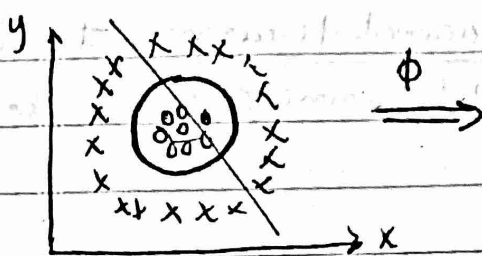


## Discussion 9

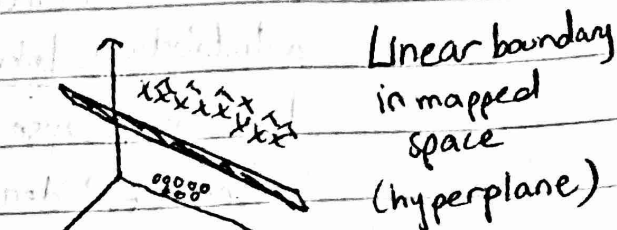
### Kernel clustering

1. Can the polynomial kernel  $K(x_1, x_2) = (x_1^T x_2 + b)^2$  cluster concentric data?

— Regular k-means  
— Goal (circle)



$\phi$



$$K(x, y) = (x^T y + b)^2 \quad \text{Let } b = 0 \text{ (we already did } b = 1 \text{ before!)} \\ = (x^T y)^2 = \underbrace{(x_1 y_1 + x_2 y_2)^2}_{2D}$$

$$= x_1^2 y_1^2 + x_2^2 y_2^2 + 2x_1 y_1 x_2 y_2$$

$$= \begin{bmatrix} x_1^2 & x_2^2 & 2x_1 x_2 \end{bmatrix} \begin{bmatrix} y_1^2 \\ y_2^2 \\ 2y_1 y_2 \end{bmatrix} = \phi(x)^T \phi(y)$$

$$\text{So, } \phi(x) = \begin{pmatrix} x_1^2 \\ x_2^2 \\ 2x_1 x_2 \end{pmatrix} \rightarrow \text{Adds 3rd dimension (what we want)}$$

As we saw in the HW, this will be a quadratic decision boundary in the input space (weighted combination of order 1 & 2 terms of original feature vector  $x$ ).

(Keep in mind that  $(x^T y + b)^2$  will create quadratic boundary  $\forall b$ )

$$\text{Decision boundary: } \|x - \mu_1\|_2^2 = \|x - \mu_2\|_2^2 \Rightarrow 2(\mu_2 - \mu_1)^T x + (\mu_1^T \mu_1 - \mu_2^T \mu_2) = 0$$

$$\text{Form: } w^T x + b = 0 \text{ (Linear)}$$

$$\text{Decision boundary: } \|\phi(x) - \mu_1\|_2^2 = \|\phi(x) - \mu_2\|_2^2 \text{ (Mapped space)}$$

$$\text{Form: } w^T \phi(x) + b = 0$$



2.) Alternative distance metric for assignment step in k-means

$$d_{\text{Mahalanobis}} = \sqrt{(x_i - \mu_j)^T \Sigma_j^{-1} (x_i - \mu_j)}$$

Write out k-means w/ this metric.

(Remember Mahalanobis distance represents distance of a point to a distribution, taking into account its variance. It fits in nicely w/ k-means because we want to minimize it, just like we did with Squared Euclidean)

1. Initialize:  $\mu, \Sigma$   $\forall$  classes ( $\Sigma = I$   $\forall$  classes usually)

2. Assignment:

for  $x_i \in i = \{1 \dots n\}$ :

Assign each  $x_i$  to closest centroid according to Mahalanobis distance, i.e.

$$\underset{c_j \in C}{\operatorname{argmin}} \sqrt{(x_i - \mu_j)^T \Sigma_j^{-1} (x_i - \mu_j)} = \text{label}_{x_i}$$

