transforming an underlying random value $\mathrm{z} \sim \mathcal{N}(z; 0, 1)$ to obtain a sample from the desired distribution:

$$y = \mu + \sigma z \tag{20.55}$$

We are now able to back-propagate through the sampling operation, by regarding it as a deterministic operation with an extra input z. Crucially, the extra input is a random variable whose distribution is not a function of any of the variables whose derivatives we want to calculate. The result tells us how an infinitesimal change in μ or σ would change the output if we could repeat the sampling operation again with the same value of z.

Being able to back-propagate through this sampling operation allows us to incorporate it into a larger graph. We can build elements of the graph on top of the output of the sampling distribution. For example, we can compute the derivatives of some loss function $J(y)$. We can also build elements of the graph whose outputs are the inputs or the parameters of the sampling operation. For example, we could build a larger graph with $\mu = f(\boldsymbol{x}; \boldsymbol{\theta})$ and $\sigma = g(\boldsymbol{x}; \boldsymbol{\theta})$. In this augmented graph, we can use back-propagation through these functions to derive $\nabla_{\boldsymbol{\theta}} J(y)$.

The principle used in this Gaussian sampling example is more generally applicable. We can express any probability distribution of the form $p(\mathrm{y}; \boldsymbol{\theta})$ or $p(\mathrm{y} \mid \boldsymbol{x}; \boldsymbol{\theta})$ as $p(\mathrm{y} \mid \boldsymbol{\omega})$, where $\boldsymbol{\omega}$ is a variable containing both parameters $\boldsymbol{\theta}$, and if applicable, the inputs $\boldsymbol{x}$. Given a value y sampled from distribution $p(\mathrm{y} \mid \boldsymbol{\omega})$, where $\boldsymbol{\omega}$ may in turn be a function of other variables, we can rewrite

$$\mathbf{y} \sim p(\mathbf{y} \mid \boldsymbol{\omega}) \tag{20.56}$$

as

$$\boldsymbol{y} = f(\boldsymbol{z}; \boldsymbol{\omega}), \tag{20.57}$$

where $\boldsymbol{z}$ is a source of randomness. We may then compute the derivatives of $\boldsymbol{y}$ with respect to $\boldsymbol{\omega}$ using traditional tools such as the back-propagation algorithm applied to f, so long as f is continuous and differentiable almost everywhere. Crucially, $\boldsymbol{\omega}$ must not be a function of $\boldsymbol{z}$, and $\boldsymbol{z}$ must not be a function of $\boldsymbol{\omega}$. This technique is often called the **reparametrization trick**, **stochastic back-propagation** or **perturbation analysis**.

The requirement that f be continuous and differentiable of course requires $\boldsymbol{y}$ to be continuous. If we wish to back-propagate through a sampling process that produces discrete-valued samples, it may still be possible to estimate a gradient on $\boldsymbol{\omega}$, using reinforcement learning algorithms such as variants of the REINFORCE algorithm (Williams, 1992), discussed in section 20.9.1.