

Conditional expectation toy example

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We start with Kolmogorov's Theorem on conditional expectations.

Theorem 1 (Thm 9.2 in Williams) *Let X be a random variable on the probability space $(\Omega, \mathcal{F}, \mathbb{P})$, with $\mathbb{E}|X| < \infty$. Let \mathcal{G} be a sub σ -algebra. Then there exists a random variable V such that*

- (a) V is \mathcal{G} -measurable,
- (b) $\mathbb{E}|V| < \infty$,
- (c) $\mathbb{E}(V; G) = \mathbb{E}(X; G)$ for any $G \in \mathcal{G}$.

This V is unique up to zero-measure sets and is called a version of the conditional expectation $\mathbb{E}(X | \mathcal{G})$.

Our toy example will be the following. Let $\Omega = \{1, 2, \dots, 12\}$, $\mathcal{F} = \mathcal{P}(\Omega)$, and \mathbb{P} be the uniform measure on the finite set Ω . Elementary outcomes in Ω will be denoted by ω . Define the random variables

$$Y := \left\lceil \frac{\omega}{4} \right\rceil = \begin{cases} 1, & \text{if } \omega = 1, 2, 3, 4, \\ 2, & \text{if } \omega = 5, 6, 7, 8, \\ 3, & \text{if } \omega = 9, 10, 11, 12, \end{cases} \quad X := \left\lceil \frac{\omega}{2} \right\rceil = \begin{cases} 1, & \text{if } \omega = 1, 2, \\ 2, & \text{if } \omega = 3, 4, \\ 3, & \text{if } \omega = 5, 6, \\ 4, & \text{if } \omega = 7, 8, \\ 5, & \text{if } \omega = 9, 10, \\ 6, & \text{if } \omega = 11, 12. \end{cases}$$

The σ -algebra generated by Y is

$$\begin{aligned} \mathcal{G} &:= \sigma(Y) := \sigma(Y^{-1}(\mathcal{B}(\mathbb{R}))) = \sigma(\{1, 2, 3, 4\}, \{5, 6, 7, 8\}, \{9, 10, 11, 12\}) \\ &= \{\emptyset, \{1, 2, 3, 4\}, \{5, 6, 7, 8\}, \{9, 10, 11, 12\}, \\ &\quad \{1, 2, 3, 4, 5, 6, 7, 8\}, \{1, 2, 3, 4, 9, 10, 11, 12\}, \{5, 6, 7, 8, 9, 10, 11, 12\}, \Omega\}. \end{aligned}$$

Similarly, the σ -algebra generated by X is

$$\mathcal{H} := \sigma(X) := \sigma(X^{-1}(\mathcal{B}(\mathbb{R}))) = \sigma(\{1, 2\}, \{3, 4\}, \{5, 6\}, \{7, 8\}, \{9, 10\}, \{11, 12\}).$$

We see that $\mathcal{G} \subset \mathcal{H} \subset \mathcal{F}$. The σ -algebra \mathcal{G} is coarser (contains less information), while \mathcal{H} is finer (more information). We also see that

- Y is \mathcal{G} -measurable (by definition).
- Y is \mathcal{H} -measurable (due to $\mathcal{G} \subset \mathcal{H}$).
- X is \mathcal{H} -measurable (by definition).
- X is *not* \mathcal{G} -measurable (e.g., $X^{-1}\{1\} = \{1, 2\} \notin \mathcal{G}$).

Next, we find the conditional expectation $\mathbb{E}(X | \mathcal{G})$ based on the definition above. As $\mathcal{G} = \sigma(Y)$, an equivalent notation for this is $\mathbb{E}(X | \mathcal{G}) = \mathbb{E}(X | Y)$. Due to $|\Omega| = 12 < \infty$, finite mean of $V = \mathbb{E}(X | \mathcal{G})$ is not an issue. We look for a \mathcal{G} -measurable random variable V with $\mathbb{E}(V; G) = \mathbb{E}(X; G)$ for any $G \in \mathcal{G}$.

