

Q2) a) $\text{Conf}(A \rightarrow B) = \text{Pr}(B|A)$
 $= \frac{\text{Pr}(B \cap A)}{\text{Pr}(A)}$

which ignores $\text{Pr}(B)$. In case $\text{Pr}(B)$ is very high or 1, ie, B occurs in every bucket, this rule does not have any relevance even though it has high confidence.

$$\text{Lift}(A \rightarrow B) = \frac{\text{Conf}(A \rightarrow B)}{\text{Pr}(B)} = \frac{\text{Pr}(A \cap B)}{\text{Pr}(A) \text{Pr}(B)}$$

Lift does not suffer from this it takes $\text{Pr}(B)$ into consideration and ~~would~~ would hence be lower for very high $\text{Pr}(B)$.

$$\text{Conv}(A \rightarrow B) = \frac{1 - \text{Pr}(B)}{1 - \text{Conf}(A \rightarrow B)} = \frac{1 - \text{Pr}(B)}{1 - \text{Conf}(A \rightarrow B)}$$

This is also safe from this drawback since it has a $\text{Pr}(B)$ factor in the numerator. What this causes is that the metric goes up as confidence increases but goes down in case $\text{Pr}(B)$ itself is too high.

Q2) b) $\text{conf}(A \rightarrow B) = \frac{Pr(A \wedge B)}{Pr(A)}$

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— x —

$$\text{Lift}(A \rightarrow B) = \frac{Pr(A \wedge B)}{Pr(A) Pr(B)}$$

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As we can see, $\text{Lift}(A \rightarrow B)$ will always be equal to $\text{Lift}(B \rightarrow A)$ hence it is symmetrical.

— x —

$$\begin{aligned} \text{conv}(A \rightarrow B) &= \frac{1 - Pr(B)}{1 - \text{conf}(A \rightarrow B)} = \frac{1 - Pr(B)}{1 - \frac{Pr(A \wedge B)}{Pr(A)}} \\ &= \frac{Pr(A) - Pr(B) Pr(A)}{Pr(A) - Pr(A \wedge B)} \end{aligned}$$

contd.

Similarly,

$$\text{Conr } (B \rightarrow A) = \frac{P_0(B) - P_0(B) P_0(A)}{P_0(A) - P_0(A \cap B)}$$

Hence, $\text{Conr } (A \rightarrow B)$ will be equal to $\text{Conr } (B \rightarrow A)$ only in case $P(A) = P(B)$.
Since that may not always be true,
Conjunction in general is not symmetric.

Q2) c). $\text{conf}(A \rightarrow B) = \frac{P_s(A \wedge B)}{P_s(A)}$

In case $A \rightarrow B$ is a perfect implication, B is always in a basket that contains A. i.e. $P(A \wedge B) = P(A)$.

$$\Rightarrow \text{conf}(A \rightarrow B) = \frac{P_s(A \wedge B)}{P_s(A)} = \frac{P_s(A)}{P_s(A)} = 1$$

which is maximal since a probability can not be > 1 .

Hence conf is desirable with max. of 1.

$$\text{Lift}(A \rightarrow B) = \frac{\text{conf}(A \rightarrow B)}{P_s(B)} = \frac{P_s(A \wedge B)}{P_s(A) P_s(B)}$$

Similar to above, in case of perfect implication, $\text{conf}(A \rightarrow B) = 1$.

$$\Rightarrow \text{Lift}(A \rightarrow B) = \frac{1}{P_s(B)}$$

For a given dataset, $P_s(B)$ can be considered constant. Thus the numerator is maximum when the rule is a perfect implication.

Therefore, lift is also desirable with maximum value of $\frac{1}{P_s(B)}$.

$$\text{conv}(A \rightarrow B) = \frac{1 - P_r(B)}{1 - \text{conf}(A \rightarrow B)}$$

As we saw, in case of perfect implication
 $\text{conf}(A \rightarrow B) = 1$

\Rightarrow as $\text{conf}(A \rightarrow B) \rightarrow 1$
 $\text{conv}(A \rightarrow B) \rightarrow \infty$.

As conf approaches 1, conv approaches ∞ .

Hence, with increase in conf the
 conv is higher.

Conviction is also desirable with a
 max val of ∞ .

★ A special case here is when

$$P(B) = 1. \Rightarrow \text{conf}(A \rightarrow B) = 1.$$

in which case it becomes undefined.

