## Projection under pairwise distance control

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## Multidimensional Data



ARMCHGGCTCOMHCGGGG GAGMTCCGIGGAACGGGACGGC H THGGMTCCGHGGARCGGGMC MCMGEMAGGACACCCAGCcG CGAGMMCCGTGGAA CGGGमGG CCGAEMMCCGMGGAMCGGG GAGTMCCGMGGAACGGGMGGGO MAACCGMGGMAA AGMCCCCA GCCATRGGAGGGTGAGAGCCCCH: CCGAGMICCORGGAACGGG coc GGACGCCAMAGAGGGHGMMGR=2. omacmmCGGGGCCCGAGMiGn


Multidimensional data in $\mathbb{R}^{p}$

Data visualization in $\mathbb{R}^{2}$
Dimensionality reduction in $\mathbb{R}^{k}$

## Short reminder of the PCA method

- Aim: Project the original data set in a reduced space by preserving as much of the variance from the original data set as possible.


## Short reminder of the PCA method

- Aim: Project the original data set in a reduced space by preserving as much of the variance from the original data set as possible.
- Local quality: Squared cosine of angle between the principal space and the vector of the point gives the local measure.
- usable in linear projection.
- unusable in non-linear projection.
- Not interpretable as distances.


## Presentation of the method

## Our objective

Propose a new non-linear projection method taking into account the local projection quality that is interpretable as distances.

- The idea is to bound the distance $d_{i j}$ by a minimal and maximal distances calculated on the projected points and the radii.



## Basic of the method:

$D=\left[\begin{array}{cccc}d_{11} & d_{12} & \cdots & d_{1 n} \\ d_{21} & d_{22} & \cdots & d_{2 n} \\ \vdots & \vdots & \vdots & \vdots \\ d_{n 1} & d_{n 1} & \cdots & d_{n n}\end{array}\right] \xrightarrow[\left(r_{1}, \cdots, r_{n}\right)]{ } X=\left[\begin{array}{ccc}x_{11} & \cdots & x_{1 k} \\ x_{21} & \cdots & x_{2 k} \\ \vdots & \vdots & \vdots \\ x_{n 1} & \cdots & x_{n k}\end{array}\right]$

- The variables $\left(r_{1}, \ldots, r_{n}\right)$ are called radii given for each point $i$ such that $r_{i} \in \mathbb{R}$ for all $i=1, \ldots, n$.


## Characteristics of Radii

- Radii are important elements introduced to assess how much the distance $\left\|x_{i}-x_{j}\right\|$ is far from $d_{i j}$.
- $\left(r_{i}, r_{j}\right)$ are small $\Rightarrow\left\|x_{i}-x_{j}\right\|$ is close to $d_{i j}$.
- Radii indicate to which extent the projection of each point is accurate.
- The local quality is then given by the values of the radii.
- Both units of $d_{i j}$ 's and $r_{i}$ 's are identical.

The projection under pairwise distance control problem can be written as the following optimization problem:

$$
\mathcal{P}_{r, x}:\left\{\begin{array}{l}
\min _{r_{1}, \ldots, r_{n} \in \mathbb{R}, x_{1}, \ldots, x_{n} \in \mathbb{R}^{k}} \sum_{i=1}^{n} r_{i} \\
\text { s.t }\left|d_{i j}-\left\|x_{i}-x_{j}\right\|\right| \leq r_{i}+r_{j}, \text { for } 1 \leq i<j \leq n
\end{array}\right.
$$

Problem $\mathcal{P}_{r, x}$ is a hard non-linear optimization problem.

## Simplification of problem $\mathcal{P}_{r, x}$ :

- $\left(x_{1}, \ldots, x_{n}\right)$ are fixed using PCA or any other projection method.
- Problem $\mathcal{P}_{r}$ is a new linear optimization problem obtained after fixing $\left(x_{1}, \ldots, x_{n}\right)$.
- It can easily be solved in $\left(r_{1}, \ldots, r_{n}\right)$ using linear programming.

$$
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\end{array}\right.
$$

- Solution of $\mathcal{P}_{r}$ is not in general the optimum of problem $\mathcal{P}_{r, x}$.

Different ways to find a solution of problem $\mathcal{P}_{r, x}$ :

- Lower bound.
- Optimization.
- Simulation.


## Lower Bound of problem $\mathcal{P}_{r, x}$

- Let $x_{1}, \cdots, x_{n} ; r_{1}, \cdots, r_{n}$ a feasible solution of $\mathcal{P}_{r, x}$, and $M \in \mathbb{R}$ such that:

$$
M=\max _{(i, j)}\left\{\left\|x_{i}-x_{j}\right\|\right\} .
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$$

- The objective is to find three functions noted $f, g, h$ depending on $M$ such that:

$$
\sum_{i=1}^{n} r_{i}^{\text {opt }} \geq \min _{M} \max \{f(M) ; g(M) ; h(M)\} \text { for all feasible solutions. }
$$

## Computation of the functions

Function $f(M)$ : This function is obtained by:

- summing all the squared constraints $d_{i j}^{2} \leq\left(\left\|x_{i}-x_{j}\right\|+r_{i}+r_{j}\right)^{2}$.
- bounding $\sum_{1 \leq i<j \leq n}\left\|x_{i}-x_{j}\right\|^{2}$ by $\frac{n(n-1)}{3} M^{2}$ after maximizing the inertia of the projected points $x_{i}$ under constraints: $\left\|x_{i}-x_{j}\right\| \leq M$ for all $(i, j)$.
Indeed, we consider:
- ( $C$ ) be the smallest circle containing the $n$ points
- $A, B$ and $C$ belong to $(C)$ and $\left\|x_{B}-x_{C}\right\|=M$.


