

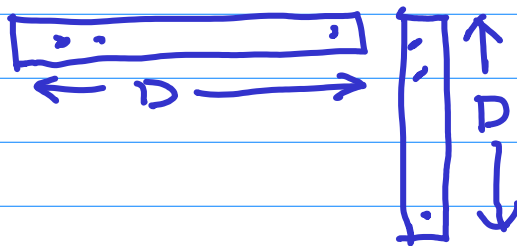
Squared Mahalanobis distance

$$d_M^2 \triangleq (\underline{x}_1 - \underline{x}_2)^T \Sigma^{-1} (\underline{x}_1 - \underline{x}_2)$$

$$d_E^2 \triangleq (\underline{x}_1 - \underline{x}_2)^T (\underline{x}_1 - \underline{x}_2)$$

↳ Euclidean

$$(x_{1_1} - x_{2_1})^2 + \dots + (x_{1_D} - x_{2_D})^2 + \dots + (x_{1_D} - x_{2_D})^2$$



Metric property

- 1. $d(\underline{a}, \underline{b}) \geq 0$
- 2. $d(\underline{a}, \underline{b}) = d(\underline{b}, \underline{a})$
- 3. Triangle inequality.

Example

temp	→	100°C
pressure	→	0.01 mbars.
.		

Euclidean distance is swamped by a term whose variation is large.

$$x = \frac{x - \mu}{\sigma}, \text{ for each feature/ dimension}$$

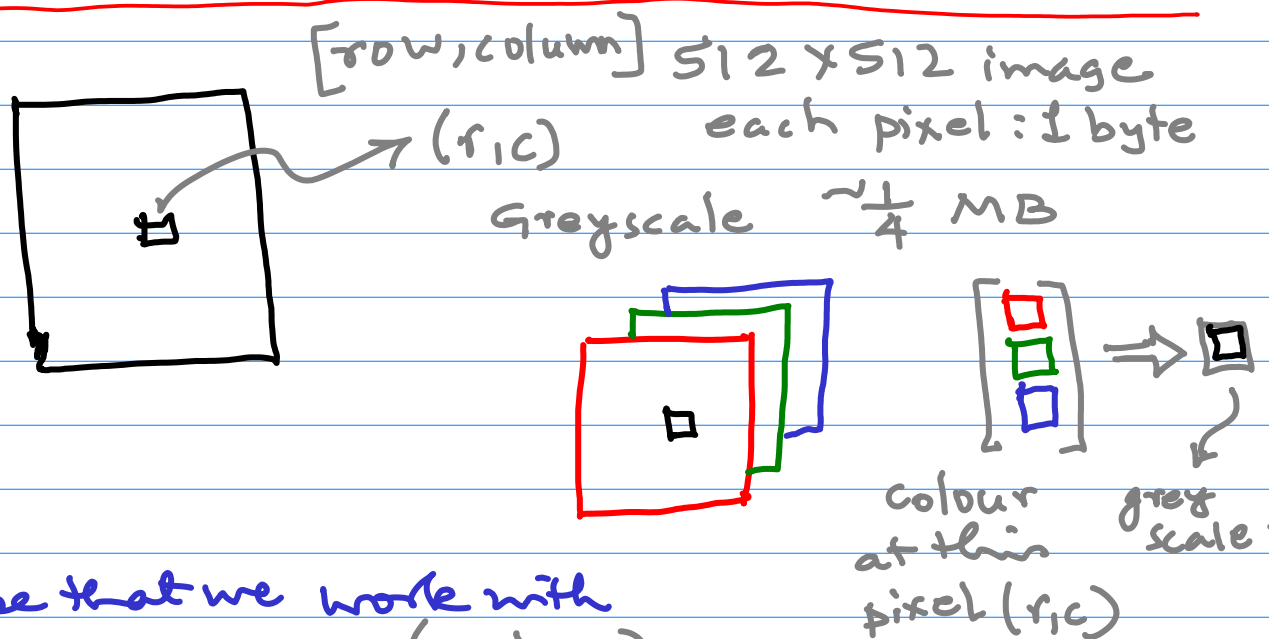
$$\begin{bmatrix} \vdots \\ x \\ \vdots \end{bmatrix}$$

Euclidean distance cannot account for 2 or more features/dimensions being correlated.

$$[(x_{11} - x_{21}) \dots (x_{1j} - x_{2j}) \dots (x_{1D} - x_{2D})] \sum^{-1} \begin{bmatrix} x_{11} \\ x_{21} \\ \vdots \end{bmatrix}$$

off-diagonal covariance terms

Mahalanobis distance \rightarrow Distance between distributions



Suppose that we work with grayscale images (scalars)

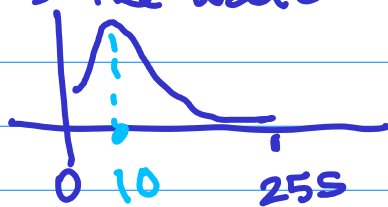
$$\text{Model } x = \sum_{j=1}^K \pi_j \mathcal{N}(x | \mu_j, \sigma^2)$$

colour images $x_{5 \times 1}$, $\mu_{5 \times 1}$, $\Sigma_{5 \times 5}$

Example: movie camera staring at the sea.

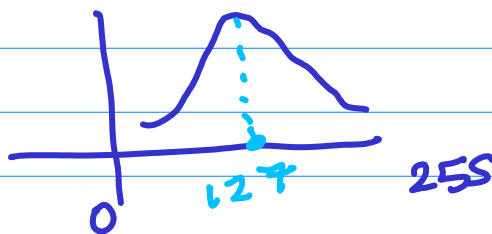
Consider the (r, c) pixel.

Realistic: (1) it sees the water (dark)

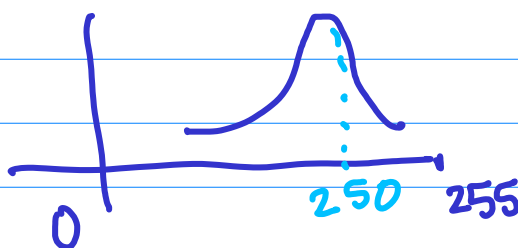


low grey
value,
close to 0

(2) a wave breaks, foam (higher grey value)



(3) Sunlight could be reflected off the water (very bright)



Mixture of $K = 3$ Gaussians.