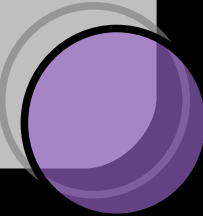




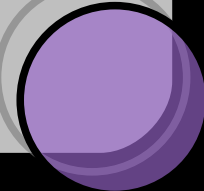
**Christopher J. Miller**  
**Asst. Professor,**  
**Astronomy**

**Computational,  
Statistical, and  
Mathematical  
Challenges in  
Astronomy**



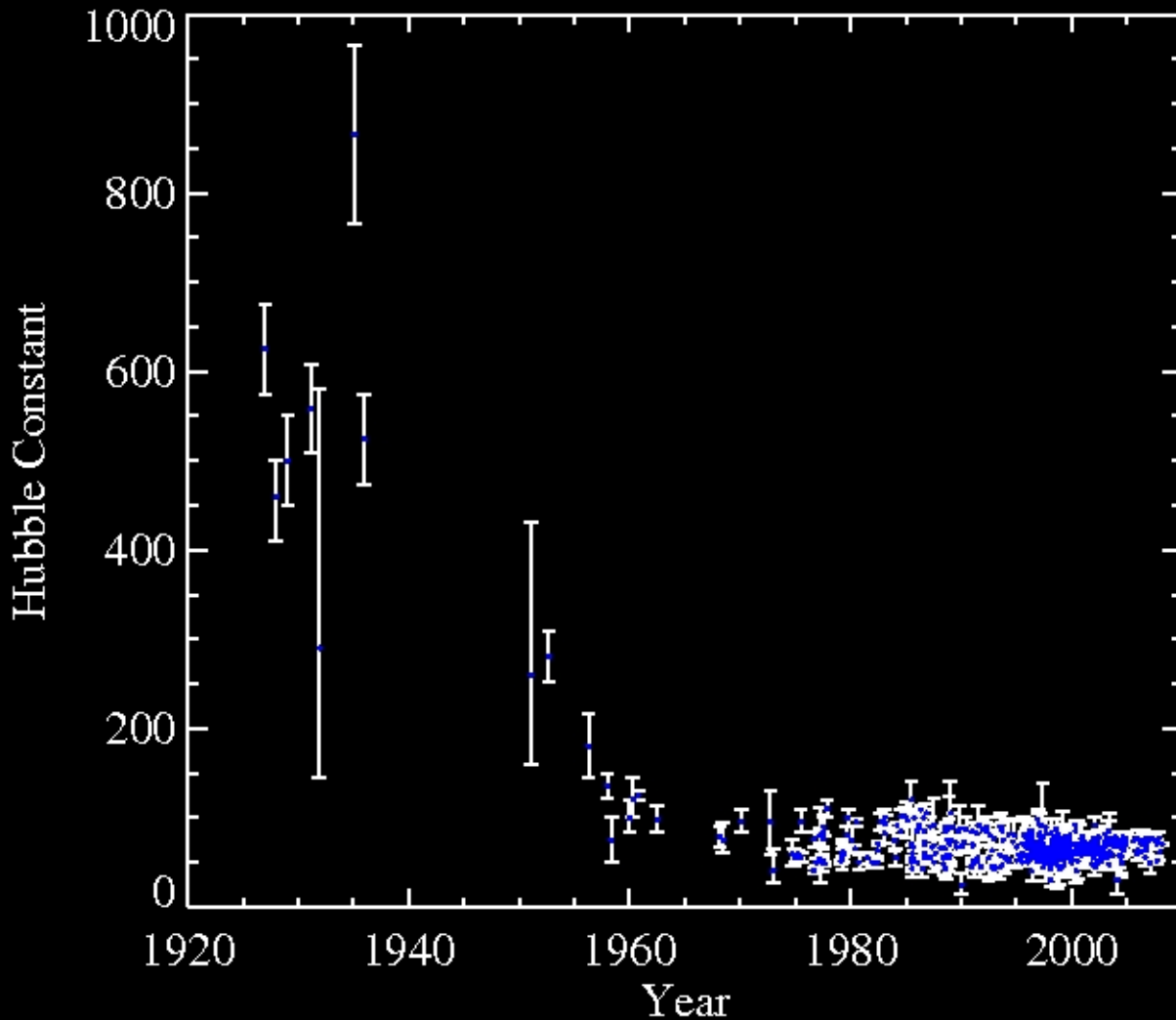
# The Challenges

- **The Demand for Higher Precision Science**
  - The Hubble Constant

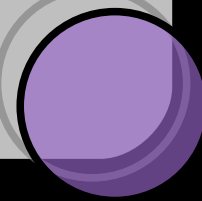


# The Challenges

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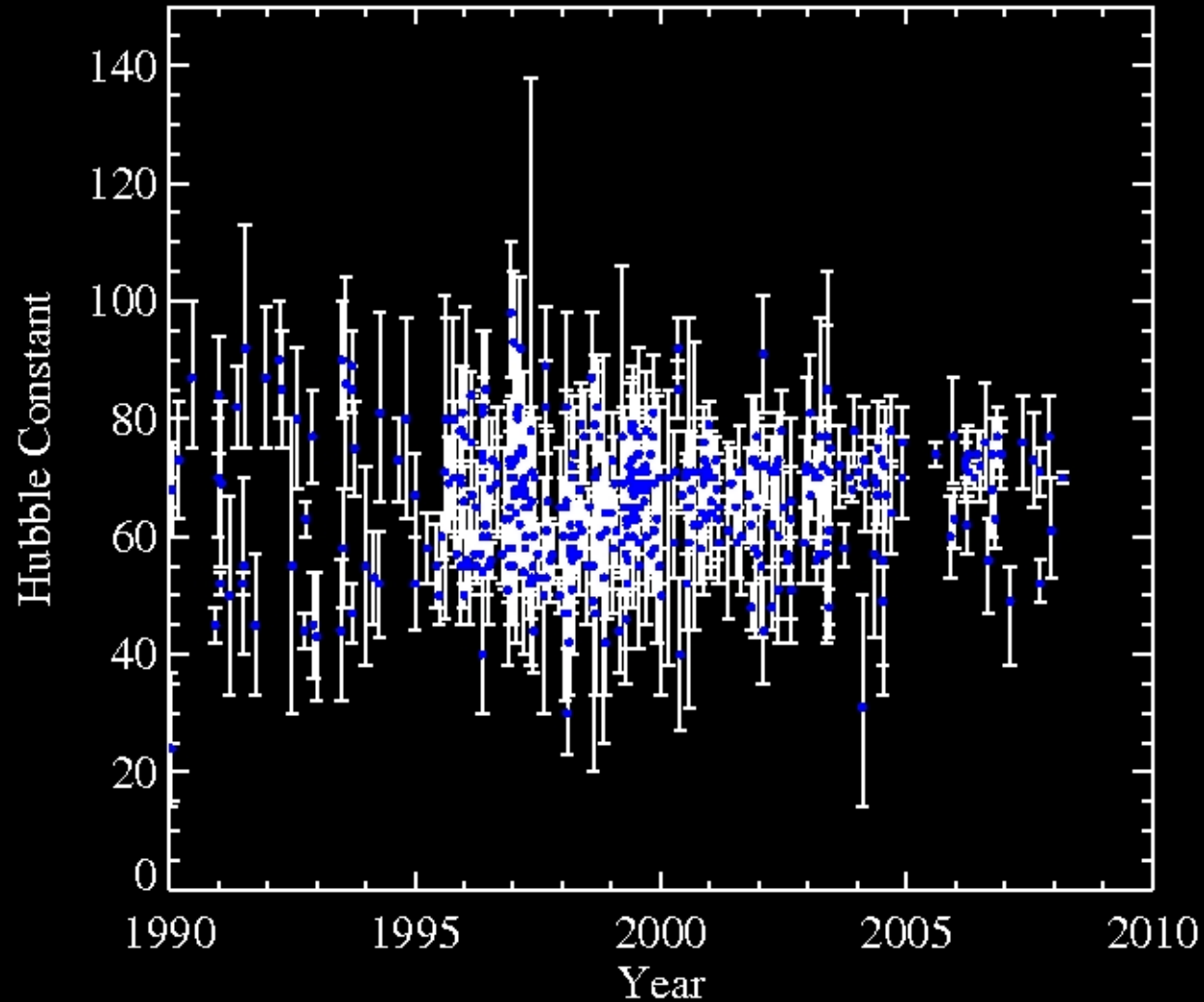


