (Donsker, 1952)

$$X_n \stackrel{d}{\rightarrow} X$$
 in $D([0,1], \|\cdot\|_{\infty})$

where X is the standard Brownian Bridge process on [0,1].

Theorem (Donsker, 1952)

$$X_n \stackrel{d}{\rightarrow} X$$
 in $D([0,1], \|\cdot\|_{\infty})$

where X is the standard Brownian Bridge process on [0,1].

Questions?

• What is a Brownian Bridge process?

Theorem (Donsker, 1952)

$$X_n \stackrel{d}{\rightarrow} X$$
 in $D([0,1], \|\cdot\|_{\infty})$

where X is the standard Brownian Bridge process on [0,1].

- What is a Brownian Bridge process?
- What is $D([0,1], \|\cdot\|_{\infty})$?

Theorem (Donsker, 1952)

$$X_n \stackrel{d}{\rightarrow} X$$
 in $D([0,1], \|\cdot\|_{\infty})$

where X is the standard Brownian Bridge process on [0,1].

- What is a Brownian Bridge process?
- What is $D([0,1], \|\cdot\|_{\infty})$?
- What does $\stackrel{d}{\rightarrow}$ mean here?

Theorem (Donsker, 1952)

$$X_n \stackrel{d}{\rightarrow} X$$
 in $D([0,1], \|\cdot\|_{\infty})$

where X is the standard Brownian Bridge process on [0,1].

- What is a Brownian Bridge process?
- What is $D([0,1], \|\cdot\|_{\infty})$?
- What does $\stackrel{d}{\rightarrow}$ mean here?
- Generalizations?



Definition (Brownian Bridge)

A stochastic process $\{B(t), t \in [0,1]\}$ is called a *Brownian bridge* process if it satisfies the following properties:

Definition (Brownian Bridge)

A stochastic process $\{B(t), t \in [0,1]\}$ is called a *Brownian bridge* process if it satisfies the following properties:

•
$$B(0) = B(1) = 0$$
.

Definition (Brownian Bridge)

A stochastic process $\{B(t), t \in [0, 1]\}$ is called a *Brownian bridge* process if it satisfies the following properties:

- B(0) = B(1) = 0.
- For any $t_1 < t_2 < \cdots < t_K$, the random vector $(B(t_1), \ldots, B(t_K))$ has a mean-zero multivariate normal distribution.

Definition (Brownian Bridge)

A stochastic process $\{B(t), t \in [0, 1]\}$ is called a *Brownian bridge* process if it satisfies the following properties:

- B(0) = B(1) = 0.
- For any $t_1 < t_2 < \cdots < t_K$, the random vector $(B(t_1), \ldots, B(t_K))$ has a mean-zero multivariate normal distribution.
- $Cov(B(s), B(t)) = min\{s, t\} st.$

Definition (Brownian Bridge)

A stochastic process $\{B(t), t \in [0, 1]\}$ is called a *Brownian bridge* process if it satisfies the following properties:

- B(0) = B(1) = 0.
- For any $t_1 < t_2 < \cdots < t_K$, the random vector $(B(t_1), \ldots, B(t_K))$ has a mean-zero multivariate normal distribution.
- $Cov(B(s), B(t)) = min\{s, t\} st$.
- The function $t \mapsto B(t)$ is (almost surely) continuous on [0,1].

The space D

Definition (D)

The space $D([0,1], \|\cdot\|_{\infty})$ is the space of all cádlag functions on [0,1] endowed with uniform metric.

cádlag = right continuous and left limit exists at each point.

When D is endowed with Skorokhod metric, it is called the Skorokhod space.

Say that, G_n converges weakly to G as elements of $D([0,1], \|\cdot\|)$ iff,

$$E(f(G_n)) \to E(f(G))$$
 for all $f \in C_b(D[0,1])$.

But, X_n as described above is not measurable with respect to $\mathcal{B}(D[0,1])$ generated by uniform topology. The Borel σ -field is too big for measurability to hold.

But, X_n as described above is not measurable with respect to $\mathcal{B}(D[0,1])$ generated by uniform topology. The Borel σ -field is too big for measurability to hold.

Remedies?

But, X_n as described above is not measurable with respect to $\mathcal{B}(D[0,1])$ generated by uniform topology. The Borel σ -field is too big for measurability to hold.

Remedies?

1. Projection σ -field.

But, X_n as described above is not measurable with respect to $\mathcal{B}(D[0,1])$ generated by uniform topology. The Borel σ -field is too big for measurability to hold.

Remedies?

- 1. Projection σ -field.
- 2. Use a different metric (Skorokhod metric).

But, X_n as described above is not measurable with respect to $\mathcal{B}(D[0,1])$ generated by uniform topology. The Borel σ -field is too big for measurability to hold.

Remedies?

- 1. Projection σ -field.
- 2. Use a different metric (Skorokhod metric).
- 3. More general notion of weak convergence.

Generalization

Let's go back to the general setup i.e $\mathcal X$ is an arbitrary space and $\mathcal G$ is an arbitrary class of real-valued measurable functions. Then,

Generalization

Let's go back to the general setup i.e $\mathcal X$ is an arbitrary space and $\mathcal G$ is an arbitrary class of real-valued measurable functions. Then,

Definition

(Donsker's Class). A class $\mathcal G$ of measurable functions $g:\mathcal X\to\mathbb R$ is Donsker if the empirical process $\{X_ng:g\in\mathcal G\}$ indexed by $\mathcal G$ converges in distribution in the space $I^\infty(\mathcal G)$ to a tight random element.

Generalization

Let's go back to the general setup i.e $\mathcal X$ is an arbitrary space and $\mathcal G$ is an arbitrary class of real-valued measurable functions. Then,

Definition

(Donsker's Class). A class $\mathcal G$ of measurable functions $g:\mathcal X\to\mathbb R$ is Donsker if the empirical process $\{X_ng:g\in\mathcal G\}$ indexed by $\mathcal G$ converges in distribution in the space $I^\infty(\mathcal G)$ to a tight random element.

Sufficient conditions: Covering numbers and Bracketing numbers

Donsker's Theorem at work!

 $[\]hbox{*Codes and GIF are available at: $https://github.com/babasanku/DonskerTheorem}$



References

- Sen, B. A Gentle Introduction to Empirical Process Theory and Applications. Lecture Notes. Columbia University.
- Doob, J. L. (1949). Heuristic approach to the Kolmogorov-Smirnov theorems. Ann. Math. Statistics, 20:393–403.
- Donsker, M. D. (1952). Justification and extension of Doob's heuristic approach to the Komogorov-Smirnov theorems. Ann. Math. Statistics, 23:277–281.
- Pollard, D. (1984). Convergence of stochastic processes (Springer Series in Statistics). Springer-Verlag, New York.
- Vaart, A. (1998). Asymptotic statistics (Cambridge Series in Statistical and Probabilistic Mathematics). Cambridge University Press, Cambridge.



Introduction Donsker's Theorem Simulation

Questions????