Linear Discriminant Analysis (LDA) with 1 Predictor

- $f_k(x)$ is normal with following density in one dimension:

$$f_k(x) = \frac{1}{\sqrt{2\pi\sigma_k}} \exp\left(-\frac{1}{2\sigma_k^2}(x - \mu_k)^2\right)$$

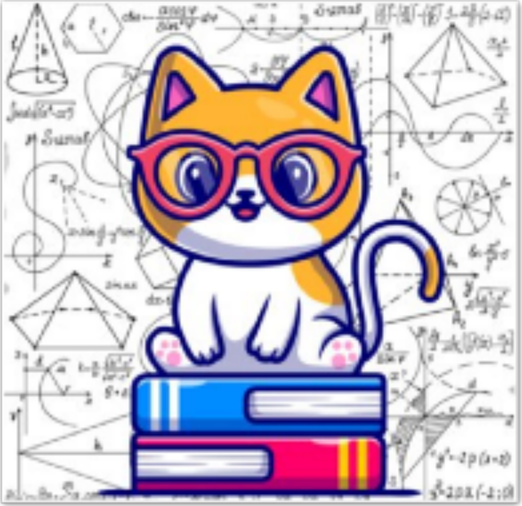
where μ_k and σ_k^2 are mean and variance of kth class and assume variances are equal

- Plug this into Bayes theorem

$$P_k(x) = \frac{\pi_k f_k(x)}{\sum_{l=1}^{K} \pi_l f_l(x)} = \frac{\pi_k \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{1}{2\sigma^2}(x-\mu_k)^2\right)}{\sum_{l=1}^{K} \pi_l \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{1}{2\sigma^2}(x-\mu_l)^2\right)}$$

- The Bayes classifier assigns an observation to where the above is the largest which is equivalent to the largest: $\delta_k(x) = x\frac{\mu_k}{\sigma^2} + \frac{\mu_k^2}{2\sigma^2} + \log(\pi_k)$

- This is **the linear discriminant classifier**



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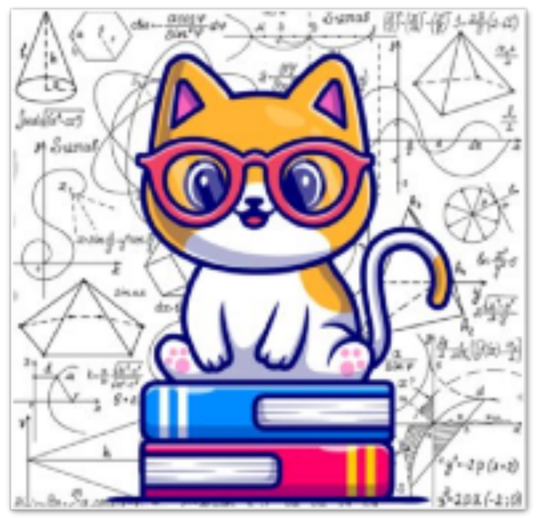

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