Lecture-03: Conditional Expectation

1 Conditional expectation

Consider a probability space $(\Omega, \mathcal{F}, P)$.

Definition 1.1. For a random variable X, the conditional distribution conditioned on an event $E \in \mathcal{F}$ is given by

$$F_{X|E}(x) \triangleq \frac{P(\{X \leqslant x\} \cap E)}{P(E)}.$$

Remark 1. We can verify that $F_{X \mid E} : \mathbb{R} \to [0,1]$ is a distribution function for any $E \in \mathcal{F}$.

Definition 1.2. For any Borel measurable function $g : \mathbb{R} \to \mathbb{R}$ and a random variable $X : \Omega \to \mathbb{R}$ defined on the probability space $(\Omega, \mathcal{F}, P)$, the conditional expectation of a random variable $g(X)$ given an event E is given by

$$\mathbb{E}[g(X) \mid E] \triangleq \int_{x \in \mathbb{R}} g(x) dF_{X|E}(x).$$

Example 1.3. Consider two random variables X, Y defined on the same probability space $(\Omega, \mathcal{F}, P)$ with the joint distribution $F_{X,Y}(x,y) = P(\{X \leqslant x, Y \leqslant y\})$. For each $y \in \mathbb{R}$, we define event $G_y \triangleq Y^{-1}(-\infty, y] \in \mathcal{F}$ such that $F_Y(y) = P(G_y)$. Then, for each $y \in \mathbb{R}$ such that $P(G_y) > 0$, we can write the conditional distribution of X given the event G_y as

$$F_{X|G_y}(x) = \frac{F_{X,Y}(x,y)}{F_Y(y)}.$$

The conditional expectation of X given the event G_y is defined as

$$\mathbb{E}[X|G_y] = \int_{x \in \mathbb{R}} x dF_{X|G_y}(x) = \int_{x \in \mathbb{R}} x \frac{d_x F_{X,Y}(x,y)}{F_Y(y)}.$$

Example 1.4. Consider a random variable $X : \Omega \to \mathbb{R}$ and a simple random variable $Y : \Omega \to \mathcal{Y}$ defined on the same probability space. We observe that the conditional distribution of X given the nontrivial event $E_y = Y^{-1}\{y\}$ for $y \in \mathcal{Y}$ is $F_{X|E_y}(x) = \frac{P(\{X \leqslant x, Y = y\})}{P(E_y)}$. Therefore, the conditional expectation of X given the event E_y is

$$\mathbb{E}[X \mid E_y] = \mathbb{E}[X \mid Y = y] = \int_{x \in \mathbb{R}} x dF_{X|E_y}(x) = \int_{x \in \mathbb{R}} x \int_{z=y} \frac{dF_{X,Y}(x,z)}{P(E_y)} = \frac{\mathbb{E}[X \mathbb{1}_{E_y}]}{P(E_y)}.$$

Since $\mathbb{E}[X \mid E_y]$ is a scalar, we can write $\mathbb{E}[X \mathbb{1}_{E_y}] = \mathbb{E}[\mathbb{E}[X \mid E_y] \mathbb{1}_{E_y}]$.

Definition 1.5. Consider a random variable $X : \Omega \to \mathbb{R}$ defined on probability space $(\Omega, \mathcal{F}, P)$, and an event subspace $\mathcal{E} \subseteq \mathcal{F}$. The **conditional expectation** of X given $\mathcal{E}$ is denoted $\mathbb{E}[X|\mathcal{E}]$ and is a random variable $Z \triangleq \mathbb{E}[X|\mathcal{E}] : \Omega \to \mathbb{R}$ where

1. **measurability:** For each $B \in \mathcal{B}(\mathbb{R})$, we have $Z^{-1}(B) \in \mathcal{E}$, and
2. **orthogonality:** for each event $E \in \mathcal{E}$, we have $\mathbb{E}[X \mathbb{1}_E] = \mathbb{E}[Z \mathbb{1}_E]$, and
3. **integrability:** $\mathbb{E}|Z| < \infty$.

