

Showing that $\mathbb{E}[\mathbb{E}[V|U,W] | W] = \mathbb{E}[V|W]$.

Consider the specific case of $W=w$:

$$\mathbb{E}[\underbrace{\mathbb{E}[V|U,W]}_{\text{Recall that this is a R.V. that is a function } f(U,W)} | W=w] = \sum_u \underbrace{\mathbb{E}[V|U=u, W=w]}_{f(u,w)} \Pr(U=u | W=w)$$

Recall that this is
a R.V. that is a
function $f(U,W)$

$$= \sum_u \left(\sum_v v \cdot \Pr(V=v | U=u, W=w) \right) \Pr(U=u, W=w)$$

$$= \sum_u \sum_v v \cdot \Pr(V=v, U=u | W=w)$$

$$= \sum_u \sum_v v \cdot \frac{\Pr(V=v, U=u, W=w)}{\Pr(W=w)} \quad \downarrow \text{Bayes}$$

$$= \sum_v \frac{v}{\Pr(W=w)} \left(\sum_u \Pr(V=v, U=u, W=w) \right)$$

\downarrow total probability

$$= \sum_v \frac{v}{\Pr(W=w)} \left(\Pr(V=v, W=w) \right)$$

$$= \sum_v v \cdot \frac{\Pr(V=v, W=w)}{\Pr(W=w)}$$

$$= \sum_v v \cdot \Pr(V=v | W=w)$$

\downarrow by definition

$$= \mathbb{E}[V | W=w]$$

Since this derivation holds for arbitrary w , we have

$$\mathbb{E}[\mathbb{E}[V|U,W] | W] = \mathbb{E}[V|W] \quad \leftarrow$$

Important "nugget"...

whatever appears in the inner conditioning
but not in the outer conditioning is
"averaged out" (i.e. disappears)