# Expectation of Random Variables with respect to Dsitribution 

## Yuchao Li

August 7, 2018

## 1 Problem statement

Probability space is given as $(\Omega, \mathscr{F}, \mathbf{P})$ with elementary outcome $\omega$. For a nonnegative random variable $X$, its expectation can be calculated by

$$
\begin{equation*}
E[X]=\int_{0}^{\infty} x d F_{X}(x) . \tag{1.1}
\end{equation*}
$$

## 2 Elaboration

1. First, we recall the definition of the expection of a nonnegative random variable, namely $E[X]$, given $X$. This follows the approach of [1].

For the given random variable $X$, we define $X_{n}$ as

$$
X_{n}(\omega)= \begin{cases}\frac{k-1}{2^{n}}, & \frac{k-1}{2^{n}} \leq X(\omega)<\frac{k}{2^{n}}, k=1,2, \ldots, n 2^{n}  \tag{2.1}\\ n, & X(\omega) \geq n\end{cases}
$$

Denote $f_{n}: \mathbf{R}_{+} \cup\{0\} \rightarrow \mathbf{R}$ as

$$
f_{n}(x)= \begin{cases}\frac{k-1}{2^{n}}, & \frac{k-1}{2^{n}} \leq x<\frac{k}{2^{n}}, k=1,2, \ldots, n 2^{n}  \tag{2.2}\\ n, & x \geq n\end{cases}
$$

we can show that $f_{n}$ is a Borel function. Since $X$ is a random variable, then $X_{n}=f_{n}(X)$ is a random variable. Further we can see that in fact $X_{n}$ is a simple random variable.

Then, it can be shown (refer to [1, 2]) that $X_{n}(\omega) \rightarrow X(\omega)$ as $n \rightarrow \infty \forall \omega$. Based on $X_{n}$, the expectation $E[X]$ is defined as a Lebesgue integral (refer to [1]) that

$$
\begin{equation*}
E[X]=\lim _{n \rightarrow \infty} \sum_{k=1}^{n 2^{n}} \frac{k-1}{2^{n}} \mathbf{P}\left(\frac{k-1}{2^{n}} \leq X(\omega)<\frac{k}{2^{n}}\right) . \tag{2.3}
\end{equation*}
$$

Note that compared to [2], the term $n \mathbf{P}(X \geq n)$ does not show up in the definition. Clearly, the term makes no difference if $X(\omega)<M \forall \omega$. In this case, we would have that $\lim _{n \rightarrow \infty} n \mathbf{P}(X \geq n)=0$. Since $\exists N>M$ such that $\forall n>N$ that $X<n \forall \omega$. Therefore, $\mathbf{P}(X \geq n)=0 \forall n>N$. As a result, $\lim _{n \rightarrow \infty} n \mathbf{P}(X \geq n)=0$. If $X(\omega)<M \forall \omega$ does not hold, due to Theorem 4.2 (Consistency), P.50, [1], we have

$$
\begin{equation*}
\lim _{n \rightarrow \infty} E\left[X_{n}\right]=E[X] \tag{2.4}
\end{equation*}
$$

where on the left hand side $n \mathbf{P}(X \geq n)$ appears while on the right-hand side, due to definition Eq. (2.3), $n \mathbf{P}(X \geq n)$ does not appear.

Regarding the convergence related to the definition, refer to $[1,2,3]$.
Eq. (2.3) by definition is also rewritten as

$$
\begin{equation*}
E[X]=\int_{\Omega} X(\omega) d \mathbf{P}(\omega) \text { (Lebesgue). } \tag{2.5}
\end{equation*}
$$

2. Second, we show that for two random variables, $X$ defined on $(\Omega, \mathscr{F}, \mathbf{P})$ and $Y$ defined on $\left(\Omega^{\prime}, \mathscr{F}^{\prime}, \mathbf{P}^{\prime}\right)$. If $F_{X}(a)=F_{Y}(a) \forall a \in \mathbf{R}$, then $E[X]=E[Y]$.
Since $F_{X}(a)=F_{Y}(a)$, namely $\mathbf{P}(X \leq a)=\mathbf{P}^{\prime}(Y \leq a)$. One can show for any Borel set $A$, $\mathbf{P}(A)=\mathbf{P}^{\prime}(A)$. As a result, $\mathbf{P}\left(\frac{k-1}{2^{n}} \leq X(\omega)<\frac{k}{2^{n}}\right)=\mathbf{P}^{\prime}\left(\frac{k-1}{2^{n}} \leq Y\left(\omega^{\prime}\right)<\frac{k}{2^{n}}\right) \forall n, k$. Therefore, the constructed $X_{n}$ and $Y_{n}$ used to define $E[X]$ and $E[Y]$, as shown in the previous step, would have the property that

$$
\begin{equation*}
E\left[X_{n}\right]=E\left[Y_{n}\right], \forall n \tag{2.6}
\end{equation*}
$$

