# Big Data Management \& Analytics 

EXERCISE 9 - SVD, CUR
11th of January, 2016

PCA
REVISION

## PCA - Summary

1. Center the data $X: x_{i}-\mu_{i}$
2. Calculate the covariance-matrix: $\Sigma=\frac{1}{n} X^{T} X$
3. Calculate the eigenvalues and eigenvectors of $\Sigma$


- Calculate eigenvalues $\lambda$ by finding the zeros of the characteristic polynomial: $\operatorname{det}(\Sigma-\lambda I)$
- Calculate the eigenvectors by solving $(\Sigma-\lambda I) v=0$

4. Select the $k$ eigenvectors with the biggest eigenvalues and create $\mathrm{P}=\left(v_{1}, v_{2}, \ldots v_{k}\right)$
5. Transform the original ( $\mathrm{n} \times \mathrm{d}$ ) matrix $X$ to a $(\mathrm{n} \times \mathrm{k})$ representation: $X P=Y$

## Goals of PCA

- Detect hidden correlations
- Remove redundant and noisy features
- Interpretation and visualization
- Easier storage and processing of dat
-> Most helpful when there is a linear relationship between observed and hidden variables





## Problems with PCA

When applying PCA to a dataset of unknown structure

1. Unnormalized data can skew the result -> before PCA, norm the data!
2. Relevant structures might get lost
original dataset in 2D

dataset reconstructed from 1st principal component


## Problems with PCA

3. Outliers can skew the PCA result
original dataset in 2D with outlier

dataset reconstructed from 1st principal component

# Single Value Decomposition (SVD) 

REVISION AND EXERCISE

## SVD

Any matrix X can be written as $X=U \Sigma V^{T}$
(singular value decomposition)

- $\boldsymbol{X}$ Data matrix ( $n \times d$ )
- V Right singular vectors: eigenvectors of $X^{T} X$
- $\boldsymbol{U}$ Left-singular vectors of X : eigenvectors of $X X^{T}$
$\circ \boldsymbol{\Sigma}$ Singular Values: square roots of eigenvalues (elements on diagonal)

https://de.wikipedia.org/wiki/Singul\�\�rwertzerlegung

Usage example: Image compression

## SVD

Let $X_{n x d}$ be a data matrix and let k be its rank. We can decompose $X$ into matrices $U, \Sigma, V$ as follows:

$$
\begin{gathered}
\boldsymbol{X} \\
\left(\begin{array}{ccc}
x_{1,1} & \ldots & x_{1, d} \\
\vdots & \ddots & \vdots \\
x_{n, 1} & \ldots & x_{n, d}
\end{array}\right)=\left(\begin{array}{ccc}
u_{1,1} & \ldots & u_{1, n} \\
\vdots & \ddots & \vdots \\
u_{n, 1} & \ldots & u_{n, n}
\end{array}\right) *\left(\begin{array}{ccc}
\lambda_{1} & \cdots & 0 \\
\vdots & \ddots & \vdots \\
0 & \cdots & \lambda_{d}
\end{array}\right) *\left(\begin{array}{ccc}
v_{1,1} & \cdots & v_{1, d} \\
\vdots & \ddots & \vdots \\
v_{d, 1} & \cdots & v_{d, d}
\end{array}\right) \\
\mathrm{n} \times \mathrm{d} \\
\mathrm{n} \times \mathrm{n}
\end{gathered}
$$

## SVD- How to find matrices?

Remember the Eigenwertproblem:

$$
A v=\lambda v \quad \text { or } \quad A T=T \Lambda
$$

$$
\begin{aligned}
& \mathrm{v}=\text { eigenvector } \\
& \lambda=\text { eigenvalue } \\
& \mathrm{T}=\text { eigenvector matrix } \\
& \Lambda \text { diagonal eigenvalue matrix }
\end{aligned}
$$

For $X=U \Sigma V^{T}$

- Find V : $\left(X^{T} X\right) V=V \Sigma^{2}$
- Find $U$ : $\left(X X^{T}\right) U=U \Sigma^{2}$. or use: $X V=U \Sigma \quad u_{i}=\frac{1}{\sigma_{1}} X * v_{i}$