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An efficient choice for G is $\{1, 2, 3, 4\}$. As V is \mathcal{G} -measurable, and \mathcal{G} has no set that distinguishes between these four outcomes, we find that $V(\omega)$ is the same for $\omega = 1, 2, 3, 4$. The above expectations turn into

$$\begin{aligned} V(1)\mathbb{P}\{1\} + V(2)\mathbb{P}\{2\} + V(3)\mathbb{P}\{3\} + V(4)\mathbb{P}\{4\} &= X(1)\mathbb{P}\{1\} + X(2)\mathbb{P}\{2\} + X(3)\mathbb{P}\{3\} + X(4)\mathbb{P}\{4\} \\ V(1)\mathbb{P}\{1\} + V(1)\mathbb{P}\{2\} + V(1)\mathbb{P}\{3\} + V(1)\mathbb{P}\{4\} &= X(1)\mathbb{P}\{1\} + X(2)\mathbb{P}\{2\} + X(3)\mathbb{P}\{3\} + X(4)\mathbb{P}\{4\} \\ V(1) = V(2) = V(3) = V(4) &= \frac{1 \cdot \frac{1}{12} + 1 \cdot \frac{1}{12} + 2 \cdot \frac{1}{12} + 2 \cdot \frac{1}{12}}{\frac{1}{12} + \frac{1}{12} + \frac{1}{12} + \frac{1}{12}} = 1.5. \end{aligned}$$

Similarly, with the respective choices $G = \{5, 6, 7, 8\}$ and $G = \{9, 10, 11, 12\}$,

$$\begin{aligned} V(5) = V(6) = V(7) = V(8) &= \frac{3 \cdot \frac{1}{12} + 3 \cdot \frac{1}{12} + 4 \cdot \frac{1}{12} + 4 \cdot \frac{1}{12}}{\frac{1}{12} + \frac{1}{12} + \frac{1}{12} + \frac{1}{12}} = 3.5, \\ V(9) = V(10) = V(11) = V(12) &= \frac{5 \cdot \frac{1}{12} + 5 \cdot \frac{1}{12} + 6 \cdot \frac{1}{12} + 6 \cdot \frac{1}{12}}{\frac{1}{12} + \frac{1}{12} + \frac{1}{12} + \frac{1}{12}} = 5.5. \end{aligned}$$

Hence the conditional expectation is the random variable

$$\mathbb{E}(X | \mathcal{G})(\omega) = V(\omega) = \begin{cases} 1.5, & \text{if } \omega = 1, 2, 3, 4, \\ 3.5, & \text{if } \omega = 5, 6, 7, 8, \\ 5.5, & \text{if } \omega = 9, 10, 11, 12, \end{cases}$$

being just the average of X over the smallest nontrivial respective units in \mathcal{G} .

In a similar way one can check

$$\mathbb{E}(Y | \mathcal{G})(\omega) = \begin{cases} 1, & \text{if } \omega = 1, 2, 3, 4, \\ 2, & \text{if } \omega = 5, 6, 7, 8, \\ 3, & \text{if } \omega = 9, 10, 11, 12 \end{cases} = Y(\omega),$$

and indeed it is always the case that $\mathbb{E}(Y | Y) = Y$ almost everywhere (a.e.).

Further examples are $\mathbb{E}(X | \{\emptyset, \Omega\})$, where the random variable V we are looking for is measurable w.r.t. the trivial σ -algebra $\{\emptyset, \Omega\}$, in other words is a constant. Picking $G = \emptyset$ gives $\mathbb{E}(V; \emptyset) = 0 = \mathbb{E}(X; \emptyset)$, which is not very informative. The choice $G = \Omega$ on the other hand fixes the value of the constant V :

$$\begin{aligned} \mathbb{E}(V; \Omega) &= \mathbb{E}(X; \Omega) \\ \mathbb{E}V &= \mathbb{E}X \\ V &= \mathbb{E}X, \end{aligned}$$

that is, $\mathbb{E}(X | \{\emptyset, \Omega\}) = \mathbb{E}X$. This is again true a.e. in general, conditioning on the trivial σ -algebra always produces a full expectation.

If, on the other hand, one conditions on the full σ -algebra \mathcal{F} that has all information that can be available in the probability space $(\Omega, \mathcal{F}, \mathbb{P})$, then every event $G \in \mathcal{F}$ can be substituted, and the very detailed ones completely fix the conditional expectation. In our example we can e.g., take $\{7\}$ to obtain

$$\begin{aligned} \mathbb{E}(V; \{7\}) &= \mathbb{E}(X; \{7\}), \\ V(7) \cdot \mathbb{P}\{7\} &= X(7) \cdot \mathbb{P}\{7\}, \\ V(7) &= X(7) = 4. \end{aligned}$$

Similarly, for any $\omega \in \Omega$ one has $V(\omega) = X(\omega)$, which leads us to $\mathbb{E}(X | \mathcal{F}) = V = X$. This is again a.e. true for general probability spaces: conditioning on the full information does not do any averaging and gives back the random variable instead.

