

Big Data Management and Analytics Assignment 10

Finding similar items

Suppose that the universal set is given by $\{1, \dots, 10\}$. Construct minhash signatures for the following sets:

(a) $S_1 = \{3, 6, 9\}$

(b) $S_2 = \{2, 4, 6, 8\}$

(c) $S_3 = \{2, 3, 4\}$

1. Construct the signatures for the sets using the following list of permutations:

- $(1, 2, 3, 4, 5, 6, 7, 8, 9, 10)$
- $(10, 8, 6, 4, 2, 9, 7, 5, 3, 1)$
- $(4, 7, 2, 9, 1, 5, 3, 10, 6, 8)$

i. Create first a characteristic matrix for each permutation

(a) Set one column with the shingles

(b) Set columns for each document

(c) Fill the document columns by setting a 1 where there is an occurrence for each shingle, and 0 else

Element	S_1	S_2	S_3
1	0	0	0
2	0	1	1
3	1	0	1
4	0	1	1
5	0	0	0
6	1	1	0
7	0	0	0
8	0	1	0
9	1	0	0
10	0	0	0

- i. Create first a characteristic matrix for each permutation

Element	S_1	S_2	S_3
1	0	0	0
2	0	1	1
3	1	0	1
4	0	1	1
5	0	0	0
6	1	1	0
7	0	0	0
8	0	1	0
9	1	0	0
10	0	0	0

1st permutation

Element	S_1	S_2	S_3
10	0	0	0
8	0	1	0
6	1	1	0
4	0	1	1
2	0	1	1
9	1	0	0
7	0	0	0
5	0	0	0
3	1	0	1
1	0	0	0

2nd permutation

Element	S_1	S_2	S_3
4	0	1	1
7	0	0	0
2	0	1	1
9	1	0	0
1	0	0	0
5	0	1	0
3	1	0	1
10	0	1	0
6	1	1	0
8	0	1	0

3rd permutation

ii. Compute the minhash for each permutation

Element	S_1	S_2	S_3
1	0	0	0
2	0	1	1
3	1	0	1
4	0	1	1
5	0	0	0
6	1	1	0
7	0	0	0
8	0	1	0
9	1	0	0
10	0	0	0

Select the first occurrence of 1 per set and get the elements at which they can be found

Which leads to the following minhash:

$$h(S_1) = 3$$

$$h(S_2) = 2$$

$$h(S_3) = 2$$

1st permutation

ii. Compute the minhash for each permutation

Element	S_1	S_2	S_3
10	0	0	0
8	0	1	0
6	1	1	0
4	0	1	1
2	0	1	1
9	1	0	0
7	0	0	0
5	0	0	0
3	1	0	1
1	0	0	0

The same procedure for the 2nd permutation...

$$h(S_1) = 6$$

$$h(S_2) = 8$$

$$h(S_3) = 4$$

2nd permutation

ii. Compute the minhash for each permutation

Element	S_1	S_2	S_3
4	0	1	1
7	0	0	0
2	0	1	1
9	1	0	0
1	0	0	0
5	0	1	0
3	1	0	1
10	0	1	0
6	1	1	0
8	0	1	0

3rd permutation

...and for the 3rd permutation

Which leads to the following minhash:

$$h(S_1) = 9$$

$$h(S_2) = 4$$

$$h(S_3) = 4$$

This yields the following signatures:

$$SIG(S_1) = \{3,6,9\}$$

$$SIG(S_2) = \{2,8,4\}$$

$$SIG(S_3) = \{2,4,4\}$$

2. Instead of using the previously given permutations use hash functions:

$$h_1(x) = x \text{ mod } 10$$
$$h_2(x) = (2x + 1) \text{ mod } 10$$
$$h_3(x) = (3x + 2) \text{ mod } 10$$

2. Instead of using the previously given permutations use hash functions:

i. Set up a table:

Element	S_1	S_2	S_3	$h_1(x)$	$h_2(x)$	$h_3(x)$
1	0	0	0			
2	0	1	1			
3	1	0	1			
4	0	1	1			
5	0	0	0			
6	1	1	0			
7	0	0	0			
8	0	1	0			
9	1	0	0			
10	0	0	0			

ii. Compute the hash values (except for zero-rows):

