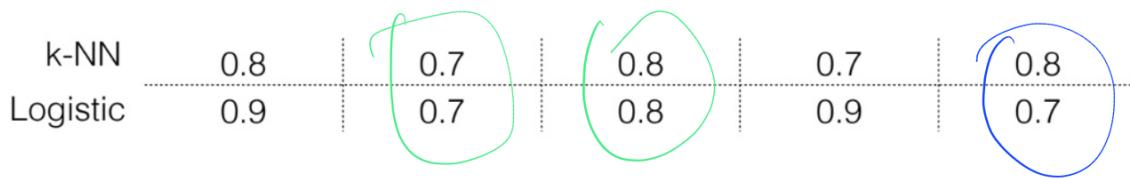


# Homework #7

equal  
 $x > y$



Given 5 variants of the training set obtained by bootstrap, the accuracies of k-NN and Logistic Regression are given above.

Compute the two mean accuracies and the Vargha-Delaney effect size. Based on the two means and the effect size, knowing that  $p\text{-value} = 0.6$  and power = 0.33, what is your conclusion on the superiority of k-NN vs Logistic (or Logistic vs k-NN)?

Since the accuracies were obtained through by bootstrapping then this is the case of paired data,

K-NN mean

Logistic mean

$$\frac{3 \times 0.8 + 2 \times 0.7}{5} = 0.76$$

$$\frac{2 \times 0.9 + 2 \times 0.7 + 0.8}{5} = 0.8$$

$\hat{A}_{12} = P(x > y)$  so we have to see pair-wise how many are equal and how many  $x > y$

$$\begin{aligned} \text{equal} &= 2 \\ (x > y) &= 1 \end{aligned}$$

$$\hat{A}_{12} = \frac{1 + 0.5 \times 2}{5} = \frac{2}{5}$$

$$\begin{aligned} &2 |\hat{A}_{12} - 0.5| \\ &= 2 \left| \frac{2}{5} - \frac{1}{2} \right| = \\ &= 2 \left| \frac{4 - 5}{10} \right| = 0.2 \end{aligned}$$

Small d-effect size

the p-value is  $0.6 > 0.05$  so we cannot reject the null hypothesis. Since the power is  $0.33 < 0.8$  cannot accept it either because we need more data. So the result is inconclusive

# Homework #8

|    | I1  | I2  | I3  | I4  | I5  |
|----|-----|-----|-----|-----|-----|
| x1 | 1   | 5   | 3   | 4   | 1   |
| x2 | 0.9 | 0.5 | 0.6 | 1.0 | 0.8 |
| y  | A   | B   | B   | A   | A   |

The training set  $X = \{I_1, I_2, I_3, I_4, I_5\}$  contains input vectors with two attributes  $x_1, x_2$ .

Evaluate the quality of splitting of  $X$  using Gini Impurity for the two following candidate splitting conditions:

$$a_1: x_1 < 5$$

$$a_2: x_2 < 0.8$$

$$GI(X) = 1 - \sum_{C \in C} p_C^2 \quad , \quad p_C = \frac{|\{x \in X \mid x \in C\}|}{|X|}$$

$$GI(X_{a_1}) = p_a GI(X_a) + (1-p_a) GI(X_{\tilde{a}}), \quad p_a = \frac{|\{x \in X \mid a(x)\}|}{|X|}$$

$a(x) := x \text{ meets condition } a$

$$\underline{a_1}: x_1 < 5$$

$$a_1 = \{I_1, I_3, I_4, I_5\}, \quad \tilde{a}_1 = \{I_2\}$$

$$p_{a_1} = \frac{4}{5}, \quad p_{\tilde{a}_1} = \frac{1}{5}$$

$$GI(X_{a_1}) = 1 - \left(\frac{3}{4}\right)^2 - \left(\frac{1}{5}\right)^2 = 1 - \frac{10}{16} = \frac{3}{8}$$

$$GI(X_{\tilde{a}_1}) = 1 - \frac{0}{1} - \left(\frac{1}{5}\right)^2 = 0$$

$$GI(X_{a_1}) = \frac{4}{5} \times \frac{3}{8} + \frac{1}{5} \times 0 = \frac{3}{10}$$

$$\underline{\alpha_2}: x_2 < 0.8$$

$$\alpha_2 = \{l_2, l_3\}, \tilde{\alpha}_2 = \{l_1, l_4, l_5\}$$

$$P_{\alpha_2} = \frac{2}{5}, \quad P_{\tilde{\alpha}_2} = \frac{3}{5}$$

$$GI(X_{\alpha_2}) = 1 - 0^2 - \left(\frac{2}{2}\right)^2 = 0$$

$$GI(X_{\tilde{\alpha}_2}) = 1 - \left(\frac{3}{3}\right)^2 - 0^2 = 0$$

$$GI(X, \alpha_2) = \frac{2}{5} \times 0 + \frac{3}{5} \times 0 = 0$$

# Homework #9

|    | v1 | v2 | v3 | v4 | v5 |
|----|----|----|----|----|----|
| x1 | 1  | 4  | 2  | 3  | 1  |
| x2 | 0  | 0  | 1  | 1  | 1  |
| y  | A  | B  | B  | A  | A  |

