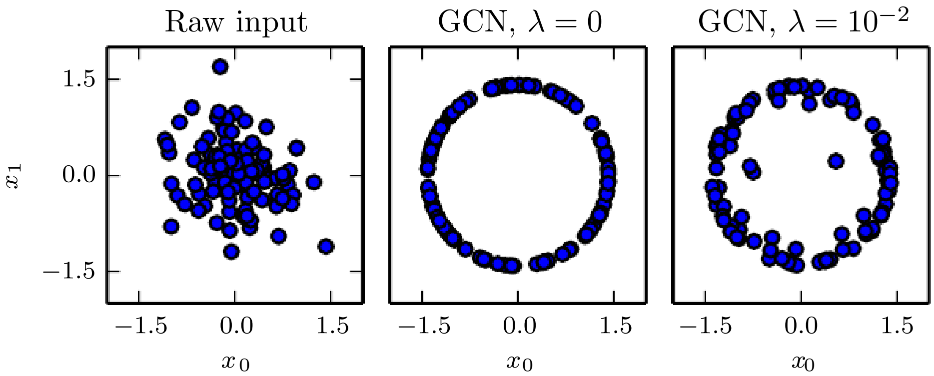

Figure 12.1: GCN maps examples onto a sphere. *(Left)*Raw input data may have any norm. *(Center)*GCN with $\lambda = 0$ maps all non-zero examples perfectly onto a sphere. Here we use $s = 1$ and $\epsilon = 10^{-8}$. Because we use GCN based on normalizing the standard deviation rather than the L^2 norm, the resulting sphere is not the unit sphere. *(Right)*Regularized GCN, with $\lambda > 0$, draws examples toward the sphere but does not completely discard the variation in their norm. We leave s and ϵ the same as before.

equal variance, so that the multivariate normal distribution used by PCA has spherical contours. Sphering is more commonly known as **whitening**.

Global contrast normalization will often fail to highlight image features we would like to stand out, such as edges and corners. If we have a scene with a large dark area and a large bright area (such as a city square with half the image in the shadow of a building) then global contrast normalization will ensure there is a large difference between the brightness of the dark area and the brightness of the light area. It will not, however, ensure that edges within the dark region stand out.

This motivates **local contrast normalization**. Local contrast normalization ensures that the contrast is normalized across each small window, rather than over the image as a whole. See figure 12.2 for a comparison of global and local contrast normalization.

Various definitions of local contrast normalization are possible. In all cases, one modifies each pixel by subtracting a mean of nearby pixels and dividing by a standard deviation of nearby pixels. In some cases, this is literally the mean and standard deviation of all pixels in a rectangular window centered on the pixel to be modified (Pinto *et al.*, 2008). In other cases, this is a weighted mean and weighted standard deviation using Gaussian weights centered on the pixel to be modified. In the case of color images, some strategies process different color