Element	S_1	S_2	S_3	$h_1(x)$	$h_2(x)$	$h_3(x)$
1	0	0	0	-	-	-
2	0	1	1	2	5	8
3	1	0	1	3	7	1
4	0	1	1	4	9	4
5	0	0	0	-	-	-
6	1	1	0	6	3	0
7	0	0	0	-	-	-
8	0	1	0	8	7	6
9	1	0	0	9	9	9
10	0	0	0	-	-	-

iii. Create a table for all hash functions and sets and initialize them with infinite distance:

e	S_1	S_2	S_3	$h_1(x)$	$h_2(x)$	$h_3(x)$
1	0	0	0	-	-	-
2	0	1	1	2	5	8
3	1	0	1	3	7	1
4	0	1	1	4	9	4
5	0	0	0	-	-	-
6	1	1	0	6	3	0
7	0	0	0	-	-	-
8	0	1	0	8	7	6
9	1	0	0	9	9	9
10	0	0	0	-	-	-

	S_1	S_2	S_3
h_1	∞	∞	∞
h_2	∞	∞	∞
h_3	∞	∞	∞

iii. Create a table for all hash functions and sets and initialize them with infinite distance:

e	S_1	S_2	S_3	$h_1(x)$	$h_2(x)$	$h_3(x)$
1	0	0	0	-	-	-
2	0	1	1	2	5	8
3	1	0	1	3	7	1
4	0	1	1	4	9	4
5	0	0	0	-	-	-
6	1	1	0	6	3	0
7	0	0	0	-	-	-
8	0	1	0	8	7	6
9	1	0	0	9	9	9
10	0	0	0	-	-	-

Update only S_2, S_3 !

$$S_2:$$

$$\min(\infty, 2) = 2$$

$$\min(\infty, 5) = 5$$

$$\min(\infty, 8) = 8$$

$$S_3:$$

$$\min(\infty, 2) = 2$$

$$\min(\infty, 5) = 5$$

$$\min(\infty, 8) = 8$$

Update of 2nd row:

	S_1	S_2	S_3
h_1	∞	2	2
h_2	∞	5	5
h_3	∞	8	8

iii. Create a table for all hash functions and sets and initialize them with infinite distance:

e	S_1	S_2	S_3	$h_1(x)$	$h_2(x)$	$h_3(x)$
1	0	0	0	-	-	-
2	0	1	1	2	5	8
3	1	0	1	3	7	1
4	0	1	1	4	9	4
5	0	0	0	-	-	-
6	1	1	0	6	3	0
7	0	0	0	-	-	-
8	0	1	0	8	7	6
9	1	0	0	9	9	9

Update only S_1, S_3 !

$$S_1:$$

$$\min(\infty, 3) = 3$$

$$\min(\infty, 7) = 7$$

$$\min(\infty, 1) = 1$$

$$S_3:$$

$$\min(2, 3) = 2$$

$$\min(5, 7) = 5$$

$$\min(8, 1) = 1$$

Update of 3rd row:

	S_1	S_2	S_3
h_1	3	2	2
h_2	7	5	5
h_3	1	8	1

iii. Create a table for all hash functions and sets and initialize them with infinite distance:

e	S_1	S_2	S_3	$h_1(x)$	$h_2(x)$	$h_3(x)$
1	0	0	0	-	-	-
2	0	1	1	2	5	8
3	1	0	1	3	7	1
4	0	1	1	4	9	4
5	0	0	0	-	-	-
6	1	1	0	6	3	0
7	0	0	0	-	-	-
8	0	1	0	8	7	6
9	1	0	0	9	9	9
10	0	0	0	-	-	-

Update only S_2, S_3 !

$$S_2:$$

$$\min(2,4) = 2$$

$$\min(5,9) = 5$$

$$\min(8,4) = 4$$

$$S_3:$$

$$\min(2,4) = 2$$

$$\min(5,9) = 5$$

$$\min(1,4) = 1$$

Update of 4th row:

	S_1	S_2	S_3
h_1	3	2	2
h_2	7	5	5
h_3	1	4	1

iii. Create a table for all hash functions and sets and initialize them with infinite distance:

e	S_1	S_2	S_3	$h_1(x)$	$h_2(x)$	$h_3(x)$
1	0	0	0	-	-	-
2	0	1	1	2	5	8
3	1	0	1	3	7	1
4	0	1	1	4	9	4
5	0	0	0	-	-	-
6	1	1	0	6	3	0
7	0	0	0	-	-	-
8	0	1	0	8	7	6
9	1	0	0	9	9	9
10	0	0	0	-	-	-

Update only $S_1, S_2!$

$$S_1:$$

$$\min(3,6) = 3$$

$$\min(7,3) = 3$$

$$\min(1,0) = 0$$

$$S_2:$$

$$\min(2,6) = 2$$

$$\min(5,3) = 3$$

$$\min(4,0) = 0$$

Update of 6th row:

	S_1	S_2	S_3
h_1	3	2	2
h_2	3	3	5
h_3	0	0	1

iii. Create a table for all hash functions and sets and initialize them with infinite distance:

e	S_1	S_2	S_3	$h_1(x)$	$h_2(x)$	$h_3(x)$
1	0	0	0	-	-	-
2	0	1	1	2	5	8
3	1	0	1	3	7	1
4	0	1	1	4	9	4
5	0	0	0	-	-	-
6	1	1	0	6	3	0
7	0	0	0	-	-	-
8	0	1	0	8	7	6
9	1	0	0	9	9	9
10	0	0	0	-	-	-

Update only S_2 !

$$S_2:$$

$$\min(2,8) = 2$$

$$\min(3,7) = 3$$

$$\min(0,6) = 0$$

Update of 8th row:

	S_1	S_2	S_3
h_1	3	2	2
h_2	3	3	5
h_3	0	0	1

iii. Create a table for all hash functions and sets and initialize them with infinite distance:

e	S_1	S_2	S_3	$h_1(x)$	$h_2(x)$	$h_3(x)$
1	0	0	0	-	-	-
2	0	1	1	2	5	8
3	1	0	1	3	7	1
4	0	1	1	4	9	4
5	0	0	0	-	-	-
6	1	1	0	6	3	0
7	0	0	0	-	-	-
8	0	1	0	8	7	6
9	1	0	0	9	9	9
10	0	0	0	-	-	-

Update only S_1 !

$$S_1:$$

$$\min(3,9) = 3$$

$$\min(3,9) = 3$$

$$\min(0,9) = 0$$

Update of 8th row:

	S_1	S_2	S_3
h_1	3	2	2
h_2	3	3	5
h_3	0	0	1

iii. Create a table for all hash functions and sets and initialize them with infinite distance:

	S_1	S_2	S_3
h_1	3	2	2
h_2	3	3	5
h_3	0	0	1

This yields the following signatures:

$$SIG(S_1) = (3,3,0)$$

$$SIG(S_2) = (2,3,0)$$

$$SIG(S_3) = (2,5,1)$$

3. How does the estimated Jaccard similarity from (1.) and (2.) compare with the true Jaccard similarity of the original data? How to reduce deviations in the approximated Jaccard similarities?

RECAP: Jaccard similarity:

$$d_{Jaccard}(D_1, D_2) = \frac{|D_1 \cap D_2|}{|D_1 \cup D_2|}$$

RECAP: Jaccard similarity:

$$d_{Jaccard}(D_1, D_2) = \frac{|D_1 \cap D_2|}{|D_1 \cup D_2|}$$

i. Actual Jaccard similarity:

- (a) $S_1 = \{3,6,9\}$
- (b) $S_2 = \{2,4,6,8\}$
- (c) $S_3 = \{2,3,4\}$

	S_1	S_2	S_3
S_1	-	$1/6$	$1/5$
S_2	-	-	$2/5$
S_3	-	-	-

RECAP: Jaccard similarity:

$$d_{Jaccard}(D_1, D_2) = \frac{|D_1 \cap D_2|}{|D_1 \cup D_2|}$$

ii. Permutation estimated Jaccard similarity:

- (a) $S_1 = \{3,6,9\}$
- (b) $S_2 = \{2,8,4\}$
- (c) $S_3 = \{2,4,4\}$

	S_1	S_2	S_3
S_1	-	0/6	0/5
S_2	-	-	2/3
S_3	-	-	-

RECAP: Jaccard similarity:

$$d_{Jaccard}(D_1, D_2) = \frac{|D_1 \cap D_2|}{|D_1 \cup D_2|}$$

iii. Hash estimated Jaccard similarity:

- (a) $S_1 = \{3,3,0\}$
- (b) $S_2 = \{2,3,0\}$
- (c) $S_3 = \{2,5,1\}$

	S_1	S_2	S_3
S_1	-	$2/3$	$0/5$
S_2	-	-	$1/5$
S_3	-	-	-

iv. Comparison:

Actual J. similarity

	S_1	S_2	S_3
S_1	-	$1/6$	$1/5$
S_2	-	-	$2/5$
S_3	-	-	-

Perm. est. J similarity

	S_1	S_2	S_3
S_1	-	$0/6$	$0/5$
S_2	-	-	$2/3$
S_3	-	-	-

Hash. est. J similarity

	S_1	S_2	S_3
S_1	-	$2/3$	$0/5$
S_2	-	-	$1/5$
S_3	-	-	-

Estimation of the actual J. similarity is rather poor, why?

→ Too small minhash vectors. Get more permutations of the universal set or more hash functions to extend the minhash vectors!

(a) Describe what a PCA aims for and under what circumstances it is most helpful

From the lecture slides:

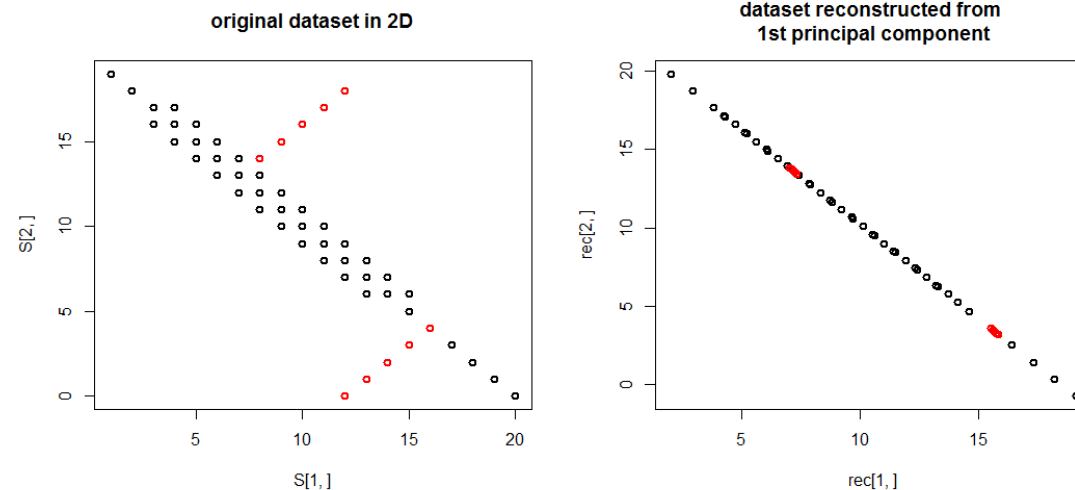
- Detect hidden linear correlations
- Remove redundant and noisy features
- Interpretation and visualization
- Easier storage and processing of the data

When is PCA most helpful:

- The assumption is that the observed variable can be expressed as a linear combination of the hidden variables $x = \mu + Uw + \epsilon$. If that is not the case, another heuristics should be used (e.g. LDA,RCA etc.)

(b) Which possibly netgative consequences might arise when applying PCA to a dataset of unknown structure?

