University of London

MTH793P
Advanced Machine Learning, Semester B, 2023/24
Coursework 5

## 1 Evaluating clustering algorithms

In this problem we assume that we have a data set $\left\{x_{1}, \ldots, x_{6}\right\} \subset \mathbb{R}^{2}$ that looks as follows:


The Euclidean distances along all the edges segments is equal to 1 .
We will consider to alternative clusterings on these data:

- $\mathcal{C}=\left\{C_{1}, C_{2}\right\}$, with $C_{1}=\left\{x_{1}, x_{2}, x_{3}\right\}$ and $C_{2}=\left\{x_{4}, x_{5}, x_{6}\right\}$.
- $\mathcal{C}^{\prime}=\left\{C_{1}^{\prime}, C_{2}^{\prime}, C_{3}^{\prime}\right\}$, with $C_{1}^{\prime}=\left\{x_{1}, x_{2}\right\}, C_{2}^{\prime}=\left\{x_{3}, x_{4}\right\}$, and $C_{3}^{\prime}=\left\{x_{5}, x_{6}\right\}$.

1. Compute the Dunn-Index (DI) for $\mathcal{C}$ and $\mathcal{C}^{\prime}$, using the single-linkage inter-cluster distance, and the diameter intra-cluster distance. Which clustering is better?
2. Compute the mean Silhouette Coefficient (SC) for $\mathcal{C}$ and $\mathcal{C}^{\prime}$. Which one is better?
3. Suppose that we know that $\mathcal{C}^{\prime}$ is the ground-truth for this dataset. Compute the Rand Index (RI) for $\mathcal{C}$.

## Solution:

1. Using the single-linkage distance, we have:

$$
\delta\left(C_{1}, C_{2}\right)=\delta\left(C_{1}^{\prime}, C_{2}^{\prime}\right)=\delta\left(C_{2}^{\prime}, C_{3}^{\prime}\right)=1, \quad \delta\left(C_{1}^{\prime}, C_{3}^{\prime}\right)=1+\sqrt{3}
$$

Using the diameter:

$$
\Delta\left(C_{1}\right)=\Delta\left(C_{2}\right)=\Delta\left(C_{1}^{\prime}\right)=\Delta\left(C_{2}^{\prime}\right)=\Delta\left(C_{3}^{\prime}\right)=1
$$

Therefore,

$$
\mathrm{DI}(\mathcal{C})=\frac{1}{1}=1, \quad \mathrm{DI}\left(\mathcal{C}^{\prime}\right)=\frac{\min (1,1+\sqrt{3})}{1}=1
$$

In other words, the Dunn index we computed does not favour any of the clusterings.
2. Start with $\mathcal{C}$ :

$$
a\left(x_{1}\right)=a\left(x_{2}\right)=a\left(x_{3}\right)=a\left(x_{4}\right)=a\left(x_{5}\right)=a\left(x_{6}\right)=1
$$

Next,

$$
\begin{aligned}
& \left\|x_{1}-x_{4}\right\|=\sqrt{(1 / 2)^{2}+(\sqrt{3} / 2+1)^{2}}=1.9319 \\
& \left\|x_{1}-x_{5}\right\|=1+\sqrt{3}=2.7321 \\
& \left\|x_{1}-x_{6}\right\|=\sqrt{1+(1+\sqrt{3})^{2}}=2.9093
\end{aligned}
$$

Therefore,

$$
b\left(x_{1}\right)=b\left(x_{2}\right)=b\left(x_{5}\right)=b\left(x_{6}\right)=\frac{1}{3}(1.9319+2.7321+2.9093)=2.5244
$$

and

$$
b\left(x_{3}\right)=b\left(x_{4}\right)=\frac{1}{3}(1+1.9319+1.9319)=1.6213
$$

We conclude that

$$
s\left(x_{1}\right)=s\left(x_{2}\right)=s\left(x_{5}\right)=s\left(x_{6}\right)=\frac{2.5244-1}{2.5244}=0.6039
$$

and

$$
s\left(x_{3}\right)=s\left(x_{4}\right)=\frac{1.6213-1}{1.6213}=0.3832
$$

Overall, we have

$$
\mathrm{SC}(\mathcal{C})=\frac{1}{6}(4 \times 0.6039+2 \times 0.3832)=0.5303
$$

Next, we do the same for $\mathcal{C}^{\prime}$ :

$$
a\left(x_{1}\right)=a\left(x_{2}\right)=a\left(x_{3}\right)=a\left(x_{4}\right)=a\left(x_{5}\right)=a\left(x_{6}\right)=1
$$

