Bayesian Visual Analytics (BaVA): A Formal Visual Updating Procedure

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> FODAVA Dec 2009



Foraging + Sensemaking



Deep Interaction

User guided modeling, via direct manipulation

Analyst injects domain knowledge into the visualization

The visualization responds meaningfully



Mapping Visual to Model

Natural interaction within the visual metaphor
Level of detail of interactive input control
Visual feedback of underlying model updates



A New Framework...

Beyond the Visualization Pipeline





Outline

- 1. The BaVA process of incorporating visualizable feedback.
- 2. A Cartoon Illustration of the BaVA process
- 3. Formalities
- 4. Insights



The BaVA paradigm is a hierarchical process, entailing 5 layers. Some of these layers will rely on stochastic models, while others might utilize deterministic transformations.



Figure 1: Schematic illustration of the BaVA process.



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Preliminary: Obtain data D, which will in general be high dimensional, and massive in size. Like most analyses, our objective is to find hidden structure, and associations within the data.



Figure 2: Schematic illustration of the BaVA process.





Step 1: From a parameterized mathematical model, $\pi(\boldsymbol{D}|\boldsymbol{\theta})$, which relates relevant unknowns $(\boldsymbol{\theta})$ to the data \boldsymbol{D} , obtain inferences about $\boldsymbol{\theta}$ using Bayes' Theorem: $\pi(\boldsymbol{\theta}|\boldsymbol{D}) = \pi(\boldsymbol{D}|\boldsymbol{\theta})\pi(\boldsymbol{\theta})/\int \pi(\boldsymbol{D}|\boldsymbol{\theta})\pi(\boldsymbol{\theta})d\boldsymbol{\theta}$.



Figure 3: Schematic illustration of the BaVA process.





Step 2: Visualize both data (D) and inferences (θ) (perhaps only a summary: $\hat{\theta}$) in a *meaningful way*.



Figure 4: Schematic illustration of the BaVA process.





Step 3: Allow the user to reconfigure the visualization, in order to express relationships between a small set of objects. We refer to this as *cognitive feedback*.



Figure 5: Schematic illustration of the BaVA process.





Step 4: The information contained in the cognitive feedback is translated (parameterized) back into model parameters (θ). This is referred to as *parametric feedback*, and usually invokes a black-box layer, which does not involve the user.



Figure 6: Schematic illustration of the BaVA process.



Step 5: The parameterized feedback is injected into the system, to provide updated parameter assessments, and subsequently updated visualizations. This relies on the a new iteration of Bayes' Theorem:

 $\pi(\boldsymbol{\theta}|f, v, \boldsymbol{D}) = \pi(f|v, \boldsymbol{\theta})\pi(\boldsymbol{\theta}|\boldsymbol{D}) / \int \pi(f|v, \boldsymbol{\theta})\pi(\boldsymbol{\theta}|\boldsymbol{D})d\boldsymbol{\theta}$, where $f = \{f_p, f_c\}$



Figure 7: Schematic illustration of the BaVA process.



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Step 1: Perform Bayesian analysis to obtain model inferences. For this example, we will focus on projection based clustering (PCA), but will rely on its model based variant Probabilistic-PCA (PPCA) (Tipping and Bishop, 1999).





Step 1: Perform Bayesian analysis.

Step 2: Visualize the inferences. (Project through principal subspace)



Figure 8: RAW PCA projection





Step 2: Visualize the inferences. (Project through principal subspace)



Figure 9: RAW PCA projection

This is really pretty uninformative, but is not unlikely to occur in real applications.



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Step 2: Visualize the inferences.

Step 3: Identify anomalous structure in the visual display.



Figure 10: Identify odd structure





Step 2: Visualize the inferences.

Step 3: Identify anomalous structure in the visual display.



Figure 11: Identify odd structure





Step 3: Identify anomalous structure in the visual display. Supply feedback by adjusting the display



Figure 12: Supply Feedback (Cognitive)





Figure 13: Supply Feedback (Cognitive)

Given the visualization, the user is defining a random variable, governed by a cognitive distribution: $\pi(f_c|v)$.





Step 3: Supply feedback by adjusting the display (Cognitive Feedback) Step 4: Parameterize the feedback



Figure 14: Supply Feedback (Cognitive)

Express a mathematical relationship, between feedback, and parameters: $g(f_p|f_c, \theta)$.





Step 4: Parameterize the feedback Step 5: Update the display.