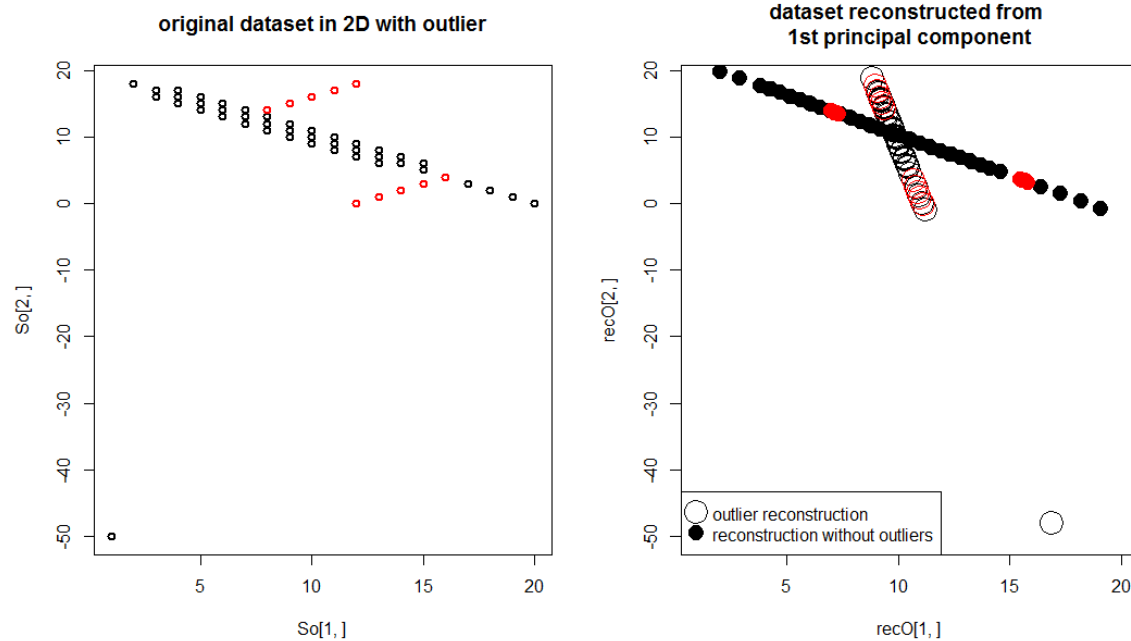
- Data which is not normed can skew the result. Therefore first norm the data!
- Loss of possibly relevant structures (see red lines within the figures)



- Solution: subspace clustering / correlation clustering

(b) Which possibly netgative consequences might arise when applying PCA to a dataset of unknown structure?

- Further, problems with outliers may arise, as they may massively skew the PCA transformation:



Consider the $X \in \mathbb{R}^{M \times N}$ matrix containing six data points $X_i \in \mathbb{R}^2$.

$$X = \begin{pmatrix} 1 & 0 \\ 2 & 0 \\ 3 & 0 \\ 5 & 6 \\ 6 & 6 \\ 7 & 6 \end{pmatrix}$$

dim 1 dim 2

Conduct a PCA on the given data, i.e. project the data onto a one-dimensional space. Please state the eigenvectors, eigenvalues, covariance matrix and visualize the data before and after PCA.

i. Center the data by subtracting the mean value for each dimension:

$$\hat{\mu} = \frac{1}{N} \sum_i X_i = \begin{pmatrix} 4 \\ 3 \end{pmatrix}$$

$$\tilde{X} = \begin{pmatrix} 1-4 & 0-3 \\ 2-4 & 0-3 \\ 3-4 & 0-3 \\ 5-4 & 6-3 \\ 6-4 & 6-3 \\ 7-4 & 6-3 \end{pmatrix} = \begin{pmatrix} -3 & -3 \\ -2 & -3 \\ -1 & -3 \\ 1 & 3 \\ 2 & 3 \\ 3 & 3 \end{pmatrix}$$

ii. Calculate the covariance matrix $E \left[(x - E(X)) \cdot (X - E(X))^T \right]$:

$$\text{cov}(X) \approx \hat{\Sigma} = \frac{1}{N} \tilde{X}^T \tilde{X} = \begin{pmatrix} 4, \bar{7} & 6 \\ 6 & 9 \end{pmatrix} = \begin{pmatrix} 14/3 & 6 \\ 6 & 9 \end{pmatrix}$$

iii. Now compute the eigenpairs (eigenvalues, eigenvectors). Construct the eigendecomposition $\hat{\Sigma} = \hat{U}\hat{S}\hat{U}^T$ with sorted eigenvalues $\hat{\lambda}_j$ in \hat{S}

