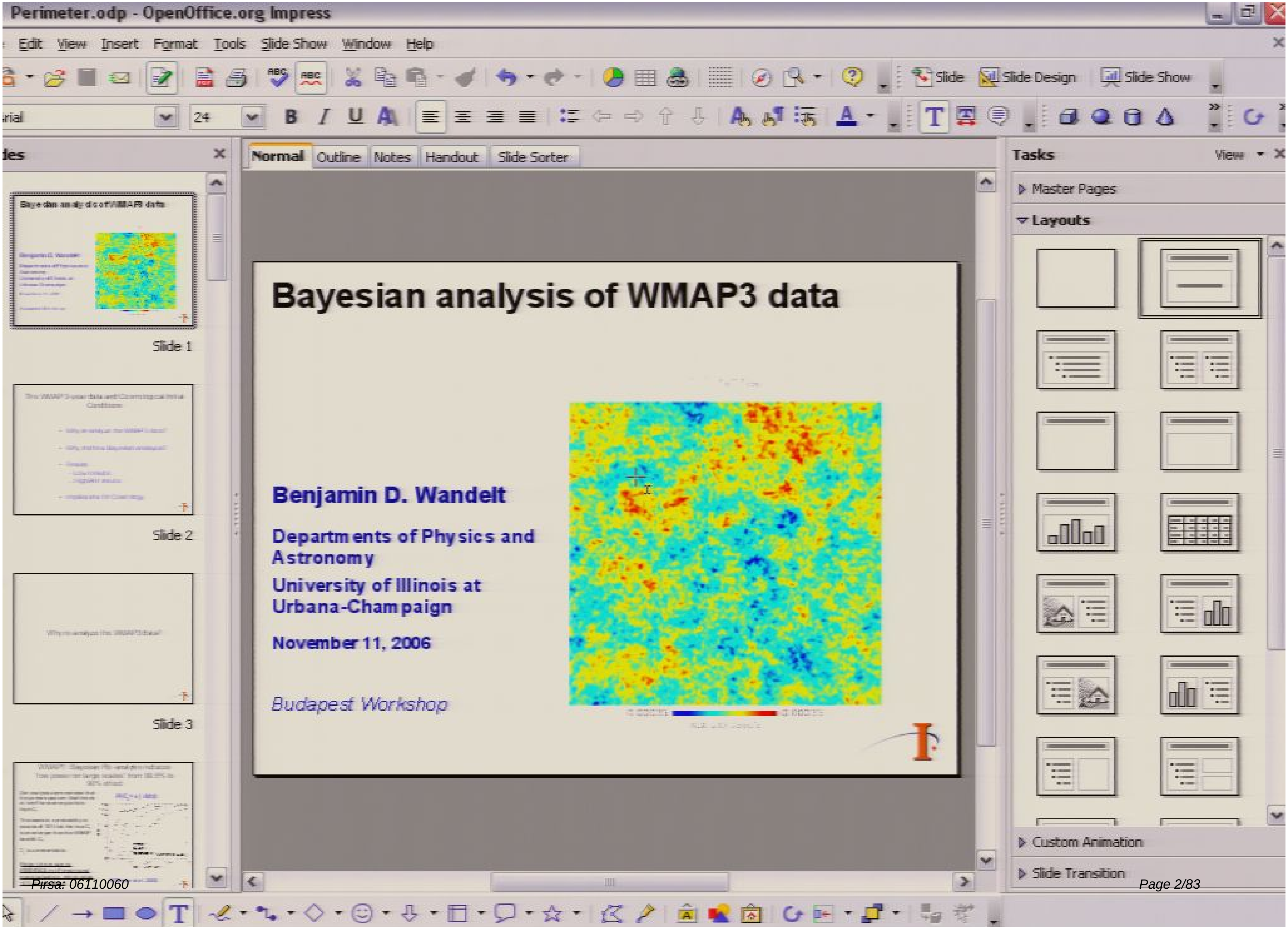
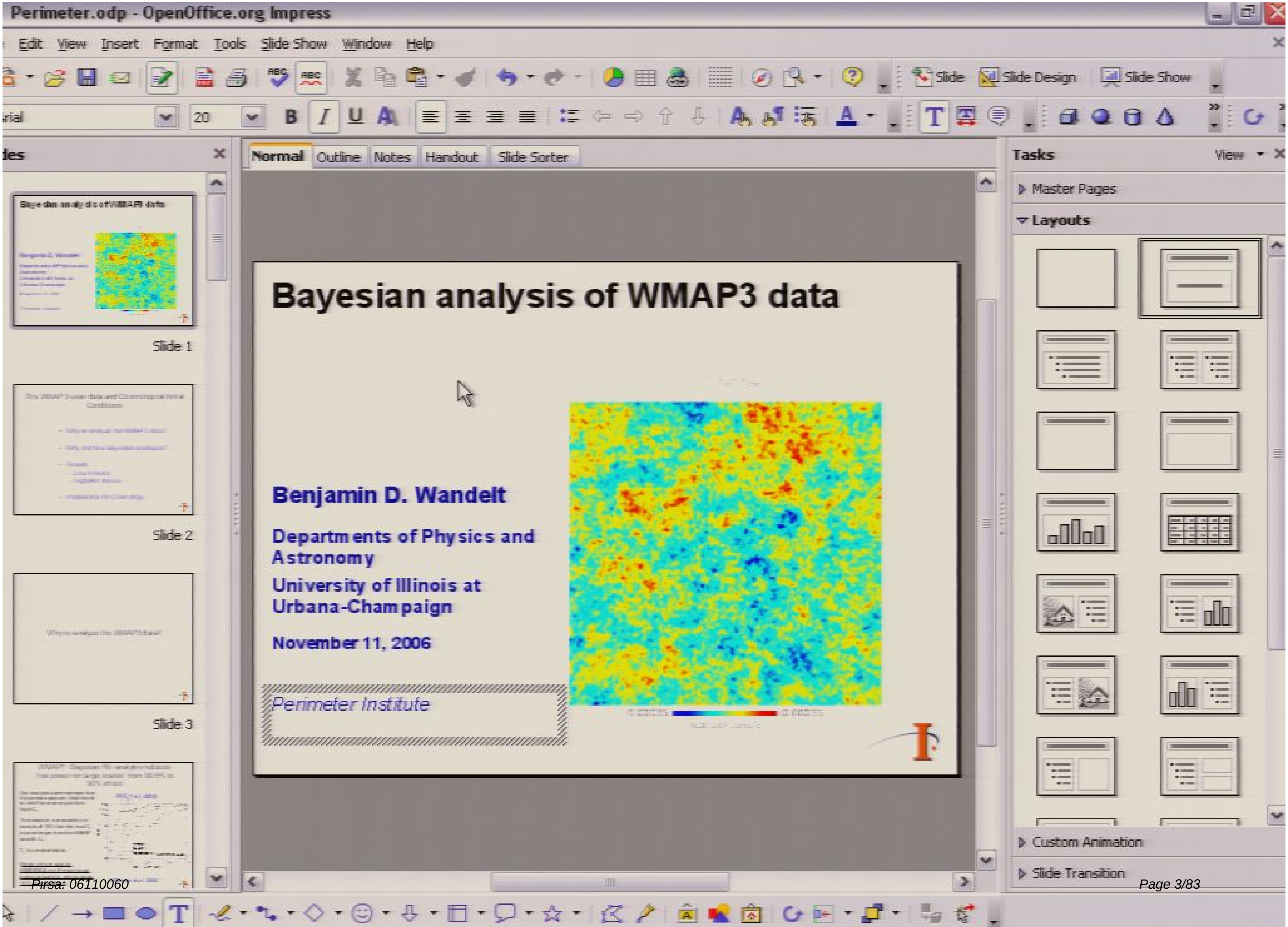
Title: Bayesian Analysis of WMAP3 Data