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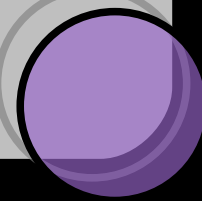


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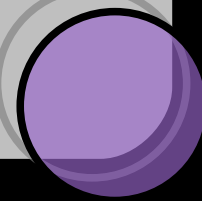


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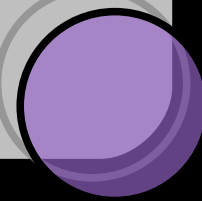
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- **The Demand for Higher Precision Science**
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  - One of dozens of Cosmological Parameter

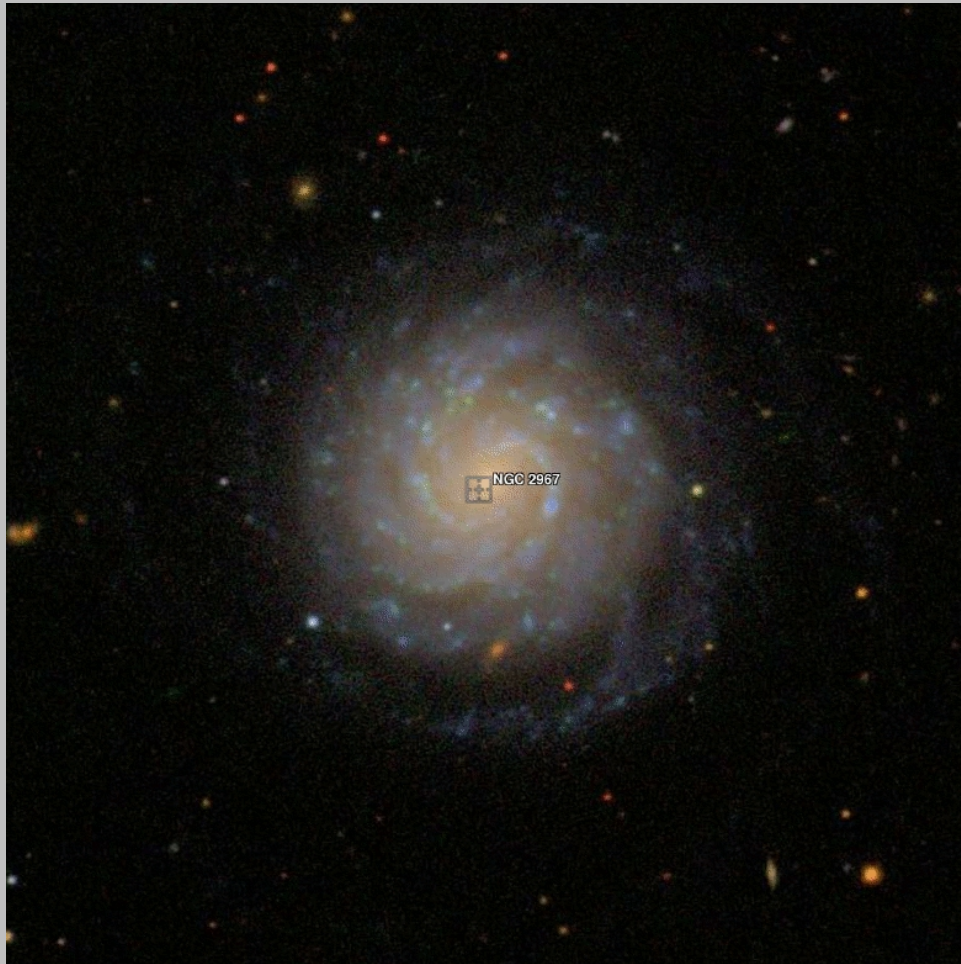


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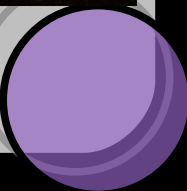
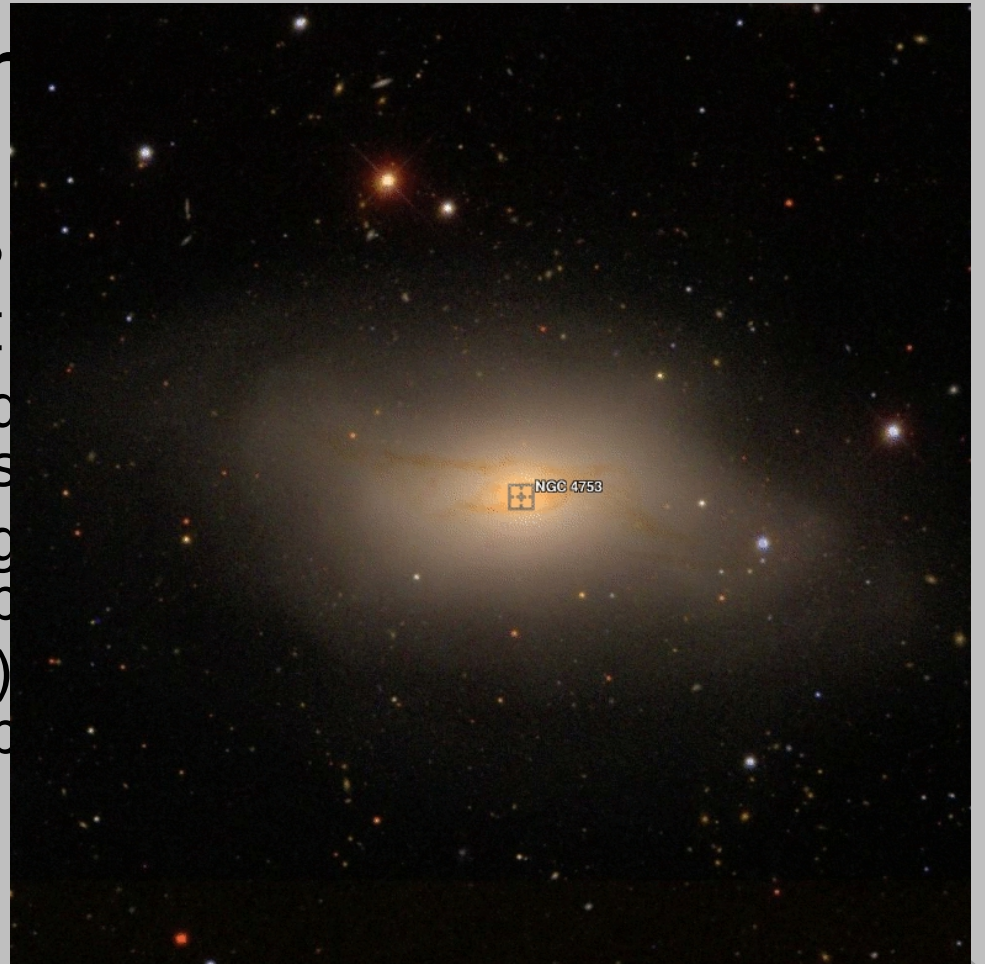
- **The Demand for Higher Precision Science**
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  - One of dozens of Cosmological Parameters
  - There is more to astronomy than cosmology
    - Galaxies have mass and stellar populations with ages, metallicities, star formation histories



