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- ▶ The marginal PMF's  $p_X$  and  $p_Y$  can be obtained from the joint PMF as follows:  
$$p_X(x) = \sum_y p_{XY}(x, y) \text{ and } p_Y(y) = \sum_x p_{XY}(x, y).$$



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Proof:

$$\begin{aligned} P_X(x) &= \mathbb{P}\{\omega \in \Omega : X(\omega) = x\} \\ &= \mathbb{P}\left\{\bigcup_y \{\omega \in \Omega : X(\omega) = x, Y(\omega) = y\}\right\} \\ &= \sum_y \mathbb{P}\{\{\omega \in \Omega : X(\omega) = x, Y(\omega) = y\}\} \end{aligned}$$

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Two random variables,  $X$  and  $Y$  are independent if the following is true:

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If  $X$  and  $Y$  are independent,  $E[XY] = E[X]E[Y]$ .

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[https://en.wikipedia.org/wiki/Law\\_of\\_the\\_unconscious\\_statistician](https://en.wikipedia.org/wiki/Law_of_the_unconscious_statistician)

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The rules for more than 2 discrete random variables are similar.

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