## SVD - Example

Given Matrix $M \quad M=\left(\begin{array}{cc}1 & 1 \\ 1 & 1 \\ 1 & -1\end{array}\right) \quad M^{T} M=\left(\begin{array}{ll}3 & 1 \\ 1 & 3\end{array}\right)$
Eigenvalues: $\operatorname{det}\left(M^{T} M-\lambda \cdot I_{2 \times 2}\right)=\lambda^{2}-6 \lambda+8=(\lambda-4)(\lambda-2)$

$$
\lambda_{1}=4 \rightarrow \text { singular value } \sigma_{1}=\sqrt{\lambda_{1}}=2 \quad \lambda_{2}=2 \rightarrow \text { singular value } \sigma_{2}=\sqrt{\lambda_{2}}=\sqrt{2}
$$

Eigenvectors: $v_{1}=\binom{1}{1} \quad \xrightarrow{\text { normalize }} \quad v_{1}=\binom{\frac{1}{\sqrt{2}}}{\frac{1}{\sqrt{2}}}$

## Eigenpairs

$\left(4,\binom{\frac{1}{\sqrt{2}}}{\frac{1}{\sqrt{2}}}\right)\left(2,\binom{\frac{1}{\sqrt{2}}}{-\frac{1}{\sqrt{2}}}\right)$

## SVD - Example

Eigenvalue decomposition $\quad X=U \Sigma V^{T}$
Now we already know: $\quad \Sigma=\left(\begin{array}{cc}2 & 0 \\ 0 & \sqrt{2} \\ 0 & 0\end{array}\right) \quad V=\left(\begin{array}{cc}\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}}\end{array}\right)$

How to find U ? Multiplying the $\operatorname{SVD} M=U \Sigma V^{T}$ with V on each side yields $M V=U \Sigma$

$$
u_{1}=\frac{1}{\sigma_{1}} \cdot M \cdot v_{1}=\frac{\sqrt{2}}{2}\left(\begin{array}{l}
1 \\
1 \\
0
\end{array}\right) \quad u_{2}=\frac{1}{\sigma_{2}} \cdot M \cdot v_{2}=\left(\begin{array}{l}
0 \\
0 \\
1
\end{array}\right)
$$

## SVD - Example

Note: At this point we could write the SVD as follows:
$M=U \Sigma V^{T}=\left(\begin{array}{ccc}\frac{1}{\sqrt{2}} & 0 & * \\ \frac{1}{\sqrt{2}} & 0 & * \\ 0 & 1 & *\end{array}\right) \cdot\left(\begin{array}{cc}2 & 0 \\ 0 & \sqrt{2} \\ 0 & 0\end{array}\right) \cdot\left(\begin{array}{cc}\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}}\end{array}\right)$
How to find $u_{3}$ ? $\quad u_{3}=u_{1} \times u_{2}=\left(\begin{array}{c}\frac{\sqrt{2}}{2} \\ -\frac{\sqrt{2}}{2} \\ 0\end{array}\right)$
$\mathrm{u}_{1}, \mathrm{u}_{2}$ and $\mathrm{u}_{3}$ must build an orthonormal basis!

## SVD - Example

One-dimensional approximation of matrix M

$$
\begin{aligned}
& M=U \Sigma V^{T}=\left(\begin{array}{ccc}
\frac{1}{\sqrt{2}} & 0 & * \\
\frac{1}{\sqrt{2}} & 0 & * \\
0 & 1 & *
\end{array}\right) \cdot\left(\begin{array}{cc}
2 & 0 \\
0 & \sqrt{2} \\
0 & 0
\end{array}\right) \cdot\left(\begin{array}{cc}
\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\
\frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}}
\end{array}\right) \\
& M \approx U_{1} \Sigma_{1} V_{1}^{T} \approx\left(\begin{array}{c}
\frac{1}{\sqrt{2}} \\
\frac{\sqrt{\sqrt{2}}}{0} \\
0
\end{array}\right) \cdot(2) \cdot\left(\begin{array}{ll}
\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}}
\end{array}\right)=\left(\begin{array}{ll}
1 & 1 \\
1 & 1 \\
0 & 0
\end{array}\right)
\end{aligned}
$$

