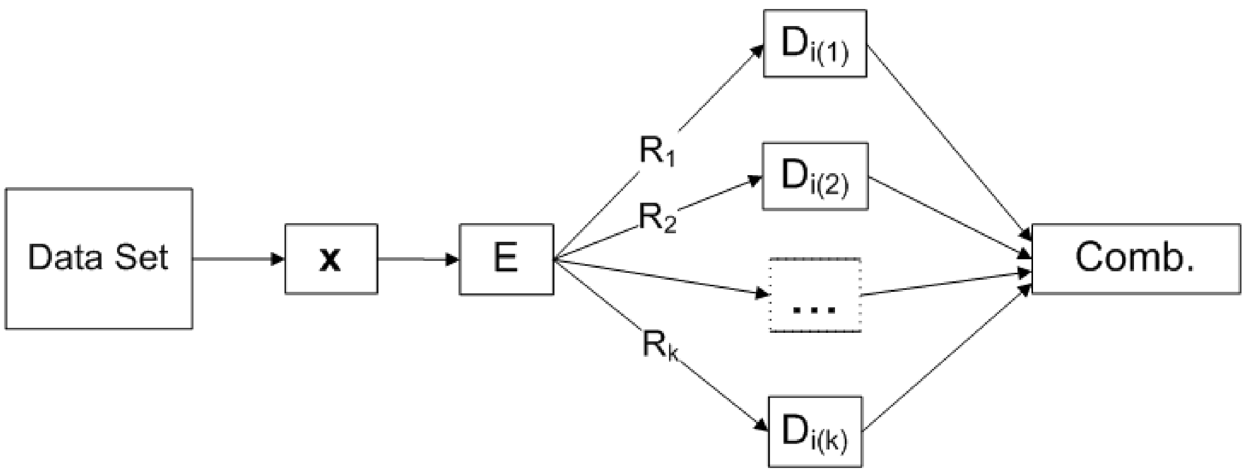
<u>Selection Regions</u>

Assume we have a set of classifiers
    $D = \{D_1, D_2, ..., D_L\}$
Let $\mathbf{R}^n$ be divided into K *selection regions* (also called *regions of competence*) called $\{R_1, R_2, ..., R_k\}$
Let E map each input **x** to its corresponding Region R_j
    E : $\mathbf{x} \rightarrow R_j$, where $R_j$is the region for which $D_{i(j)}$is applied
Feed **x** into $D_{i(j)}$ iff E(**x**) = R_j



Note: Combination for this definition is trivial (it forwards the one classification that it receives),
but may be used in extensions that require fusion.

<u>Competence Estimation</u>
Decision-independent vs. decision-dependent: whether or not label chosen by classifiers are known

<u>Direct k-nn:</u>
Decision independent: calculate accuracy of classifiers on k nearest neighbors of input **x.**
Decision dependent: determine k nearest neighbors of **x** given the same label as **x**. Competence is the accuracy of the classifier in these nearest neighbors.

<u>Distance-based k-nn:</u> uses confidence measure output by the classifier
Decision independent: weighted average of classifier outputs for each correct label in the set of neighbors

$$C(D_i|\mathbf{x}) = \frac{\sum_{\mathbf{z}_j \in N_\mathbf{x}} P_i(l(\mathbf{z}_j)|\mathbf{z}_j)(1/d(\mathbf{x}, \mathbf{z}_j))}{\sum_{\mathbf{z}_j \in N_\mathbf{x}} (1/d(\mathbf{x}, \mathbf{z}_j))}$$

Decision dependent: weighted average of classifier outputs for neighbors whose true class label is the same as that chosen for the input

$$C(D_i|\mathbf{x}) = \frac{\sum_{\mathbf{z}_j} P_i(s_i|\mathbf{z}_j) 1/d(\mathbf{x}, \mathbf{z}_j)}{\sum_{\mathbf{z}_j} 1/d(\mathbf{x}, \mathbf{z}_j)}$$

<u>Potential functions:</u>
Points contribute positively to a classifier's potential if correctly recognized and negatively otherwise. This potential field is weighted by the distance from the point to the input element.

$$C(D_i|\mathbf{x}) = \sum_{\mathbf{z}_j \in \mathbf{Z}} \phi(\mathbf{x}, \mathbf{z}_j) \quad , \quad \phi(\mathbf{x}, \mathbf{z}_j) = \frac{g_{ij}}{1 + \alpha_{ij}(d(\mathbf{x}, \mathbf{z}_j))^2}$$

Pre-estimation of Competence Regions

K = number of regions of competence
L = number of classifiers

Decide a classifier from D = $\{D_1, \ldots D_L\}$ for each region R_j, j = 1,...K.
For input **x**, find its region of competence and choose most compete classifier for that region ($D_{i(j)}$)

Selection or Fusion?

Run paired t-test to determine statistical significance of classifier $D_{i(j)}$.
If difference in accuracies between best classifier and all other classifiers is significant, use classifier selection.
Otherwise, use fusion.

P_D = Accuracy of classifier D_i in region R_j
t = Statistic with parameters α (level of significance), degrees of freedom (d.o.f.)
N = Sample size

$$\left[\hat{P}_D - t_{(0.05, N-1)} \sqrt{\frac{\hat{P}_D(1 - \hat{P}_D)}{N}}, \hat{P}_D + t_{(0.05, N-1)} \sqrt{\frac{\hat{P}_D(1 - \hat{P}_D)}{N}} \right]$$

= 95% (1-.05) Confidence Interval,

$$\Delta = \frac{7.6832\, P_1 - 3.8416 + 3.92\sqrt{N P_1 (1 - P_1)}}{N + 3.8416}$$

= threshold for statistical significance (for N>=30, α = 0.05)