

Non-Bayesian Classifiers

Part I: k -Nearest Neighbor Classifier and Distance Functions

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Non-Bayesian Classifiers

- ▶ We have been using Bayesian classifiers that make decisions according to the posterior probabilities.
- ▶ We have discussed parametric and non-parametric methods for learning classifiers by estimating the probabilities using training data.
- ▶ We will study new techniques that use training data to learn the classifiers directly without estimating any probabilistic structure.
- ▶ In particular, we will study the k -nearest neighbor classifier, linear discriminant functions and support vector machines, neural networks, and decision trees.



The Nearest Neighbor Classifier

- ▶ Given the training data $\mathcal{D} = \{\mathbf{x}_1, \dots, \mathbf{x}_n\}$ as a set of n labeled examples, the *nearest neighbor classifier* assigns a test point \mathbf{x} the label associated with its closest neighbor in \mathcal{D} .
- ▶ Closeness is defined using a distance function.
- ▶ Given the distance function, the nearest neighbor classifier partitions the feature space into cells consisting of all points closer to a given training point than to any other training points.



The Nearest Neighbor Classifier

- All points in such a cell are labeled by the class of the training point, forming a *Voronoi tessellation* of the feature space.

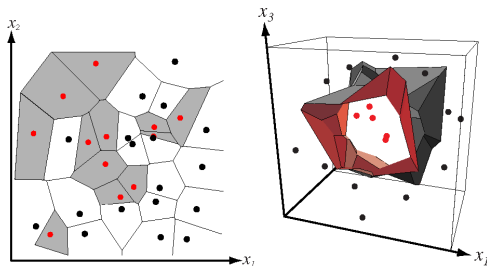


Figure 1: In two dimensions, the nearest neighbor algorithm leads to a partitioning of the input space into Voronoi cells, each labeled by the class of the training point it contains. In three dimensions, the cells are three-dimensional, and the decision boundary resembles the surface of a crystal.

The k -Nearest Neighbor Classifier

- ▶ The *k -nearest neighbor classifier* classifies x by assigning it the label most frequently represented among the k nearest samples.
- ▶ In other words, a decision is made by examining the labels on the k -nearest neighbors and taking a vote.

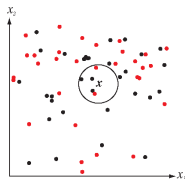


Figure 2: The k -nearest neighbor query forms a spherical region around the test point x until it encloses k training samples, and it labels the test point by a majority vote of these samples. In the case for $k = 5$, the test point will be labeled as black.



The k -Nearest Neighbor Classifier

- ▶ The computational complexity of the nearest neighbor algorithm — both in space (storage) and time (search) — has received a great deal of analysis.
- ▶ In the most straightforward approach, we inspect each stored training point one by one, calculate its distance to \mathbf{x} , and keep a list of the k closest ones.
- ▶ There are some parallel implementations and algorithmic techniques for reducing the computational load in nearest neighbor searches.



The k -Nearest Neighbor Classifier

- ▶ Examples of algorithmic techniques include
 - ▶ computing partial distances using a subset of dimensions, and eliminating the points with partial distances greater than the full distance of the current closest points,
 - ▶ using search trees that are hierarchically structured so that only a subset of the training points are considered during search,
 - ▶ editing the training set by eliminating the points that are surrounded by other training points with the same class label.



Distance Functions

- ▶ The nearest neighbor classifier relies on a *metric* or a *distance function* between points.
- ▶ For all points x , y and z , a metric $D(\cdot, \cdot)$ must satisfy the following properties:
 - ▶ Nonnegativity: $D(x, y) \geq 0$.
 - ▶ Reflexivity: $D(x, y) = 0$ if and only if $x = y$.
 - ▶ Symmetry: $D(x, y) = D(y, x)$.
 - ▶ Triangle inequality: $D(x, y) + D(y, z) \geq D(x, z)$.
- ▶ If the second property is not satisfied, $D(\cdot, \cdot)$ is called a pseudometric.



Distance Functions

- ▶ A general class of metrics for d -dimensional patterns is the *Minkowski metric*

$$L_p(\mathbf{x}, \mathbf{y}) = \left(\sum_{i=1}^d |\mathbf{x}_i - \mathbf{y}_i|^p \right)^{1/p}$$

also referred to as the L_p *norm*.

- ▶ The *Euclidean distance* is the L_2 norm

$$L_2(\mathbf{x}, \mathbf{y}) = \left(\sum_{i=1}^d |\mathbf{x}_i - \mathbf{y}_i|^2 \right)^{1/2}.$$

- ▶ The *Manhattan* or *city block distance* is the L_1 norm

$$L_1(\mathbf{x}, \mathbf{y}) = \sum_{i=1}^d |\mathbf{x}_i - \mathbf{y}_i|.$$



Distance Functions

- The L_∞ norm is the maximum of the distances along individual coordinate axes

$$L_\infty(\mathbf{x}, \mathbf{y}) = \max_{i=1}^d |\mathbf{x}_i - \mathbf{y}_i|.$$

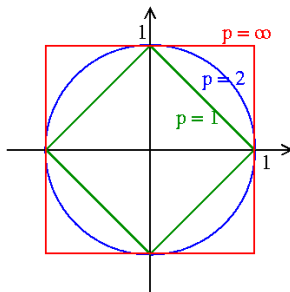


Figure 3: Each colored shape consists of points at a distance 1.0 from the origin, measured using different values of p in the Minkowski L_p metric.



Feature Normalization

- ▶ We should be careful about scaling of the coordinate axes when we compute these metrics.
- ▶ When there is great difference in the range of the data along different axes in a multidimensional space, these metrics implicitly assign more weighting to features with large ranges than those with small ranges.
- ▶ *Feature normalization* can be used to approximately equalize ranges of the features and make them have approximately the same effect in the distance computation.
- ▶ The following methods can be used to independently normalize each feature.



Feature Normalization

- ▶ *Linear scaling to unit range:*

Given a lower bound l and an upper bound u for a feature $x \in \mathbb{R}$,

$$\tilde{x} = \frac{x - l}{u - l}$$

results in \tilde{x} being in the $[0, 1]$ range.

- ▶ *Linear scaling to unit variance:*

A feature $x \in \mathbb{R}$ can be transformed to a random variable with zero mean and unit variance as

$$\tilde{x} = \frac{x - \mu}{\sigma}$$

where μ and σ are the sample mean and the sample standard deviation of that feature, respectively.



Feature Normalization

► *Normalization using the cumulative distribution function:*

Given a random variable $x \in \mathbb{R}$ with cumulative distribution function $F_x(x)$, the random variable \tilde{x} resulting from the transformation $\tilde{x} = F_x(x)$ will be uniformly distributed in $[0, 1]$.

► *Rank normalization:*

Given the sample for a feature as $x_1, \dots, x_n \in \mathbb{R}$, first we find the order statistics $x^{(1)}, \dots, x^{(n)}$ and then replace each pattern's feature value by its corresponding normalized rank as

$$\tilde{x}_i = \frac{\text{rank}(x_i) - 1}{n - 1}$$

where x_i is the feature value for the i 'th pattern. This procedure uniformly maps all feature values to the $[0, 1]$ range.