Train a naive Bayes classifier using the 5 training vectors v1, ..., v5 (whose 2 dimensions are attributes x1 and x2, both categorical) with Laplace smoothing and use it to classify:

$$v6 = \langle 4, 1 \rangle$$

$$\frac{\alpha}{\beta} \left\{ \begin{array}{l} \alpha := \text{number of times of attribute given class} + 1 \\ \beta := \text{number of times class appears} + \text{number of different attributes} \end{array} \right.$$

| $X_1$ | 1                 | 2                 | 3                 | 4                 |
|-------|-------------------|-------------------|-------------------|-------------------|
| A     | $\frac{2+1}{3+4}$ | $\frac{0+1}{3+4}$ | $\frac{1+1}{3+4}$ | $\frac{0+1}{3+4}$ |
| B     | $\frac{0+1}{2+4}$ | $\frac{1+1}{2+4}$ | $\frac{0+1}{2+4}$ | $\frac{1+1}{2+4}$ |

| $X_2$ | 0                 | 1                 |
|-------|-------------------|-------------------|
| A     | $\frac{1+1}{2+3}$ | $\frac{2+1}{2+3}$ |
| B     | $\frac{1+1}{2+2}$ | $\frac{1+1}{2+2}$ |

$$P(A) = \frac{3}{5}$$

$$P(B) = \frac{2}{5}$$

$$V_6 = \langle 4, 1 \rangle$$

$$\begin{aligned} P(A | V_6) &= P(X_1=4 | A) P(X_2=1 | A) P(A) \\ &= \frac{1}{7} \cdot \frac{3}{5} \cdot \frac{3}{5} = \frac{9}{175} \approx 0.051 \end{aligned}$$

$$\begin{aligned} P(B | V_6) &= P(X_1=4 | B) P(X_2=1 | B) P(B) \\ &= \frac{2}{6} \cdot \frac{2}{4} \cdot \frac{2}{5} = \frac{1}{15} = 0.2 \end{aligned}$$

Then  $V_6$  is classified as B.

# Homework #10

After training, an SVM classifier has the following 4 support vectors:

$$\begin{aligned}x_1 &= \langle 1, 3 \rangle, y_1 = +1 \\x_2 &= \langle 2, 5 \rangle, y_2 = +1 \\x_3 &= \langle 1, 1 \rangle, y_3 = -1 \\x_4 &= \langle 2, 3 \rangle, y_4 = -1\end{aligned}$$

Assuming the Lagrange coefficients  $c_i$  to be all  $+1$  and  $b = 0$ , how does a linear SVM classifies the following vectors?

$$\begin{aligned}x_5 &= \langle 0, 1 \rangle \\x_6 &= \langle 1, -1 \rangle\end{aligned}$$

Keeping the same support vectors and Lagrange coefficients, and  $b = 0$ , does the classification change when using a radial basis kernel with  $\sigma = 1$ ?

$C :=$  SVM classifier

$$C(x) = \operatorname{sgn} \left( \sum_i y_i c_i (x_i \cdot x) - b \right)$$

|       | <u>dot products</u> |       |       |       |
|-------|---------------------|-------|-------|-------|
|       | $u_1$               | $u_2$ | $u_3$ | $u_4$ |
| $u_5$ | 3                   | 5     | 1     | 3     |
| $u_6$ | -2                  | -3    | 0     | -1    |

$$C(x_5) = \operatorname{sgn} (1 \cdot 1 \cdot 3 + 1 \cdot 1 \cdot 5 - 1 \cdot 1 \cdot 1 - 1 \cdot 1 \cdot 3 - 0) = \operatorname{sgn}(4) = +$$

$$C(x_6) = \operatorname{sgn} (1 \cdot 1 \cdot (-2) + 1 \cdot 1 \cdot (-3) - 1 \cdot 1 \cdot 0 - 1 \cdot 1 \cdot (-1) - 0) = \operatorname{sgn}(-4) = -$$

$$K(x_i, x) = \exp \left( - \frac{d(x_i, x)^2}{2\sigma^2} \right) \stackrel{\sigma=1}{=} \exp \left( - \frac{d(x_i, x)^2}{2} \right)$$

$C_k$ : Non-linear SVM with radial basis kernel and  $\sigma = 1$

$$C_k(x) = \operatorname{sgn} \left( \sum_i y_i c_i K(x_i, x) - b \right)$$

# Homework #11

Given the training set:

$x_1 = \langle 1, 3 \rangle$   
 $x_2 = \langle 2, 4 \rangle$   
 $x_3 = \langle 1, 1 \rangle$   
 $x_4 = \langle 2, 3 \rangle$

1 2

The Lagrange coefficients and the intercept of a one-SVM classifier are  $c = [0.0004, 0, 0, 0]$ ,  $\rho = 0.0002$ . Determine if  $x_5 = \langle 0, 1 \rangle$  and  $x_6 = \langle 1, 0 \rangle$  are outliers, assuming a Gaussian kernel with  $\sigma = 1$ .