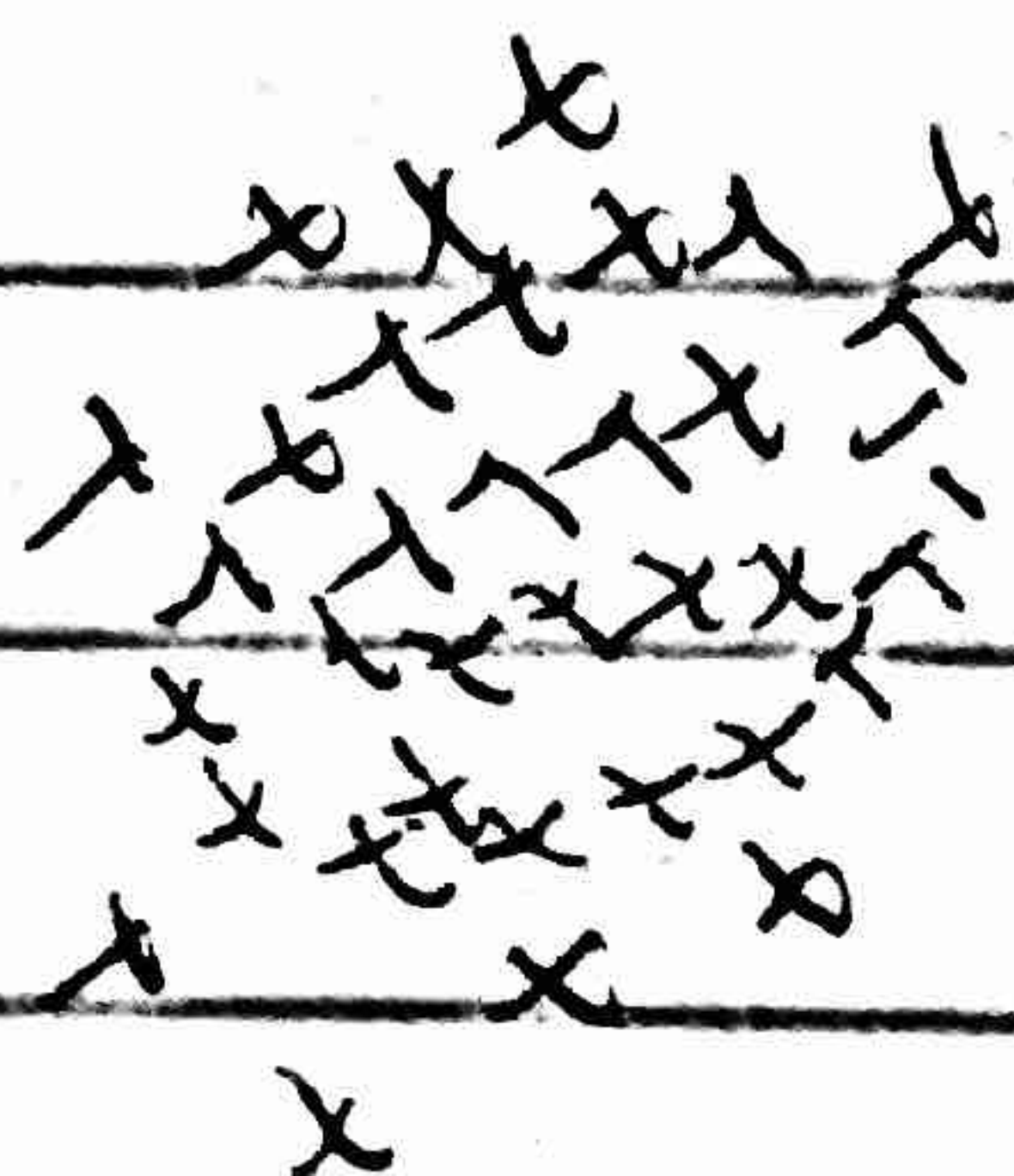
3. Update:

$$\mu_j = \frac{1}{n_j} \sum_{i \in c_j} x_i$$

$$\Sigma_j = \frac{1}{n_j} \sum_{i \in c_j} (x_i - \mu_j)(x_i - \mu_j)^T$$

4. Repeat until convergence

This distance metric might be useful because it takes into account the variance of a cluster, i.e.



vs.



(k-means assumes covariance = identity)