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(1)

recall that

$$\begin{aligned}
 \bar{p}_n(x) &= \mathbf{E}(p_n(x)) \\
 &= \frac{1}{n} \sum_{i=1}^n \mathbf{E}\left[\frac{1}{V_n} \varphi\left(\frac{x - x_i}{h_n}\right)\right] \\
 &= \int \frac{1}{V_n} \varphi\left(\frac{x - v}{h_n}\right) p(v) dv \\
 &= \int \delta_n(x - v) p(v) dv
 \end{aligned}$$

what we need to verify is $\lim_{n \rightarrow \infty} \delta_n(x - v) = \delta(x - v)$ where $\delta(x - v)$ refers to Dirac function. Dirac function is defined as below

$$\delta(x) = \begin{cases} \infty, & x = 0 \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

$$\int_R \delta(x) dx = 1 \quad (2)$$

Thus

$$\begin{aligned}
 \delta_n(x - v) &= \frac{1}{V_n} \varphi\left(\frac{x - v}{h_n}\right) \\
 &= \frac{1}{\prod_{i=1}^d h_{ni}} \prod_{i=1}^d \frac{x_i - v_i}{h_{ni}} \varphi\left(\frac{x - v}{h_n}\right) \prod_{i=1}^d \frac{h_{ni}}{x_i - v_i} \\
 &= \prod_{i=1}^d \frac{1}{x_i - v_i} \varphi(u) \prod_{j=1}^d u_j \\
 &\quad \because \lim_{n \rightarrow \infty} V_n = 0 \\
 &\quad \therefore \lim_{n \rightarrow \infty} h_{ni} = 0, \quad i = 1, 2, \dots, d \\
 &\quad \therefore u_i = \lim_{n \rightarrow \infty} \frac{x - v}{h_{ni}} = \begin{cases} 0, & x = v \\ \infty, & x \neq v \end{cases} \\
 &\quad \therefore \lim_{\|u\| \rightarrow \infty} \varphi(u) \prod_{i=1}^d u_i = 0, \quad x \neq v
 \end{aligned}$$

Since

$$\int_R \delta_n(x - v) dx = \int_R \frac{1}{V_n} \varphi\left(\frac{x - v}{h_n}\right) dx = \int_R \varphi(u) du = 1$$

We can conclude that equations (19)~(22) are sufficient to the convergence of equation (17)

(2)

Recall that

$$\begin{aligned}
\sigma_n^2(x) &= \sum_{i=1}^n \mathbf{E} \left[\left(\frac{1}{nV_n} \varphi \left(\frac{x - x_i}{h_n} \right) - \frac{1}{n} \bar{p}_n(x) \right)^2 \right] \\
&= n \mathbf{E} \left[\frac{1}{n^2 V_n^2} \varphi^2 \left(\frac{x - x_i}{h_n} \right) \right] p(v) dv - \frac{1}{n} \bar{p}_n^2(x) \\
&= \frac{1}{nV_n} \int \frac{1}{V_n} \varphi^2 \left(\frac{x - v}{h_n} \right) p(v) dv - \frac{1}{n} \bar{p}_n^2(x) \\
&\quad \because \sup_u \varphi(u) < \infty \\
\sigma_n^2(x) &\leq \frac{\sup_u \varphi(u) \bar{p}_n(x)}{nV_n} \\
&\because \lim_{n \rightarrow \infty} \bar{p}_n(x) = p(x), \quad \lim_{n \rightarrow \infty} nV_n = \infty \\
&\therefore \lim_{n \rightarrow \infty} \sigma_n^2(x) = 0
\end{aligned}$$

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(a)

$$g_i(x) = \sum_{j=1}^n (a_{ji}) \left(e^{\frac{-(x-w_j)^t(x-w_j)}{2\sigma^2}} \right) = nP(w_i)P(x|w_i)$$

(b)

$$Risk(\alpha_i|x) = \sum_{j=1}^c \lambda_{ji} P(w_j|x) = \sum_{j=1}^c \lambda_{ji} \frac{P(x|w_j)P(w_j)}{P(x)}$$

