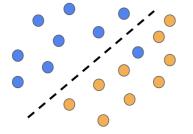
Introduction to Machine Learning

Classification Linear Classifiers





Learning goals

- Linear classifier
- Linear decision boundaries
- Linear separability

LINEAR CLASSIFIERS

Important subclass of classification models.

Definition: If discriminant(s) $f_k(\mathbf{x})$ can be written as affine linear function(s) (possibly through a rank-preserving, monotone transformation g):

$$g(f_k(\mathbf{x})) = \mathbf{w}_k^{\top} \mathbf{x} + b_k,$$

we will call the classifier linear.

- \mathbf{w}_k and b_k do not necessarily refer to parameters θ_k , although they often coincide; discriminant simply must be writable in an affine-linear way
- reasonsfor the transformation is that we only care about the position of the decision boundary



LINEAR DECISION BOUNDARIES

We can also easily show that the decision boundary between classes i and j is a hyperplane. For every \mathbf{x} where there is a tie in scores:

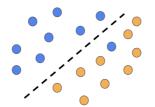
$$f_i(\mathbf{x}) = f_j(\mathbf{x})$$

$$g(f_i(\mathbf{x})) = g(f_j(\mathbf{x}))$$

$$\mathbf{w}_i^{\top} \mathbf{x} + b_i = \mathbf{w}_j^{\top} \mathbf{x} + b_j$$

$$(\mathbf{w}_i - \mathbf{w}_i)^{\top} \mathbf{x} + (b_i - b_j) = 0$$

This represents a **hyperplane** separating two classes:

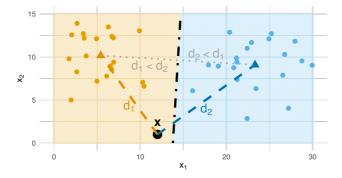




EXAMPLE: 2 CLASSES WITH CENTROIDS

- Model binary problem with centroid μ_k per class as "parameters"
- Don't really care how the centroids are estimated;
 could use class means, but the following doesn't depend on it
- Classify point x by assigning it to class k of nearest centroid





EXAMPLE: 2 CLASSES WITH CENTROIDS

Let's calculate the decision boundary:

$$d_1 = ||\mathbf{x} - \boldsymbol{\mu}_1||^2 = \mathbf{x}^\top \mathbf{x} - 2\mathbf{x}^\top \boldsymbol{\mu}_1 + \boldsymbol{\mu}_1^\top \boldsymbol{\mu}_1 = \mathbf{x}^\top \mathbf{x} - 2\mathbf{x}^\top \boldsymbol{\mu}_2 + \boldsymbol{\mu}_2^\top \boldsymbol{\mu}_2 = ||\mathbf{x} - \boldsymbol{\mu}_2||^2 = d_2$$
Where d is measured using Euclidean distance. This implies:

$$-2\mathbf{x}^{ op}\mu_\mathbf{1} + \mu_\mathbf{1}^{ op}\mu_\mathbf{1} = -2\mathbf{x}^{ op}\mu_\mathbf{2} + \mu_\mathbf{2}^{ op}\mu_\mathbf{2}$$

Which simplifies to:

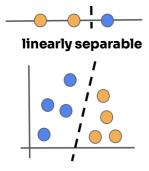
$$2\mathbf{x}^{ op}(\mu_\mathbf{2}-\mu_\mathbf{1})=\mu_\mathbf{2}^{ op}\mu_\mathbf{2}-\mu_\mathbf{1}^{ op}\mu_\mathbf{1}$$

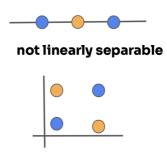
Thus, it's a linear classifier!

LINEAR SEPARABILITY

If there exists a linear classifier that perfectly separates the classes of some dataset, the data are called **linearly separable**.



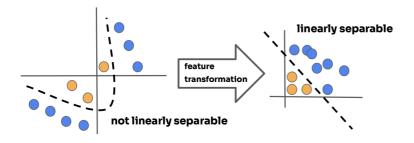




FEATURE TRANSFORMATIONS

Note that linear classifiers can represent **non-linear** decision boundaries in the original input space if we use derived features like higher order interactions, polynomial features, etc.





Here we used absolute values to find suitable derived features.