Proposition 1.6. *Conditional expectation is unique almost surely.*

Proof. Consider a random variable $X : \Omega \to \mathbb{R}$ defined on a probability space $(\Omega, \mathcal{F}, P)$ and a sub event space $\mathcal{E} \subseteq \mathcal{F}$. Let Z_1 and Z_2 be conditional expectations of X given $\mathcal{E}$. It suffices to show that $A_\epsilon \triangleq \{\omega \in \Omega : Z_1 - Z_2 > \epsilon\} \in \mathcal{E}$ and $B_\epsilon \triangleq \{\omega \in \Omega : Z_2 - Z_1 > \epsilon\} \in \mathcal{E}$ defined for each $\epsilon > 0$ has measure $P(A_\epsilon) = P(B_\epsilon) = 0$. From the definition of conditional expectation and linearity of expectation, we can write

$$0 \leqslant \epsilon P(A_\epsilon) < \mathbb{E}[(Z_1 - Z_2)\mathbb{1}_{A_\epsilon}] = \mathbb{E}[X\mathbb{1}_{A_\epsilon}] - \mathbb{E}[X\mathbb{1}_{A_\epsilon}] = 0.$$

Similarly, we can show that $P(B_\epsilon) = 0$, and the result follows. □

Remark 2. Any random variable $Z : \Omega \to \mathbb{R}$ that satisfies the measurability, orthogonality, and integrability, is the conditional expectation of X given the sub-event space $\mathcal{E}$ from the a.s. uniqueness of conditional expectations.

Remark 3. Intuitively, we think of the event subspace $\mathcal{E}$ as describing the information we have. For each $A \in \mathcal{E}$, we know whether or not A has occurred. The conditional expectation $\mathbb{E}[X|\mathcal{E}]$ is the "best guess" of the value of X given the information $\mathcal{E}$.

Definition 1.7. Consider a random variable $X : \Omega \to \mathbb{R}$ and a random vector $Y : \Omega \to \mathbb{R}^n$ defined on the same probability space $(\Omega, \mathcal{F}, P)$. The conditional expectation of X given Y is defined as

$$\mathbb{E}[X \mid Y] \triangleq \mathbb{E}[X \mid \sigma(Y)].$$

Proposition 1.8. *For two random variables $X, Y : \Omega \to \mathbb{R}$ defined on the same probability space $(\Omega, \mathcal{F}, P)$, the conditional expectation $\mathbb{E}[X \mid Y]$ is a function of Y.*

Proof. We denote the conditional expectation $\mathbb{E}[X \mid Y]$ by a $\sigma(Y)$-measurable random variable $Z : \Omega \to \mathbb{R}$. It suffices to show that for any $y \in \mathbb{R}$, the conditional expectation $Z(\omega)$ remains constant on the set of outcomes $\omega \in Y^{-1}\{y\}$. First, we show that for any event $A \in \sigma(Y)$, either $Y^{-1}\{y\} \subseteq A$ or $A \cap Y^{-1}\{y\} = \emptyset$. This follows from the fact that either $y \in A$ or $y \notin A$. Next, we suppose that there exists a $y \in \mathbb{R}$ and $\omega_1, \omega_2 \in Y^{-1}\{y\}$ such that $Z(\omega_1) \neq Z(\omega_2)$. It follows that there exists an event $B \triangleq Z^{-1}\{Z(\omega_1)\} \in \sigma(Z)$ such that $\omega_1 \in B$ and $\omega_2 \notin B$. Since Z is $\sigma(Y)$-measurable, it follows that $B \in \sigma(Z) \subseteq \sigma(Y)$. This leads to a contradiction. □

Proposition 1.9. *Let X, Y be random variables on the probability space $(\Omega, \mathcal{F}, P)$ such that $\mathbb{E}|X|, \mathbb{E}|Y| < \infty$. Let $\mathcal{G}$ and $\mathcal{H}$ be sub-event spaces of $\mathcal{F}$. Then*