Next,

$$
b\left(x_{1}\right)=b\left(x_{2}\right)=b\left(x_{5}\right)=b\left(x_{6}\right)=\frac{1}{2}(1+1.9319)=1.4660
$$

and

$$
b\left(x_{3}\right)=b\left(x_{4}\right)=1
$$

Therefore,

$$
s\left(x_{1}\right)=s\left(x_{2}\right)=s\left(x_{5}\right)=s\left(x_{6}\right)=\frac{0.4660}{1.4660}=0.3179
$$

and

$$
s\left(x_{3}\right)=s\left(x_{4}\right)=0 .
$$

We conclude that

$$
\mathrm{SC}\left(\mathcal{C}^{\prime}\right)=\frac{1}{6}(4 \times 0.3179)=0.2119
$$

For the silhouette coefficient, clearly the $\mathcal{C}$ is better than $\mathcal{C}^{\prime}$.
3. Since $\mathcal{C}^{\prime}$ is assumed to be the correct clustering, we have

- True Positives: $\left(x_{1}, x_{2}\right),\left(x_{5}, x_{6}\right)$.
- True Negatives: $\left(x_{1}, x_{4}\right),\left(x_{1}, x_{5}\right),\left(x_{1}, x_{6}\right),\left(x_{2}, x_{4}\right),\left(x_{2}, x_{5}\right),\left(x_{2}, x_{6}\right),\left(x_{3}, x_{5}\right),\left(x_{3}, x_{6}\right)$.

Therefore

$$
\mathrm{RI}=\frac{\mathrm{TP}+\mathrm{TN}}{\binom{6}{2}}=\frac{10}{15}=0.666
$$

## 2 SVD

1. Find vectors $u \in \mathbb{R}^{2}$ and $v \in \mathbb{R}^{3}$ such that the following identity is satisfied for all known values:

$$
u v^{\top}=\left(\begin{array}{ccc}
1 & 0 & ? \\
-2 & ? & 4
\end{array}\right)
$$

What value do you obtain at the missing entry denoted by a question mark?
2. Compute the singular value decomposition of the matrix

$$
X=\left(\begin{array}{ccc}
3 & 2 & 2 \\
2 & 3 & -2
\end{array}\right)
$$

by hand. Hint: Find the eigenvalues of $X X^{\top}$ by computing the characteristic polynomial. Then compute vectors in the nullspace of $X^{\top} X-\lambda I$, where $\lambda$ are the roots of the characteristic polynomial and zero, in order to compute the eigenvectors $u_{1}, u_{2}$ and $v_{1}, v_{2}, v_{3}$ that form the matrices $U$ and $V$.
3. Compute an approximation $\hat{L} \in \mathbb{R}^{2 \times 3}$ with $\operatorname{rank}(\hat{L})=1$ of the matrix

$$
X:=\left(\begin{array}{ccc}
-2 & 3 & 2 \\
2 & 2 & 3
\end{array}\right)
$$

by hand that satisfies $\|\hat{L}-X\|_{\text {Fro }} \leq\|L-X\|_{\text {Fro }}$, for all $L \in \mathbb{R}^{2 \times 3}$ with $\operatorname{rank}(L)=1$.

## Solution:

1. In order to satisfy the equality, the $2 \times 3$-matrix has to have rank one. Hence, if we choose

$$
\left(\begin{array}{ccc}
1 & 0 & -2 \\
-2 & 0 & 4
\end{array}\right)
$$

we ensure that the entries of the first row are the entries of the second row multiplied by -2 . This way both rows are linearly dependent, leading to a matrix of rank one. Two possible vectors $u$ and $v$ that satisfy

$$
u v^{\top}=\left(\begin{array}{ccc}
1 & 0 & -2 \\
-2 & 0 & 4
\end{array}\right)
$$

are $u=\left(\begin{array}{ll}1 & -2\end{array}\right)^{\top}$ and $v=\left(\begin{array}{lll}1 & 0 & -2\end{array}\right)^{\top}$.
2. The main equations to compute SVD are

$$
\begin{align*}
& X^{\top} X=V \Sigma^{\top} \Sigma V^{\top}  \tag{1}\\
& X X^{\top}=U \Sigma \Sigma^{\top} U^{\top} \tag{2}
\end{align*}
$$

Since $\Sigma$ is diagonal and $V$ is orthogonal, Eq.(1)-(2) show that $\Sigma$ and $V$ (or $U$ ) can be respectively computed from the eigenvalues and the eigenvectors of $X^{\top} X$ (or $X X^{\top}$ ). If you need to solve this by hand, a useful trick is to start with $X^{\top} X$ if $X$ has more rows than columns, otherwise you should start with $X X^{\top}$. For this exercise it is better to start with Eq.(2).

