

FIGURE 9.9. The basis functions $(x-t)_+$ (solid orange) and $(t-x)_+$ (broken blue) used by MARS.

As an example, the functions $(x - 0.5)_+$ and $(0.5 - x)_+$ are shown in Figure 9.9.

Each function is piecewise linear, with a knot at the value t. In the terminology of Chapter 5, these are linear splines. We call the two functions a reflected pair in the discussion below. The idea is to form reflected pairs for each input X_j with knots at each observed value x_{ij} of that input. Therefore, the collection of basis functions is

$$C = \{ (X_j - t)_+, (t - X_j)_+ \} \underset{j = 1, 2, \dots, p}{t \in \{x_{1j}, x_{2j}, \dots, x_{Nj}\}}$$

$$(9.18)$$

If all of the input values are distinct, there are 2Np basis functions altogether. Note that although each basis function depends only on a single X_j , for example, $h(X) = (X_j - t)_+$, it is considered as a function over the entire input space \mathbb{R}^p .

The model-building strategy is like a forward stepwise linear regression, but instead of using the original inputs, we are allowed to use functions from the set \mathcal{C} and their products. Thus the model has the form

$$f(X) = \beta_0 + \sum_{m=1}^{M} \beta_m h_m(X), \tag{9.19}$$

where each $h_m(X)$ is a function in C, or a product of two or more such functions.

Given a choice for the h_m , the coefficients β_m are estimated by minimizing the residual sum-of-squares, that is, by standard linear regression. The real art, however, is in the construction of the functions $h_m(x)$. We start with only the constant function $h_0(X) = 1$ in our model, and all functions in the set \mathcal{C} are candidate functions. This is depicted in Figure 9.10.

At each stage we consider as a new basis function pair all products of a function h_m in the model set \mathcal{M} with one of the reflected pairs in \mathcal{C} . We add to the model \mathcal{M} the term of the form

$$\hat{\beta}_{M+1}h_{\ell}(X)\cdot(X_j-t)_+ + \hat{\beta}_{M+2}h_{\ell}(X)\cdot(t-X_j)_+, \ h_{\ell}\in\mathcal{M},$$