(83) a) To prove:

$$d(x, y) + d(y, z) \geq d(x, z) \quad \forall (x, y, z)$$

where,

$$\begin{aligned} d(x, y) &= 1 - \sin(x, y) \\ &= 1 - \Pr[h(x) = h(y)] \\ &= \Pr[h(x) \neq h(y)] \quad \text{--- (A)} \end{aligned}$$

We can make the following observations-

- (1) The event $h(x) \neq h(y) \quad \forall (x, y)$ is a binary event and can take values true or false.
- (2) $h(x) \neq h(y)$ implies that ~~both either~~ ~~either~~ one of the following must hold
 - $h(x) \neq h(z)$
 - $h(y) \neq h(z)$

Because if both do not hold, by transitivity property of equality, $h(x) = h(z) = h(y)$ which is against our assumption above.

Hence,

We can say that for event

$h(x) \neq h(y)$ to occur, one of

$h(x) \neq h(z)$ or $h(y) \neq h(z)$ must occur.

Therefore,

$$P_x[h(x) \neq h(y)] \leq P_x[h(x) \neq h(z)] + P_x[h(y) \neq h(z)]$$

from equation (A)

$$d(x, y) \leq d(x, z) + d(y, z)$$

Q3) b)
$$\text{Sim}_{\text{over}}(A, B) = \frac{|A \cap B|}{\min(|A|, |B|)}$$

Assume $A = \{1, 2, 3\}$

$B = \{1\}$

$C = \{2\}$

$\text{Sim}_0(A, B) = 1/1 = 1$

$\text{Sim}_0(A, C) = 1/1 = 1$

$\text{Sim}_0(B, C) = 0/1 = 0$

$\Rightarrow d(A, B) = 1 - 1 = 0$

$d(A, C) = 1 - 1 = 0$

$d(B, C) = 1 - 0 = 1$

These distances do not obey the triangle inequality as

$d(A, B) + d(A, C) \neq d(B, C)$

Hence, there is no LSH scheme for overlap similarity.

$$Q3.) c) \quad \text{Sim}_{\text{Dice}}(A, B) = \frac{|A \cap B|}{\frac{1}{2}(|A| + |B|)}$$

$$= \frac{2 |A \cap B|}{|A| + |B|}$$

Assume $A = \{1, 2, 3\}$

$$B = \{1\}$$

$$C = \{2\}$$

$$\text{Sim}_D(A, B) = \frac{2 \times 1}{3} = 2/3$$

$$\text{Sim}_D(A, C) = \frac{2 \times 1}{3} = 2/3$$

$$\text{Sim}_D(B, C) = 0/3 = 0$$

$$\Rightarrow d(A, B) = 1 - 2/3 = 1/3$$

$$d(A, C) = 1 - 2/3 = 1/3$$

$$d(B, C) = 1 - 0 = 1$$

These distances do not obey the triangle inequality as

$$d(A, B) + d(A, C) \neq d(B, C)$$

Hence this similarity does not have a LSH scheme.

Q4.) a) $W_j = \{x \in A : g_j(x) = g_j(z)\} \quad (1 \leq i \leq p)$

That is W_j is the set of elements in the same bucket as z hashed by g_j

Also, $T = \{x \in A : d(x, z) > c\lambda\}$.

$$\Rightarrow P_0[g(x) = g(z)] \\ = [P_0[h(x) = h(z)]]^k$$

$\because H$ is $(\lambda, c\lambda, p_1, p_2)$ -sensitive.

$$\begin{aligned} [P_0[h(x) = h(z)]]^k &\leq p_2^k \\ &\leq p_2^{\lceil \log_{1/p_2} n \rceil} \\ &\leq n^{\log_{1/p_2} p_2} \\ &\leq n^{-\log_{1/p_2} 1/p_2} \\ &\leq n^{-1} \end{aligned}$$

$$\Rightarrow P_r(g(x) = g(z)) \leq 1/n. \quad \text{--- (A)}$$

To prove

$$P_0\left[\sum_i^L |T \cap W_j| \geq 3L\right] \leq 1/3$$

using Markov inequality on LHS.

$$P_r \left[\sum_{i=1}^L |T \cap w_j| \geq 3L \right] \leq \frac{E \left[\sum_{i=1}^L |T \cap w_j| \right]}{3L} \quad \text{--- (B)}$$

LHS represents the probability that all the $3L$ points that we gather from L buckets are greater than $C\lambda$ from the query point, i.e., an error condition.

From (A), we know that for pts (x, z) such that $d(x, z) \geq C\lambda$
 $P_r(g(x) = g(z)) \leq 1/n$.