$$
X X^{\top}=\left(\begin{array}{ccc}
3 & 2 & 2 \\
2 & 3 & -2
\end{array}\right)\left(\begin{array}{cc}
3 & 2 \\
2 & 3 \\
2 & -2
\end{array}\right)=\left(\begin{array}{cc}
17 & 8 \\
8 & 17
\end{array}\right)
$$

Its eigenvalues can be computed by solving $\operatorname{det}\left(X X^{\top}-\lambda I\right)=0$.
$\operatorname{det}\left(X X^{\top}-\lambda I\right)=\operatorname{det}\left(\begin{array}{cc}17-\lambda & 8 \\ 8 & 17-\lambda\end{array}\right)=(17-\lambda)^{2}-64=\lambda^{2}-34 \lambda+17^{2}-64=0$
whose solutions are $\lambda_{1}=25$ and $\lambda_{2}=9$. Since $\sigma_{i}^{2}=\lambda_{i}$ and $\sigma_{i}>0$ for all $i$, it results $\sigma_{1}=5, \sigma_{2}=3$.
Now let's compute the eigenvectors of $X X^{\top}$. It is sufficient to compute the kernel of $X X^{\top}-\lambda_{i} I$

$$
\begin{gathered}
\bar{u}_{1} \in \operatorname{ker}\left(X X^{\top}-\lambda_{1} I\right)=\operatorname{ker}\left(\begin{array}{cc}
17-25 & 8 \\
8 & 17-25
\end{array}\right)=\operatorname{ker}\left(\begin{array}{cc}
-8 & 8 \\
8 & -8
\end{array}\right)=\left\{\binom{1}{1} t\right\} \\
\bar{u}_{2} \in \operatorname{ker}\left(X X^{\top}-\lambda_{2} I\right)=\operatorname{ker}\left(\begin{array}{cc}
17-9 & 8 \\
8 & 17-9
\end{array}\right)=\operatorname{ker}\left(\begin{array}{ll}
8 & 8 \\
8 & 8
\end{array}\right)=\left\{\binom{1}{-1} t\right\}
\end{gathered}
$$

where we can arbitrarily select $t=1 . \bar{u}_{1}$ and $\bar{u}_{2}$ need to be orthonormal vectors, we have to divide both of them by their modulus:

$$
\begin{aligned}
& u_{1}=\bar{u}_{1} \frac{1}{\sqrt{2}} \\
& u_{2}=\bar{u}_{2} \frac{1}{\sqrt{2}}
\end{aligned}
$$

$u_{1}$ and $u_{2}$ are now orthonormal vectors and they are the columns of $U$ accordingly to Eq.(2).

So far we have computed:

$$
\begin{gathered}
\Sigma=\left(\begin{array}{lll}
5 & 0 & 0 \\
0 & 3 & 0
\end{array}\right) \\
U=\left(\begin{array}{cc}
1 / \sqrt{2} & 1 / \sqrt{2} \\
1 / \sqrt{2} & -1 / \sqrt{2}
\end{array}\right)
\end{gathered}
$$

To find V, we need to compute the eigenvectors of $X^{\top} X$ :

$$
X^{\top} X=\left(\begin{array}{cc}
3 & 2 \\
2 & 3 \\
2 & -2
\end{array}\right)\left(\begin{array}{ccc}
3 & 2 & 2 \\
2 & 3 & -2
\end{array}\right)=\left(\begin{array}{ccc}
13 & 12 & 2 \\
12 & 13 & -2 \\
2 & -2 & 8
\end{array}\right)
$$

Its eigenvalues can be computed by solving $\operatorname{det}\left(X^{\top} X-\lambda I\right)=0$

$$
\operatorname{det}\left(X^{\top} X-\lambda I\right)=\operatorname{det}\left(\begin{array}{ccc}
13-\lambda & 12 & 2 \\
12 & 13-\lambda & -2 \\
2 & -2 & 8-\lambda
\end{array}\right)=0
$$

But we don't have to go through that! Indeed, we already know that, for $X X^{\top}$, $\lambda_{1}=25$ and $\lambda_{2}=9$. What about $\lambda_{3}$ ? Since there are only 2 singular values, it must be $\lambda_{3}=0$.