Our final example is

$$\begin{aligned} \mathcal{I} &:= \sigma(\{1, 5, 9\}, \{3, 7, 11\}) \\ &= \{\emptyset, \{1, 5, 9\}, \{3, 7, 11\}, \{2, 4, 6, 8, 10, 12\}, \{1, 3, 5, 7, 9, 11\}, \\ &\quad \{1, 2, 4, 5, 6, 8, 9, 10, 12\}, \{2, 3, 4, 6, 7, 8, 10, 11, 12\}, \Omega\}. \end{aligned}$$

We compute $V = \mathbb{E}(Y | \mathcal{I})$ as before. This is \mathcal{I} -measurable, hence constant on $\{1, 5, 9\}$, as well as on $\{3, 7, 11\}$ and on $\{2, 4, 6, 8, 10, 12\}$. Substituting these as G (the rest in \mathcal{I} will not provide additional help) in $\mathbb{E}(V; G) = \mathbb{E}(Y; G)$ results in

$$\begin{aligned} V(1) = V(5) = V(9) &= \frac{Y(1)\mathbb{P}\{1\} + Y(5)\mathbb{P}\{5\} + Y(9)\mathbb{P}\{9\}}{\mathbb{P}\{1\} + \mathbb{P}\{5\} + \mathbb{P}\{9\}} = \frac{1 \cdot \frac{1}{12} + 2 \cdot \frac{1}{12} + 3 \cdot \frac{1}{12}}{\frac{1}{12} + \frac{1}{12} + \frac{1}{12}} = 2, \\ V(3) = V(7) = V(11) &= \frac{Y(3)\mathbb{P}\{3\} + Y(7)\mathbb{P}\{7\} + Y(11)\mathbb{P}\{11\}}{\mathbb{P}\{3\} + \mathbb{P}\{7\} + \mathbb{P}\{11\}} = \frac{1 \cdot \frac{1}{12} + 2 \cdot \frac{1}{12} + 3 \cdot \frac{1}{12}}{\frac{1}{12} + \frac{1}{12} + \frac{1}{12}} = 2, \\ V(2) = V(4) = V(6) \\ &= V(8) = V(10) = V(12) = \frac{Y(2)\mathbb{P}\{2\} + Y(4)\mathbb{P}\{4\} + Y(6)\mathbb{P}\{6\} + Y(8)\mathbb{P}\{8\} + Y(10)\mathbb{P}\{10\} + Y(12)\mathbb{P}\{12\}}{\mathbb{P}\{2\} + \mathbb{P}\{4\} + \mathbb{P}\{6\} + \mathbb{P}\{8\} + \mathbb{P}\{10\} + \mathbb{P}\{12\}} \\ &= \frac{1 \cdot \frac{1}{12} + 1 \cdot \frac{1}{12} + 2 \cdot \frac{1}{12} + 2 \cdot \frac{1}{12} + 3 \cdot \frac{1}{12} + 3 \cdot \frac{1}{12}}{\frac{1}{12} + \frac{1}{12} + \frac{1}{12} + \frac{1}{12} + \frac{1}{12} + \frac{1}{12}} = 2. \end{aligned}$$

We find that $\mathbb{E}(Y | \mathcal{I})$ is actually a constant, and in fact $= \mathbb{E}Y$.

We can repeat this calculation with any function $f : \mathbb{R} \rightarrow \mathbb{R}$ (in general this is chosen to be bounded and measurable) to find $\mathbb{E}(f(Y) | \mathcal{I}) = \mathbb{E}(f(Y))$, a constant. This is when we say that the random variable Y is independent of the σ -algebra \mathcal{I} . Knowing which of the events $\{1, 5, 9\}$ and $\{3, 7, 11\}$ did or did not happen will not tell us any information about Y .

If \mathcal{I} happens to be generated by yet another random variable Z , $\mathcal{I} = \sigma(Z)$, then the above is equivalent to variables Y and Z being independent.