# The Challenges



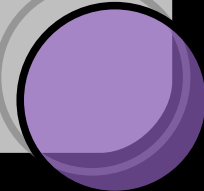
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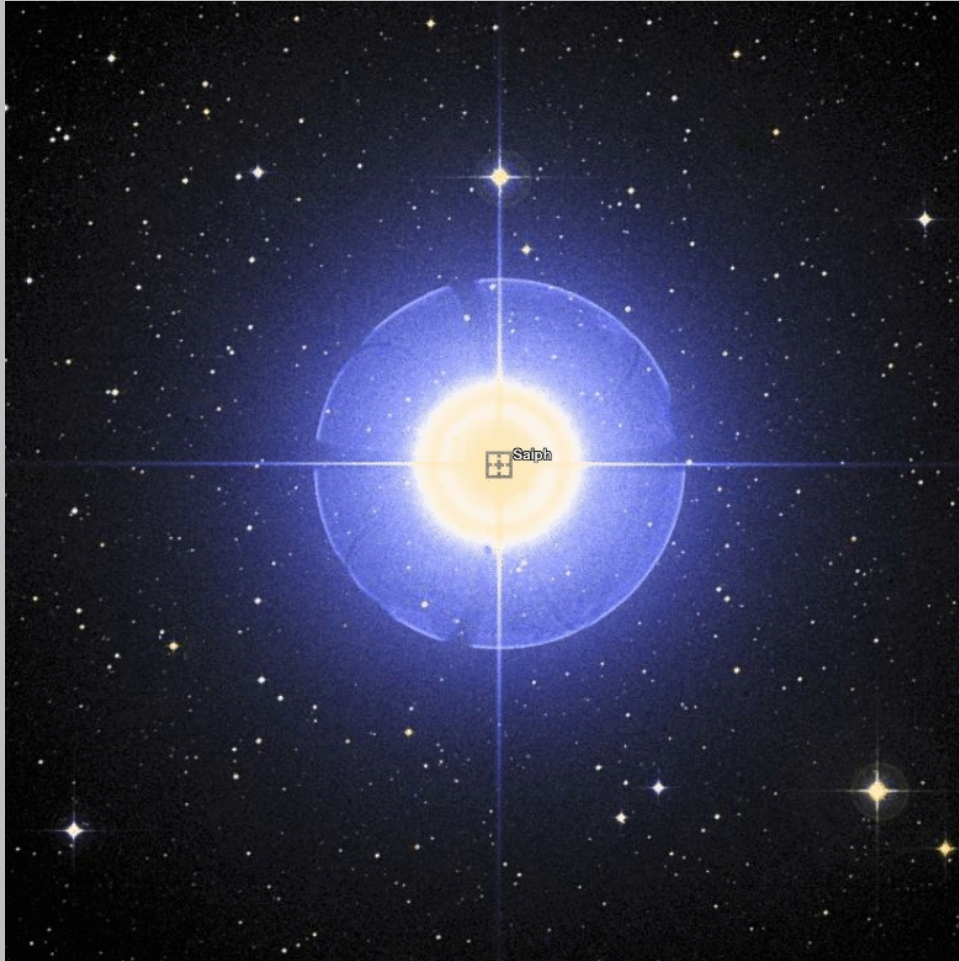


# The Challenges

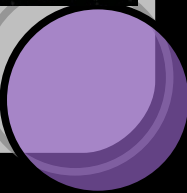
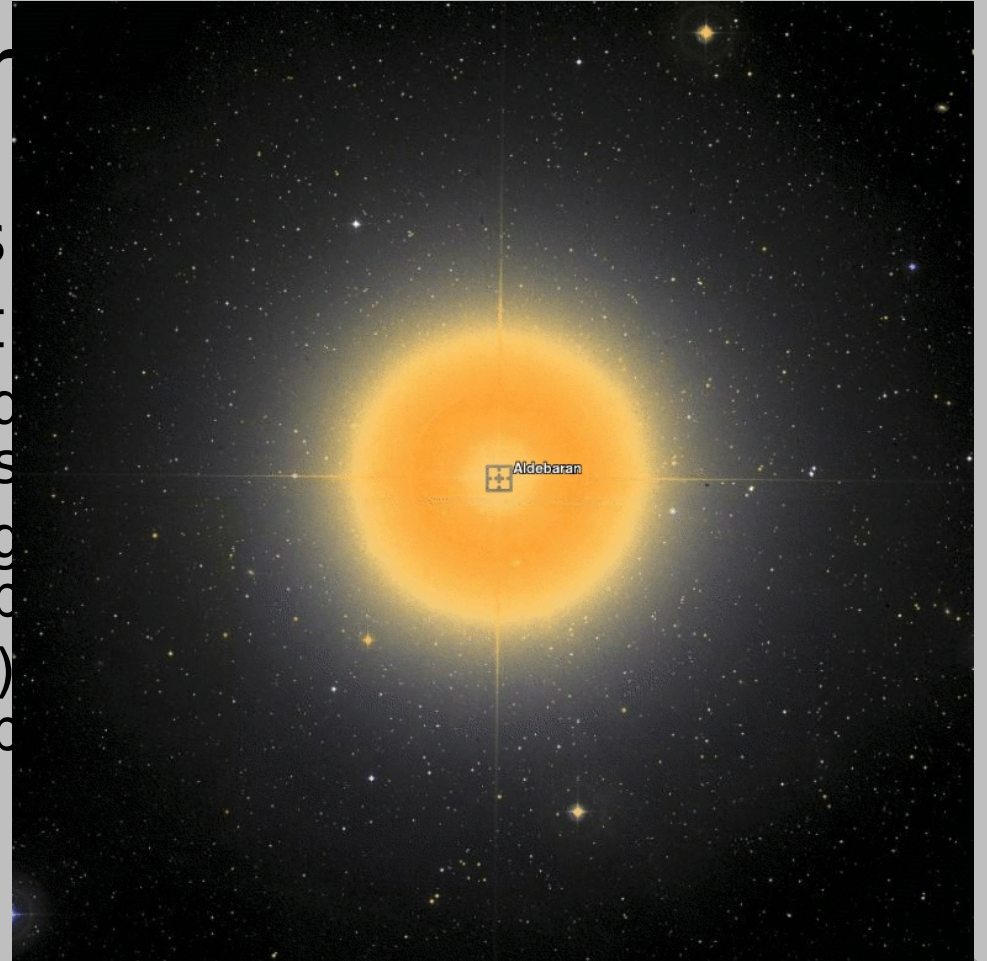
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    - Stars (which make up galaxies) have mass, temperatures, ages, abundances



# The Challenges

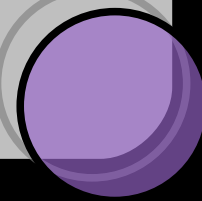


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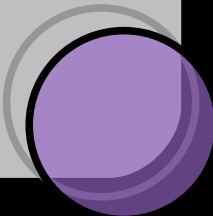
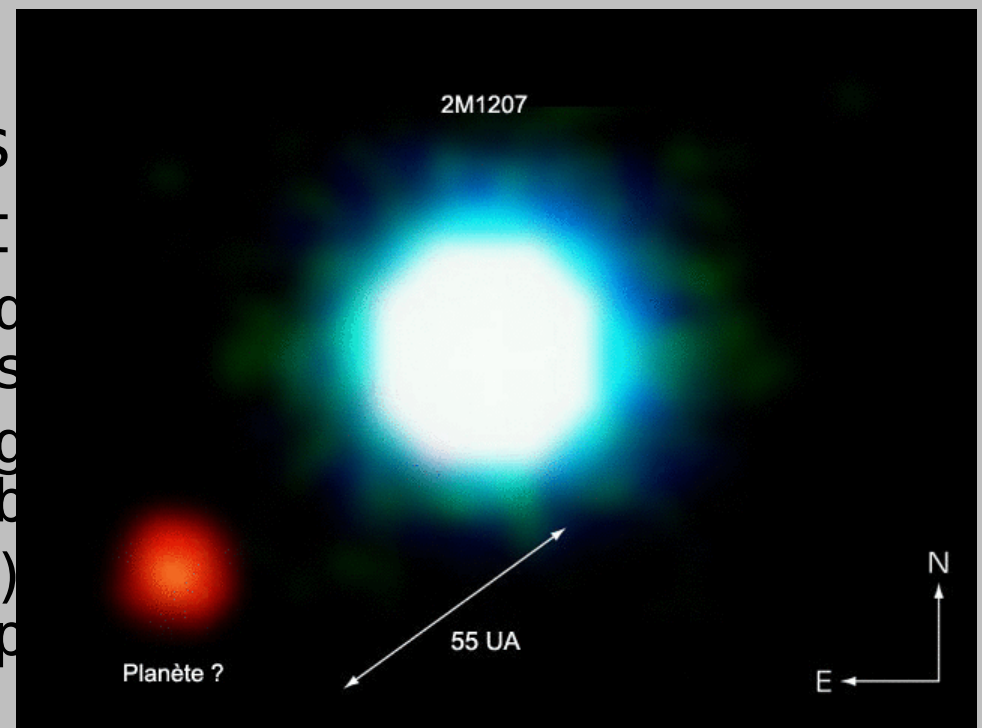
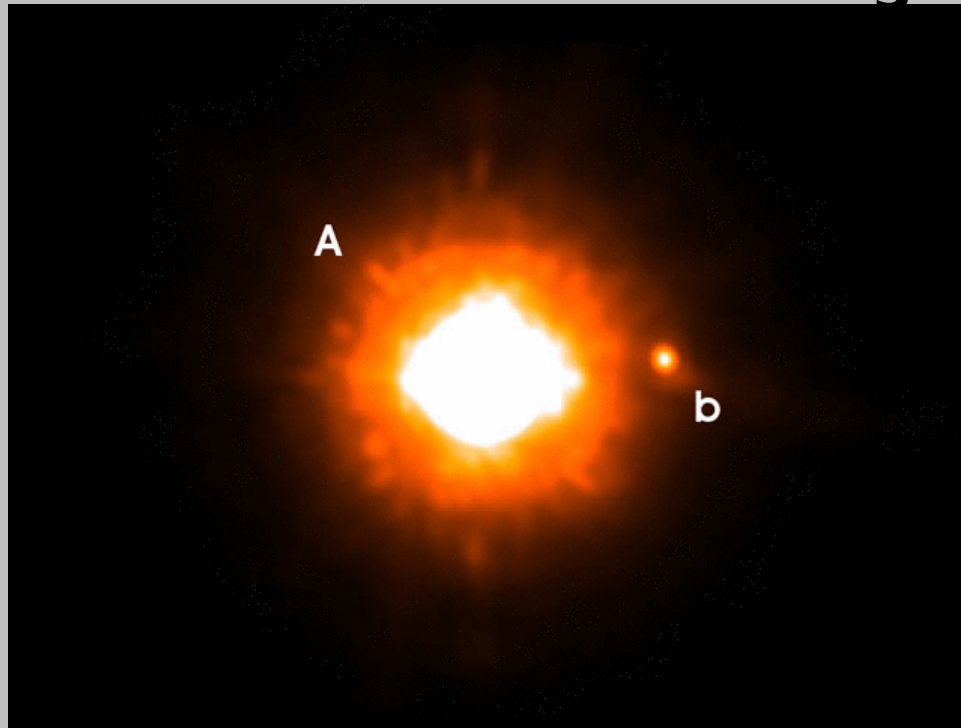
# The Challenges