If we use agglomerative clustering with complete linkage, cutting the hierarchy at  $k = 3$ , how are  $x_5$  and  $x_6$  classified? Are they outside or inside the closest cluster, based on the cluster's radius?

$$C_h(x) = \operatorname{sgn} \left( \sum_i c_i k(x_i, x) - \rho \right)$$

$$k(x_i, x) = \exp \left( - \frac{d(x_i, x)^2}{2\sigma^2} \right)$$

$$C_K(x_5) = \operatorname{sgn}(-0.0002) = -$$

$$C_K(x_6) = \operatorname{sgn}(-0.0002) = -$$

The points are classified as anomalies.

agglomerative w/ complete linkage

distances<sup>2</sup>

|       | $x_1$ | $x_2$ | $x_3$ | $x_4$ |
|-------|-------|-------|-------|-------|
| $x_1$ | 0     | 2     | 4     | 1     |
| $x_2$ |       | 0     | 10    | 1     |
| $x_3$ |       |       | 0     | 5     |
| $x_4$ |       |       |       | 0     |

$\{x_1\}, \{x_2\}, \{x_3\}, \{x_n\}$ 

$\{x_1, u_4\}, \{x_2\}, \{x_3\}$  or  $\{u_1\}, \{x_2, u_n\}, \{x_3\}$

|                    |       |       |
|--------------------|-------|-------|
| centroids          | $x_1$ | $x_2$ |
| $(\frac{3}{2}, 1)$ | $x_2$ | $x_3$ |
| $c_1$              |       |       |

|                    |       |       |
|--------------------|-------|-------|
| centroids          | $x_1$ | $x_3$ |
| $(2, \frac{7}{2})$ | $x_1$ | $x_3$ |
| $c_2$              |       |       |

## Identifying anomalies w/ clusters

① Anomalies don't belong to any cluster

$$d(x, c_i) > p(c_i), \quad p(c_i) = \max_{x \in C_i} d(x, c_i)$$

② Anomalies is far from centroids  $c_i$

$$d(x, c_i) > \alpha p(c_i)$$

③ Anomalies belong to small/sparse centroids

cluster  $C_i$  closest to  $x$  is small if  $|C_i| < \beta N$

cluster  $C_i$  closest to  $x$  is sparse if  $p(C_i) > \gamma \bar{r}$

distances

|       | $c_1$             | $x_2$ | $x_3$ |   |
|-------|-------------------|-------|-------|---|
| $x_5$ | $4 + \frac{q}{q}$ | 13    | 1     | } |
| $x_6$ | $9 + \frac{1}{q}$ | 17    | 1     |   |

$x_5$  and  $x_6$  are assigned to  $x_3$ . The radius of  $x_3$  is 0. Hence they are classified as anomalies by criteria ①.

There is no home work #12!!

## Homework #13

Compute association rules from the following database of transactions, with min confidence and support threshold set to 0.75:

p q r  
p s  
p s  
p s r

Determine the lift of the resulting association rules. Is any association rule interesting?

① first consider only singletons with support  $\geq 0.75$

$$\left. \begin{array}{l} \text{Supp}(\{p\}) = \frac{4}{4} = 1 \\ \text{Supp}(\{q\}) = \frac{1}{4} \\ \text{Supp}(\{r\}) = \frac{2}{4} = \frac{1}{2} \\ \text{Supp}(\{s\}) = \frac{3}{4} \end{array} \right\} L_1 = \{\{p\}, \{s\}\}$$

② combine singletons and assess support

$$\left. \begin{array}{l} \text{Supp}(\{p, s\}) = \frac{3}{4} \end{array} \right\} L_2 = \{\{p, s\}\}$$

③ For each of the sets  $L_i$  remove an item and make it a consequent, then compute confidence

Rule                      Confidence

$$\{\} \Rightarrow \{P\} \quad \frac{4}{4} = 1$$

$$\{\} \Rightarrow \{S\} \quad \frac{3}{4}$$

$$\{P\} \Rightarrow \{S\} \quad \frac{3}{4}$$

$$\{S\} \Rightarrow \{P\} \quad \frac{3}{3} = 1$$

④ See if we can merge roles with same antecedent

$$\{\} \Rightarrow \{P, S\} \quad \text{confidence } \frac{3}{4} \quad \checkmark$$

Final set of roles:

$$\{\} \Rightarrow \{P, S\}$$

$$\{P\} \Rightarrow \{S\}$$

$$\{S\} \Rightarrow \{P\}$$

Q5 Given  $A \Rightarrow B$ , lift is computed by  $\frac{\text{Conf}(A \Rightarrow B)}{\text{Supp}(B)}$

| Rule                                      | conf          | $\text{Supp}(B)$ | Lift |
|---|---------------|------------------|------|
| $\{\delta\} \Rightarrow \{\rho, \sigma\}$ | $\frac{3}{4}$ | $\frac{3}{4}$    | 1    |
| $\{\rho\} \Rightarrow \{\sigma\}$         | $\frac{3}{4}$ | $\frac{3}{9}$    | 1    |
| $\{\sigma\} \Rightarrow \{\rho\}$         | 1             | 1                | 1    |

All have the same lift, hence are equally interesting.