Analysis of the Potential of Manifold Learning Algorithms to Improve Classification Performance

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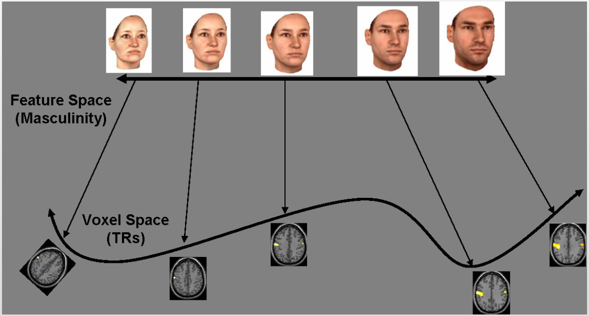
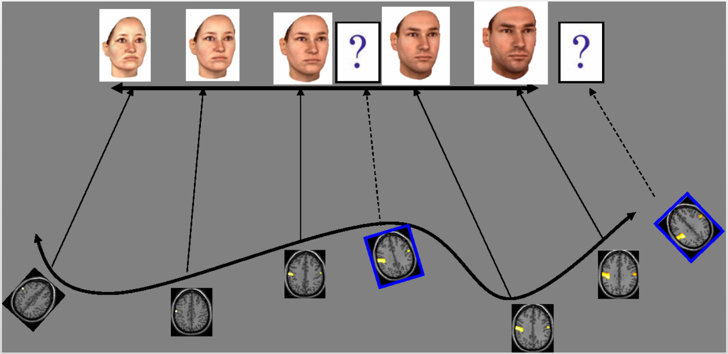
Introduction: The Continuity Hypothesis



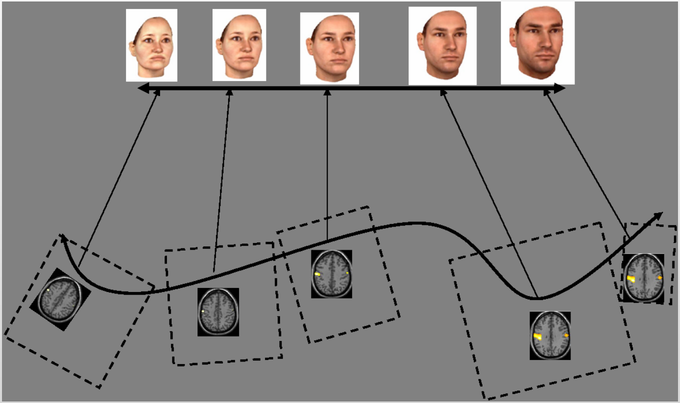
We hypothesize that points which are close together in stimulus space are close in brain state space.

Manifold Learning Algorithms

Manifold Learning as a Tool for Learning the Brain Response Between Sample Points



Manifold Learning as a Classification Tool



Outline of Topics

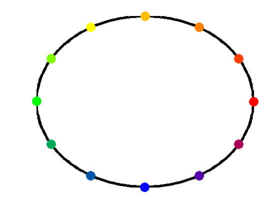
Manifold Learning Algorithms

Manifold learning algorithms use local distances between points to estimate the global structure of the manifold.

Examples of manifold learning algorithms

- ISOMAP - Tenenbaum, de Silva, Langford 2002
- Laplacian eigenmaps - Belkin, Niyogi, 2003
- Diffusion maps - Coifman, Lafon, 2004

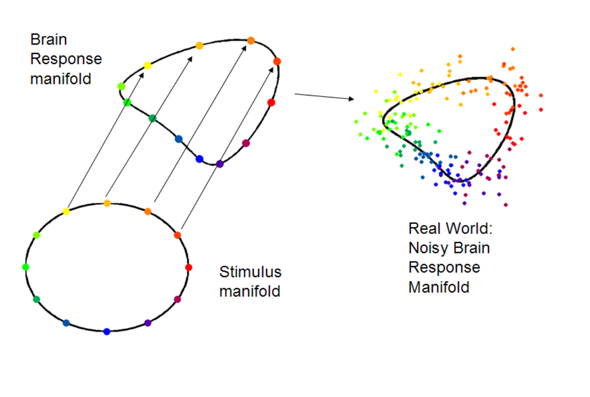
Analysis on Real Data



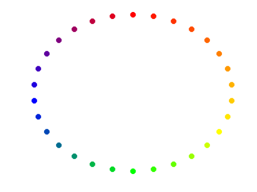
Example experiment: Sequential saccades

- Carried out in Sabine Kastner's lab
- Subjects are shown dots at each of the different clock positions in order and then look in that direction.
  - 12 clock positions
  - 5 seconds = 2.5 TRs at each position (no rest between)
  - 30 TRs/cycle
  - 8 cycles/run
  - 6 runs/subject

Manifold We Expect to Learn



First test: Is the manifold we expect there in the real data?

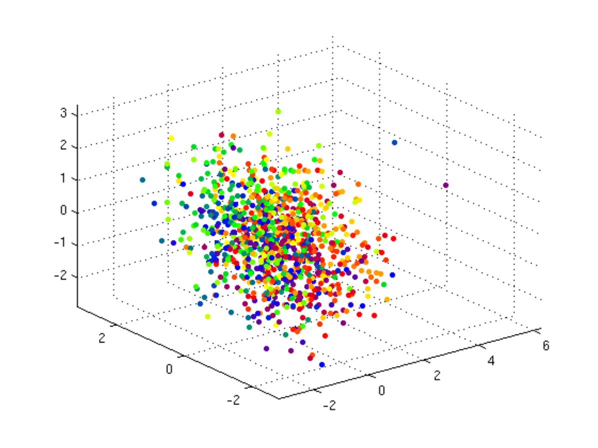


Assigning a color to each of the 30 TRs in a cycle

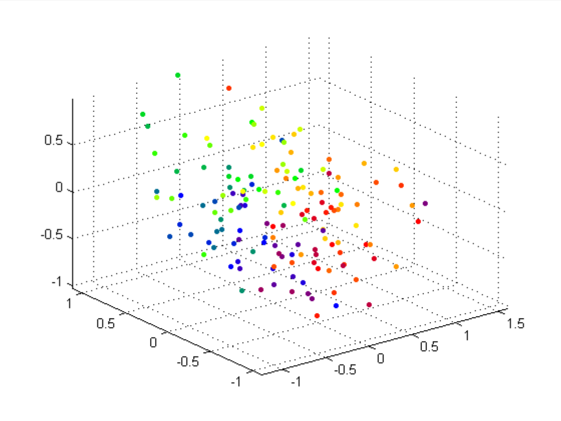
To test for presence of the manifold, we start with a simple visualization of the data:

- We pick the three most significant voxels (as judged by ANOVA: $P \leq 1 \times 10^{-8}$) so that each TR is a point in 3 dimensional space.
- Each of the 30 TRs in a cycle is assigned a color.
- TRs which are close together in the time (similar clock positions) are assigned similar colors.
- Each TR is plotted in 3 dimensional space in its assigned color.

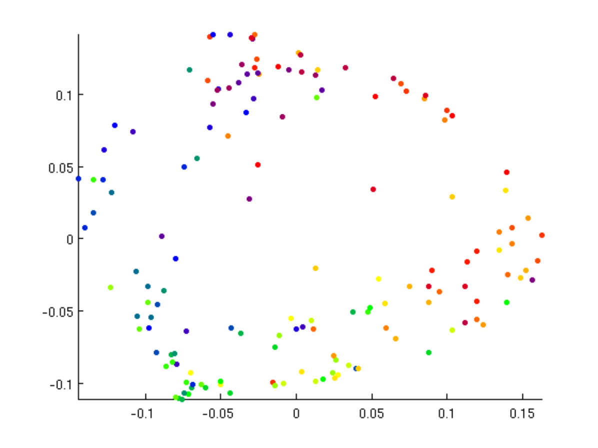
First test: Is the manifold we expect there in the real data?



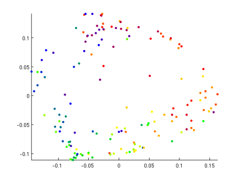
With within-run averaging

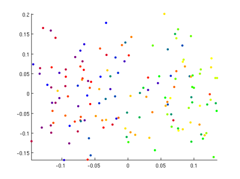


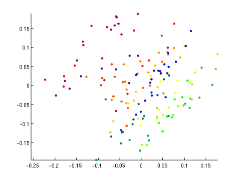
Our 3 Voxel Example after Manifold Learning



Using More Voxels: Tradeoff Between More Information and More Noise



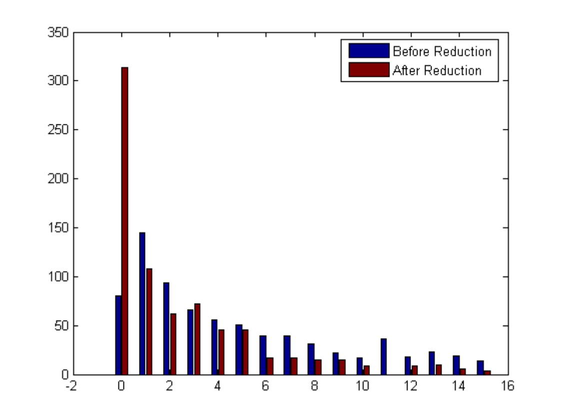




Quantitative Measurement of Manifold Learning's Potential to Improve Classification

- We expect that classification will be easier if points from the same condition end up close to one another.
- To measure how much this is true, we:
  - Find the k nearest neighbors of each point.
  - Count number of these neighbors at each distance from the point in condition space.
  - Average these numbers over all points to create a histogram.
- We compare this histogram before and after manifold learning.

Results of the Quantitative Test



Our Ideas on Where to Go Next

- Finish implementing modification to cross validation in the MVPA toolbox to allow the user the option of using a manifold learning algorithm before classification.
- Look at incorporating information about the stimulus manifold into the manifold learning procedure.
- Long term: Try to create a complete continuous mapping between an n-dimensional stimulus space and the n-dimensional manifold it corresponds to in brain state space.

Group Discussion