## CUR

REVISION AND EXERCISE

## CUR

Alternative to SVD, which better respects the structure of the data

Definition CUR : A CUR matrix decomposition is a low-rank approximation explicitly expressed in terms of a small number of columns and rows of $A$


## Example

|  | $\begin{aligned} & 3 \\ & \frac{3}{7} \\ & \frac{7}{x} \end{aligned}$ | $\frac{\xrightarrow[\overline{\bar{D}}]{\triangle}}{}$ | $\begin{aligned} & \stackrel{0}{0} \\ & \sum_{\substack{10}}^{\sim} \end{aligned}$ |  | $\stackrel{\text { 겔 }}{\text { ¢ }}$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Joe | 1 | 1 | 1 | 0 | 0 |
| Jim | 3 | 3 | 3 | 0 | 0 |
| John | 4 | 4 | 4 | 0 | 0 |
| Jack | 5 | 5 | 5 | 0 | 0 |
| Jill | 0 | 0 | 0 | 4 | 4 |
| Jenny | 0 | 0 | 0 | 5 | 5 |
| Jane | 0 | 0 | 0 | 2 | 2 |

Find CUR-decomposition of the given matrix with two rows and two columns!
Sample size $r=2$

## Steps

1. Create sample matrices $C$ and $R$
2. Construct U from C and R

## 1a. Create sample matrix C

## Sample columns for C :

Input: matrix $M \in \mathbb{R}^{m x n}$, sample size $r$
Output: $C \in \mathbb{R}^{m x r}$

1. For $x=1: n$ do
2. $\mathrm{P}(\mathrm{x})=\sum_{i}\left(m_{i, x}\right)^{2} /\|M\|_{F}^{2}$
3. For $y=1$ : r do

Frobenius-Norm:

$$
\|M\|_{F}=\sqrt{\sum_{i} \sum_{j}\left(m_{i, j}\right)^{2}}
$$

4. Pick $z \in 1: n$ based on $\operatorname{Prob}(x)$
5. $\quad \mathrm{C}(:, \mathrm{y})=\mathrm{M}(:, \mathrm{z}) / \sqrt{r * P(z)}$

## 1a. Create sample matrix C

$$
\begin{aligned}
& \sum_{i} m_{i, 1}=\sum_{i} m_{i, 2}=\sum_{i} m_{i, 3}=1^{2}+3^{2}+4^{2}+5^{2}=51 \\
& \sum_{i} m_{i, 4}=\sum_{i} m_{i, 5}=4^{2}+5^{2}+2^{2}=45 \\
& \text { FrobeniusNorm : }\|M\|_{F}^{2}=243=3 * 51+2 * 45 \\
& \rightarrow P\left(x_{1}\right)=P\left(x_{2}\right)=P\left(x_{3}\right)=\frac{51}{243}=0.210 \\
& \rightarrow P\left(x_{4}\right)=P\left(x_{5}\right)=\frac{45}{243}=0.185
\end{aligned}
$$

## 1a. Create sample matrix C



## 1b. Create sample matrix $R$

|  | $\begin{aligned} & \frac{3}{\mathbf{m}} \\ & \frac{7}{\bar{x}} \end{aligned}$ | $\stackrel{\geqq}{\overline{\bar{D}}}$ | $\sum_{\substack{\infty \\ j}}^{\substack{\infty}}$ |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Joe | 1 | 1 | 1 | 0 | 0 |
| Jim | 3 | 3 | 3 | 0 | 0 |
| John | 4 | 4 | 4 | O | 0 |
| Jack | 5 | 5 | 5 | 0 | 0 |
| Jill | 0 | 0 | 0 | 4 | 4 |
| Jenny | 0 | 0 | 0 | 5 | 5 |
| Jane | 0 | 0 | 0 | 2 | 2 |

$$
\begin{aligned}
& \sum_{j} m_{4, j}=5^{2}+5^{2}+5^{2}=75 \\
& \sum_{j} m_{5, j}=4^{2}+4^{2}=32
\end{aligned}
$$