1. ***linearity:*** *$\mathbb{E}[\alpha X + \beta Y \mid \mathcal{G}] = \alpha\mathbb{E}[X \mid \mathcal{G}] + \beta E[Y \mid \mathcal{G}]$, a.s.*
2. ***monotonicity:*** *If $X \leqslant Y$ a.s., then $\mathbb{E}[X \mid \mathcal{G}] \leqslant E[Y \mid \mathcal{G}]$, a.s.*
3. ***identity:*** *If X is $\mathcal{G}$-measurable and $\mathbb{E}|X| < \infty$, then $X = \mathbb{E}[X \mid \mathcal{G}]$ a.s. In particular, $c = \mathbb{E}[c \mid \mathcal{G}]$, for any constant $c \in \mathbb{R}$.*
4. ***conditional Jensen's inequality:*** *If $\psi : \mathbb{R} \to \mathbb{R}$ is convex and $\mathbb{E}|\psi(X)| < \infty$, then $\mathbb{E}[\psi(X) \mid \mathcal{G}] \geqslant \psi(\mathbb{E}[X \mid \mathcal{G}])$, a.s.*
5. ***pulling out what's known:*** *If Y is $\mathcal{G}$-measurable and $\mathbb{E}|XY| < \infty$, then $\mathbb{E}[XY \mid \mathcal{G}] = Y\mathbb{E}[X \mid \mathcal{G}]$, a.s.*
6. *L^2**-projection:*** *If $\mathbb{E}|X|^2 < \infty$, then $\zeta^* = \mathbb{E}[X \mid \mathcal{G}]$ minimizes $\mathbb{E}[(X - \zeta)^2]$ over all $\mathcal{G}$-measurable random variables ζ such that $\mathbb{E}|\zeta|^2 < \infty$.*
7. ***tower property:*** *If $\mathcal{H} \subseteq \mathcal{G}$, then $\mathbb{E}[\mathbb{E}[X \mid \mathcal{G}] \mid \mathcal{H}] = \mathbb{E}[X \mid \mathcal{H}]$, a.s..*
8. ***irrelevance of independent information:*** *If $\mathcal{H}$ is independent of $\sigma(\mathcal{G}, \sigma(X))$ then*

   $$\mathbb{E}[X|\sigma(\mathcal{G}, \mathcal{H})] = \mathbb{E}[X \mid \mathcal{G}], \text{ a.s.}$$

   In particular, if X is independent of $\mathcal{H}$, then $\mathbb{E}[X \mid \mathcal{H}] = \mathbb{E}[X]$, a.s.

Proof. Let X, Y be random variables on the probability space $(\Omega, \mathcal{F}, P)$ such that $\mathbb{E}|X|, \mathbb{E}|Y| < \infty$. Let $\mathcal{G}$ and $\mathcal{H}$ be event spaces such that $\mathcal{G}, \mathcal{H} \subseteq \mathcal{F}$.

1. **linearity:** Let $Z \triangleq \alpha\mathbb{E}[X \mid \mathcal{G}] + \beta\mathbb{E}[Y \mid \mathcal{G}]$, then since $\mathbb{E}[X \mid \mathcal{G}], \mathbb{E}[Y \in \mathcal{G}]$ are $\mathcal{G}$-measurable, it follows that their linear combination Z is also $\mathcal{G}$-measurable. The integrability follows from the following triangle inequality and the monotonicity of expectation
$$|Z| \leqslant |\alpha| |\mathbb{E}[X \mid \mathcal{G}]| + |\beta| |\mathbb{E}[Y \mid \mathcal{G}]|.$$
Further, for any event $F \in \mathcal{G}$, from the linearity of expectation and definition of conditional expectation, we have
$$\mathbb{E}[Z\mathbb{1}_G] = \alpha\mathbb{E}[\mathbb{E}[X \mid \mathcal{G}]\mathbb{1}_G] + \beta\mathbb{E}[\mathbb{E}[Y \mid \mathcal{G}]\mathbb{1}_G] = \mathbb{E}[(\alpha X + \beta Y)\mathbb{1}_G].$$
2. **monotonicity:** Let $\epsilon > 0$ and define $A_\epsilon \triangleq \{\mathbb{E}[X \mid \mathcal{G}] - \mathbb{E}[Y \mid \mathcal{G}] > \epsilon\} \in \mathcal{G}$. Then from the definition of conditional expectation, we have
$$0 \leqslant \mathbb{E}[(\mathbb{E}[X \mid \mathcal{G}] - \mathbb{E}[Y \mid \mathcal{G}])\mathbb{1}_{A_\epsilon}] = \mathbb{E}[(X - Y)\mathbb{1}_{A_\epsilon}] \leqslant 0.$$
Thus, we obtain that $P(A_\epsilon) = 0$ for all $\epsilon > 0$. Taking limit $\epsilon \downarrow 0$, we get $0 = \lim_{\epsilon \downarrow 0} P(A_\epsilon) = P(\lim_\epsilon A_\epsilon) = P(A_0)$.
3. **identity:** It follows from the definition that X satisfies all three conditions for conditional expectation. The event space generated by any constant function is the trivial event space $\{\emptyset, \Omega\} \subseteq \mathcal{G}$ for any event space. Hence, $\mathbb{E}[c \mid \mathcal{G}] = c$.
4. **conditional Jensen's inequality:** We will use the fact that a convex function can always be represented by the supremum of a family of affine functions. Accordingly, we will assume for a convex function $\psi : \mathbb{R} \to \mathbb{R}$, we have linear functions $\phi_i : \mathbb{R} \to \mathbb{R}$ and constants $c_i \in \mathbb{R}$ for all $i \in I$ such that $\psi = \sup_{i \in I}(\phi_i + c_i)$.