Since priori probability of each class is identical, we can define new $g_i(\hat{x})$

$$g_i(\hat{x}) = - \sum_{j=1}^c \lambda_{ji} P(x|w_j)$$

(c)

Without the condition that the priori probability of each class is identical, $g_i(\hat{x})$ can be written as

$$g_i(\hat{x}) = - \sum_{j=1}^c \lambda_{ji} g_j(x)$$

In classification algorithm, after we update g_i totally, we calculate $g_i(\hat{x})$ with the equation above, and we select one of the class k that satisfies $k = \arg \max_i g_i(x)$

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(a)

$$\begin{aligned}
P(\text{error}) &= P(w_1)P(n_{w_1} < n_{w_2}) + P(w_2)P(n_{w_2} < n_{w_1}) \\
&= P(n_{w_1} < n_{w_2}) \\
&= \sum_{j=0}^{(k-1)/2} \binom{n}{j} \left(\frac{1}{2}\right)^j \left(\frac{1}{2}\right)^{n-j} \\
&= \frac{1}{2^n} \sum_{j=0}^{(k-1)/2} \binom{n}{j}
\end{aligned}$$

(b)

$$\begin{aligned}
&\because \binom{n}{j} > 0, \quad j = 0, 1, 2, \dots, n \\
&\therefore \sum_{j=0}^{(k-1)/2} \binom{n}{j} > \sum_{j=0}^0 \binom{n}{j}, \quad k > 1
\end{aligned}$$

The right hand side represents the nearest neighbor rule. Therefore, it has lower error rate.

(c)

$$P_n(e) < \frac{1}{2^n} \sum_{j=0}^{c\sqrt{n}} \binom{n}{j}$$

Since

$$(1+1)^n = \sum_{j=0}^n \binom{n}{j}$$

can be divided into $m = \lfloor \frac{n}{c\sqrt{n}} \rfloor$ pieces in order. (Elements in interval $[\lfloor \frac{n}{c\sqrt{n}} \rfloor \times c\sqrt{n}, n]$ are merged into the last piece)

Note that $\binom{n}{j}$ is a symmetric convex function. We can conclude that

$$\sum_{j \in \text{Piece}_1} \binom{n}{j} = \min \sum_{j \in \text{Piece}_k} \binom{n}{j}, \quad k = 1, 2, \dots, m$$