Suppose t elements from T fall into w_j for any j .
 $\Rightarrow P_r[\text{having } t \text{ elements from } T \text{ in } w_j] \leq 1/n^t$
 --- (C)

From equation (B),

$$\frac{E \left[\sum_{i=1}^L |T \cap w_j| \right]}{3L} = \frac{E[|T \cap w_1|] + E[|T \cap w_2|] + \dots + E[|T \cap w_L|]}{3L}$$

From (C)

$$\leq \frac{1 + 1 + \dots + 1}{3L} \leq \frac{1L}{3L} \leq 1/3$$

Q4) b). $x^* \in A : d(x^*, z) \leq \lambda$

To prove -

$$\Pr[\forall 1 \leq j \leq L, g(x^*) \neq g(z)] \leq 1/e.$$

$$\Pr[\forall 1 \leq j \leq L, g(x^*) \neq g(z)]$$

$$= [\Pr[g(x^*) \neq g(z)]]^L$$

(x^* & z do not hash to any of the buckets)

$$= [1 - \Pr[g(x^*) = g(z)]]^L$$

$\because g \in G$ is an and construct for $h \in H^k$, we get

$$= [1 - [\Pr[h(x^*) = h(z)]]^k]^L \quad \text{--- (A)}$$

Also, H is a family with $(\lambda, c\lambda, p_1, p_2)$ sensitive

$$\Pr[h(x^*) = h(z)] \geq p_1$$

$$\Rightarrow 1 - \Pr[h(x^*) = h(z)] \leq 1 - p_1$$

(A) becomes -

$$[1 - [\Pr[h(x^*) = h(z)]]^k]^L \leq [1 - p_1^k]^L \quad \text{--- (B)}$$

We know.

$$k = \log_{1/p_2} n$$

Hence,

$$p_1^k = p_1^{\lceil \log_{1/p_2} n \rceil}$$

$$= n^{\lceil \log_{1/p_2} p_1 \rceil} \quad (\text{base shift})$$

$$= n^{\lceil \frac{-\log_e 1/p_1}{\log_e 1/p_2} \rceil} \quad (\text{base change})$$

$$= \bar{n}^e \quad \text{where } e = \frac{\log 1/p_1}{\log 1/p_2}.$$

Equation (B) becomes

$$\Rightarrow [1 - \bar{n}^e]^L$$

$$\text{Since, } \forall x \in \mathbb{R}, (1 - x/n)^n \leq e^{-x}$$

$$\Rightarrow (1 - x)^1 \leq e^{-x}$$

$$\Rightarrow [1 - n^{-e}] \leq \bar{e}^{n^{-e}}$$

$$\Rightarrow [1 - n^{-e}]^L \leq [\bar{e}^{n^{-e}}]^L$$
$$\leq \bar{e}^{-L/n^e}$$

$$\therefore \therefore L = n^e$$

$$\Rightarrow [1 - n^{-e}]^L \leq e^{-1} \leq 1/e$$

$$\Rightarrow \boxed{P_r [\forall 1 \leq j \leq L, g(x^*) \neq g(z)] \leq 1/e}$$

Q4) c). ~~For~~ To prove:

Point chosen is $C\lambda$ -ANN
That is, the pt chosen (x) is such
that
 $d(x, z) \leq C\lambda$, where z is the query.

We know that x is a point chosen
uniformly from L buckets and is among
the total of $3L$. In case the total of
 L buckets $> 3L$, then from part 4a
we know the probability

Pr [Choosing $3L$ from L buckets where all ~~are~~
points are greater than $C\lambda$ dist] $\leq \frac{1}{3}$ — (A)

Also, from 4b) we know that for a pt.

$$x^* \in A: d(x^*, z) \leq \lambda$$

$$\text{pr}[g_j(x^*) \neq g_j(z), 1 \leq j \leq L] \leq \frac{1}{e}.$$

Suppose there are q pts. that are within λ
distance from z .

Pr [none of q pts map to same bucket as z] $\leq \frac{1}{e^q}$ — (B)

~~From (A), (B)~~

~~Pr [point cho~~

From (A) & (B) equations

$$\Pr[\text{point chosen has dist} \geq c\lambda] \leq \frac{1}{3} + \frac{1}{e^{\epsilon}}$$

$$\Pr[\text{point chosen is } (c, \lambda)\text{-ANN}] \geq 1 - \frac{1}{3} - \frac{1}{e^{\epsilon}}$$

$$\geq \frac{2}{3} - \frac{1}{e^{\epsilon}}$$