2.27

$$\begin{split} \mathbb{E}[\mathbf{y}] &= \mathbb{E}[\mathbf{x} + \mathbf{z}] \\ &= \mathbb{E}[\mathbf{x}] + \mathbb{E}[\mathbf{z}] \end{split}$$

simply using linearity of expectation.

Using 2.63 to define covariance,

$$\begin{split} \Sigma_{\mathbf{y}\mathbf{y}} &= \mathbb{E}[(\mathbf{y} - \mathbb{E}[\mathbf{y}])(\mathbf{y} - \mathbb{E}[\mathbf{y}])^T] \\ &= \mathbb{E}[((\mathbf{x} + \mathbf{z}) - (\mathbb{E}[\mathbf{x}] + \mathbb{E}[\mathbf{z}]))((\mathbf{x} + \mathbf{z}) - (\mathbb{E}[\mathbf{x}] + \mathbb{E}[\mathbf{z}]))^T] \\ &= \mathbb{E}[((\mathbf{x} - \mathbb{E}[\mathbf{x}]) + (\mathbf{z} - \mathbb{E}[\mathbf{z}]))((\mathbf{x} - \mathbb{E}[\mathbf{x}]) + (\mathbf{z} - \mathbb{E}[\mathbf{z}]))^T] \\ &= \mathbb{E}[(\mathbf{x} - \mathbb{E}[\mathbf{x}])(\mathbf{x} - \mathbb{E}[\mathbf{x}])(\mathbf{z} - \mathbb{E}[\mathbf{z}])^T + (\mathbf{z} - \mathbb{E}[\mathbf{z}])(\mathbf{z} - \mathbb{E}[\mathbf{z}])^T] \\ &= \mathbb{E}[(\mathbf{x} - \mathbb{E}[\mathbf{x}])(\mathbf{x} - \mathbb{E}[\mathbf{x}])^T] \\ &+ \mathbb{E}[(\mathbf{z} - \mathbb{E}[\mathbf{z}])(\mathbf{z} - \mathbb{E}[\mathbf{z}])^T] \\ &+ \mathbb{E}[(\mathbf{z} - \mathbb{E}[\mathbf{z}])(\mathbf{z} - \mathbb{E}[\mathbf{z}])^T] \\ &= \Sigma_{\mathbf{x}\mathbf{x}} + \Sigma_{\mathbf{x}\mathbf{z}} + \Sigma_{\mathbf{z}\mathbf{x}} + \Sigma_{\mathbf{z}\mathbf{z}} \end{split}$$

Since \mathbf{x} and \mathbf{z} are independent, their covariance is $\mathbf{0}$, giving us:

$$= \Sigma_{\mathbf{x}\mathbf{x}} + \mathbf{0} + \mathbf{0} + \Sigma_{\mathbf{z}\mathbf{z}}$$

$$= \Sigma_{\mathbf{x}\mathbf{x}} + \Sigma_{\mathbf{z}\mathbf{z}}$$