$$\therefore \sum_{j=0}^{c\sqrt{n}} \binom{n}{j} < \frac{2^n}{m}$$

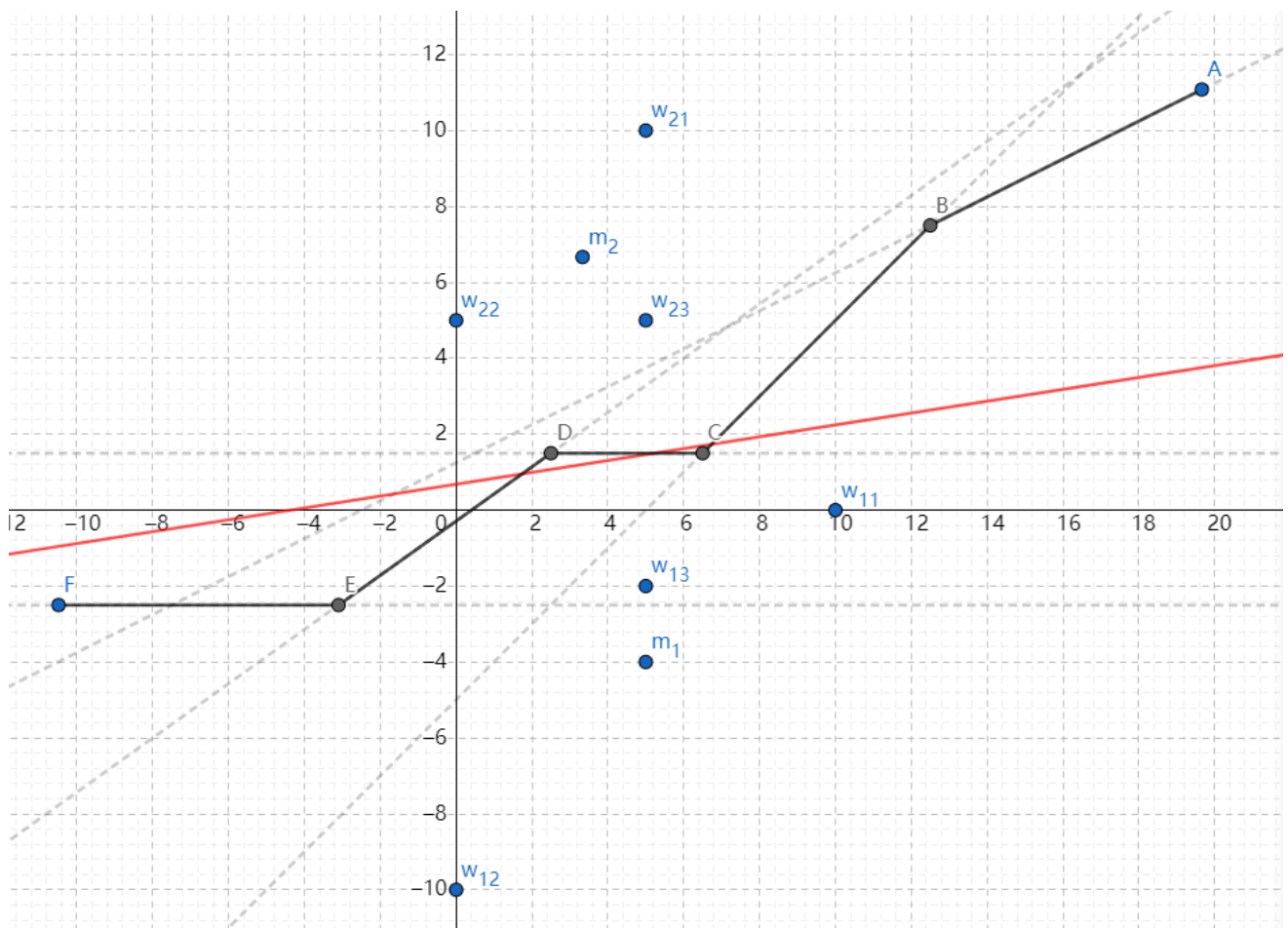
$$\frac{1}{2^n} \sum_{j=0}^{c\sqrt{n}} \binom{n}{j} < \frac{1}{m} = O\left(\frac{1}{\sqrt{n}}\right)$$