Take limits on both sides of Eq. (2.6), we get $E[X]=E[Y]$, namely

$$
\begin{equation*}
\text { (Lebesgue) } \int_{\Omega} X(\omega) d \mathbf{P}(\omega)=\int_{\Omega^{\prime}} Y\left(\omega^{\prime}\right) d \mathbf{P}^{\prime}\left(\omega^{\prime}\right) \text { (Lebesgue) } \tag{2.7}
\end{equation*}
$$

3. Then we define the canoical random variable. Since $X$ is a random variable on $(\Omega, \mathscr{F}, \mathbf{P})$ with distribution function $F_{X}$. Then we can find a probability space $(\mathbf{R}, \mathscr{B}, \tilde{\mathbf{P}})$ where $\mathscr{B}$ is Borel sigma field and $\tilde{\mathbf{P}}((a, b])=F_{X}(b)-F_{X}(a)$. By extension theorem, $\tilde{\mathbf{P}}$ is well defined. Then define $Y: \mathbf{R} \rightarrow \mathbf{R}$ as a random variable on $(\mathbf{R}, \mathscr{B}, \tilde{\mathbf{P}})$ and is given by $Y(y)=y$. Then the distribution function of $Y$, written as $F_{Y}$, would have the property that $F_{Y}(a)=F_{X}(a) \forall a \in \mathbf{R}$. As a direct result of step 2, we have

$$
\begin{equation*}
\text { (Lebesgue) } \int_{-\infty}^{\infty} Y(r) d \tilde{\mathbf{P}}(r)=\int_{\Omega} X(\omega) d \mathbf{P}(\omega) \text { (Lebesgue). } \tag{2.8}
\end{equation*}
$$

Please refer to Prop. 1.4 [3] for origin.
4. Finally, according to Sec. 11.5.4 [3], if $F_{X}$ is a distribution function, a Lebesgue-Stieltjes integration of $F_{X}$ is defined by the Lebesgue integration of its caniocal random variable, namely

$$
\begin{equation*}
\text { (Lebesgue-Stieltjes) } \int_{-\infty}^{\infty} g(x) d F_{X}(x)=\int_{-\infty}^{\infty} g(Y(r)) d \tilde{\mathbf{P}}(r) \text { (Lebesgue). } \tag{2.9}
\end{equation*}
$$

where $Y(r)=r$ as introduced above. Set $g(x)=x$, then we get

$$
\begin{equation*}
\text { (Lebesgue-Stieltjes) } \int_{-\infty}^{\infty} x d F_{X}(x)=\int_{-\infty}^{\infty} Y(r) d \tilde{\mathbf{P}}(r) \text { (Lebesgue). } \tag{2.10}
\end{equation*}
$$

Combine Eqs. (2.5), (2.8) and (2.10), we have

$$
\begin{equation*}
E[X]=\int_{-\infty}^{\infty} x d F_{X}(x) \text { (Lebesgue-Stieltjes). } \tag{2.11}
\end{equation*}
$$

Note in the Eq. (2.9), if $g$ is continuous (in our case, $g(x)=x$ is continuous) and the integral is finite, then the Lebesgue-Stieltjes integration and Riemann-Stieltjes integration (conventional one) agrees [3]. This is the reason we can calculate in most cases the expection $E[X]$ as

$$
\begin{equation*}
E[X]=\int_{-\infty}^{\infty} x d F_{X}(x) \text { (Riemann-Stieltjes). } \tag{2.12}
\end{equation*}
$$

Remark. Above discussion has established the case when $X$ is nonnegative. For general case, we define $E[X]=E\left[X^{+}\right]-E\left[X^{-}\right]$. Notice that the $X_{n}$ used to setablish $E[X]$ in [3] is given as

$$
X_{n}(\omega) \begin{cases}\frac{k-1}{2^{n}}, & \frac{k-1}{2^{n}} \leq X(\omega)<\frac{k}{2^{n}}, k=1,2, \ldots, n 2^{n}  \tag{2.13}\\ 0, & X(\omega) \geq n\end{cases}
$$

which is different from Eq. (2.1) from [1]. And [3] gives a better definition of $X^{+}$and $X^{-}$. However, it should be understood that double counting $\mathbf{P}(X=0)$ in both $E\left[X^{+}\right]$and $E\left[X^{-}\right]$does not alter the true value of $E[X]$ since its contribution to $E[X]$ would be 0 anyway.

## References

[1] Allan Gut, Probability: A graduate course, 2nd Edition, Springer \& Verlag, 2012.
[2] Timo Koski, Lecture notes: Probability and random processes at KTH, 2017.
[3] Bruce Hajek, Random processes for engineers, Cambridge University Press, 2015.