Date: Nov 11, 2006 10:00 AM

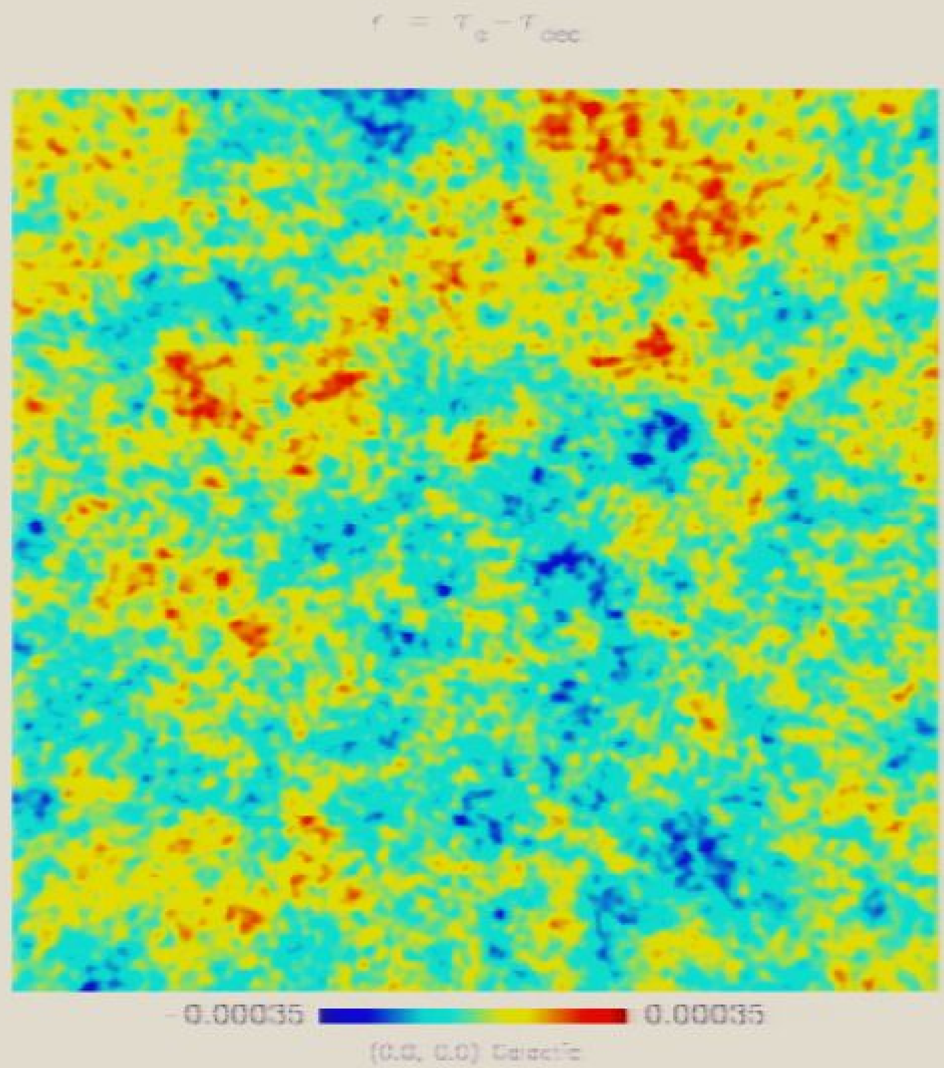
URL: http://pirsa.org/06110060

Abstract:


Perimeter.odp - OpenOffice.org Impress
Edit View Insert Format Tools Slide Show Window Help
Slide Slide Design Slide Show
Normal Outline Notes Handout Slide Sorter
Tasks
Master Pages
Layouts
Custom Animation
Slide Transition
Slide 1
Slide 2
Slide 3
Bayesian analysis of WMAP3 data
Benjamin D. Wandelt
Departments of Physics and Astronomy
University of Illinois at Urbana-Champaign
November 11, 2006
Budapest Workshop


Perimeter.odp - OpenOffice.org Impress
Edit View Insert Format Tools Slide Show Window Help
Normal Outline Notes Handout Slide Sorter
Tasks
Master Pages
Layouts
Custom Animation
Slide Transition
Slide 1
Slide 2
Slide 3
Bayesian analysis of WMAP3 data
Benjamin D. Wandelt
Departments of Physics and Astronomy
University of Illinois at Urbana-Champaign
November 11, 2006
Perimeter Institute

Bayesian analysis of WMAP3 data



Benjamin D. Wandelt

Departments of Physics and Astronomy

University of Illinois at Urbana-Champaign

November 11, 2006

Perimeter Institute

The WMAP 3-year data and Cosmological Initial Conditions

- Why re-analyze the WMAP3 data?
- Why and how Bayesian analaysis?
- Results
  - Low l results
  - High/All l results
- Implications for Cosmology

The WMAP 3-year data and Cosmological Initial Conditions

- Why re-analyze the WMAP3 data?
- Why and how Bayesian analaysis?
- Results
  - Low l results
  - High/All l results
- Implications for Cosmology

Why re-analyze the WMAP3 data?

WMAP1: Bayesian Re-analysis reduces "low power on large scales" from 99.5% to 90% effect

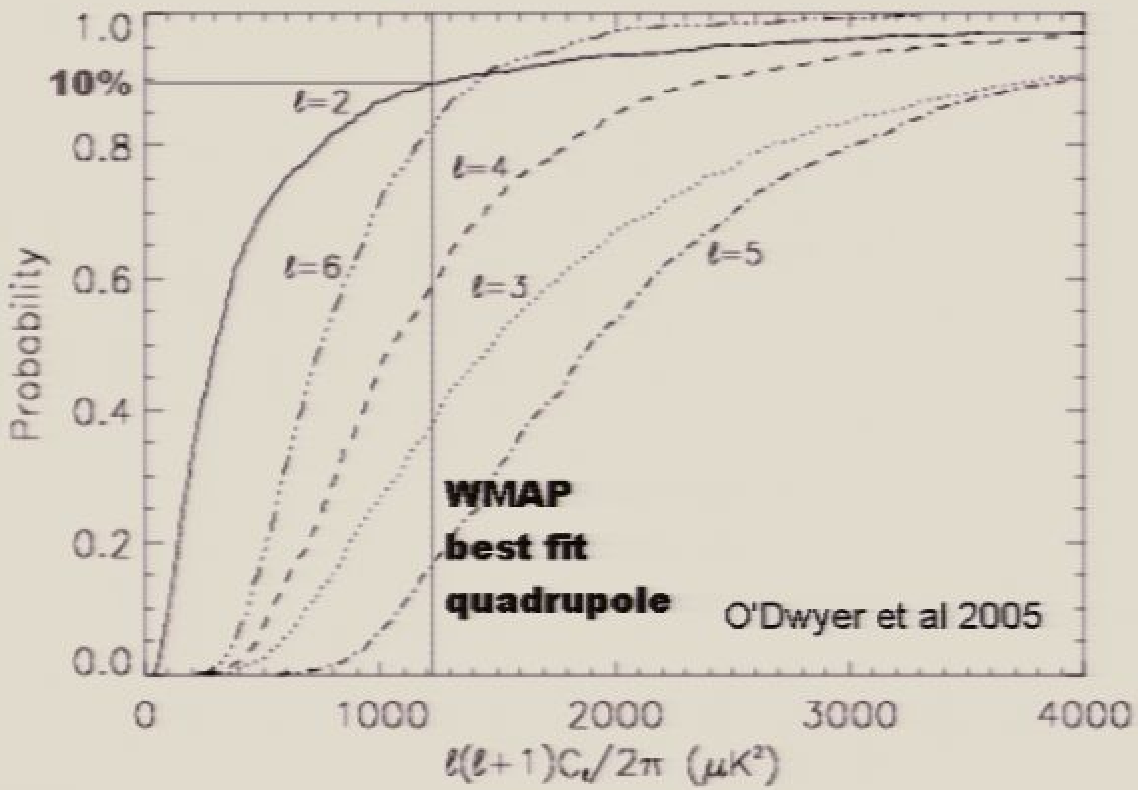
Our analysis demonstrated that the power spectrum likelihoods at low ℓ have strong tails to high C_ℓ.

This leads to a probability in excess of 10% that the true C_2 is even larger than the WMAP best fit C_2.

C_3 is unremarkable.

