Data Analysis Methods

Successes, Opportunities, and Challenges

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The Astro/Data Science Community

LSST Informatics and Statistics Science Collaboration
Over 75 Members

International Astrostatistics Association
Over 400 Members

American Stat. Assoc. Astrostatistics Interest Group
Over 50 Members

Individuals motivated by **advancing science with novel data analysis tools**
Success Story: MCMC in Cosmology

Markov Chain Monte Carlo (MCMC) - Class of methods for parameter estimation, approximation of posterior

Algorithms date to mid-20th Century, but development took off in Statistics during 1990s

By the 2000s, MCMC playing key role in cosmology, including WMAP analysis. (Spergel 2013)

Focus on development of resources for MCMC in cosmology (e.g., CosmoMC)
Success Story: Redshift Estimation

Estimation of Redshifts using Photometry - Crucial challenge faced by photometric surveys

Range of methods proposed and attempted, using training sets built from spectroscopic samples.

Graham, et al. (2017): “Photometric redshifts are an essential part of every cosmological science goal of the LSST.”
Success Stories

What do these successes have in common?

Smaller gap between existing, advanced methods and the application

- **MCMC** naturally addressed challenges of estimation of cosmological parameters with CMB
- **Photometric redshift estimation** can be viewed as a standard supervised learning problem

In both cases the methodology is crucial to the science
The Potential

Theme: Making full use of data from large surveys

Sample size alone does not quantify information content.

More data reduces variance, **better modelling** reduces bias.

Specific areas for potential gains:

- Information preservation when “representing” raw data
- Improved propagation of errors
- Lessening bias from incorrect distributional assumptions
- Joint analyses of data sets
Example: Filament Catalog

Chen, et al. (2015): Density ridges in galaxy map lead to finding **filamentary structure**

**SDSS filament catalog:** [https://sites.google.com/site/yenchicr/catalogue](https://sites.google.com/site/yenchicr/catalogue)

Plans to create for LSST
Example: Filament Catalog

Example of **complex data representation**

**Nonparametric** - Does not make restrictive assumptions

Emphasis on **error quantification**

**Broad Potential:** Create catalogs of rich scientific information, avoiding overcompression
Example: Model Misspecification Bias

Long (2017): Improving period estimation from light curves through better adjustment for measurement errors

Models for light curves **misspecified**, but period estimates remain accurate

**Broad Potential:** Accept that models are incorrect, bias can be reduced through error quantification

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**Figure 1.** (a) SDSS-III RR Lyrae light curve. (b) Folded light curve (x-axis is time modulo period) after estimating the period using the data in (a).
Example: Variational Inference


Variational inference approximates posterior when using models of such complexity

Instead, we use optimization to find a distribution that best approximates the posterior. For any distribution \( q \) over \( \Theta \),

\[
\log p(x) \geq E_q[\log p(x, \Theta)] - E_q[\log q(\Theta)] =: \mathcal{L}(q). \tag{21}
\]

Here \( E_q \) is expectation with respect to \( q \). We call \( \mathcal{L} \) the evidence lower bound (ELBO). To find a distribution \( q^* \) that approximates the exact posterior, we maximize the ELBO over a set \( \mathcal{Q} \) of candidate \( q \)'s. We restrict \( \mathcal{Q} \) to distributions of the factored form

\[
q(\Theta) = \prod_{s=1}^{S} q(a_s)q(r_s|a_s)q(k_x|a_x) \prod_{b=1}^{B-1} q(c_{sb}|a_s). \tag{23}
\]
Example: Variational Inference

Reiger, et al. (2015): Multiparameter, hierarchical **generative model** for pixel intensity from a star/galaxy

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Here \( E_q \) is expectation with respect to \( q \). We call \( \mathcal{L} \) the evidence lower bound (ELBO). To find a distribution \( q^* \) that approximates the exact posterior, we maximize the ELBO with respect to \( q \). This leads to factorizations of the factored form

\[
q(\Theta) = \prod_{s=1} q(a_s)q(r_s|a_s)q(k_s|a_s) \prod_{b=1} q(c_{sb}|a_s). \tag{23}
\]

**Broad Potential:** Variational inference could enable more realistic model fits
Example: Light Curve Classification


**Bootstrap sampling** of models fit to light curves in order to assess stability of features

**Probabilistic classification** based on feature uncertainty

**Broad Potential:** Quantification of uncertainty crucial in classification
Example: Likelihood Free Inference

Hahn, et al. (2017): “Approximate Bayesian computation in large-scale structure.”

Complexity of LSS makes impossible writing likelihood function of sufficient accuracy.

ABC offers approach which circumvents likelihood

**Broad Potential:** Errors in likelihood are magnified with large samples, esp. comparing simulations and data
The Examples

What do the examples have in common?

The shift from the *variance-dominated era* to the *bias-dominated era* requires careful thought about methods, not just the scaling of existing methods.

The gap from method to application is larger, and requires

- adaptation of existing methods
- deep knowledge of application
- expertise on both data science and astronomy sides
Barriers to Progress

Complexities
Communication
Computations
Compensation
Why am I here?

Working to **close the gap**

Increased role in this discussion

Data analysis tools as a **crucial community resource**

Start of work towards a community white paper

Massive, rich data sets are an huge opportunity, but reaching full potential requires **avoiding overcompression** and **adequate modelling**
References


Graham, et al. (2017) arXiv 1706.09507

