2.31 In $p(\mathbf{y}|\mathbf{x})$, $\mathbf{x}$ is fixed and $\mathbf{z}$ is unknown. So, the mean of $p(\mathbf{y}|\mathbf{x})$ is given by $(\mathbf{x}+\boldsymbol{\mu}_{\mathbf{z}})$.

The variance is accounted for solely by $\mathbf{z}$ here, so the variance of $p(\mathbf{y}|\mathbf{x})$ is $\boldsymbol{\Sigma}_{\mathbf{z}}$.

$$\implies p(\mathbf{y}|\mathbf{x}) = \mathcal{N}(\mathbf{y}|(\mathbf{x} + \boldsymbol{\mu}_{\mathbf{z}}), \boldsymbol{\Sigma}_{\mathbf{z}})$$

Using 2.109 and 2.110, we can see that here,

$$\mathbf{A} \text{ is } \mathbf{I}$$
$$\mathbf{x} \text{ is } \mathbf{x}$$
$$\mathbf{b} \text{ is } \boldsymbol{\mu}_{\mathbf{z}}$$
$$\boldsymbol{\Lambda}^{-1} \text{ is } \boldsymbol{\Sigma}_{\mathbf{x}}^{-1}$$
$$\mathbf{L}^{-1} \text{ is } \boldsymbol{\Sigma}_{\mathbf{z}}^{-1}$$

Which gives us:

$$\mathbb{E}[\mathbf{y}] = \boldsymbol{\mu}_{\mathbf{x}} + \boldsymbol{\mu}_{\mathbf{z}}$$

$$var[\mathbf{y}] = \boldsymbol{\Sigma}_{\mathbf{x}} + \boldsymbol{\Sigma}_{\mathbf{z}}$$