- **The Demand for Higher Precision Science**
  - The Hubble Constant
  - One of dozens of Cosmological Parameters
  - There is more to astronomy than cosmology
    - Galaxies have mass and stellar populations with ages, metallicities, star formation histories
    - Stars (which make up galaxies) have mass, temperatures, ages, abundances
    - Planets (around stars) have masses, compositions, atmospheres, orbital parameters



# The Challenges

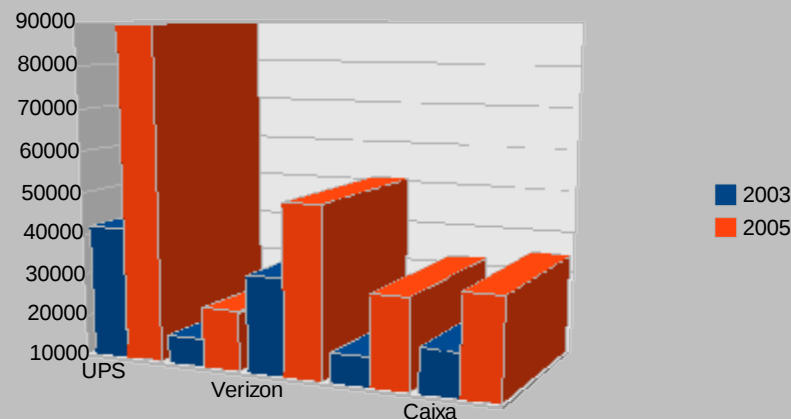
- The Demand for Higher Precision Science



# The Challenges

## • The “Data Flood”

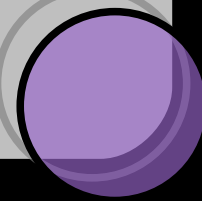
- Astronomical catalogs today contain about 1.5 billion objects (SDSS is ~300 million, IRSA is ~1 billion).
  - A factor of 20 smaller than the largest commercial DBs
- LSST (~2020) will have ~50 billion objects
  - Large by today's standards. But average (or even small) by 2015
- Astronomy has “Real World” DB challenges



Data volumes grow as well.....20 times increase from 2003-2005

# The Challenges

- **Astronomy Data is Distributed**

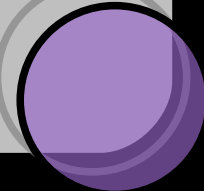


# The Challenges



# The Solutions

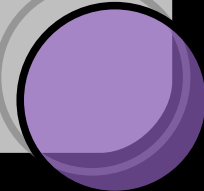
- Astronomical data creates opportunities for Computer Science, Information Technologies, and Statistics
  - **Astronomy** provides the (interesting) datasets, the distributed network, and the scientific questions
  - **IT** connects the network
  - **CS** handles the datasets and algorithms
  - **MATHEMATICS** and **STATISTICS** quantifies the answers



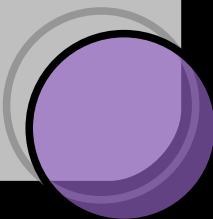
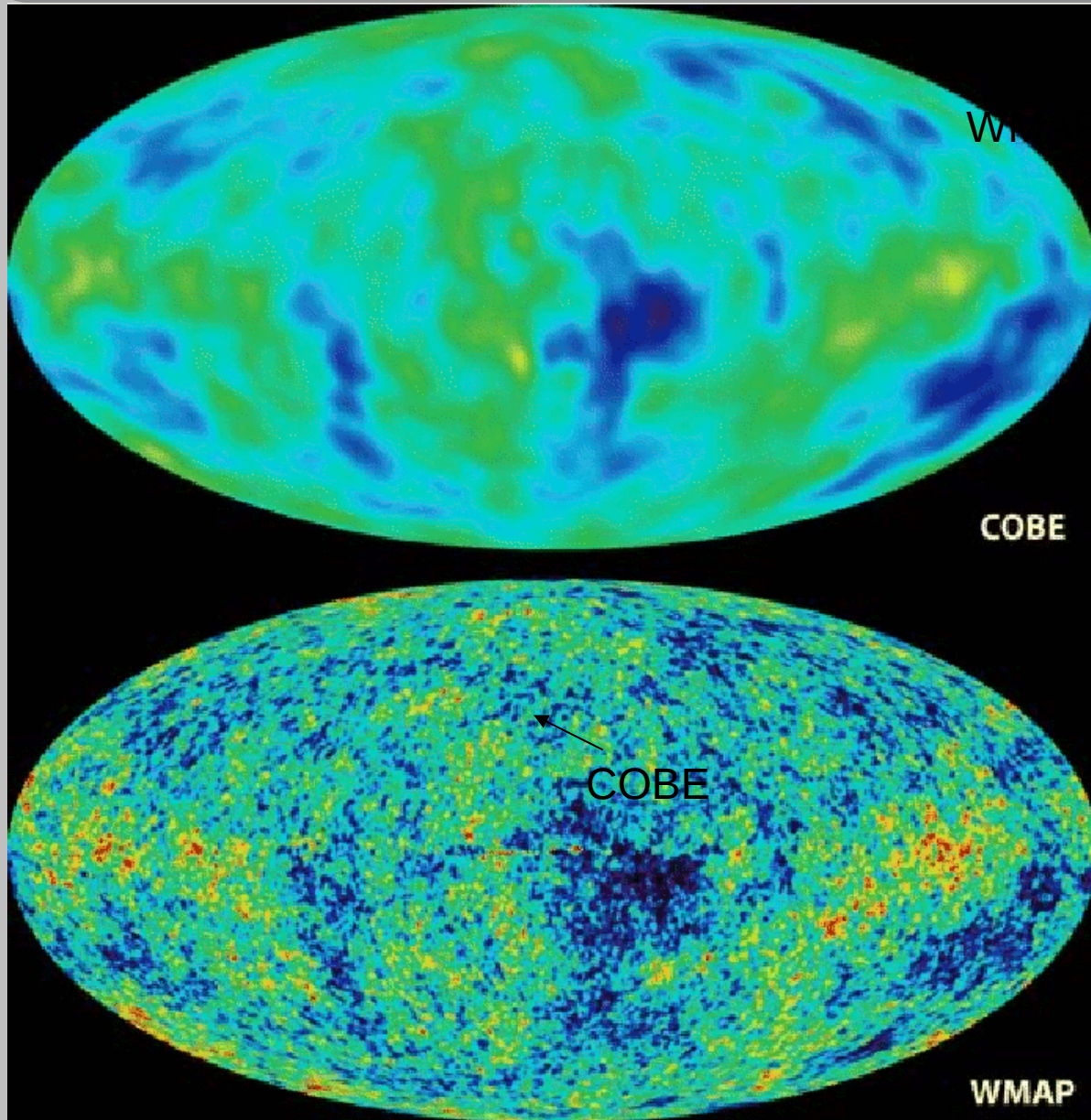