$$\therefore \lim_{n \rightarrow \infty} P_n(e) = 0$$

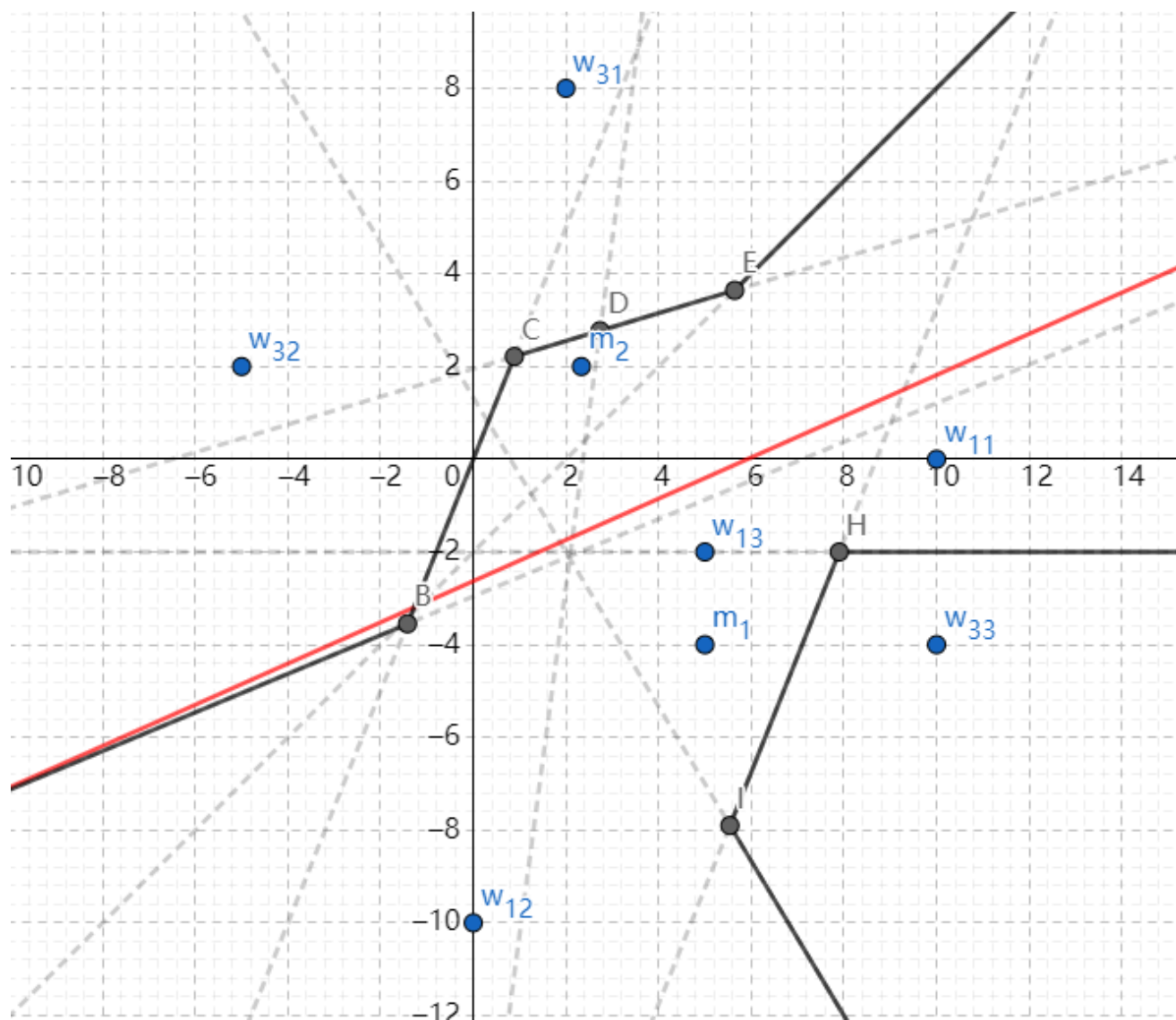
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$$m_1 = (5, -4), \quad m_2 = \left(\frac{10}{3}, \frac{20}{3}\right), \quad m_3 = \left(\frac{7}{3}, 2\right)$$

