



**Figure 5.2** Attempting to construct a  $K$ -class discriminant from a set of two-class discriminant functions leads to ambiguous regions, as shown in green. On the left is an example with two discriminant functions designed to distinguish points in class  $\mathcal{C}_k$  from points not in class  $\mathcal{C}_k$ . On the right is an example involving three discriminant functions each of which is used to separate a pair of classes  $\mathcal{C}_k$  and  $\mathcal{C}_j$ .

In this case, the decision surfaces are  $D$ -dimensional hyperplanes passing through the origin of the  $(D + 1)$ -dimensional expanded input space.

### 5.1.2 Multiple classes

Now consider the extension of linear discriminant functions to  $K > 2$  classes. We might be tempted to build a  $K$ -class discriminant by combining a number of two-class discriminant functions. However, this leads to some serious difficulties (Duda and Hart, 1973), as we now show.

Consider a model with  $K - 1$  classifiers, each of which solves a two-class problem of separating points in a particular class  $\mathcal{C}_k$  from points not in that class. This is known as a *one-versus-the-rest* classifier. The left-hand example in Figure 5.2 shows an example involving three classes where this approach leads to regions of input space that are ambiguously classified.

An alternative is to introduce  $K(K - 1)/2$  binary discriminant functions, one for every possible pair of classes. This is known as a *one-versus-one* classifier. Each point is then classified according to a majority vote amongst the discriminant functions. However, this too runs into the problem of ambiguous regions, as illustrated in the right-hand diagram of Figure 5.2.

We can avoid these difficulties by considering a single  $K$ -class discriminant comprising  $K$  linear functions of the form

$$y_k(\mathbf{x}) = \mathbf{w}_k^T \mathbf{x} + w_{k0} \quad (5.7)$$

and then assigning a point  $\mathbf{x}$  to class  $\mathcal{C}_k$  if  $y_k(\mathbf{x}) > y_j(\mathbf{x})$  for all  $j \neq k$ . The decision boundary between class  $\mathcal{C}_k$  and class  $\mathcal{C}_j$  is therefore given by  $y_k(\mathbf{x}) = y_j(\mathbf{x})$  and