(Note: this is due to **statistics**, not Foreground marginalization, which adds ~5% to this effect)

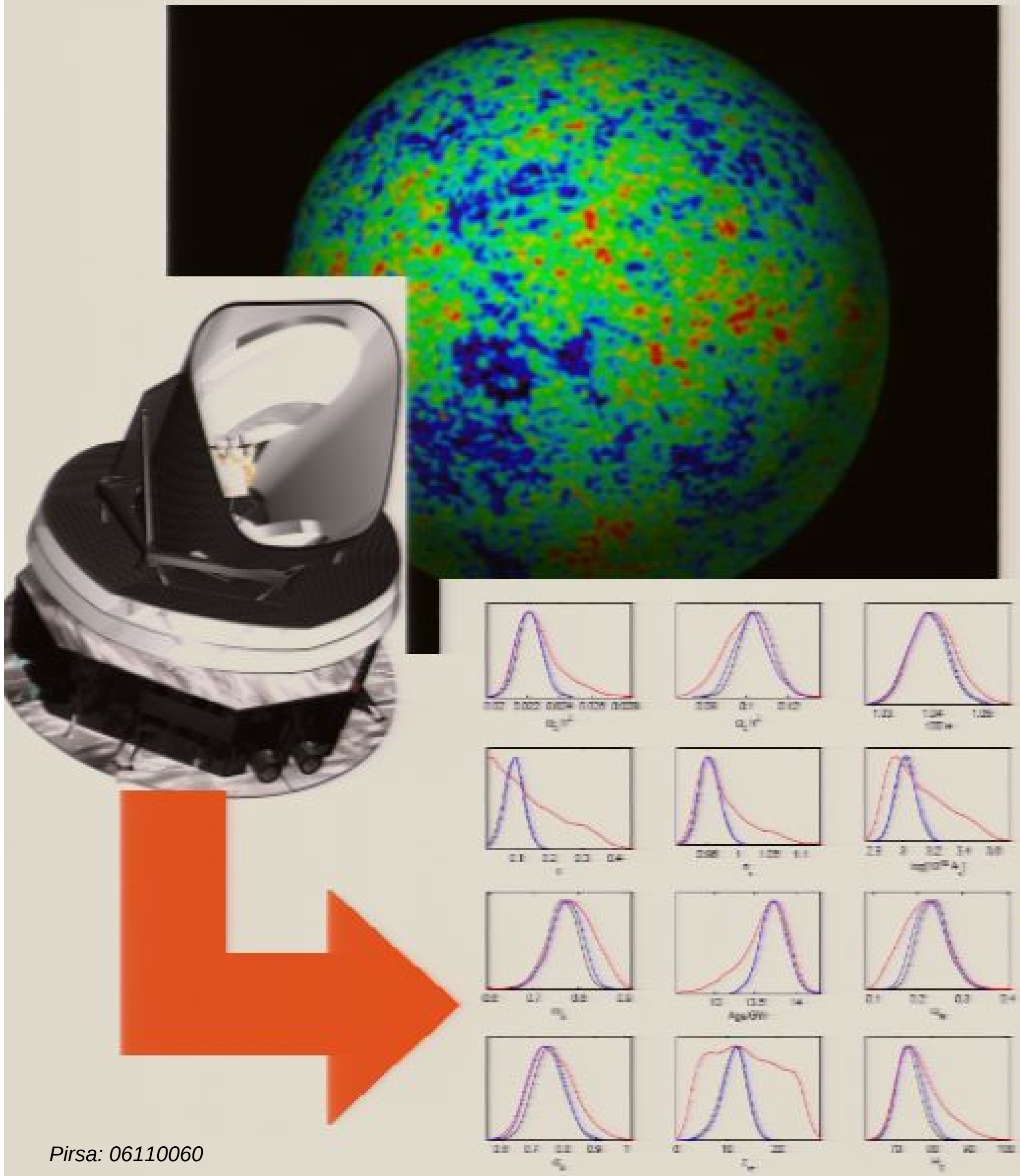
P(C_2 > x | data)



(O'Dwyer et al. 2005)

Why Bayesian analysis?

Bayesian Cosmological Data Analysis



Cosmological data analysis takes

astronomical observations (D)

and turns them into

statistical statements about the parameters (θ) that define our Universe

- Conceptually straightforward:

$$P(\theta|D) \propto P(D|\theta)P(\theta)$$

- After COBE –for more than a decade– the field has had to cope with approximations that avoid the computational difficulty of evaluating the terms in this equation.

THE COSMOSTATISTICS PROBLEM

- Black bar: size of data set
- Red area: work required to evaluate $P(\theta|D) \propto P(D|\theta)P(\theta)$

THE COSMOSTATISTICS PROBLEM

- Black bar: size of data set
- Red area: work required to evaluate $P(\theta|D)\propto P(D|\theta)P(\theta)$

THE CMB ANALYSIS PROBLEM

THE COSMOSTATISTICS PROBLEM

- Black bar: size of data set
- Red area: work required to evaluate

$$P(\theta|D) \propto P(D|\theta)P(\theta)$$

THE COSMOSTATISTICS PROBLEM

- Black bar: size of data set
- Red area: work required to evaluate

$$P(\theta|D) \propto P(D|\theta)P(\theta)$$

THE COSMOSTATISTICS PROBLEM

- Black bar: size of data set
- Red area: work required to evaluate

$$P(\theta|D) \propto P(D|\theta) P(\theta)$$

THE COSMOSTATISTICS PROBLEM

- Black bar: size of data set
- Red area: work required to evaluate

$$P(\theta|D) \propto P(D|\theta) P(\theta)$$

THE COSMOSTATISTICS PROBLEM

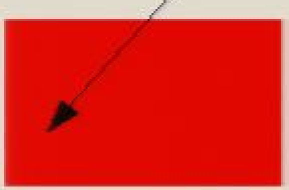
- Black bar: size of data set
- Red area: work required to evaluate