FrobeniusNorm: $\|M\|_{F}^{2}=243$
$P\left(y_{4}\right)=\frac{75}{243}=0.309$
$P\left(y_{5}\right)=\frac{32}{243}=0.132$

## 1b. Create sample matrix C

|  | $\begin{aligned} & \frac{3}{\mathbf{m}} \\ & \frac{7}{7} \end{aligned}$ |  | $\sum_{\frac{9}{\omega}}^{\stackrel{0}{m}}$ |  | - |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Joe | 1 | 1 | 1 | 0 | 0 |
| Jim | 3 | 3 | 3 | 0 | 0 |
| John | 4 | 4 | 4 | 0 | 0 |
| Jack | 5 | 5 | 5 | 0 | 0 |
| Jill | 0 | 0 | 0 | 4 | 4 |
| Jenny | 0 | 0 | 0 | 5 | 5 |
| Jane | 0 | 0 | 0 | 2 | 2 |

$$
\begin{aligned}
& \text { Row } 5 * \frac{1}{\sqrt{r \cdot P\left(y_{4}\right)}}=\frac{1}{\sqrt{2 \cdot 0.309}} \\
& \text { Row } 6 * \frac{1}{\sqrt{r \cdot P\left(y_{5}\right)}}=\frac{1}{\sqrt{2 \cdot 0.132}} \\
& R=\left(\begin{array}{ccccc}
6.36 & 6.36 & 6.36 & 0 & 0 \\
0 & 0 & 0 & 7.78 & 7.78
\end{array}\right)
\end{aligned}
$$

## 2. Construct $U$ from $C$ and $R$

a) Create rxr matrix $W$ as intersection of $C$ and $R$
b) Apply SVD on $W=X \Sigma Y^{T}$
c) Compute $\Sigma^{+}$as the pseudoinverse of $\Sigma$
d) Compute $U=Y\left(\Sigma^{+}\right)^{2} X^{T}$

## 2. Construct U from C and R

|  | $\begin{aligned} & 3 \\ & \frac{3}{7} \\ & \frac{7}{x} \end{aligned}$ | $\xrightarrow{\text { D }}$ |  |  | - |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Joe | 1 | 1 | 1 | 0 | 0 |
| Jim | 3 | 3 | 3 | 0 | 0 |
| John | 4 | 4 | 4 | 0 | 0 |
| Jack | 5 | 5 | 5 | 0 | 0 |
| Jill | 0 | 0 | 0 | 4 | 4 |
| Jenny | 0 | 0 | 0 | 5 | 5 |
| Jane | 0 | 0 | 0 | 2 | 2 |

a) Create matrix W: $\quad W=\left(\begin{array}{ll}5 & 5 \\ 0 & 0\end{array}\right)$
b) Apply SVD on W:

$$
W=X \Sigma Y^{T}=\left(\begin{array}{ll}
1 & 0 \\
0 & 1
\end{array}\right)\left(\begin{array}{cc}
\sqrt{50} & 0 \\
0 & 0
\end{array}\right)\left(\begin{array}{cc}
\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\
\frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}}
\end{array}\right)
$$

c) Pseudo-Inverse of $\Sigma$ : $\quad \Sigma^{+}=\left(\begin{array}{cc}\frac{1}{\sqrt{50}} & 0 \\ 0 & 0\end{array}\right)$
d) Calculate $U=Y\left(\Sigma^{+}\right)^{2} X^{T}=\left(\begin{array}{cc}\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}}\end{array}\right) \cdot\left(\begin{array}{cc}\frac{1}{50} & 0 \\ 0 & 0\end{array}\right)=\left(\begin{array}{cc}\frac{1}{50 \sqrt{2}} & 0 \\ \frac{1}{50 \sqrt{2}} & 0\end{array}\right)$

## Result of CUR decomposition