   For each $i \in I$, we have $\phi_i(\mathbb{E}[X \mid \mathcal{G}]) + c_i = \mathbb{E}[\phi_i(X) \mid \mathcal{G}] + c_i \leqslant \mathbb{E}[\psi(X) \mid \mathcal{G}]$ from the linearity and monotonicity of conditional expectation. It follows that
$$\psi(\mathbb{E}[X \mid \mathcal{G}]) = \sup_{i \in I}(\phi_i(\mathbb{E}[X \mid \mathcal{G}]) + c_i) \leqslant \mathbb{E}[\psi(X) \mid \mathcal{G}].$$
5. **pulling out what's known:** Let Y be $\mathcal{G}$-measurable and $\mathbb{E}|XY| < \infty$. Since Y is given to be $\mathcal{G}$-measurable, conditional expectation $\mathbb{E}[X \mid \mathcal{G}]$ is $\mathcal{G}$-measurable by definition, and product function is Borel measurable, it follows that $Y\mathbb{E}[X \mid \mathcal{G}]$ is $\mathcal{G}$-measurable.

   It suffices to show that $\mathbb{E}[XY\mathbb{1}_G] = \mathbb{E}[Y\mathbb{E}[X \mid \mathcal{G}]\mathbb{1}_G]$ for all events $G \in \mathcal{G}$ and $\mathbb{E}|Y\mathbb{E}[X \mid \mathcal{G}]| < \infty$, when Y is a simple $\mathcal{G}$-measurable random variable such that $\mathbb{E}|XY| < \infty$. It follows that, we can write $Y = \sum_{y \in \mathcal{Y}} y\mathbb{1}_{E_y}$ for finite $\mathcal{Y}$ and $E_y \triangleq Y^{-1}\{y\} \in \mathcal{G}$ for all $y \in \mathcal{Y}$. From the definition of conditional expectation and linearity, we obtain for any $G \in \mathcal{G}$
$$\mathbb{E}[Y\mathbb{E}[X \mid \mathcal{G}]\mathbb{1}_G] = \sum_{y \in \mathcal{Y}} y\mathbb{E}[\mathbb{1}_{G \cap E_y}\mathbb{E}[X \mid \mathcal{G}]] = \sum_{y \in \mathcal{Y}} y\mathbb{E}[X\mathbb{1}_{G \cap E_y}] = \mathbb{E}[X\sum_{y \in \mathcal{Y}} y\mathbb{1}_{G \cap E_y}] = \mathbb{E}[XY\mathbb{1}_G].$$
   Conditional Jensen's inequality applied to convex function $|| : \mathbb{R} \to \mathbb{R}_+$, we get $|\mathbb{E}[X \mid \mathcal{G}]| \leqslant \mathbb{E}[|X| \mid \mathcal{G}]$. Therefore,
$$\mathbb{E}[|Y| |\mathbb{E}[X \mid \mathcal{G}]|] = \sum_{y \in \mathcal{Y}} |y| \mathbb{E}[|\mathbb{E}[X \mid \mathcal{G}]| \mathbb{1}_{E_y}] \leqslant \sum_{y \in \mathcal{Y}} |y| \mathbb{E}[|X| \mathbb{1}_{E_y}] = \mathbb{E}|XY|.$$
6. **L^2-projection:** We define $L^2(\mathcal{G}) \triangleq \{\zeta \text{ a } \mathcal{G} \text{ measurable random variable} : \mathbb{E}\zeta^2 < \infty\}$. From the conditional Jensen's inequality applied to convex function $()^2 : \mathbb{R} \to \mathbb{R}_+$, we get that $\mathbb{E}(\mathbb{E}[X \mid \mathcal{G}])^2 \leqslant \mathbb{E}[X^2 \mid \mathcal{G}]$. Since $X \in L^2$, it follows that $X^2 \in L^1$ and hence $\mathbb{E}[X \mid \mathcal{G}] \in L^2$. It follows that $\zeta^* \triangleq \mathbb{E}[X \mid \mathcal{G}] \in L^2(\mathcal{G})$ from the definition of conditional expectation.