- We have proved that the maximum of the inertia $\sum_{i=1}^{n}\left\|y_{i}-g\right\|^{2}$, under the constraint that $y_{1}, \ldots, y_{n}$ are inside (C), is equal to $n r^{2}=n \frac{M^{2}}{3}$.
- Thus,

$$
\sum_{i=1}^{n}\left\|x_{i}-g\right\|^{2} \leq n \frac{M^{2}}{3}
$$

Function $g(M)$ : This function is obtained using the maximal distance of $d_{i j}$.

$$
g(M)=\left|M-d_{\max }\right|
$$

Function $h(M)$ : This function is obtained by taking four distinct points $i, j, k$ and $/$ such that:

- For couple $(i, j),\left\|x_{i}-x_{j}\right\|=M$ and $x_{i}$ or $x_{j}$ is equal to zero.
- We consider the following linear combinations:



## Illustration of the three function $f, g$ and $h$.



## Simulation algorithm

Stochastic optimization method $\Rightarrow$ Metropolis-Hastings algorithm .

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## Target distribution

- The target distribution is related with the objective function of problem $\mathcal{P}_{r, x}$.
- An application $E$ is given by:

$$
\begin{array}{lll}
E: & \mathcal{M}_{n \times p} & \longmapsto \mathbb{R} \\
& X=\left(x_{1}, \ldots, x_{n}\right) & \longmapsto E(X)=\text { Solution of } \mathcal{P}_{r} \text { with } x \text { fix. }
\end{array}
$$

- The target distribution is: $\pi(s) \propto \exp (-E(x) / T)$.

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## Proposal distribution

- For each point $i$, choose a point $j^{(i)}$ with probability equal to:

$$
P_{j^{(i)}}=\frac{\exp \left(-\lambda\left(r_{i}+r_{j(i)}-\left|d_{i j(i)}-\left\|x_{i}-x_{j(i)}\right\|\right|\right)\right)}{\sum_{k=1, k \neq i}^{n} \exp \left(-\lambda\left(r_{i}+r_{k}-\left|d_{i k}-\left\|x_{i}-x_{k}\right\|\right|\right)\right)} \text {. }
$$

- Choose a constant $c_{i j}{ }^{(i)}$ using Gaussian distribution $\mathcal{N}_{k}(0, \sigma)$.
- Generate a matrix $X^{*}$ by moving each vector $x_{i}$ of matrix $X^{t-1}$ as follows:
- If $d_{i j^{(i)}}-\left\|x_{i}-x_{j^{(i)}}\right\|>0$ then $x_{i}^{*}=x_{i}+\left|c_{i j^{(i)}}\right| L_{i}$.
- else $x_{i}^{*}=x_{i}-\left|c_{i j^{(i)}}\right| L_{i}$.
with $L_{i}=\frac{x_{i}-x_{j^{(i)}}}{\left\|x_{i}-x_{j^{(i)}}\right\|}$.

```
    for \(t=1\) to \(N\) do
    if \(\alpha=1\) then
        Take \(X^{t}=X^{*}\).
        else
            \(u=\mathcal{U}(0 ; 1)\).
            if \(u \leq \alpha\) then
                Take \(X^{t}=X^{*}\)
            else
                \(X^{t}=X^{t-1}\).
            end if
        end if
    end for
```

Algorithm 1 Metropolis-Hastings Algorithm:
Generate $X^{*}$ from the proposal distribution $q\left(X^{t-1} \rightarrow X^{*}\right)$.
Solve linear optimization problem $\mathcal{P}_{r}$.
Calculate $\alpha=\frac{g\left(s^{*}\right) q\left(X^{*} \rightarrow X^{t-1}\right)}{g\left(s^{t-1}\right) q\left(X^{t-1} \rightarrow X^{*}\right)}=\frac{g\left(s^{*}\right) \prod_{i=1}^{n} P_{j}^{i^{*}}}{g\left(s^{t-1}\right) \prod_{i=1}^{n} P_{j}^{i^{t-1}}}$.

## Application

- Different types of real data sets are used.
- For example: Quantitative data( Iris data set).
- Parameters of Metropolis-Hastings:
- Parameter $\lambda=100$.
- The standard deviation $\sigma=0.01$.
- Temperature $T=100$

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## PCA



Projection under pairwise distance control

## Projection under pairwise distance



Projection under pairwise distance control

## Conclusions \& Perspectives

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- new non-linear projection method based on a new local measure of projection quality.
- The quality of projection is given here by additional variables called radii.
- Radii enable to give a bound on the original distances.
- The idea can be written as an optimization problem in order to minimize the sum of the radii under some constraints.
- Different algorithms and a lower bound for the objective function are developed.


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## Perspectives

- Improvement of the lower bound in order to assess how close the algorithms are from the minimum.


## Thank you!

