

# The Reward Function

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The *reward*  $R$  of being in state  $\mathbf{s}$  is

$$R(\mathbf{s}) = \exp\left(-\frac{1}{2}(\mathbf{s} - \mathbf{z})^\top \mathbf{T}^{-1}(\mathbf{s} - \mathbf{z})\right),$$

where  $\mathbf{z}$  and  $\mathbf{T}$  are parameters of the reward function, which typically depend on the specific task. We assume that the state is uncertain, with a Gaussian distribution

$$\mathbf{s} \sim \mathcal{N}(\mathbf{m}, \mathbf{S}),$$

with mean  $\mathbf{m}$  and covariance matrix  $\mathbf{S}$ . We wish to compute the *expected* reward

$$\mu = \mathbb{E}[R] = \langle R(\mathbf{s}) \rangle_{\mathbf{s} \sim \mathcal{N}(\mathbf{m}, \mathbf{S})} = |\mathbf{I} + \mathbf{S}\mathbf{T}^{-1}|^{-1/2} \exp\left(-\frac{1}{2}(\mathbf{m} - \mathbf{z})^\top (\mathbf{S} + \mathbf{T})^{-1}(\mathbf{m} - \mathbf{z})\right),$$

and to compute the *variance* of the reward we first define

$$\mathbf{r}^2 = \mathbb{E}[R^2] = |\mathbf{I} + 2\mathbf{S}\mathbf{T}^{-1}|^{-1/2} \exp\left(-(\mathbf{m} - \mathbf{z})^\top (2\mathbf{S} + \mathbf{T})^{-1}(\mathbf{m} - \mathbf{z})\right),$$

so that

$$\sigma^2 = \mathbb{V}[R] = \mathbb{E}[R^2] - \mathbb{E}^2[R] = \mathbf{r}^2 - \mu^2.$$

We also need the derivatives of these two quantities wrt the parameters of the state distribution. For the expected reward we have

$$\frac{d\mu}{d\mathbf{m}} = -\mu(\mathbf{S} + \mathbf{T})^{-1}(\mathbf{m} - \mathbf{z}), \quad \frac{d\mu}{d\mathbf{S}} = \frac{1}{2}\mu[(\mathbf{S} + \mathbf{T})^{-1}(\mathbf{m} - \mathbf{z})(\mathbf{m} - \mathbf{z})^\top - \mathbf{I}](\mathbf{S} + \mathbf{T})^{-1},$$

and for the variance

$$\frac{d\sigma^2}{d\mathbf{m}} = -2\mathbf{r}^2(2\mathbf{S} + \mathbf{T})^{-1}(\mathbf{m} - \mathbf{z}) - 2\mu \frac{d\mu}{d\mathbf{m}}, \quad \frac{d\sigma^2}{d\mathbf{S}} = \mathbf{r}^2[2(2\mathbf{S} + \mathbf{T})^{-1}(\mathbf{m} - \mathbf{z})(\mathbf{m} - \mathbf{z})^\top - \mathbf{I}](2\mathbf{S} + \mathbf{T})^{-1} - 2\mu \frac{d\mu}{d\mathbf{S}}.$$