As we did before, compute the kernel of $X^{\top} X-\lambda_{i} I$

$$
\begin{aligned}
& \bar{v}_{1} \in \operatorname{ker}\left(X^{\top} X-\lambda_{1} I\right)=\operatorname{ker}\left(\begin{array}{ccc}
13-25 & 12 & 2 \\
12 & 13-25 & -2 \\
2 & -2 & 8-25
\end{array}\right)=\operatorname{ker}\left(\begin{array}{ccc}
-12 & 12 & 2 \\
12 & -12 & -2 \\
2 & -2 & -17
\end{array}\right) \\
& =\left\{\left(\begin{array}{l}
1 \\
1 \\
0
\end{array}\right) t\right\} \\
& \bar{v}_{2} \in \operatorname{ker}\left(X^{\top} X-\lambda_{2} I\right)=\operatorname{ker}\left(\begin{array}{ccc}
13-9 & 12 & 2 \\
12 & 13-9 & -2 \\
2 & -2 & 8-9
\end{array}\right)=\operatorname{ker}\left(\begin{array}{ccc}
4 & 12 & 2 \\
12 & 4 & -2 \\
2 & -2 & -1
\end{array}\right) \\
& =\left\{\left(\begin{array}{c}
1 \\
-1 \\
4
\end{array}\right) t\right\} \\
& \bar{v}_{3} \in \operatorname{ker}\left(X^{\top} X-\lambda_{3} I\right)=\operatorname{ker}\left(\begin{array}{ccc}
13-0 & 12 & 2 \\
12 & 13-0 & -2 \\
2 & -2 & 8-0
\end{array}\right)=\operatorname{ker}\left(\begin{array}{ccc}
13 & 12 & 2 \\
12 & 13 & -2 \\
2 & -2 & 8
\end{array}\right) \\
& =\left\{\left(\begin{array}{c}
2 \\
-2 \\
-1
\end{array}\right) t\right\}
\end{aligned}
$$

where we can arbitrarily select $t=1$. Again, note that $\bar{v}_{1}, \bar{v}_{2}$, and $\bar{v}_{3}$ needs to be orthonormal vectors, so we have to divide each of them by their modulus:

$$
\begin{aligned}
& v_{1}=\bar{v}_{1} \frac{1}{\sqrt{2}} \\
& v_{2}=\bar{v}_{2} \frac{1}{\sqrt{18}} \\
& v_{3}=\bar{v}_{3} \frac{1}{\sqrt{9}}
\end{aligned}
$$

$v_{1}, v_{2}$, and $v_{3}$ are now orthonormal vectors and they are the columns of $V$ accordingly to Eq.(1). $V$ can then be written as:

$$
V=\left(\begin{array}{ccc}
1 / \sqrt{2} & 1 / \sqrt{18} & 2 / 3 \\
1 / \sqrt{2} & -1 / \sqrt{18} & -2 / 3 \\
0 & 4 / \sqrt{18} & -1 / 3
\end{array}\right)
$$

3. From the lecture notes we know that the best possible rank-one approximation in terms of the Frobenius norm can be computed by computing the (incomplete) singular value decomposition of $X$. Hence, we compute the eigenvalues of $X X^{\top}$ by
solving the characteristic polynomial $\operatorname{det}\left(X X^{\top}-\lambda I\right)=0$, i.e.

$$
\operatorname{det}\left(X X^{\top}-\lambda I\right)=\operatorname{det}\left(\left(\begin{array}{cc}
17-\lambda & 8 \\
8 & 17-\lambda
\end{array}\right)\right)=\lambda^{2}-34 \lambda+225
$$

whose solutions are $\lambda_{1}=25$ and $\lambda_{2}=9$. Since the singular values are $\sigma_{i}=\sqrt{\lambda_{i}}$ for $i=1,2$, we obtain $\sigma_{1}=5$ and $\sigma_{2}=3$. The best rank one approximation can be computed by computing $\tilde{X}=u_{1} u_{1}^{\top} X$, where $u_{1}$ is the singular vector that corresponds to $\sigma_{1}$. We determine $u_{1}$ by computing the kernel of $X X^{\top}-\lambda_{1} I$, i.e.

$$
\operatorname{ker}\left(X X^{\top}-\lambda_{1} I\right)=\operatorname{ker}\left(\left(\begin{array}{cc}
-8 & 8 \\
8 & -8
\end{array}\right)\right)=\left\{\left.t\binom{1}{1} \right\rvert\, t \in \mathbb{R}\right\}
$$

Since $u_{1} \in \operatorname{ker}\left(X X^{\top}-\lambda_{1} I\right)$ has to have norm one, we easily compute

$$
u_{1}=\frac{1}{\sqrt{2}}\binom{1}{1}
$$

As a consequence, the best rank-one approximation of $X$ in terms of the Frobenius norm is computed via

$$
\begin{aligned}
\tilde{X} & =u_{1} u_{1}^{\top} X=\frac{1}{2}\binom{1}{1}\left(\begin{array}{ll}
1 & 1
\end{array}\right)\left(\begin{array}{ccc}
-2 & 3 & 2 \\
2 & 2 & 3
\end{array}\right) \\
& =\frac{1}{2}\left(\begin{array}{lll}
0 & 5 & 5 \\
0 & 5 & 5
\end{array}\right) .
\end{aligned}
$$

