k- Nearest Neighbor

$$S = \{(\bar{x}_1, y_1), \ldots, (\bar{x}_n, y_n)\}.$$

$(\bar{x}_i, y_i) \in \mathcal{X} \times \mathcal{Y}$

$\mathcal{X}$ – feature space (all possible values the features can take).

e.g., $\mathcal{X} = \{0, \ldots 255\}^{784}$ for MNIST, etc...

QN:- what is $\mathcal{X}$ for the "TENNIS"?

$\mathcal{Y}$ - label space (possible values of labels)

$d: \mathcal{X} \times \mathcal{X} \longrightarrow [0, \infty)$, a notion of distance between features.

i.e., for $\bar{x}_i, \bar{x}_j \in \mathcal{X}$, $d(\bar{x}_i, \bar{x}_j)$ = distance between $\bar{x}_i, \bar{x}_j$.

k-NN algorithm

- Given $k \in \mathbb{N}$, 'S' (trng set), 'd' (distance).
- For a new test feature $\bar{x}_{n+1} \in \mathcal{X}$,

- find the k closest examples to $\bar{X}_{n+1}$ in 'S'.
- out put the **majority** of the labels of these k examples.

1-NN :- find $j^* = \arg\min_j d(\bar{X}_{n+1}, \bar{X}_j)$ $\left\{ X_{j^*} \text{ - closest to } \bar{X}_{n+1} \right\}$

output y_{j^*}

3-NN :- find '3' closest points to $\bar{X}_{n+1}$ in 'S'.

say $\bar{X}_{j_1}, \bar{X}_{j_2}, \bar{X}_{j_3}$ → closest

then consider $y_{j_1}, y_{j_2}, y_{j_3}$ → o/p majority.

Advantages :-
1. Good performance.
2. No training time
3. Simplest (?)

Disadvantages :-
1. High run-time for each example
2. Storage.
3. choose right 'd'.
4. Normalization (related to '3').

EXAMPLE :- Let $\mathcal{X} = \mathbb{R}^2$ (2-dimensional features).
$\mathcal{Y} = \{-1, 1\}$ (binary labels)

d :- squared Euclidean distance between features

Consider data :-

Each $(\bar{X}_i, y_i) = ((x_i^1, x_i^2), y_i)$ is generated independently as follows:-

$x_i^1 \longrightarrow$ uniform $(-10^4, 10^4)$

$x_i^2 \longrightarrow$ uniform $(-1, 1)$.

Label $y_i = \text{sign}(x_i^2) = \begin{cases} 1 \text{ if } x_i^2 \geq 0, \\ 0 \text{ otherwise.} \end{cases}$

sign of second attribute is the label $\longrightarrow$ perfect classification.

Suppose we get about 40 examples.

* distance to closest point will be dominated by closeness in first coordinate, which is just noise wrt labels.

--- a decision tree would be much better