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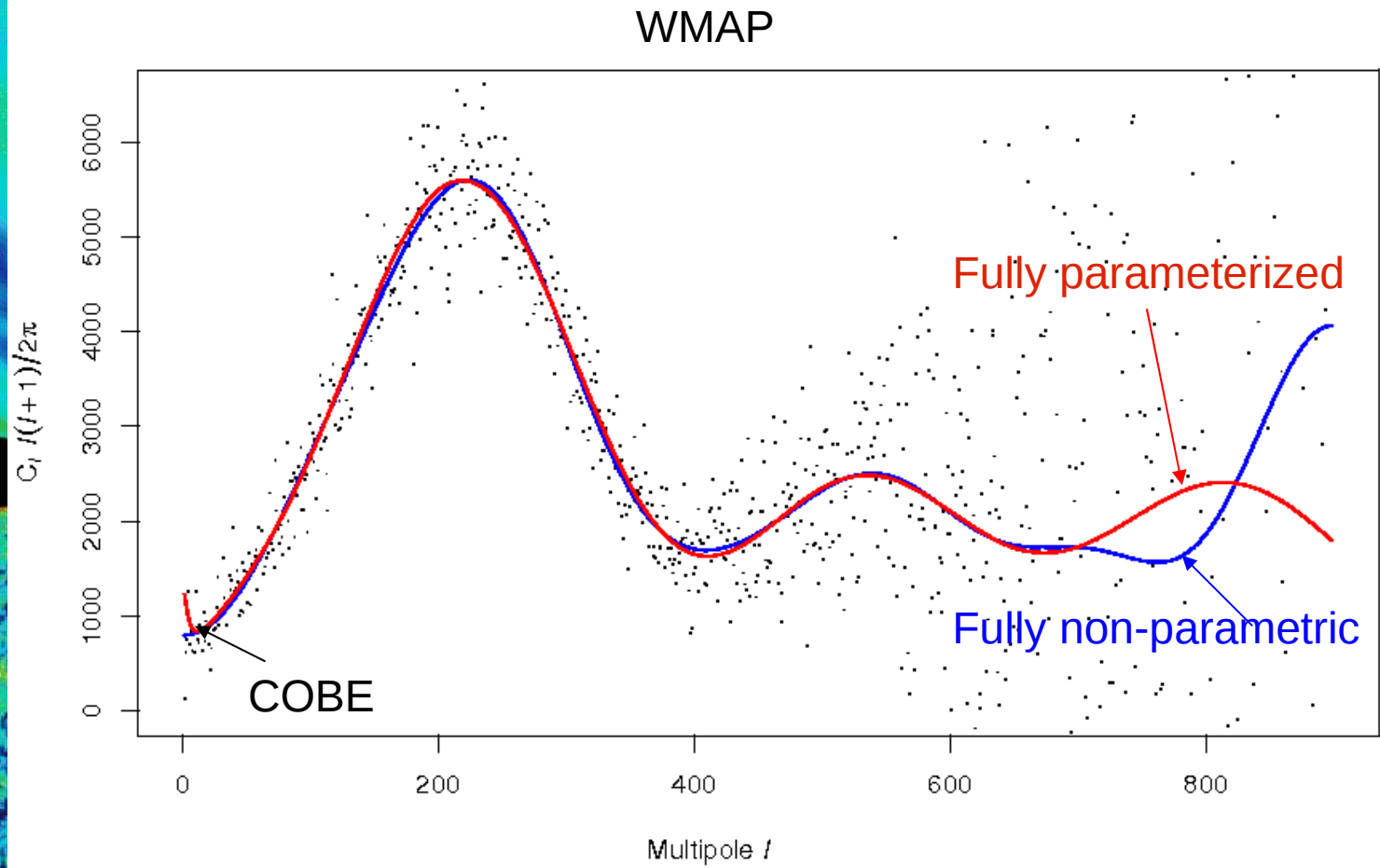
- Possible Detection of Baryonic Fluctuations in the Large-Scale Structure Power Spectrum: Miller, Nichol, Batuski 2001, ApJ
- Acoustic Oscillations in the Early Universe and Today: Miller, Nichol, Batuski 2001, Science
- Controlling the False Discovery Rate in Astrophysical Data Analysis: Miller, Genovese, Nichol, Wasserman, Connolly Reichart, Hopkins, Schneider, Moore, 2001 AJ
- A new source detection algorithm using FDR Hopkins, Miller, Connolly, Genovese, Nichol, Wasserman, 2002 AJ
- A non-parametric analysis of the CMB Power Spectrum Miller, Genovese, Nichol Wasserman, ApJ
- Non-parametric Inference in Astrophysics, Wasserman, Miller, Nichol, Genovese, Jang, Connolly, Moore, Schneider, 2002
- Detecting the Baryons in Matter Power Spectra Miler, Nichol, Chen 2002 ApJ
- Galaxy ecology: groups and low-density environments in the SDSS and 2dFGRS Balogh, Eke, Miller, Gray et al. 2002, MNRAS
- The Clustering of AGN in the SDSS Wake, Miller, Di Matteo, Nichol, Pope, Szalay, Gray, Schnieder, York 2004 ApJ
- Nonparametric Inference for the Cosmic Microwave Background Genovese, Miller, Nichol, Arjunwadkar, Wasserman. 2004 Annals of Statistics
- The C4 Clustering Algorithm: Clusters of Galaxies in the SDSS Miller et al. 2005 AJ
- The Effect of Large-Scale Structure on the SDSS Galaxy Three-Point Correlation Function Nichol et al. 2006, MNRAS
- Mapping the Cosmological Confidence Ball Surface Bryan, Schneider, Miller, Nichol, Genovese, Wasserman, 2007 ApJ
- Inference for the Dark Energy Equation of State Using Type Ia SN data Genovese, Freeman, Wasserman, Nichol, Miller 2008, Annals of Statistics



# Example: Non-parametric fits of the CMB

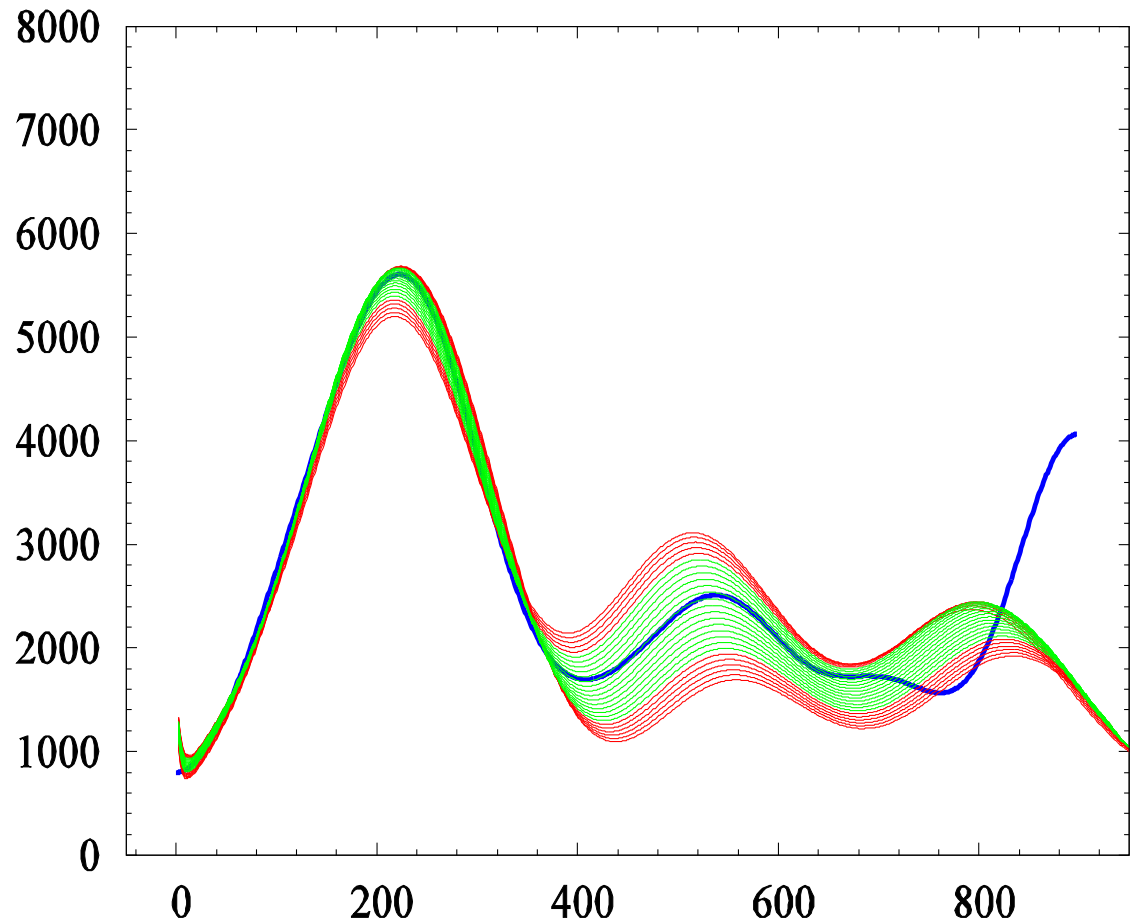
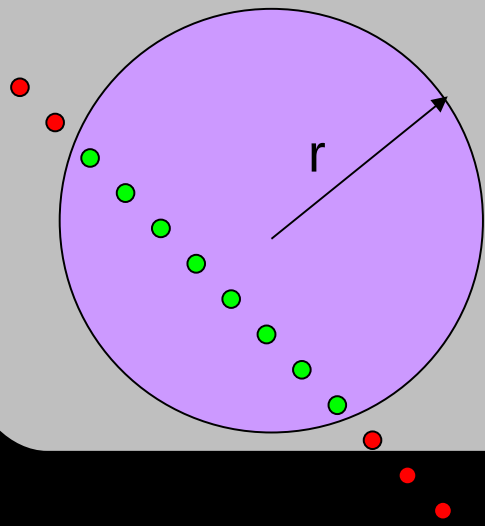


