# Equivariant Dimensionality Reduction on Stiefel Manifolds 

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## Outline

- general problem: dimensionality reduction
- our setting: Stiefel manifolds
- our problem
- our solution


## Dimensionality Reduction

- General Idea: Let $n<N$. Suppose we have a data set $X \subset \mathbb{R}^{N}$ of intrinsic dimension $n$. We wish to find an $n$-dimensional subspace $S \subset \mathbb{R}^{N}$ and a subset $\tilde{X} \subset S$ that best represents $X$.
- Our Setting: We will present an algorithm for dimensionality reduction on Stiefel manifolds that respects their topology.


## Stiefel Manifolds

- Let $0<t<s$. The Stiefel manifold $V_{t}\left(\mathbb{R}^{s}\right) \subset \mathbb{R}^{s \times t}$ is the set of orthonormal $t$-frames in $\mathbb{R}^{s}$.
- The orthogonal group $O(t)$ acts on $V_{t}\left(\mathbb{R}^{s}\right)$ from the right via matrix multiplication. The quotient is the real Grassmannian $G_{t}\left(\mathbb{R}^{s}\right)$.


## Equivariant Maps

- Let $X, Y$ be spaces with an action of a group $G$, and $\pi: X \rightarrow Y$ be a map. We say that $\pi$ is $G$-equivariant if for all $x \in X$, we have $\pi(g \cdot x)=g \cdot \pi(x)$.
- If a map $\pi$ is equivariant, then it respects equivalence classes. That is, if $x_{1} \sim x_{2}$, then $\pi\left(x_{1}\right) \sim \pi\left(x_{2}\right)$.
- In particular, if our dimension reduction map $\pi$ from a subset of $V_{k}\left(\mathbb{R}^{N}\right)$ to a subset of $V_{k}\left(\mathbb{R}^{n}\right)$ is $O(k)$-equivariant, then frames that span the same $k$-dimensional subspace of $\mathbb{R}^{N}$ will map to frames that span the same $k$-dimensional subspace of $\mathbb{R}^{n}$. Thus $\pi$ will descend to a map from a subset of $G_{k}\left(\mathbb{R}^{N}\right)$ to a subset of $G_{k}\left(\mathbb{R}^{n}\right)$.


## The Problem

Let $k<n \ll N$. Suppose that we are given a data set $X \subset V_{k}\left(\mathbb{R}^{N}\right)$.
We seek:

- An embedding $\alpha: V_{k}\left(\mathbb{R}^{n}\right) \rightarrow V_{k}\left(\mathbb{R}^{N}\right)$ that is optimal with respect to $X$.
- The set of possible embeddings $\alpha$ is parametrized by the Stiefel manifold $V_{n}\left(\mathbb{R}^{N}\right)$.
- An embedding $\alpha$ is optimal with respect to $X$ if it minimizes the sum of the squared distances between each data point $x_{i} \in X$ and its image $\pi_{\alpha}\left(x_{i}\right)$.
- An equivariant projection map $\pi_{\alpha}: X \rightarrow \alpha\left(V_{k}\left(\mathbb{R}^{n}\right)\right)$.

The image $\tilde{X}:=\pi_{\alpha}(X)$ is a lower-dimensional representation of $X$.

## An Equivariant Dimension Reduction Map

Suppose we have chosen an embedding $\alpha$. We now define $\pi_{\alpha}$.

- Polar decomposition: Let $A \in \mathbb{R}^{n \times k}$ with $n \geq k$. There exists a matrix $U \in \mathbb{R}^{n \times k}$ with orthonormal columns and a unique self-adjoint positive semidefinite matrix $H \in \mathbb{R}^{k \times k}$ such that $A=U H$. If $\operatorname{rank}(A)=k$, then $H$ is positive definite, hence invertible, and $U$ is uniquely determined by $U=A H^{-1}$.
- Fix $\alpha \in V_{n}\left(\mathbb{R}^{N}\right)$. Let $L=\left\{y \in V_{k}\left(\mathbb{R}^{N}\right) \mid \operatorname{rank}\left(\alpha^{T} y\right)<k\right\}$. Define $\pi_{\alpha}: V_{k}\left(\mathbb{R}^{N}\right) \backslash L \rightarrow \alpha\left(V_{k}\left(\mathbb{R}^{n}\right)\right)$ as follows. Let $\alpha^{T} y=U H$ be the unique polar decomposition of $\alpha^{T} y$. Define $\pi_{\alpha}$ by $\pi_{\alpha}(y):=\alpha U$.
- Proposition: For fixed $\alpha, \pi_{\alpha}$ minimizes the sum of squared distances from $x_{i} \in X$ to their images in $\alpha\left(V_{k}\left(\mathbb{R}^{n}\right)\right)$.
- Proposition: $\pi_{\alpha}$ is $O(k)$-equivariant.


## Finding an Optimal Embedding

- The set of possible embeddings $\alpha$ is parametrized by the Stiefel manifold $V_{n}\left(\mathbb{R}^{N}\right)$.
- Under strict assumptions on the data set $X$, PCA supplies a critical embedding $\alpha$.
- Under looser assumptions on the data set $X$, we use gradient descent with the $\alpha$ supplied by PCA as an initial point.
- The software package manopt implements gradient descent on Stiefel manifolds.


## Thank you!

