A. Estimation Function $(f(\hat{Y}_n))$ (Cost Function)

$$f(\hat{Y}_n) = \left(\sum_{i=0}^{n} w_i \, f(K)_i \right)^{-1} \cdot \left(\sum_{i=0}^{n} w_i \cdot f(k)_i \cdot x_i \right).$$

$$f(\hat{Y}_{n=0}) = \left(w_i \cdot f(k)_i \right)^{-1} \cdot w_i \cdot f(k)_i \cdot x_i = \hat{X}_{in}$$

$$\hat{X}_{in} = \begin{cases} \hat{x}_{in} & \text{if } g(D_i) = 1 \\ 0 & \text{if } g(D_i) = 0 \end{cases}$$

B. Loss Function $(\sigma(f(\hat{Y}_n))) \rightarrow \sigma(\hat{Y}_n)$.

$$\sigma(\hat{Y}_n) = \sum_{i=0}^{n} (Y - \hat{Y})^2$$; Mean Squared Error

$$\sigma(\hat{Y}_n) = - \sum_{i=0}^{n} Y \cdot \log(\hat{Y}_n)$$; Cross Entropy Error

C. Gradient Descent Function (Stochastic)

$$\frac{d}{dw_i} = 2 \cdot (Y - \hat{Y}) \cdot (-f(k)_i) \cdot \eta$$

alternative:

$$\frac{d_a}{d_a w_i} = 2 \cdot (Y - \hat{Y}) \cdot (-x_i / f(k)_i) \cdot \eta$$

D. Distance Function (Kernel Function $(f(k))$.)

$$f(k)_i = 1 / \text{Euclidean\_Distance}.$$

alternative:

$$f(k)_i = 1 - \text{Manhattan Distance}.$$

E. Activation Condition & Activation Function.

$$g(D_i) = \begin{cases} 0 & \text{if } \ldots \\ 1 & \text{if } \ldots \end{cases}$$

$$A(\hat{Y}_i) = (\text{Softmax}) \,||\, (\text{Sigmoid}) \,||\, (\text{Standard-normalization}) \,||\, (\text{Nothing}).$$