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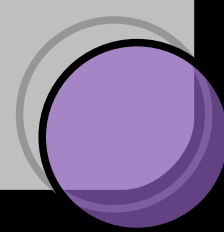
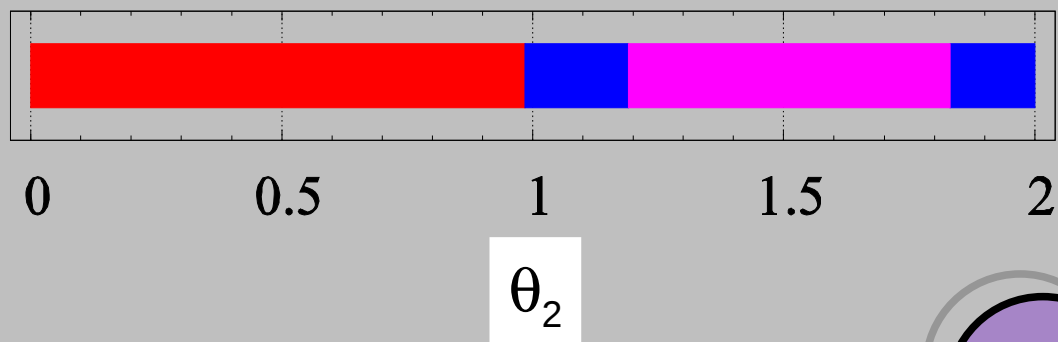
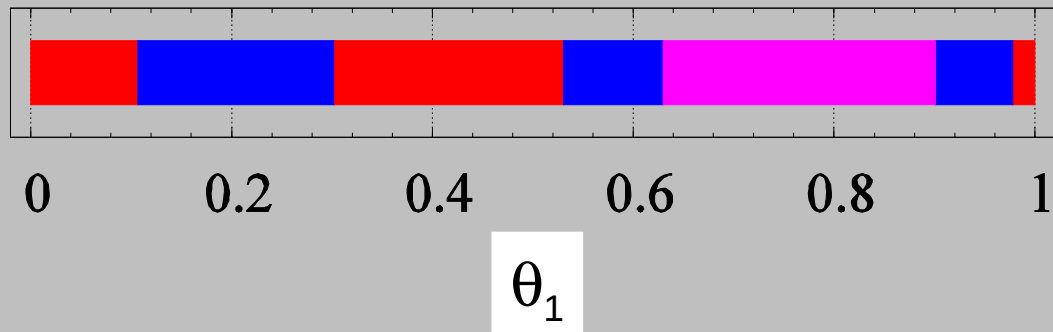
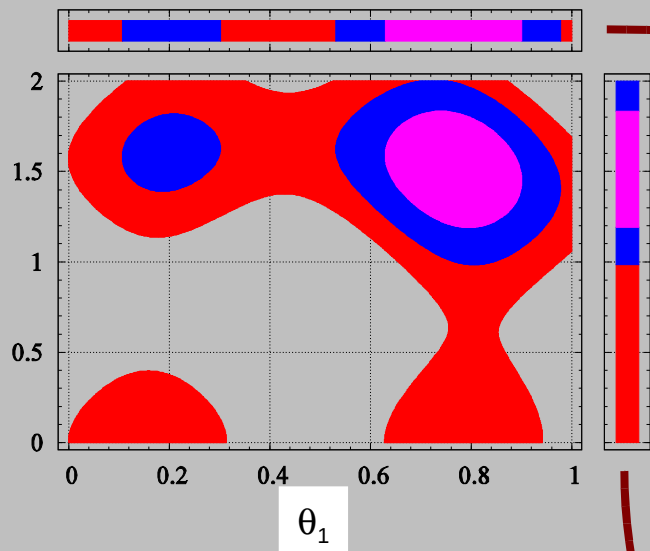


# Confidence Balls: Pictorially

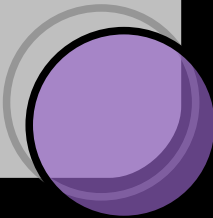
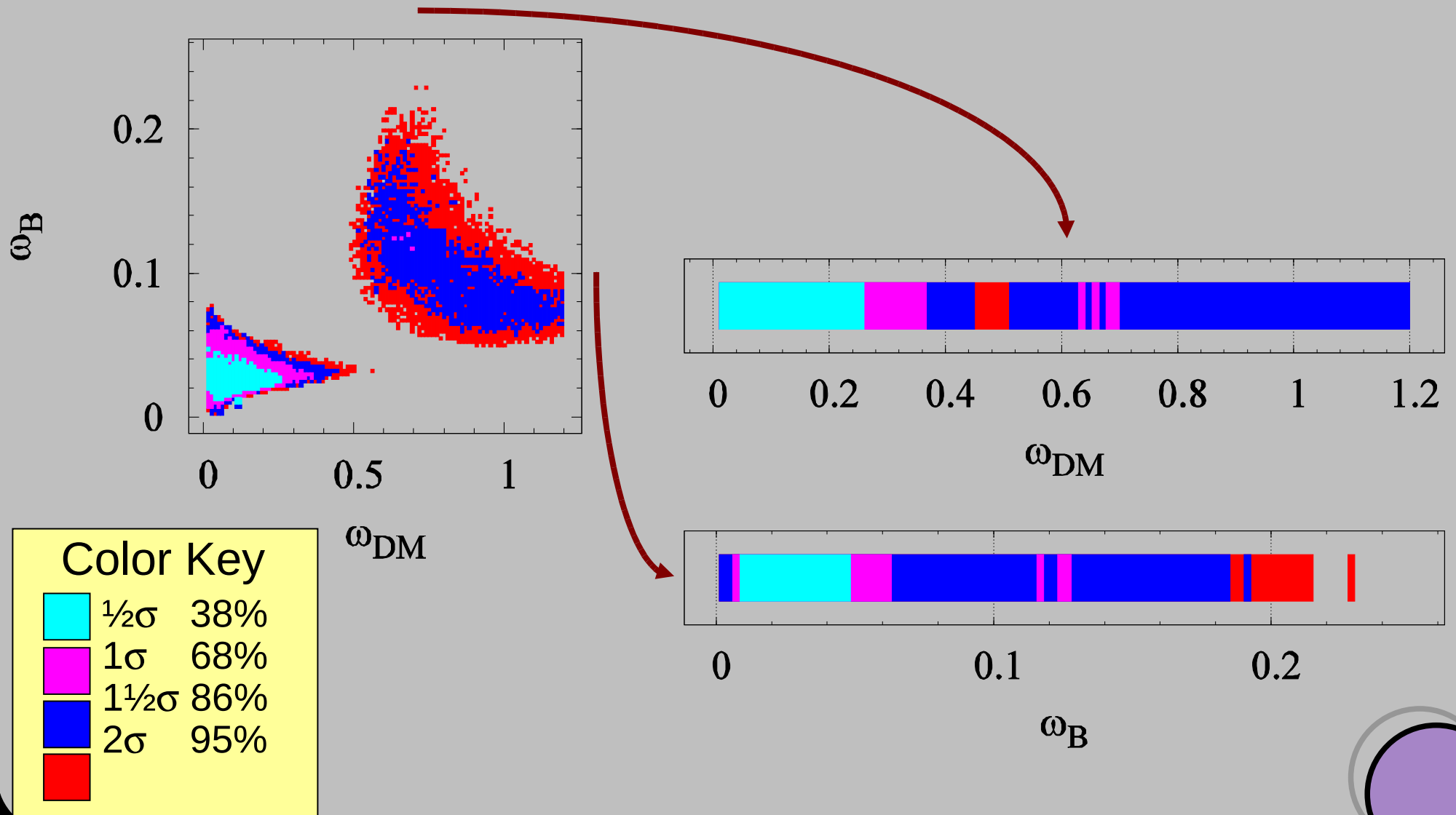
1. obtain experimental data
2. compute non-parametric fit
3. compute confidence ball
4. Iterate through parameters to determine confidence.