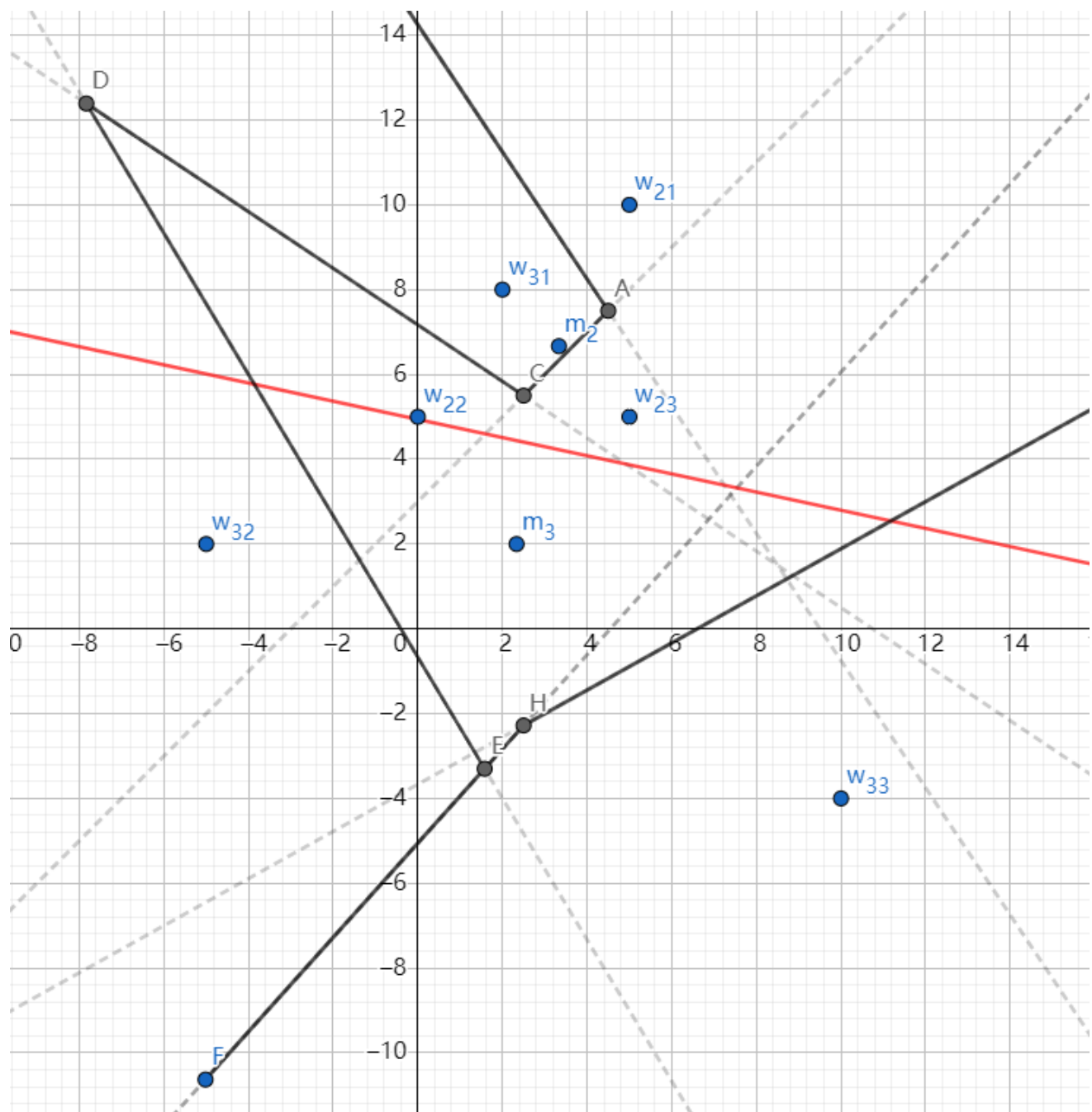
(a)