$$P(\theta|D) \propto P(D|\theta)P(\theta)$$

THE COSMOSTATISTICS PROBLEM

- Black bar: size of data set
- Red area: work required to evaluate

$$P(\theta|D) \propto P(D|\theta) P(\theta)$$



THE COSMOSTATISTICS PROBLEM

- Black bar: size of data set
- Red area: work required to evaluate

$$P(\theta|D) \propto P(D|\theta)P(\theta)$$

THE COSMOSTATISTICS PROBLEM

- Black bar: size of data set
- Red area: work required to evaluate

$$P(\theta|D) \propto P(D|\theta)P(\theta)$$

THE COSMOSTATISTICS PROBLEM

- Black bar: size of data set
- Red area: work required to evaluate

$$P(\theta|D) \propto P(D|\theta)P(\theta)$$

THE COSMOSTATISTICS PROBLEM

- Black bar: size of data set
- Red area: work required to evaluate

$$P(\theta|D) \propto P(D|\theta)P(\theta)$$

THE COSMOSTATISTICS PROBLEM

- Black bar: size of data set
- Red area: work required to evaluate

$$P(\theta|D) \propto P(D|\theta)P(\theta)$$

THE COSMOSTATISTICS PROBLEM

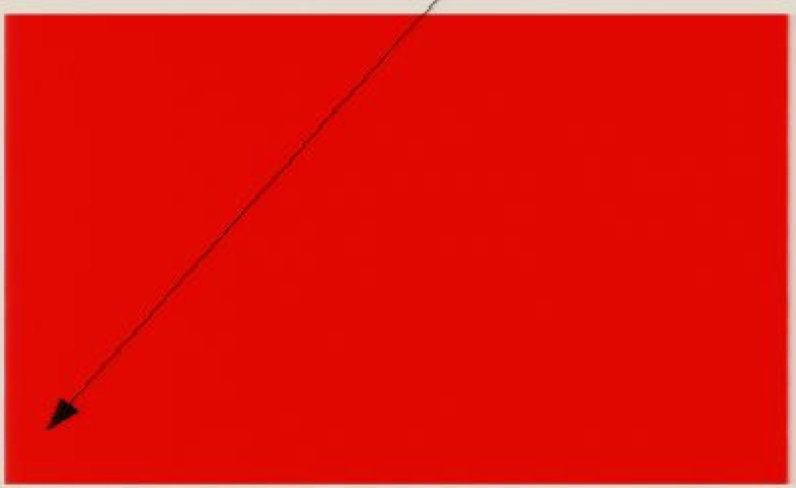
- Black bar: size of data set
- Red area: work required to evaluate

$$P(\theta|D) \propto P(D|\theta)P(\theta)$$

THE COSMOSTATISTICS PROBLEM

- Black bar: size of data set
- Red area: work required to evaluate

$$P(\theta|D) \propto P(D|\theta)P(\theta)$$



THE COSMOSTATISTICS PROBLEM

- Black bar: size of data set
- Red area: work required to evaluate

$$P(\theta|D) \propto P(D|\theta)P(\theta)$$

THE COSMOSTATISTICS PROBLEM

- Black bar: size of data set
- Red area: work required to evaluate

$$P(\theta|D) \propto P(D|\theta)P(\theta)$$

THE COSMOSTATISTICS PROBLEM

- Black bar: size of data set
- Red area: work required to evaluate

$$P(\theta|D) \propto P(D|\theta) P(\theta)$$

THE COSMOSTATISTICS PROBLEM

- Black bar: size of data set
- Red area: work required to evaluate $P(\theta|D) \propto P(D|\theta)P(\theta)$

THE COSMOSTATISTICS PROBLEM

- Black bar: size of data set
- work required to evaluate $P(\theta|D) \propto P(D|\theta)P(\theta)$

THE COSMOSTATISTICS PROBLEM

- Black bar: size of data set
- work required to evaluate $P(\theta|D) \propto P(D|\theta)P(\theta)$

THE COSMOSTATISTICS PROBLEM

- Black bar: size of data set
- work required to evaluate $P(\theta|D) \propto P(D|\theta)P(\theta)$

THE CMB ANALYSIS PROBLEM

THE CMB ANALYSIS PROBLEM

- COBE-DMR

THE CMB ANALYSIS PROBLEM

- COBE-DMR

10x COBE-DMR

THE CMB ANALYSIS PROBLEM

- COBE-DMR

10x COBE-DMR

THE CMB ANALYSIS PROBLEM

Planck would take 4,000,000 years on a TeraFlop facility

Computational Speed of Gibbs Sampling

- Black bar: size of data set
- Red area: work required to Gibbs sample

Computational Speed of Gibbs Sampling

- Black bar: size of data set
- Red area: work required to Gibbs sample

Computational Speed of Gibbs Sampling

- Black bar: size of data set
- Red area: work required to Gibbs sample

Computational Speed of Gibbs Sampling

- Black bar: size of data set
- Red area: work required to Gibbs sample

Computational Speed of Gibbs Sampling

- Black bar: size of data set
- Red area: work required to Gibbs sample

Computational Speed of Gibbs Sampling

Feasible on existing facilities

Computational Speed of Gibbs Sampling

- The computational effort for each Gibbs sample is $O(N^{1.5})$ less than for the brute force techniques.

Feasible on existing facilities

Computational Speed of Gibbs Sampling

- The computational effort for each Gibbs sample is $O(N^{1.5})$ less than for the brute force techniques.