Figure 15: Sequentially update



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Formalities

Core BaVA steps:

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- 1. Posterior inferences: $\pi(\boldsymbol{\theta}|\boldsymbol{D}) = \pi(\boldsymbol{D}|\boldsymbol{\theta})\pi(\boldsymbol{\theta}) / \int \pi(\boldsymbol{D}|\boldsymbol{\theta})\pi(\boldsymbol{\theta}) d\boldsymbol{\theta}$.
- 2. Visualize: $g(v|\hat{\theta}, D)$, or $g(v|D) = \int g(v|\theta, D) d\theta$.
- 3. Supply Cognitive Feedback: $\pi(f_c|v)$.
- 4. Parameterize Feedback: $g(f_p|f_c, v)$.
- 5. Sequentially update using Bayes' Sequential updating formula:

$$\begin{aligned} \pi(\boldsymbol{\theta}|f, v, \boldsymbol{D}) &= \pi(f|v, \boldsymbol{\theta}) \pi(\boldsymbol{\theta}|\boldsymbol{D}) / \int \pi(f|v, \boldsymbol{\theta}) \pi(\boldsymbol{\theta}|\boldsymbol{D}) d\boldsymbol{\theta} \\ &\propto \pi(f|v, \boldsymbol{\theta}) \pi(\boldsymbol{\theta}|\boldsymbol{D}) \\ &= g(f_p|f_c, \boldsymbol{\theta}) \pi(f_c|v) \pi(\boldsymbol{\theta}|\boldsymbol{D}), \end{aligned}$$

where $f = \{f_p, f_c\}$





Figure 16: a cartoon illustration of the BaVA process







The mathematics suggests an uninteresting projection.



Figure 17: An uninteresting projection







A user keys into interesting structure.



Figure 18: An uninteresting projection





Insights

A user keys into interesting structure and provides feedback.



Figure 19: User provides cognative feedback





Insights

This feedback is parameterized, using information in both the low and high dimensional feature spaces.



Figure 20: Feedback is parameterized

 $\Delta_R^t = [\Delta_{R_x}, \Delta_{R_y}, \Delta_{R_z}]$, is the vector of residues in the high dimensional feature space.









$$f_p =$$

$$(\Delta_R \Delta_R^t)^{[-f_c]} = \begin{pmatrix} (\Delta_{R_x})^{-2f_c} & (\Delta_{R_x} \Delta_{R_y})^{-f_c} & (\Delta_{R_x} \Delta_{R_z})^{-f_c} \\ (\Delta_{R_y} \Delta_{R_x})^{-f_c} & (\Delta_{R_y})^{-2f_c} & (\Delta_{R_y} \Delta_{R_z})^{-f_c} \\ (\Delta_{R_z} \Delta_{R_x})^{-f_c} & (\Delta_{R_z} \Delta_{R_y})^{-f_c} & (\Delta_{R_z})^{-2f_c} \end{pmatrix}$$

 $g(f_p|\Sigma, f_c) = \mathsf{Inv-Wish}(f_p|\Sigma)$





Insights

The new principal directions corresponding to the parameterized feedback matrix $f_p = (\Delta_R \Delta_R^t)^{[-f_c]}$ are displayed.







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The system is sequentially updated



Figure 21: Feedback is parameterized





The system is sequentially updated

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Figure 22: Feedback is parameterized

$$\begin{aligned} \pi(\boldsymbol{\theta}|f, v, \boldsymbol{D}) &= \pi(f|v, \boldsymbol{\theta}) \pi(\boldsymbol{\theta}|\boldsymbol{D}) / \int \pi(f|v, \boldsymbol{\theta}) \pi(\boldsymbol{\theta}|\boldsymbol{D}) d\boldsymbol{\theta} \\ &\propto \pi(f|v, \boldsymbol{\theta}) \pi(\boldsymbol{\theta}|\boldsymbol{D}) \\ &= g(f_p|f_c, \boldsymbol{\theta}) \pi(f_c|v) \pi(\boldsymbol{\theta}|\boldsymbol{D}), \end{aligned}$$





Demonstration

Enough already. Does this actually work??



Summary:

- Motivation (Chris)
- BaVA process (Scotland)
- Proof of concept by demo (Leanna)



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- Goal: Generalize BaVA to update any visualization
- Fine tune PPCA to assess complex, large datasets
- Develop BaVA methods for different types of models e.g., tree diagrams, graphical models
- Develop meaningful visualizations that relate to update-able parameters
- Test our tool at PNNL with real analysts



Thank you very much

