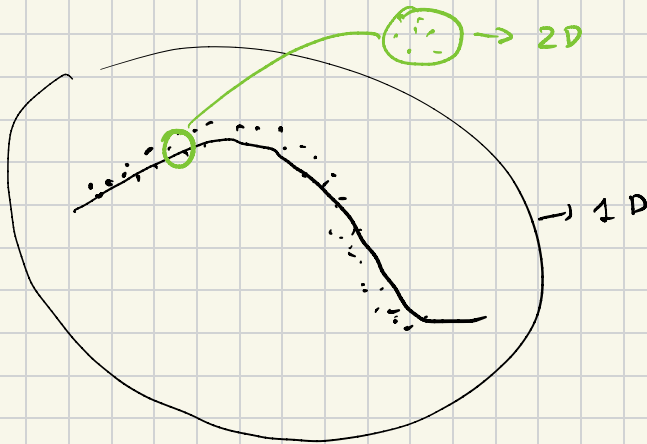
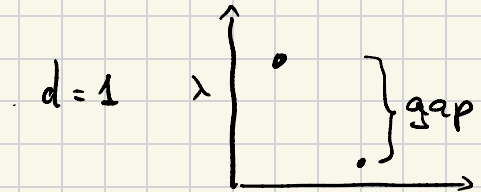


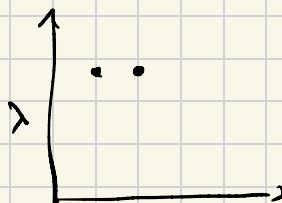
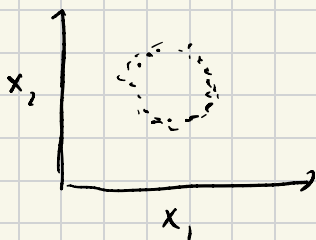
# Intrinsic Dim.

- a) Minimum Number of variables needed for represent the data with minimum information loss
- b) The dimension of the manifold in which our data lies.



PCA is a method that performs  $\text{Id} = d$  estimation

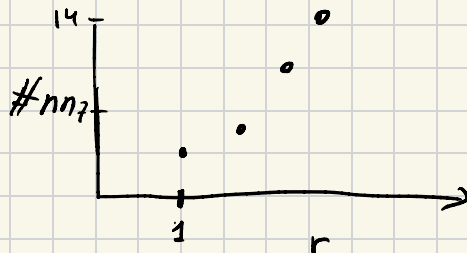
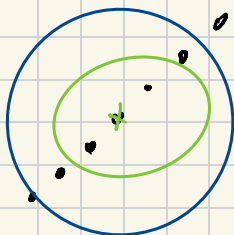
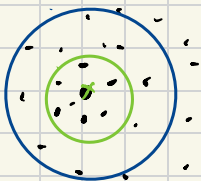




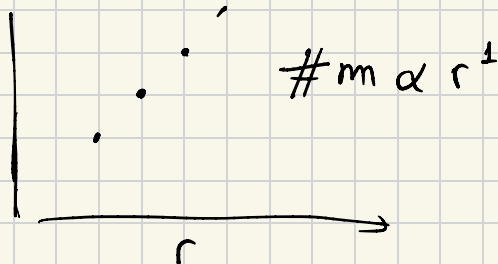
$$I_d(\text{PCA}) = 2$$

From the data ; learn directly the  $I_d$

Fractal



$$\#nn \propto r^2$$

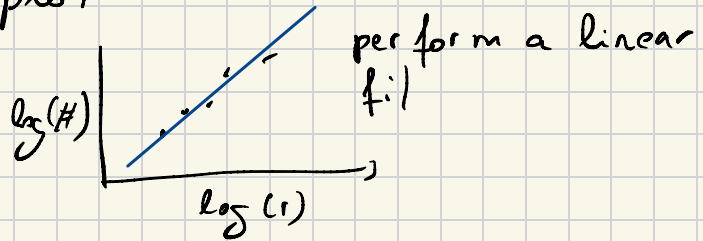


$$\#m \propto r^1$$

$$\# \text{ nn} \propto r^d$$

- fix a set of different values of  $r$
- for each data point: count the number of neighbors within  $r$  (take the average)

c) log vs log plot



d) Slope of the fit  $\rightarrow d$

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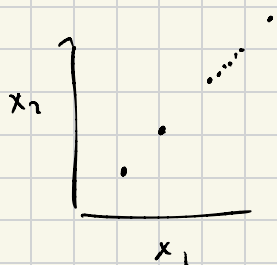
For each data point

- Compute the distances from its  $K$ -NN
- Plot the log of the rank as a function of the log of the distances
- linear fit
- slope will be  $d$

$$\log(\#)_{\text{count}} = \underbrace{\log P}_{\text{rank}} + \frac{d}{d} \log(r)_{\text{distances}}$$

$$\# = \underbrace{p}_{\text{}} r^d$$

We need to disentangle  $\text{Id}$  &  $p$  estimations



Two-NN

$$\mu^i = [1, \infty)$$

$$\mu^i = \frac{r_2^i}{r_1^i}$$

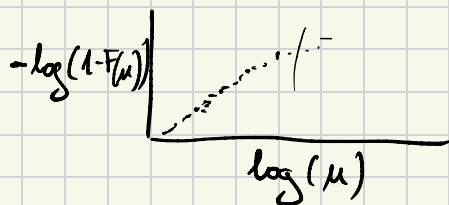
$$\text{i.i.d } p(\mu) = \underbrace{\mu^{-d-1}}_{\text{pareto distribution}} \cdot d$$

$p$  within  $r_i^i$  can be considered constant

$$\mu^i = \frac{\# r_2^i}{\# r_1^i}$$

$$\textcircled{a} \quad F(\mu) = \int_1^{\mu} \mu^{*-d-1} \cdot d \, d\mu^* = 1 - \mu^{-d}$$

$$\frac{-\log(1 - F(\mu))}{\log(\mu)} = d$$



(3) KL

$$p(\mu) = \mu^{-d-1} \cdot d$$

$$\log L = \sum \log(\mu_i^{-d-1} \cdot d) = N \log(d) - (d+1) \cdot \sum_i \log(\mu_i)$$

$$\frac{\partial \log L}{\partial d} = \frac{N}{d} - \sum_i \log(\mu_i) = 0$$

$$d = \frac{N}{\sum_i \log(\mu_i)}$$