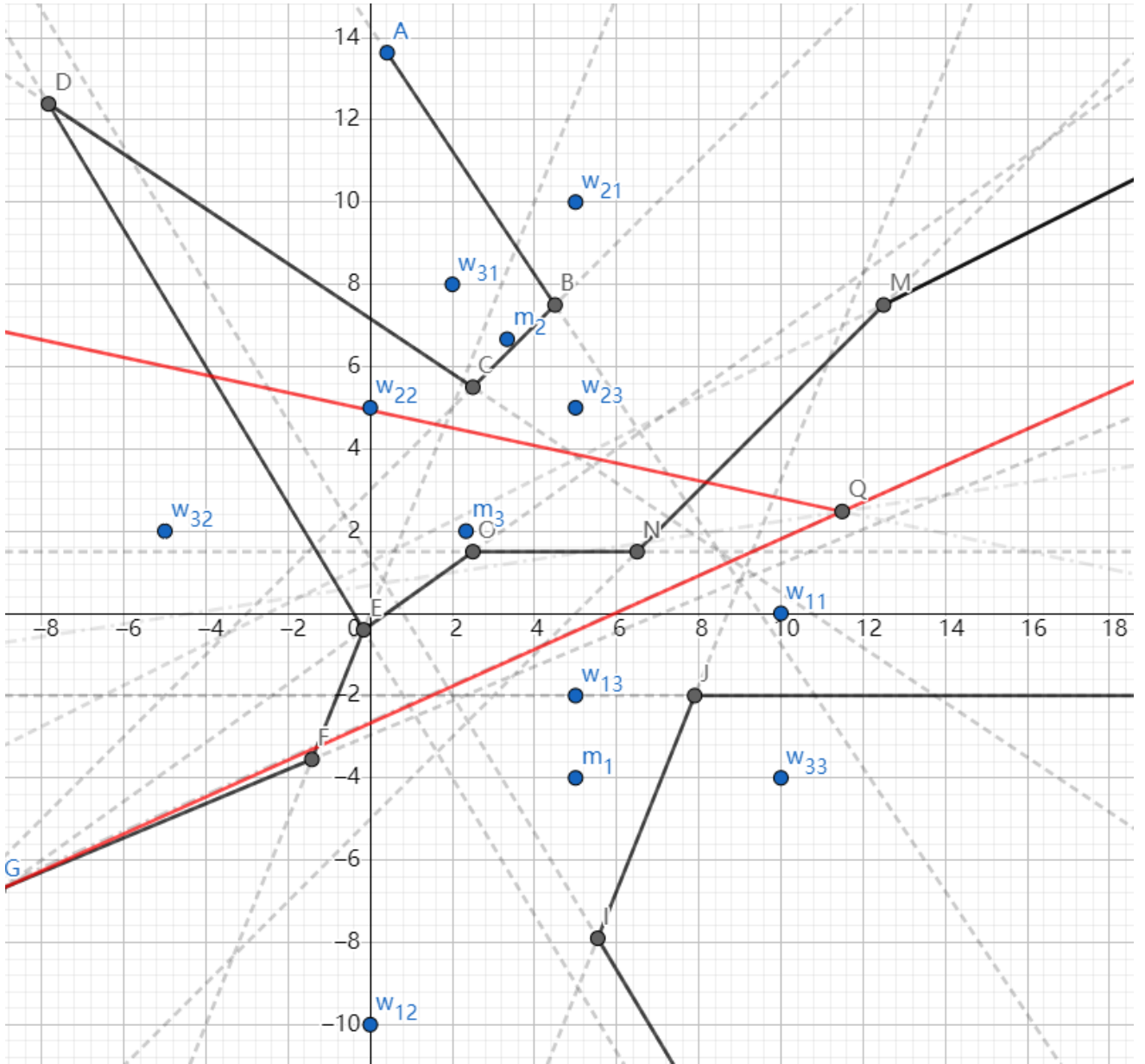
(b)



(c)



(d)



17

Since the probability distribution of each class is identical, we have $P(x|w_i) = P(x|w)$, $i = 1, 2, \dots, c$.

$$P(x) = \sum_{i=1}^c P(x|w_i)P(w_i) = \frac{1}{c} \sum_{i=1}^c P(x|w_i) = P(x|w)$$

$$\therefore P(w_i|x) = \frac{P(x|w_i)P(w_i)}{P(x)} = P(w_i) = \frac{1}{c}$$

$$\begin{aligned} P &= \lim_{n \rightarrow \infty} P_n(e) = \lim_{n \rightarrow \infty} \int P_n(e|x)p(x)dx \\ &= \int [1 - \sum_{i=1}^c P^2(w_i|x)]p(x)dx \\ &= 1 - \frac{1}{c} \end{aligned}$$

$$P^* = \int P^*(error|x)p(x)dx = \int (1 - P(w_j|x))p(x)dx = 1 - \frac{1}{c}$$

$$\therefore P = P^*(2 - \frac{c}{c-1}P^*) = 1 - \frac{1}{c}$$