   We first show that $X - \zeta^*$ is uncorrelated with all $\zeta \in L^2(\mathcal{G})$. Towards this end, we let $\zeta \in L^2(\mathcal{G})$ and observe that
$$\mathbb{E}[(X - \zeta^*)\zeta] = \mathbb{E}[\zeta X] - \mathbb{E}[\zeta\mathbb{E}[X \mid \mathcal{G}]] = \mathbb{E}[\zeta X] - \mathbb{E}[\mathbb{E}[\zeta X \mid \mathcal{G}]] = 0.$$
   The above equality follows from the linearity of expectation, the $\mathcal{G}$-measurability of ζ, and the definition of conditional expectation. Since $\zeta^* \in L^2(\mathcal{G})$, we have $(\zeta - \zeta^*) \in L^2(\mathcal{G})$. Therefore, $\mathbb{E}[(X - \zeta^*)(\zeta - \zeta^*)] = 0$. For any $\zeta \in L^2(\mathcal{G})$, we can write from the linearity of expectation
$$\mathbb{E}(X - \zeta)^2 = \mathbb{E}(X - \zeta^*)^2 + \mathbb{E}(\zeta - \zeta^*)^2 - 2\mathbb{E}(X - \zeta^*)(\zeta - \zeta^*) \geqslant \mathbb{E}(X - \zeta^*)^2.$$

7. **tower property:** Measurability follows from the definition of conditional expectation, since $\mathbb{E}[X \mid \mathcal{H}]$ is $\mathcal{H}$ measurable. Integrability follows from the application of conditional Jensen's inequality to convex function $|| : \mathbb{R} \to \mathbb{R}_+$ to get $\left|\mathbb{E}[X \mid \mathcal{H}]\right| \leqslant \mathbb{E}[|X| \mid \mathcal{H}]$, which implies $\mathbb{E}\left|\mathbb{E}[X \mid \mathcal{H}]\right| \leqslant \mathbb{E}|X| < \infty$. Orthogonality follows from the definition of conditional expectation, since for any $H \in \mathcal{H} \subseteq \mathcal{G}$, we have
$$\mathbb{E}[\mathbb{E}[\mathbb{E}[X \mid \mathcal{G}] \mid \mathcal{H}]\mathbb{1}_H] = \mathbb{E}[\mathbb{E}[X \mid \mathcal{G}]\mathbb{1}_H] = \mathbb{E}[X\mathbb{1}_H] = \mathbb{E}[\mathbb{E}[X \mid \mathcal{H}]\mathbb{1}_H].$$

8. **irrelevance of independent information:** Measurability follows from the definition of conditional expectation and the definition of $\sigma(\mathcal{G},\mathcal{H})$. Since $\mathbb{E}[X \mid \mathcal{G}]$ is $\mathcal{G}$-measurable, it is $\sigma(\mathcal{G},\mathcal{H})$ measurable.

   Integrability follows from the conditional Jensen's inequality applied to convex function $|| : \mathbb{R} \to \mathbb{R}_+$ to get $\left|\mathbb{E}[X \mid \mathcal{G}]\right| \leqslant \mathbb{E}[|X| \mid \mathcal{G}]$, which implies that $\mathbb{E}\left|\mathbb{E}[X \mid \mathcal{G}]\right| \leqslant \mathbb{E}|X| < \infty$.

   Orthogonality follows from the fact that it suffices to show for events $A = G \cap H \in \sigma(\mathcal{G},\mathcal{H})$ where $G \in \mathcal{G}$ and $H \in \mathcal{H}$. In this case,
$$\mathbb{E}[\mathbb{E}[X \mid \mathcal{G}]\mathbb{1}_{G\cap H}] = \mathbb{E}[\mathbb{E}[X \mid \mathcal{G}]\mathbb{1}_G\mathbb{1}_H] = \mathbb{E}[\mathbb{E}[X \mid \mathcal{G}]\mathbb{1}_G]E[\mathbb{1}_H] = \mathbb{E}[X\mathbb{1}_G]\mathbb{E}[\mathbb{1}_H] = \mathbb{E}[X\mathbb{1}_{G\cap H}].$$