- For WMAP and Planck
  $N \sim 10^7 \rightarrow N^{1.5} \sim 10^{10.5}$

Feasible on existing facilities

Computational Speed of Gibbs Sampling

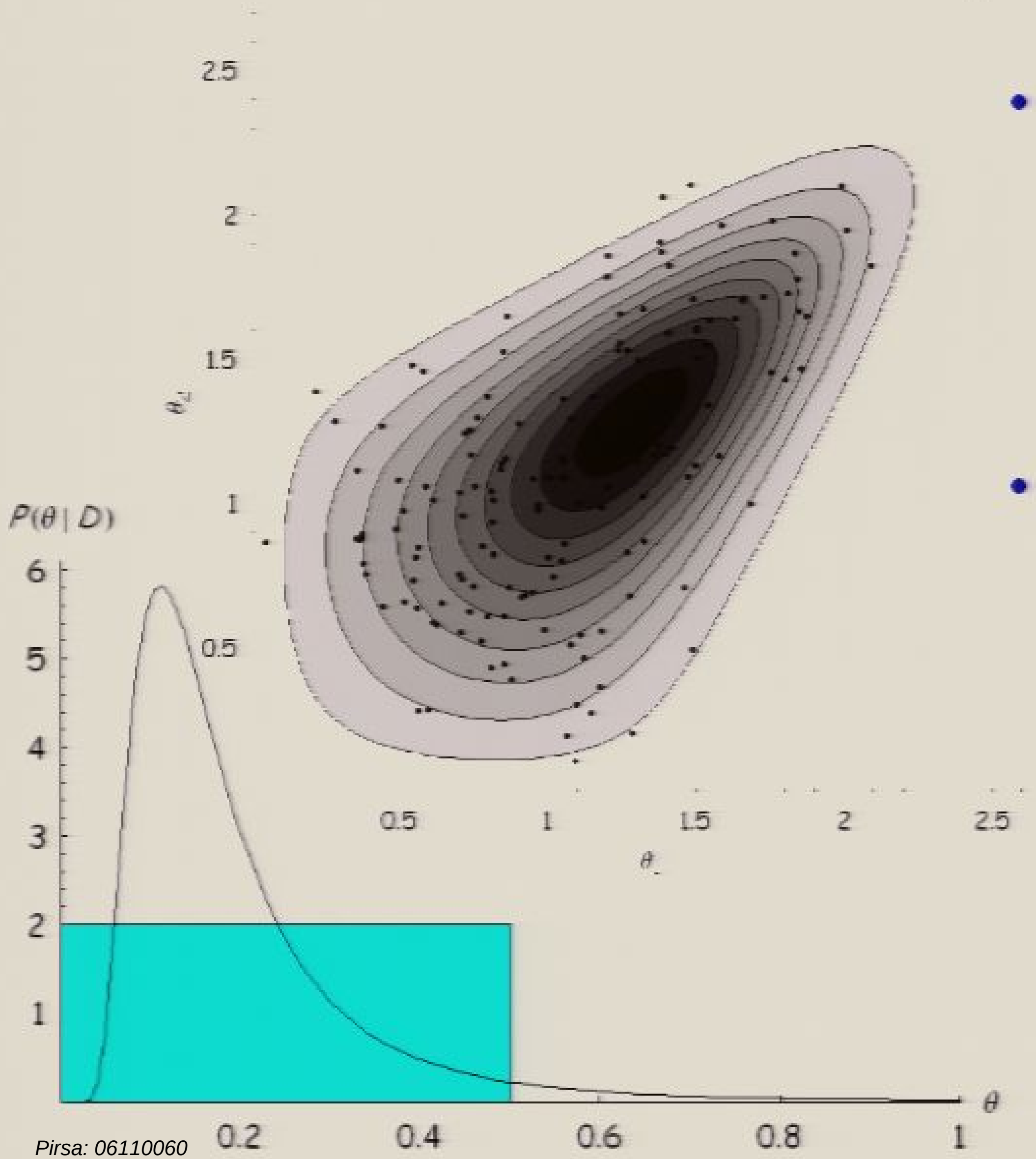
- The computational effort for each Gibbs sample is $O(N^{1.5})$ less than for the brute force techniques.

- For WMAP and Planck
  $N \sim 10^7 \rightarrow N^{1.5} \sim 10^{10.5}$

Feasible on existing facilities

- This speed-up is of the same order as the approximate (Pseudo-C_ℓ) techniques.