# Deriving Confidence Intervals

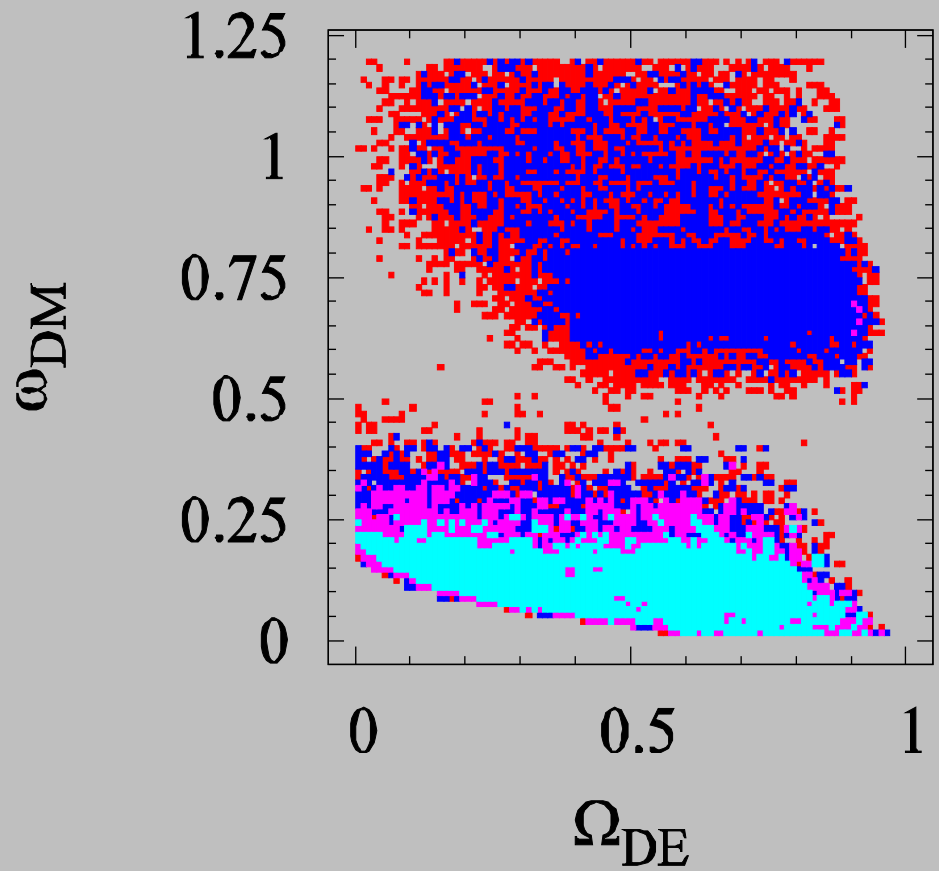
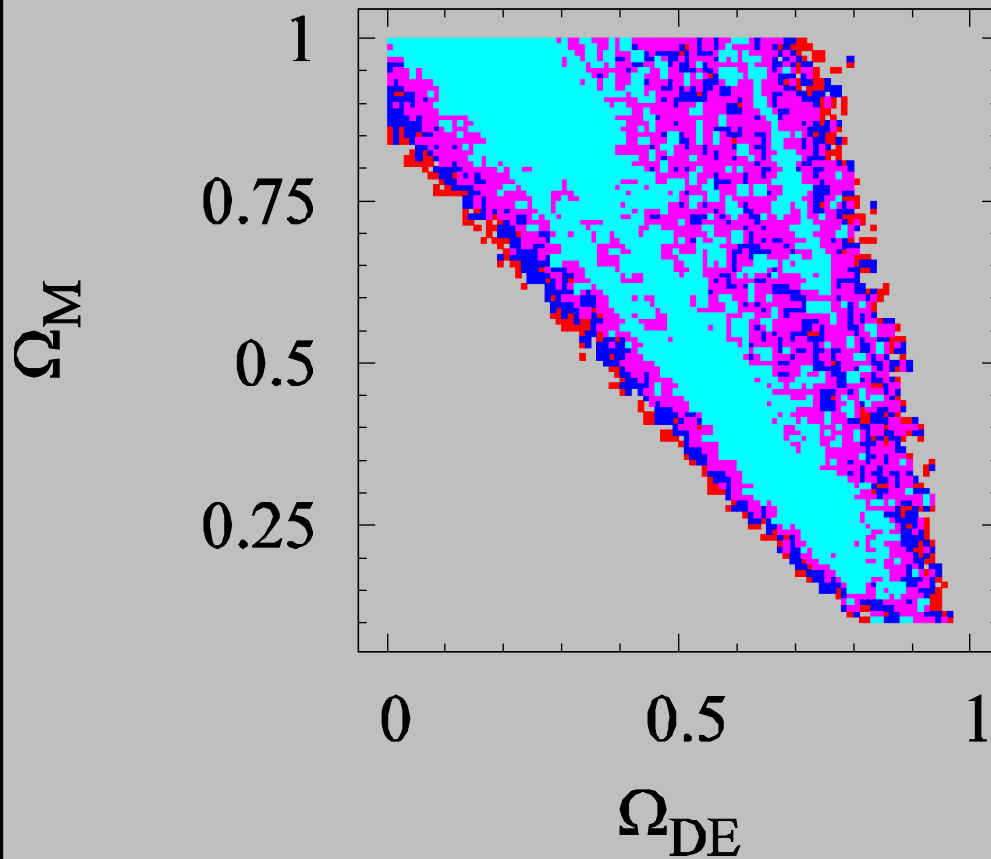


