

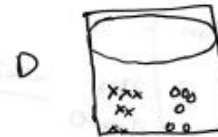
Curse of Dimensionality

↳ d is high dimension

① ML Binary features

$$\begin{cases} f_1, f_2, f_3 \rightarrow \text{Total \# datapoints} = 2^3 = 8 \\ f_1, f_2, f_3, \dots, f_{10} \rightarrow 2^{10} = 1024 \end{cases}$$

as dim \uparrow , the $\#$ datapoints to perform good model increase exponentially



Hughes phenomenon

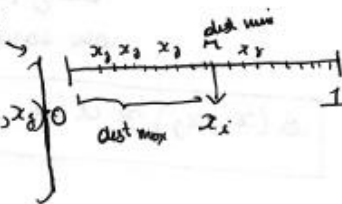
'n' \rightarrow size of dataset is fixed
performance \downarrow as dim \uparrow .

② Distance functions (Euclidean distance)

Curse of Dim :- intuition of distance in 3D is not valid in high dimensional spaces.

1-D world \rightarrow n random pt

$$\text{distance minimum} = \min_{x_j \neq x_i} \text{dist}(x_i, x_j)$$



↓
distance to nearest point from x_i where $x_i \neq x_j$

$$\text{distance maximum}(x_j) = \max_{x_j \neq x_i} \left\{ \text{euc dist}(x_i, x_j) \right\}$$

$$\textcircled{3D} \quad \frac{\text{dist max}(x_i) - \text{dist min}(x_i)}{\text{dist min}(x_i)} > 0$$

when $d=1, 2, 3$

$$\text{as dim} \uparrow \left[\lim_{d \rightarrow \infty} \frac{\text{dist max}(x_i) - \text{dist min}(x_i)}{\text{dist min}(x_i)} \rightarrow 0 \right]$$

A dimensionality increases \uparrow ratio approaches 0.

$$\Downarrow$$

$$(\text{dist max}(x_i) \approx \text{dist min}(x_i))$$

high dimensional space if you take

- n random pts

$$\textcircled{x_i} \quad \text{dist max}(x_i) \approx \text{dist min}(x_i)$$

\Downarrow

every pair of pts
are equally dist. from each other

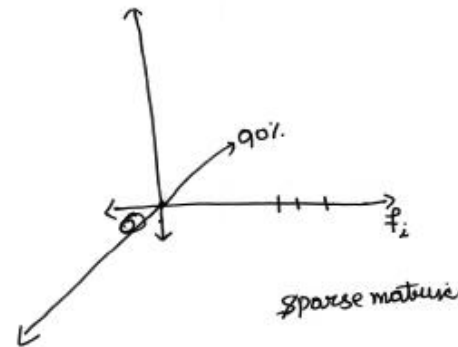
$$\boxed{d(x_i, x_j) \approx d(x_i, x_k)}$$

3) KNN \rightarrow euclidean distance
 \downarrow
 high dimensional space
 euclidean distance \rightarrow logically not make sense.
 \downarrow
 (does not make sense in high dimension space.)
 \rightarrow solution: cosine similarity \rightarrow high dimensionality
 \rightarrow but less effected

NOTE:

Twist: \rightarrow If data is high dimensional & dense \rightarrow impact of dim is high
 1) versus high dimensional & sparse \rightarrow impact of dimensionality

\downarrow is lower.
 not uniform random
 spread of data in the
 sparse dimension.
 (non zero less)



③ Overfitting & underfitting

dimensionality \uparrow , overfitting $\uparrow \rightarrow$ linear regression.
 Classification oriented \rightarrow forward feature selection: pick most useful subset of features
 \rightarrow Dimension reduction: PCA, tSNE \rightarrow do not use class label and not classification oriented

→ KNN on text data

- cosine similarity instead of Euclidean dist.
- sparse representation instead of dense representation

↓
bag of words