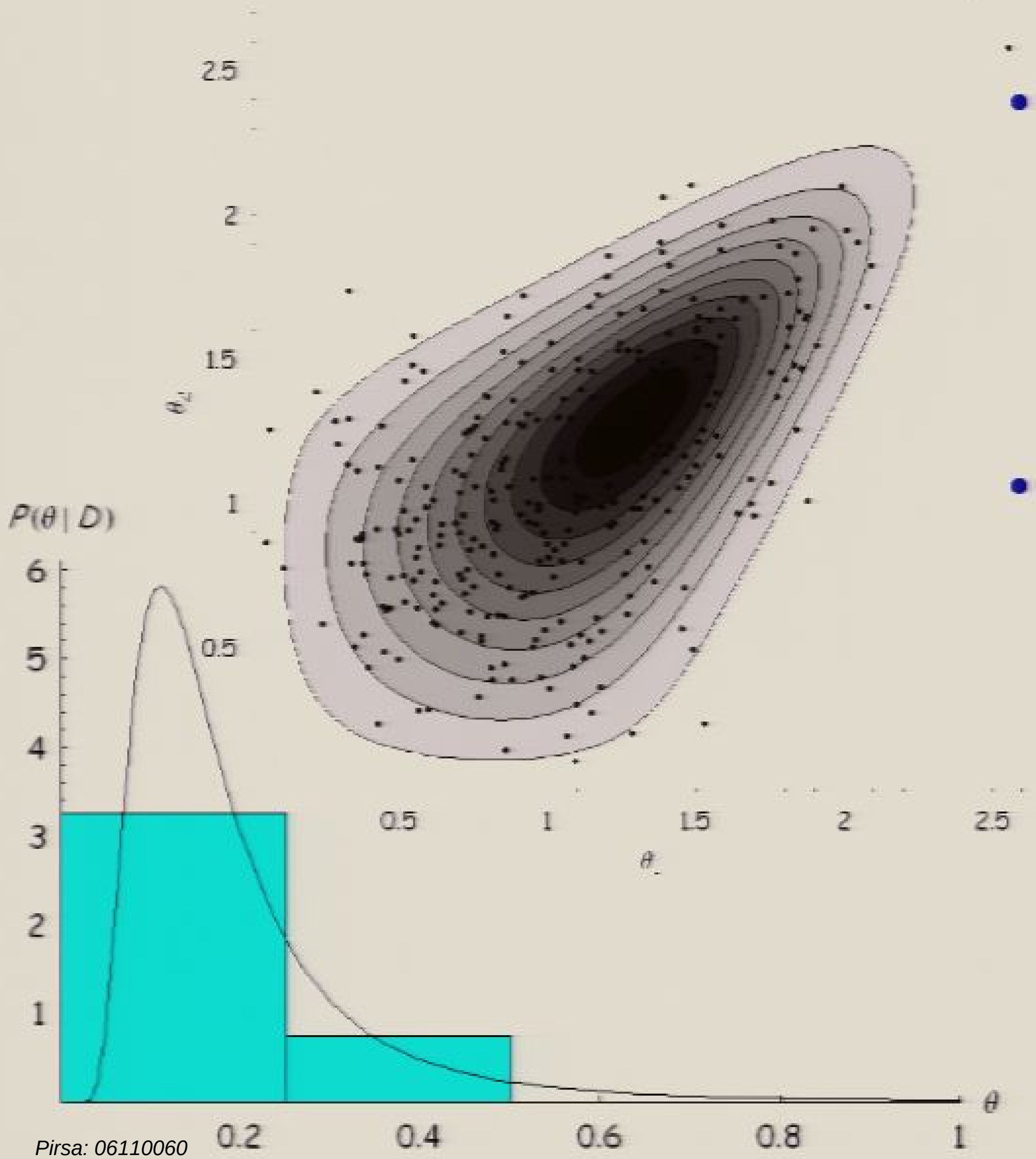
Gibbs Sampling: How?



- Gibbs sampling is a Monte Carlo technique for generating samples from the likelihood/posterior.
- It recovers the results of the full Bayesian approach without brute force evaluation of the likelihood.

(Jewell, Levin Anderson 2004,
Wandelt, Larson, Lakshm. 2004; Eriksen et al. 2(

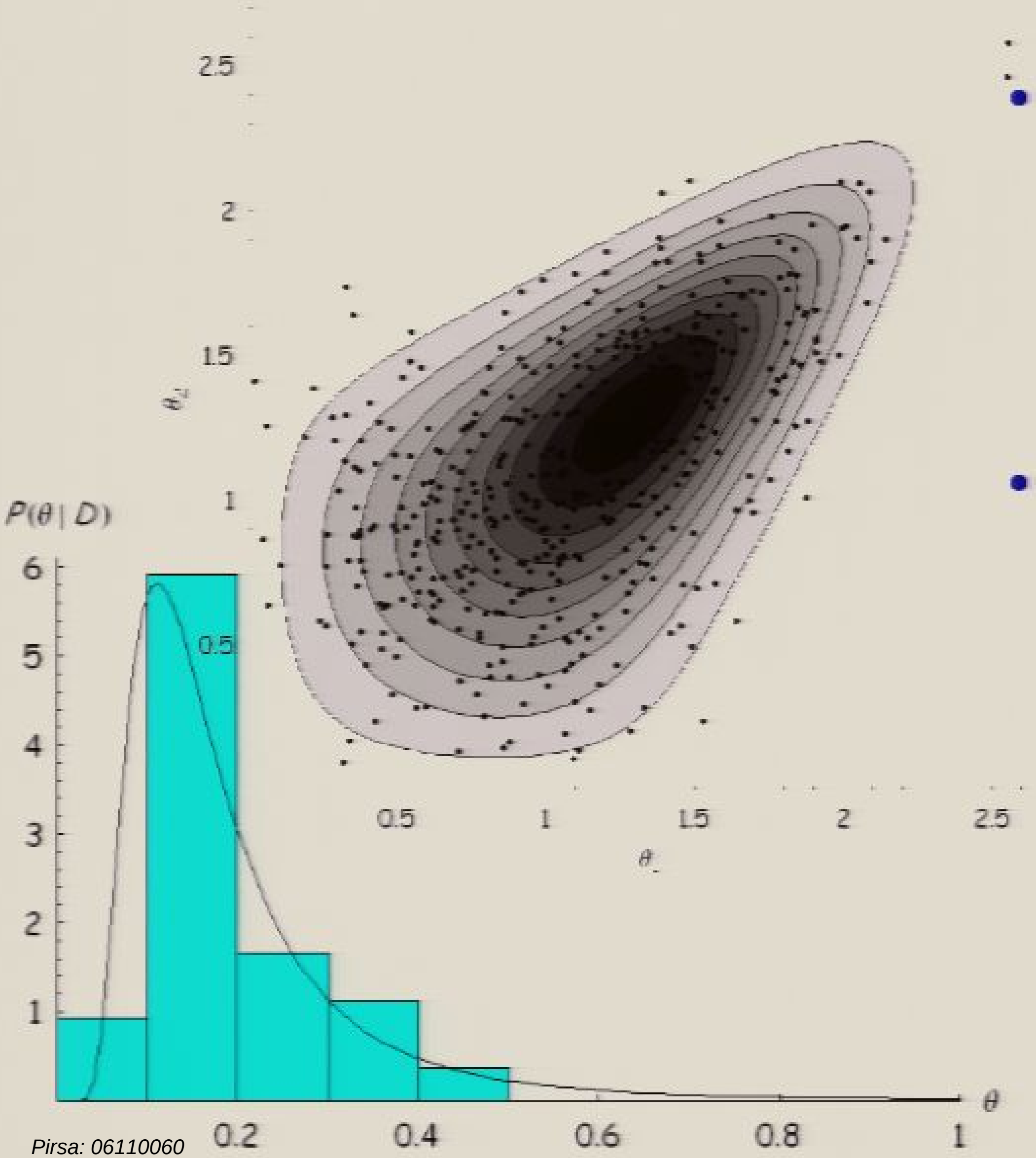
Gibbs Sampling: How?



