Manifold Learning Algorithms for Classification and Estimation: An Update

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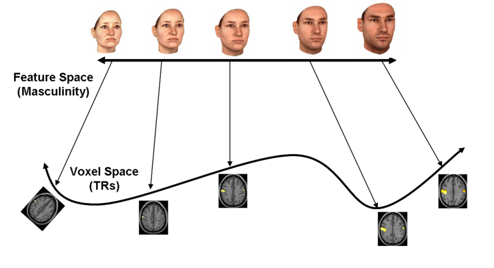
From last time....

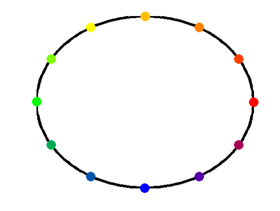


We hypothesize that points which are close together in stimulus space are close in brain state space.

Manifold Learning Algorithms

- Manifold learning algorithms use local distances between points to estimate the global structure of the manifold.
- This can be compared to using local derivatives to estimate the global structure of a function.

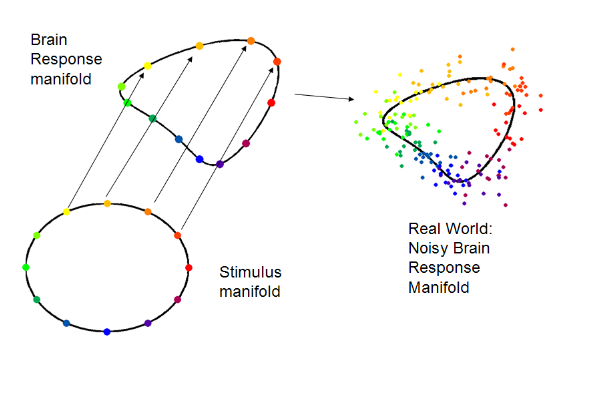
A First Experiment on Real Data



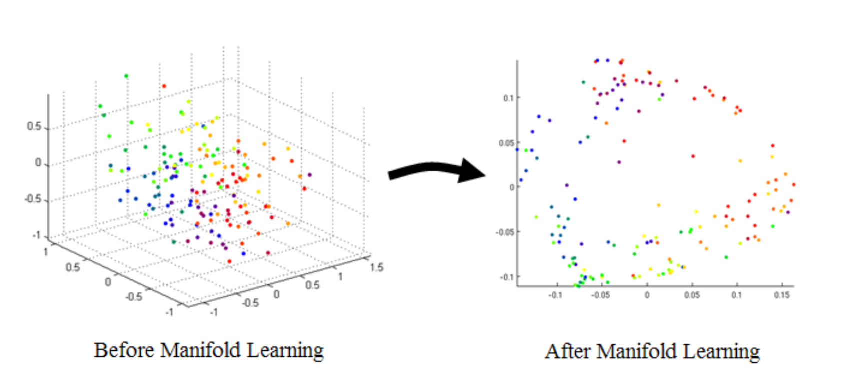
Example experiment: Sequential saccades

- 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

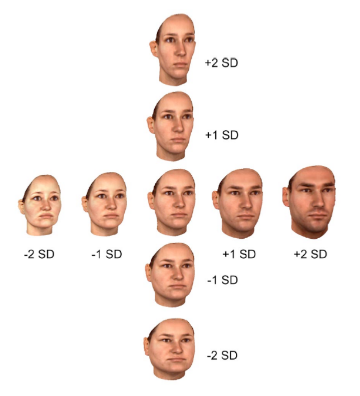


Our Findings



This time...

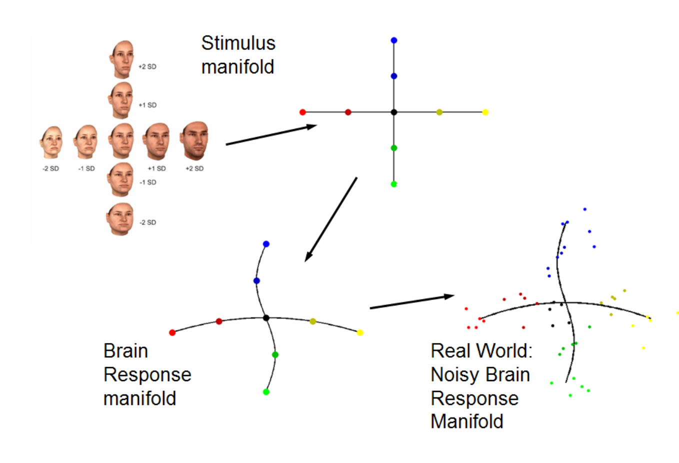
The Experiment



A second experiment: Gender/Slimness

- Carried out in Jim Haxby's lab
- Subjects are shown faces of varying gender and slimness
  - 5 different levels each of gender and slimness
  - 9 different conditions total
  - block design: 5 TRs on, 11 TRs off
  - 8 runs/subject
  - each condition shown once per run in random order

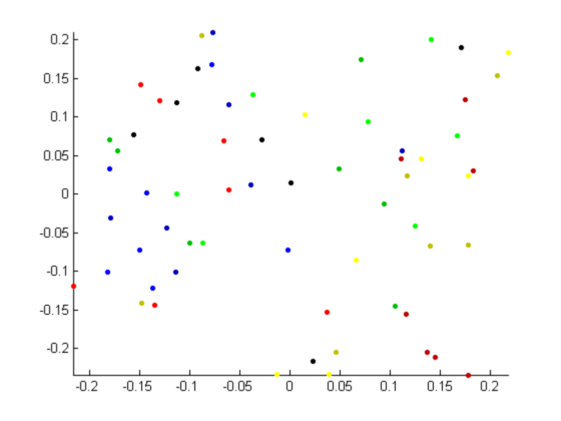
Manifold We Expect to Learn



Processing the Gender/Slimness Data

1. Run ANOVA to find top 9 significant voxels.
2. Split up data into functional blocks (a block begins 2 TRs after the first face is shown and contains 5 TRs total). These functional blocks are size 9×5.
3. Reduce the functional blocks into a 9×1 vector by averaging in each voxel across the 5 TRs.
4. We now have a point in 9-dimensional space for each block: a total of 8 points (one per run) for each of the 9 conditions.
5. Do manifold learning on this set of points.

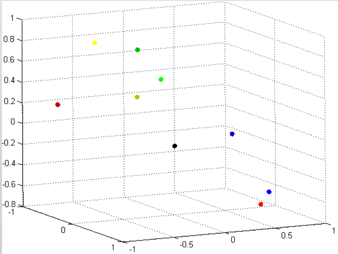
Results of Processing the Gender/Slimness Data

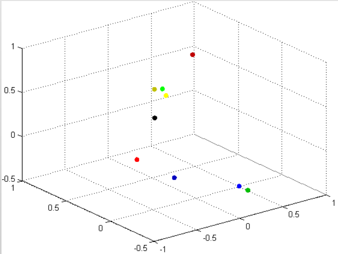


Experiment: Do we see the manifold in the data?

Idea: Take combinations of 3 voxels at a time (the largest number we can visualize) out of the 9-voxel vectors and look for a manifold in this set of three.

Result:



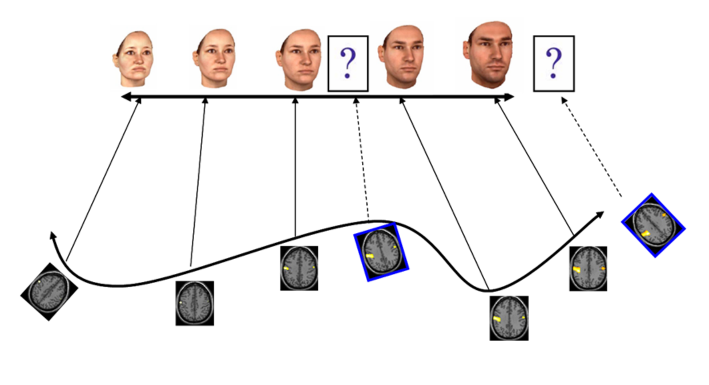


Possible Explanations

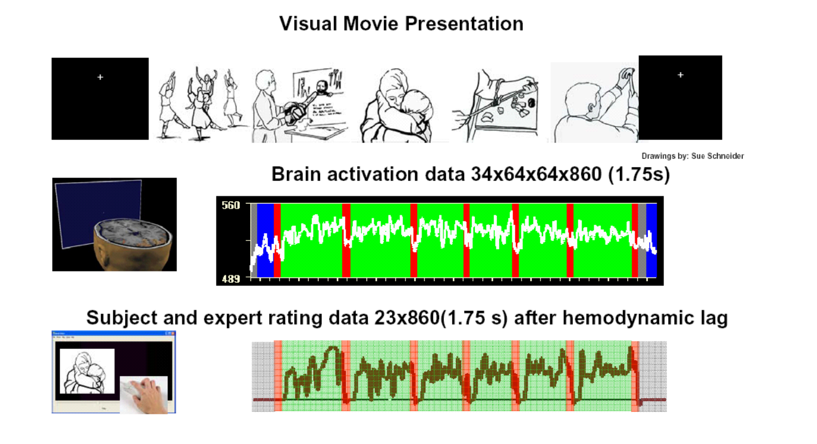
Possible reasons why we can't find the manifold

1. Too few samples and too much noise (which manifold learning may not be robust enough to deal with)
2. Not a wide enough sampling of the manifold: need points off the axes to learn a surface.
3. Faces used in experiment may not truly sit on this functional manifold (use different faces?)
4. Temporal blurring from previous blocks of the experiment?

Beyond Classification: Estimation of Regressors for New Data

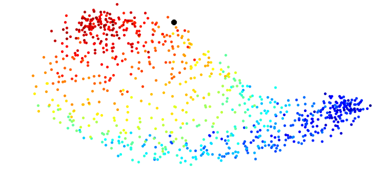


An Application: The EBC Competition



Estimating Regressor Values

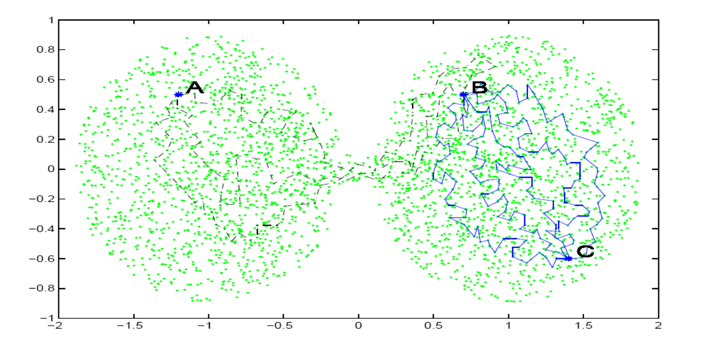
Given: the manifold of points (TRs) with known regressor values
Estimate: the regressor value of a point near the manifold



One solution: weighted average of nearest neighbors' regressors.

Properties of Diffusion Distance

We don't know the manifold! But...
When we *learn* the manifold with Diffusion Maps, points we are more likely to arrive at on a random walk are closer.



Finding Neighbors Without the Manifold

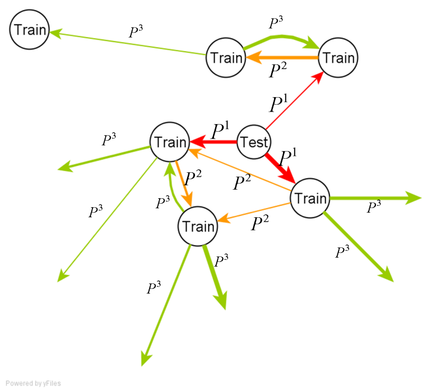
We do not need to know the manifold to find neighbors.

- Give higher weights ($\{w_i\}$) to the points we are more likely to walk to
- Use these weights when estimating the regressor of the test points:

$$\mathrm{Reg}(x_{\mathrm{test}}) = \sum_{i \in \mathrm{NN}(x_{\mathrm{test}})} w_i \mathrm{Reg}(x_i)$$

where $\mathrm{NN}(x_{\mathrm{test}})$ are the neighbors of x_{test}.

Finding the Weights



1. Assign probabilities for reaching neighbors of x_{test} in one step
2. Assign outgoing probabilities for all the neighbors
3. Find probability of reaching some extended neighbor after n steps
4. Use this probability distribution over neighbors (x_i) as our weights (w_i)

Results

	Movie 1 to Movie 2
Amusement	0.1433
Attention	0.1824
Arousal	0.1938
BodyParts	0.3299
EnvSounds	0.2113
Faces	0.577
Food	-0.1474
Language	0.2254
Laughter	0.212
Motion	0.2926
Music	-0.0494
Sadness	0.1135
Tools	0.0905

Results

Movie 1 to Movie 2			Movie 2 to Movie 1		
Subj 1	Subj 2	Subj 3	Subj 1	Subj 2	Subj 3
0.143	0.008	0.443	0.153	0.186	0.520
0.182	0.021	0.068	0.144	0.093	−0.037
0.194	0.077	0.389	0.272	0.133	0.358
0.330	0.302	0.176	0.472	0.227	−0.123
0.211	0.081	0.119	0.144	0.104	0.030
0.577	0.215	0.155	0.352	0.261	0.162
−0.147	0.033	0.147	−0.178	0.011	0.008
0.225	0.155	−0.146	0.324	0.258	0.049
0.212	0.076	0.358	0.239	0.070	0.279
0.293	0.349	0.228	0.470	0.275	0.336
−0.049	−0.067	−0.092	−0.093	0.011	0.058
0.113	−0.031	*NaN*	0.162	−0.062	−0.007
0.090	−0.080	0.165	0.263	0.115	0.257

Future Work in Manifold Learning: Short Term

- Contribute manifold learning code to MVPA toolbox.
- Try manifold learning on the mammals data set provided by Webber and Osherson.
- Look at incorporating information about the stimulus manifold into the manifold learning procedure.
- Try to find tangent vectors to manifold at specific points.

Future Work in Manifold Learning: Long Term

- Refine procedure for estimating stimulus from brain data.
- 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