□

Example 1.10 (Conditioning on simple random variables). Let X and Y be random variables defined on the probability space $(\Omega,\mathcal{F},P)$, where $Y = \sum_{y\in\mathcal{Y}} y\mathbb{1}_{E_y}$ is simple with finite $\mathcal{Y}$, $E_y \triangleq Y^{-1}\{y\} \in \mathcal{F}$ for all $y \in \mathcal{Y}$ are mutually disjoint, and $p_y \triangleq P(E_y) > 0$ for all $y \in \mathcal{Y}$. Then, we observe that
$$\mathbb{E}[X|Y] = \sum_{y\in\mathcal{Y}} \mathbb{E}[X \mid E_y]\mathbb{1}_{E_y} \text{ a.s.}$$
To show this, we will use the almost sure uniqueness of conditional expectation that satisfies three properties in the definition. For measurability, we observe that $\sigma(Y) = \sigma(E_y : y \in \mathcal{Y})$, and RHS is a simple $\sigma(Y)$-measurable random variable. For integrability, we observe that
$$\mathbb{E}\left|\sum_{y\in\mathcal{Y}} \mathbb{E}[X \mid E_y]\mathbb{1}_{E_y}\right| \leqslant \sum_{y\in\mathcal{Y}} |E[X \mid Y]|\, P(E_y).$$
Thus, integrability follows from the finiteness of $\left|\mathbb{E}[X \mid E_y]\right|$. For orthogonality, we observe that any $G \in \sigma(Y) = \cup_{y\in F} E_y$ for some finite subset $F \subseteq \mathcal{Y}$. Further, we observe that $\mathbb{E}[X\mathbb{1}_{E_y}] = \mathbb{E}[X \mid E_y]P(E_y)$. Therefore, we have
$$\mathbb{E}[\sum_{z\in F}\sum_{y\in\mathcal{Y}} \mathbb{E}[X \mid E_y]\mathbb{1}_{E_y}\mathbb{1}_{E_z}] = \mathbb{E}[\sum_{z\in F} \mathbb{E}[X \mid E_z]\mathbb{1}_{E_z}] = \mathbb{E}[X\mathbb{1}_G].$$

Example 1.11 (Conditioning on simple random variables). Consider two random variables X, Y defined on the same probability space $(\Omega,\mathcal{F},P)$, where Y is a simple random variable such that $\mathcal{Y} \subseteq \mathbb{R}$ is finite alphabet, $E_y \triangleq Y^{-1}(\{y\}) \in \sigma(Y) \subseteq \mathcal{F}$, and $p_y \triangleq P(E_y) > 0$. Thus, we can write
$$Y = \sum_{y\in\mathcal{Y}} y\mathbb{1}_{E_y}.$$
The collection $(E_y \in \mathcal{F} : y \in \mathcal{Y})$ forms a finite partition of the outcome space Ω and generates $\sigma(Y) = \left\{\cup_{y\in F} E_y \in \mathcal{F} : F \subseteq \mathcal{Y}\right\}$. For an event space $\mathcal{E} \subseteq \mathcal{F}$, we claim
$$\mathbb{E}[X \mid \sigma(\mathcal{E}, Y)] = \sum_{y\in\mathcal{Y}} \mathbb{E}[X \mid \sigma(\mathcal{E}, E_y)]\mathbb{1}_{E_y} \text{ a.s.}$$
We will show this by uniqueness of conditional expectation that satisfies the following three properties. First, we verify that RHS is $\sigma(\mathcal{E}, Y)$ measurable, which follows from the definition since $\mathbb{E}[X \mid \sigma(\mathcal{E}, E_y)] \in \sigma(\mathcal{E}, E_y) \subseteq \sigma(\mathcal{E}, Y)$. Second, it follows from the triangular and conditional Jensen's inequality, that
$$\mathbb{E}\left|\sum_{y\in\mathcal{Y}} \mathbb{E}[X \mid \sigma(\mathcal{E}, E_y)]\mathbb{1}_{E_y}\right| \leqslant \sum_{y\in\mathcal{Y}} \mathbb{E}[\mathbb{E}[|X|\mathbb{1}_{E_y} \mid \sigma(\mathcal{E}, E_y)]] \leqslant \mathbb{E}|X|.$$
It suffices to show that for any $A \in \mathcal{E}$, we have $\mathbb{E}[\sum_{y\in\mathcal{Y}} \mathbb{E}[X \mid \sigma(\mathcal{E}, E_y)]\mathbb{1}_{E_y}\mathbb{1}_A\mathbb{1}_{E_z}] = \mathbb{E}[X\mathbb{1}_A\mathbb{1}_{E_z}]$. To this end, we observe that LHS of above equation is equal to
$$\mathbb{E}[\mathbb{E}[X\mathbb{1}_{A\cap E_z} \mid \sigma(\mathcal{E}, E_z)]] = \mathbb{E}[X\mathbb{1}_{A\cap E_z}].$$