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## Knowledge Discovery in Databases II <br> WS 2014/2015

## Übungsblatt 3: High-Dimensional Data

## Aufgabe 3-1 Singular Value Decomposition

Another approach to feature reduction is Singular Value Decomposition. Given a Matrix M and its SVD decomposition:

$$
M=T * S * D^{\prime}
$$

with

$$
\begin{gathered}
M=\left[\begin{array}{ll}
1 & 2 \\
6 & 3 \\
0 & 2
\end{array}\right] \quad T=\left[\begin{array}{cc}
-0.2707 & 0.5458 \\
-0.9509 & -0.2797 \\
-0.1497 & 0.7899
\end{array}\right] \\
S=\left[\begin{array}{cc}
7.0257 & 0 \\
0 & 2.1539
\end{array}\right] \quad D=\left[\begin{array}{cc}
-0.8507 & -0.5257 \\
-0.5257 & 0.8507
\end{array}\right]
\end{gathered}
$$

Reduce to one dimension using the approach described in the lecture script.

## Aufgabe 3-2 Recapitulating DBSCAN



Compute DBSCAN on the dataset above using Manhattan distance. Indicate core points, border points, and noise points. Use the following parameters:

- Radius $\varepsilon=1.1$ and minPts $=3$
- Radius $\varepsilon=1.1$ and minPts $=4$
- Radius $\varepsilon=2.1$ and minPts $=4$


## Aufgabe 3-3 Density-based Subspace-Clustering (SubClu)

Show that the following statement (monotonicity of the core point property) holds:
Let $D$ be a set of $d$-dimensional feature vectors, $\mathcal{A}$ the set of all attributes (dimensions/features). Further let $p \in D$ and $S \subseteq \mathcal{A}$ be a subspace (attribute subset).

Then the following holds for arbitrary $\epsilon \in \mathbb{R}^{+}$and $\operatorname{minPts} \in \mathbb{N}$ :

$$
\forall T \subseteq S:\left|\mathcal{N}_{\epsilon}^{S}(p)\right| \geq \operatorname{minPts} \Rightarrow\left|\mathcal{N}_{\epsilon}^{T}(p)\right| \geq \operatorname{minPts}
$$

with $\left|\mathcal{N}_{\epsilon}^{S}(p)\right|:=\left\{q \in D \mid L_{P}\left(\pi_{S}(p), \pi_{S}(q)\right) \leq \epsilon\right\}$.

