



## Why

Linear predictors are simple and we know how to select the parameters. The main downside is that there may not be a linear relationship between inputs and outputs.

## Definition

A *feature map* (or *regression function*) for outputs  $A$  is a mapping  $\phi : A \rightarrow \mathbf{R}^d$ . In this setting, we call  $a \in A$  the *raw input record* and we call  $\phi(a)$  an *embedding*, *feature embedding* or *feature vector*. We call the components of a feature vector the *features*. We call  $\phi(A)$  the *regression range*.

A feature map is *faithful* if, whenever records  $a_i$  and  $a_j$  are in some sense “similar” in the set  $A$ , the embeddings  $\phi(a_i)$  and  $\phi(a_j)$  are close in the vector space  $\mathbf{R}^d$ .

Since it is common for raw input records  $a \in A$  to consist of many fields, it is regular to have several feature maps  $\phi_i$  which operate component-wise on the fields of  $a$ . These are sometimes called *basis functions*, by analogy with real function approximators (see [Real Function Appproximators](#)). We concatenate these field feature maps and commonly add a constant feature 1. Since  $\mathbf{R}^d$  is a vector space, it is common to refer to it in this case as the *feature space*.

Given a dataset  $a = (a^1, \dots, a^n)$  in  $A$  and a feature map  $\phi : A \rightarrow \mathbf{R}^d$ , the *embedded dataset* of  $a$  with respect to  $\phi$  is the dataset  $(\phi(a^1), \dots, \phi(a^n))$  in  $\mathbf{R}^d$ .

### Featurized consistency: a route around $X \neq \mathbf{R}^d$

Recall that a dataset is parametrically consistent with the family  $\{h_\theta : X \rightarrow Y\}_\theta$  if there exists  $\theta^*$  so that the dataset is consistent with  $\theta^*$ . We saw how to pick  $\theta$  if we use a linear model with a squared loss (see [Least Squares Linear Regressors](#)).

Let  $\mathcal{G} = \{g_\theta : \mathbf{R}^d \rightarrow \mathbf{R}\}_\theta$ . A dataset is *featurized parametrically consistent* with respect to the family  $\mathcal{G}$  and the feature map  $\phi : X \rightarrow \mathbf{R}^d$  if it is parametrically consistent with respect to  $\mathcal{G} \circ \phi = \{g \circ \phi \mid g \in \mathcal{G}\}$ .

The interpretation is that we have transformed the problem of selecting a predictor on an arbitrary space  $X$  to the problem of selecting a predictor on the space  $\mathbf{R}^d$ . In so doing, we can continue to use simple predictors, such as those that are linear and minimize the squared error on the dataset.<sup>1</sup>

In other words, we have “shifted emphasis” from the model function  $h : X \rightarrow \mathbf{R}$  to the *regression function* from  $\mathbf{R}^d \rightarrow \mathbf{R}$ . If we know the features and the input  $x$ , then we know the *regression vector*  $\phi(x)$ . The *regression range* is the set  $\{\phi(x) \mid x \in X\}$ . In this case linearity pertains to the parameters  $\theta \in \mathbf{R}^d$  instead of the inputs (or experimental conditions)  $x \in X$ .

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<sup>1</sup>Future editions are likely to modify this section.