Compute the eigenvalues:

$$\begin{aligned} \det(\hat{\Sigma} - \lambda I) &= \det \begin{pmatrix} 14/3 - \lambda & 6 \\ 6 & 9 - \lambda \end{pmatrix} = (14/3 - \lambda) \cdot (9 - \lambda) - 36 \\ &= 14 \cdot 3 - 36 - \frac{14+27}{3}\lambda + \lambda^2 = \\ &\lambda^2 - \frac{41}{3}\lambda + 6 = 0 \\ \lambda_{1,2} &= \frac{41/3 \mp \sqrt{(41/3)^2 - 4 \cdot 6}}{2} = 13.21 \text{ and } 0.45 \end{aligned}$$

iii. Now compute the eigenpairs (eigenvalues, eigenvectors). Construct the eigendecomposition $\hat{\Sigma} = \hat{U}\hat{S}\hat{U}^T$ with sorted eigenvalues $\hat{\lambda}_j$ in \hat{S}

Compute the eigenvectors:

$$\hat{\Sigma} \begin{pmatrix} x \\ y \end{pmatrix} = \lambda_{1,2} \begin{pmatrix} x \\ y \end{pmatrix}$$

$$\begin{pmatrix} 14/3 & 6 \\ 6 & 9 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \lambda_{1,2} \begin{pmatrix} x \\ y \end{pmatrix}$$

$$\begin{aligned} \lambda_1 \Rightarrow \begin{cases} 14/3 x + 6y = \lambda_1 x \\ 6x + 9y = \lambda_1 y \end{cases} &\Rightarrow \text{1st (normed) eigenvector: } \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} 0,57 \\ 0,82 \end{pmatrix} \end{aligned}$$

$$\text{Eigenvalues: } \text{diag}(\hat{S}) = \begin{pmatrix} 13,21 & 0 \\ 0 & 0,45 \end{pmatrix}$$

$$\text{Eigenvectors: } \hat{U} = \begin{pmatrix} 0,57 & 0,82 \\ 0,82 & -0,57 \end{pmatrix}$$

iv. Reduce to one-dimensional space. For this purpose remove the second eigenvector and form the transformation matrix U :

$$U = \begin{pmatrix} 0,57 & 0 \\ 0,82 & 0 \end{pmatrix} \Rightarrow \begin{pmatrix} 0,57 \\ 0,82 \end{pmatrix}$$

Now transform the data with

$$Y = \tilde{X} \cdot U = \begin{pmatrix} -3 & -3 \\ -2 & -3 \\ -1 & -3 \\ 1 & 3 \\ 2 & 3 \\ 3 & 3 \end{pmatrix} \begin{pmatrix} 0,57 \\ 0,82 \end{pmatrix} = (-4,18 \quad -3,6 \quad -3,03 \quad 3,03 \quad 3,6 \quad 4,18)^T$$

iv. Reduce to one-dimensional space. For this purpose remove the second eigenvector and form the transformation matrix U :

We can now try to reconstruct the original data matrix with

$$\hat{Z} = \mu + Y \cdot U^T = \mu + \tilde{X} \cdot U \cdot U^T$$

$$\hat{Z} = \begin{pmatrix} 1,6 & -0,42 \\ 1,93 & 0,05 \\ 2,26 & 0,52 \\ 5,74 & 5,48 \\ 6,07 & 5,95 \\ 6,40 & 6,42 \end{pmatrix}$$

v. As we have already reduced to the one-dimensional space (here we did that by eliminating the second principal component), the reconstruction does not imply the information of the second pc:

