# Bayesian Visual Analytics (BaVA)

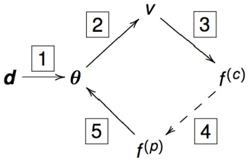
## Visual to Parametric Interaction (V2PI)

**Scotland Leman**, **Leanna House**, and **Chris North**
Department of Statistics and Computer Science,
Virginia Tech

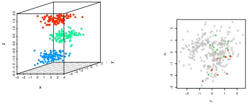
BaVA Team Members:
Chao Han (PCA, Mixture PCA), Dipayan Maiti (Graphs, IsoMap), Alex Endert (Interaction Theory, Force Directed Layouts), Lucas Roberts (Tree Models)

# BaVA and V2PI

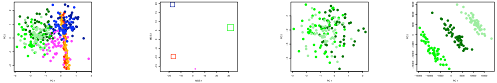
- BaVA is not a method, but an interactive framework



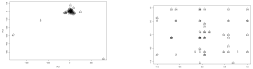

- With care, the framework is applied to methods:
  - PPCA



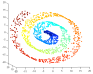
  - Mixture PPCA



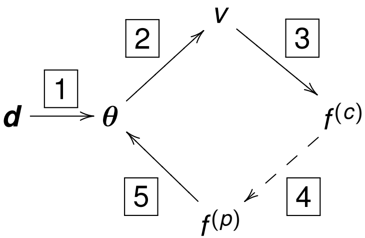
  - GTM



  - IsoMap



# BaVA Process: Overview




1. Model the data and derive $\pi(\theta|\boldsymbol{d})$
2. Display posterior estimate $\hat{\theta}$ in malleable visualization, $v$
3. Prompt expert to inject feedback - *cognitive feedback*, $f^{(c)}$
4. Parameterize feedback - *parametric feedback*, $f^{(p)}$
5. Update $\pi(\theta|\boldsymbol{d})$; Derive $\pi(\theta|\boldsymbol{d}, f^{(p)})$

Repeat!

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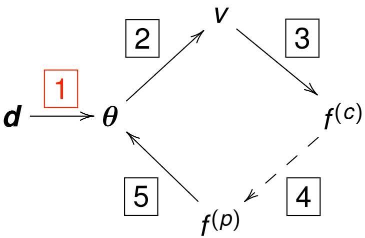


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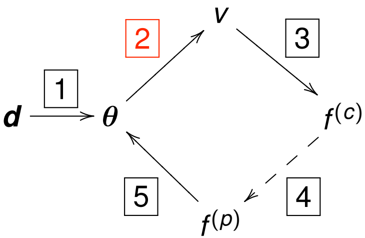


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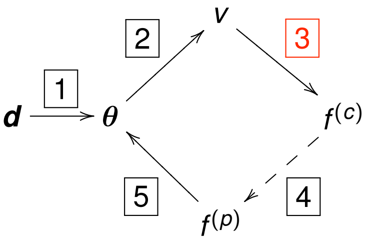


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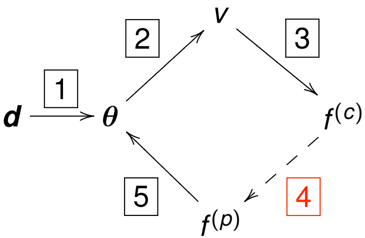


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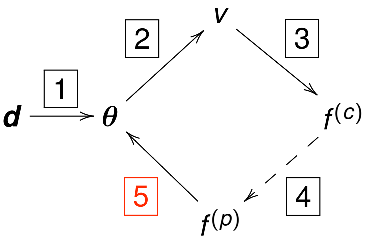


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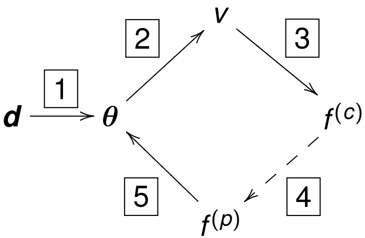


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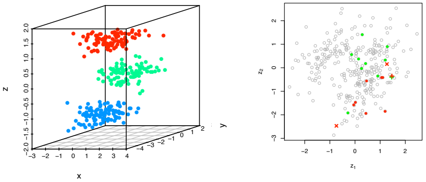
# Step 1. Derive Posterior, PCA



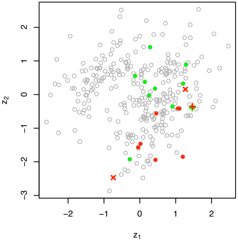

- For PCA, we consider Probabilistic PCA (Tipping and Bishop, 1999) for *standardized* data $\boldsymbol{d}$

$$d_i = \boldsymbol{W} r_i + \boldsymbol{\mu} + \epsilon_i, \quad \epsilon_i \sim \text{No}(\mathbf{0}, \mathbf{I}_p \sigma^2)$$

  - $i \in \{1, ..., n\}$ and $p = 3$ (for this ex.)
  - $\mu$ represents a $p$-vector and the mean of $\boldsymbol{d}$; Since $\boldsymbol{d}$ is standardized, $\mu = 0$
  - $r_i$ is a $q$-vector - *latent factors*
  - $\boldsymbol{W}$ is a $p \times q$ transformation matrix -*factor loadings*
  - $\epsilon_i$ represents a $p$-vector error term; $\text{E}[\epsilon_i] = \mathbf{0}$ and $\text{Var}[\epsilon_i] = \mathbf{I}_p \sigma^2$.

# Step 3. Cognitive Feedback, $f^{(c)}$ - PPCA

- For PPCA, the experts are invited to drag two observation together or apart.



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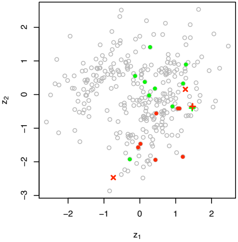

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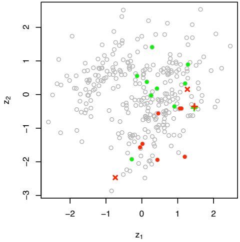

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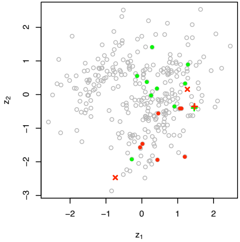
- Apart implies that two points differ by more than what is portrayed by the display
- Thus, injected feedback is at the observation level (not dimension)



# Step 4. and 5. Model Update - PPCA

Cognitive to Parametric feedback... this is the secret sauce!

$$\pi(\boldsymbol{\Sigma}_{\boldsymbol{d}} | \boldsymbol{d}, f) = \mathrm{IW}(nS_{\boldsymbol{d}} + \nu f^{(p)}, p, n + \nu - p - 1),$$

where the MAP is

$$\frac{\nu}{\nu + n} f^{(p)} + \frac{n}{\nu + n} S_{\boldsymbol{d}}.$$

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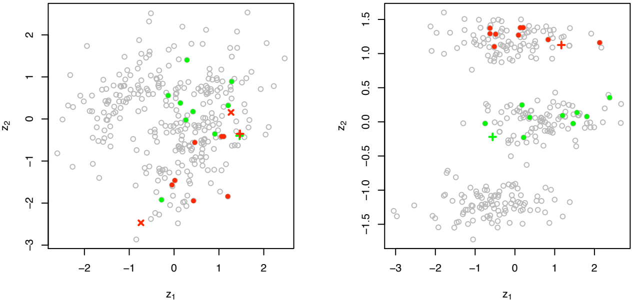
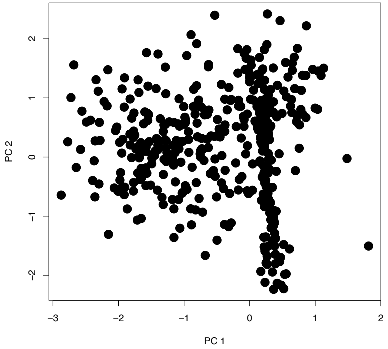


# Mixture PPCA

- What if any single projection through high dimensional data does not reveal structure, i.e., a useful visualization?
- For example:



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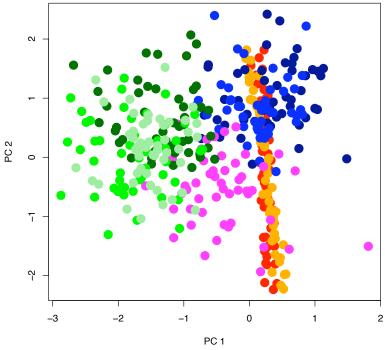
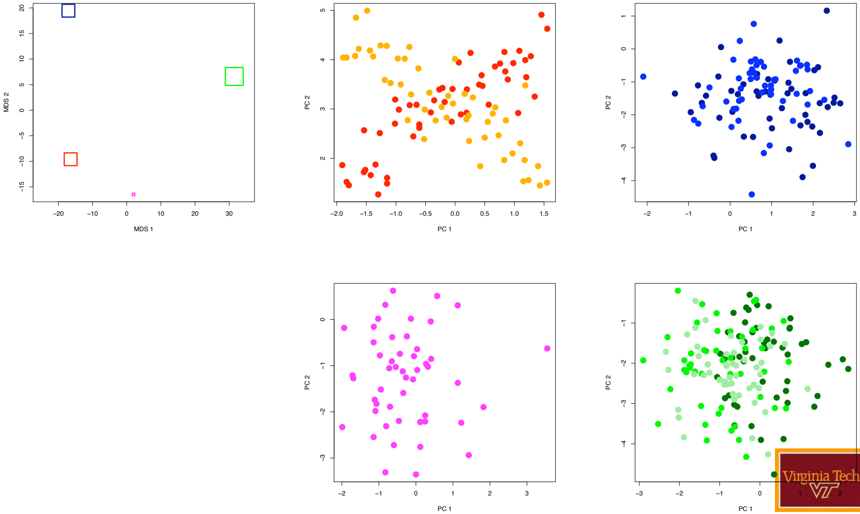


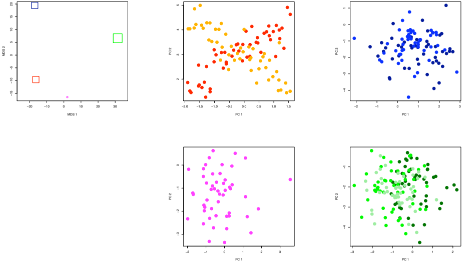
# Motivate Mixture PPCA (Cont.)

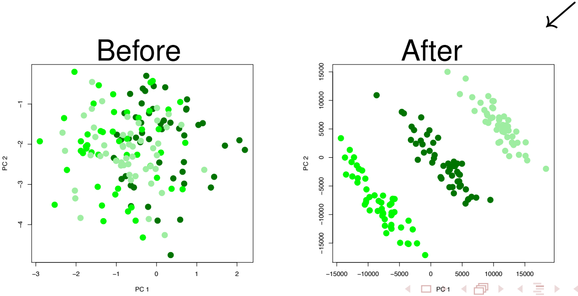
- Perhaps using a mixture of projections is useful.
- For example:



# Mixture PPCA: Use BaVA updating

- Similar to standard PPCA, we update the model based on user feedback
- For example:

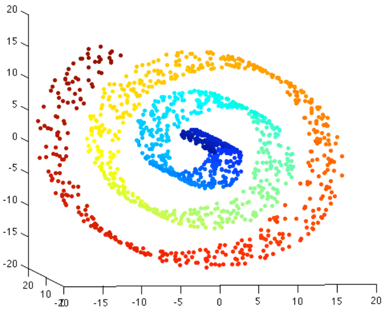




# Mixture PPCA: Movies

[Show Mixture Movie]

# IsoMap




- Complex structure in a (potentially) high dimensional (HD) space

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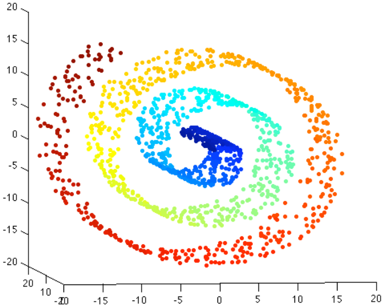
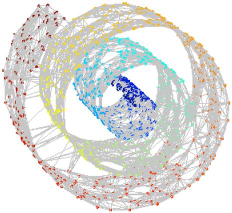



- Complex structure in a (potentially) high dimensional (HD) space
- There exists a manifold in the HD space that can be visualized trivially in 2D

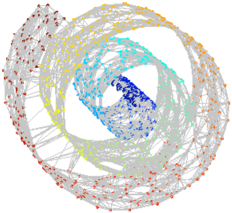
# IsoMap: The Model

- The model consists of a graphical embedding in the HD space



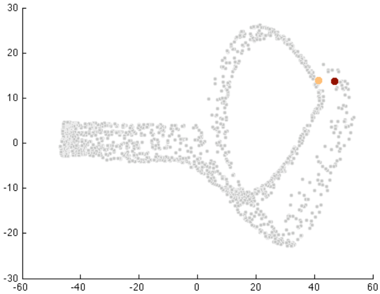
# IsoMap: The Model

- The model consists of a graphical embedding in the HD space
- Edges are constructed via a nearest neighbors (NNs) subroutine, where the number of NNs ($k$) is the typical parametric input



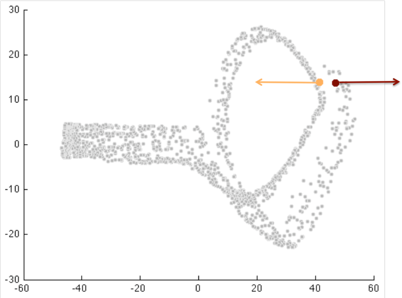
# IsoMap: BaVA Step 2

- Based on a the previous graphical embedding, the visualization follows as:



# IsoMap: BaVA Step 3

- Let the user inject a cognitive adjustment to the visualization



# IsoMap: Visual Updating

- Step 4: A parametric updating to the distance matrix

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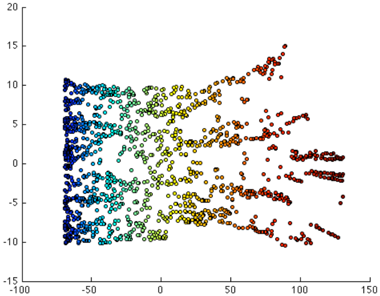
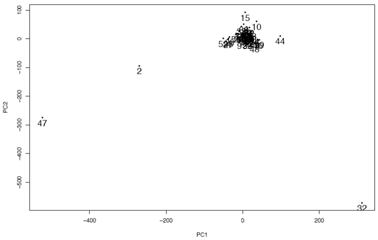
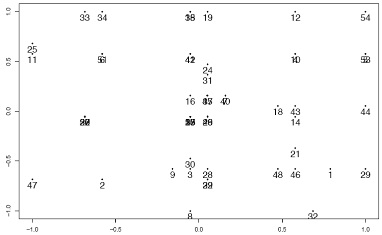
- Step 4: A parametric updating to the distance matrix
- Step 5: Updated the model/visualization



# Generative Topographical Map (GTM)

- PCA often fails because
  - Data features need not correlate with variance
  - Projection methods may not always reveal structure
- GTM is a kernel based neural network that reduces data dimension.
- GTM has lots of tunable model parameters which are difficult to understand by most users.
- PPCA is to PCA as GTM is the Self Organizing Map (SOM)



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[Show GTM Movie]

# Acknowledge


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Thank you!