# Cosmological Confidence Intervals



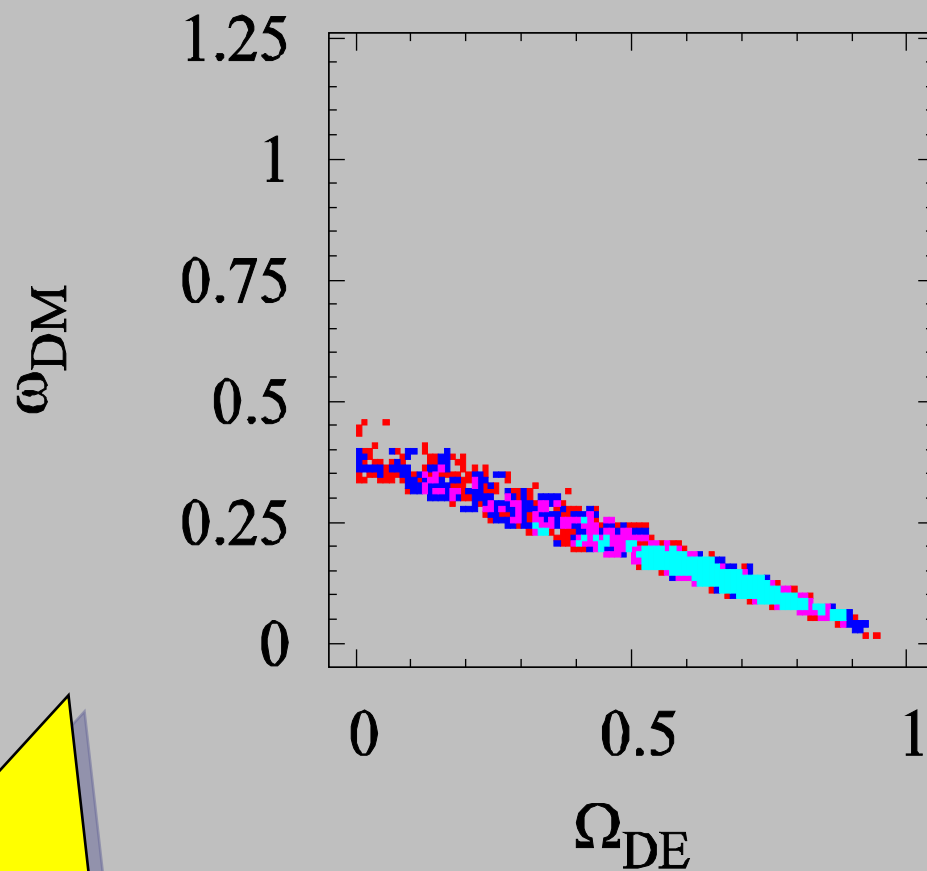
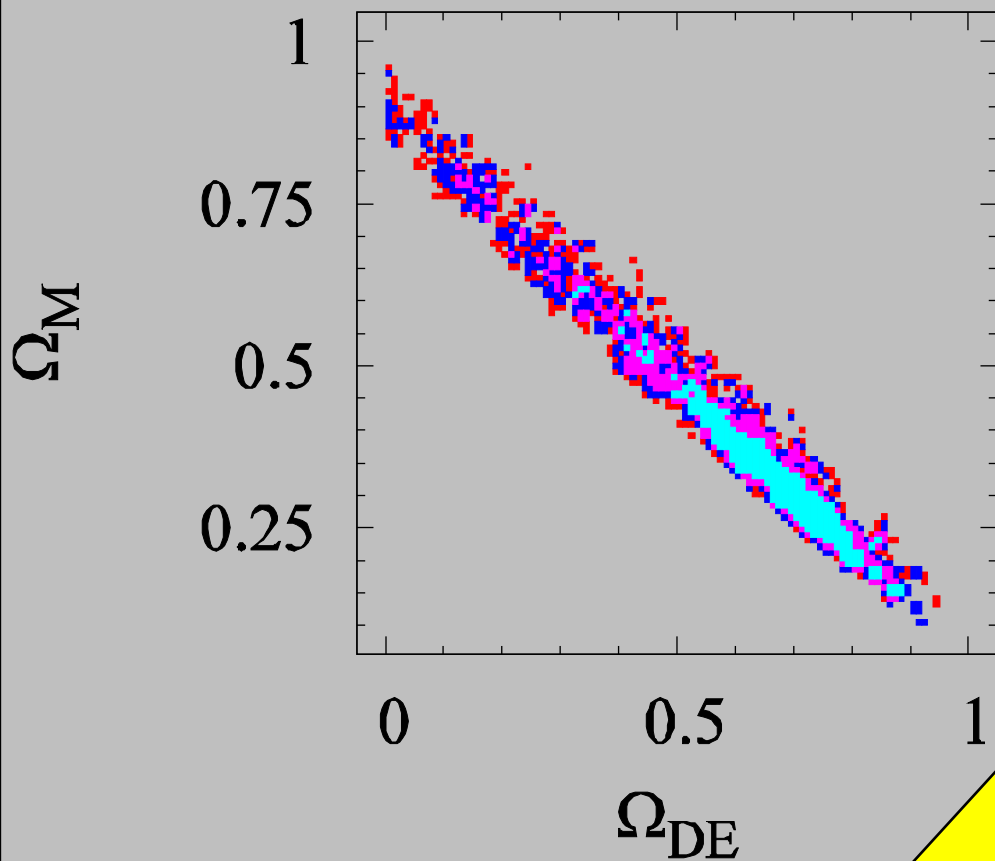
# Including Assumptions

(Bryan et al., ApJ 2007)

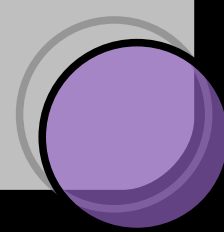


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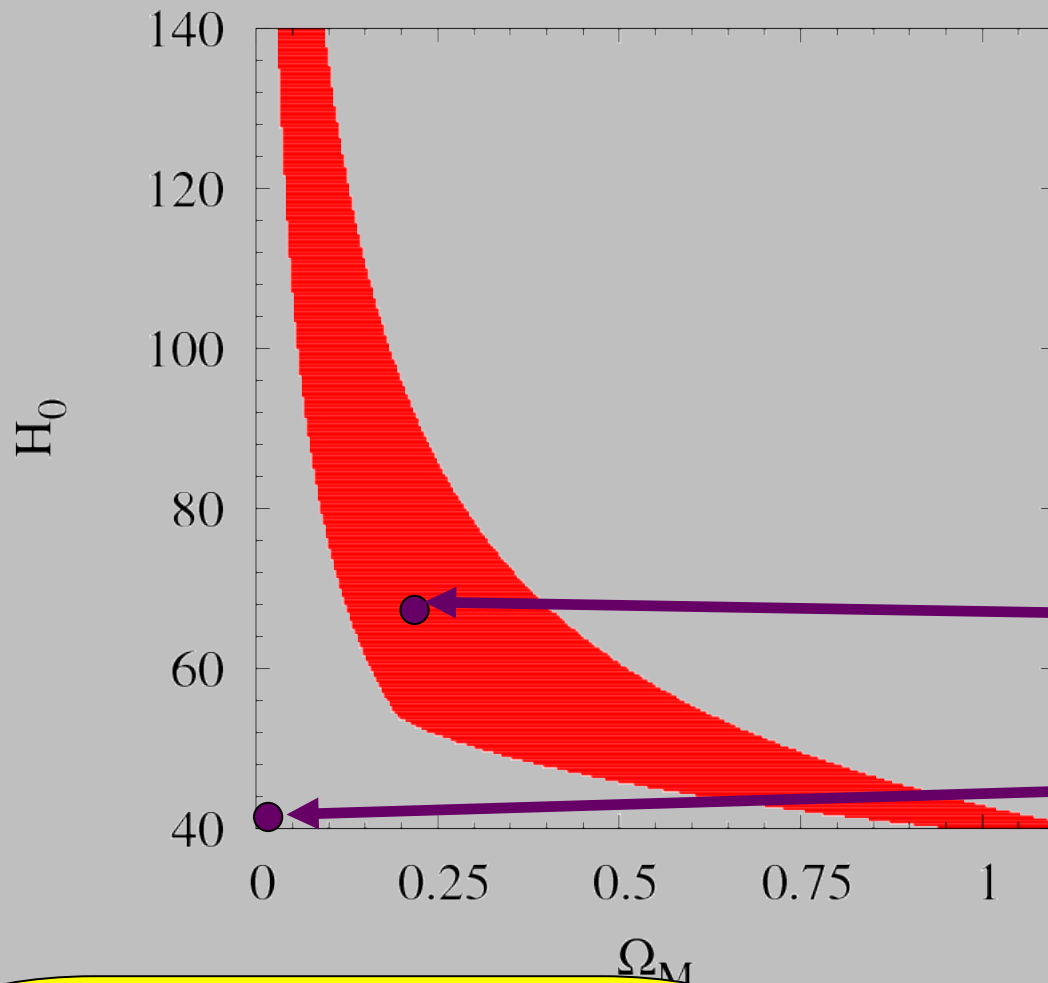


Assumes  $60 \leq H_0 \leq 75$   
(km/s)/Mpc





# What Does "Convergence" Mean?



To prove  $p_1$  is within the confidence region:  
 $\exists \Omega_\Lambda$  such that  $m(\theta)$  is accepted

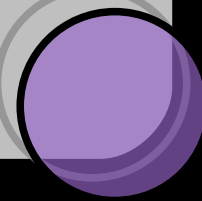
- $\theta = \{H_0, \Omega_M, \Omega_\Lambda\}$
- $p_1 = \{65, 0.23, ?\}$
- $p_2 = \{0.02, 42, ?\}$

To prove  $p$  is not within the region:  
 $\forall \Omega_\Lambda, m(\theta)$  is rejected

can't check all  $\Omega_\Lambda$  is from based

# A Summary of the INCA Group Activities in Astronomy

- Originated at Carnegie Mellon University and the University of Pittsburgh (PiCA Group).
  - Membership expanded and members moved so that we changed the name to the INternational Computational Astrostatistics Group).
- A loose group of committed researchers (no formal structure)
- Astronomy provides the data and drives the science
  - Real work is done in developing, proving, and applying novel statistical methods and computational algorithms to astronomical datasets
  - Success is shared equally amongst the domains
- What are we interested in?



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- What are we interested in?
  - Parametrics
    - Dis-entangling multiple -components via Expectation Maximization
  - Nonparametrics
    - Reducing the size of the error ellipse
  - Non-linear SVM-like spaces
    - Focusing the available model space
  - High-dimensional searches and surface fitting
    - Constraining (as opposed to finding) the truth