- Gibbs sampling is a Monte Carlo technique for generating samples from the likelihood/posterior.
- It recovers the results of the full Bayesian approach without brute force evaluation of the likelihood.

(Jewell, Levin Anderson 2004,
Wandelt, Larson, Lakshm. 2004; Eriksen et al. 2(

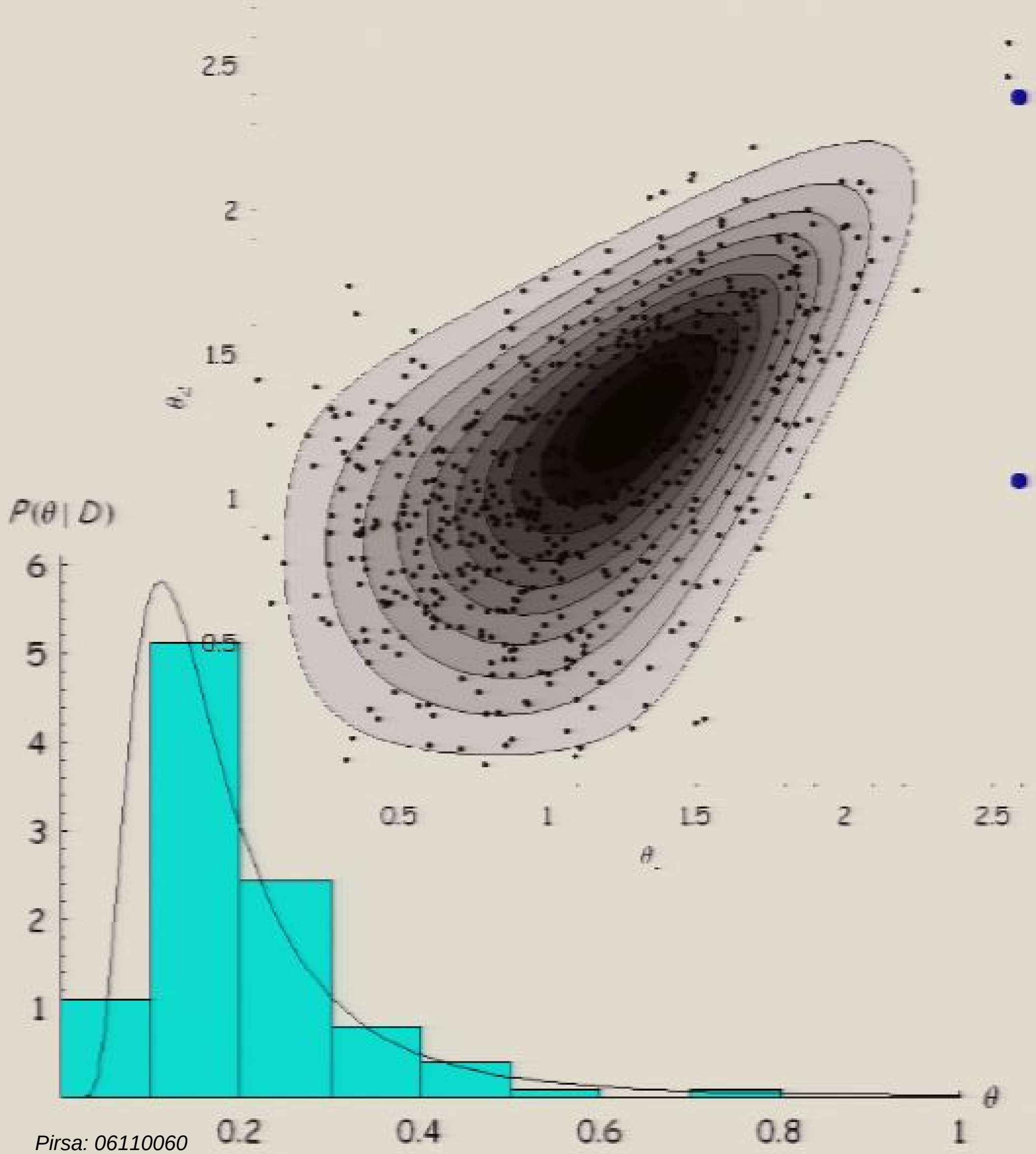
Gibbs Sampling: How?



- Gibbs sampling is a Monte Carlo technique for generating samples from the likelihood/posterior.
- It recovers the results of the full Bayesian approach without brute force evaluation of the likelihood.

(Jewell, Levin Anderson 2004,
Wandelt, Larson, Lakshm. 2004; Eriksen et al. 2(

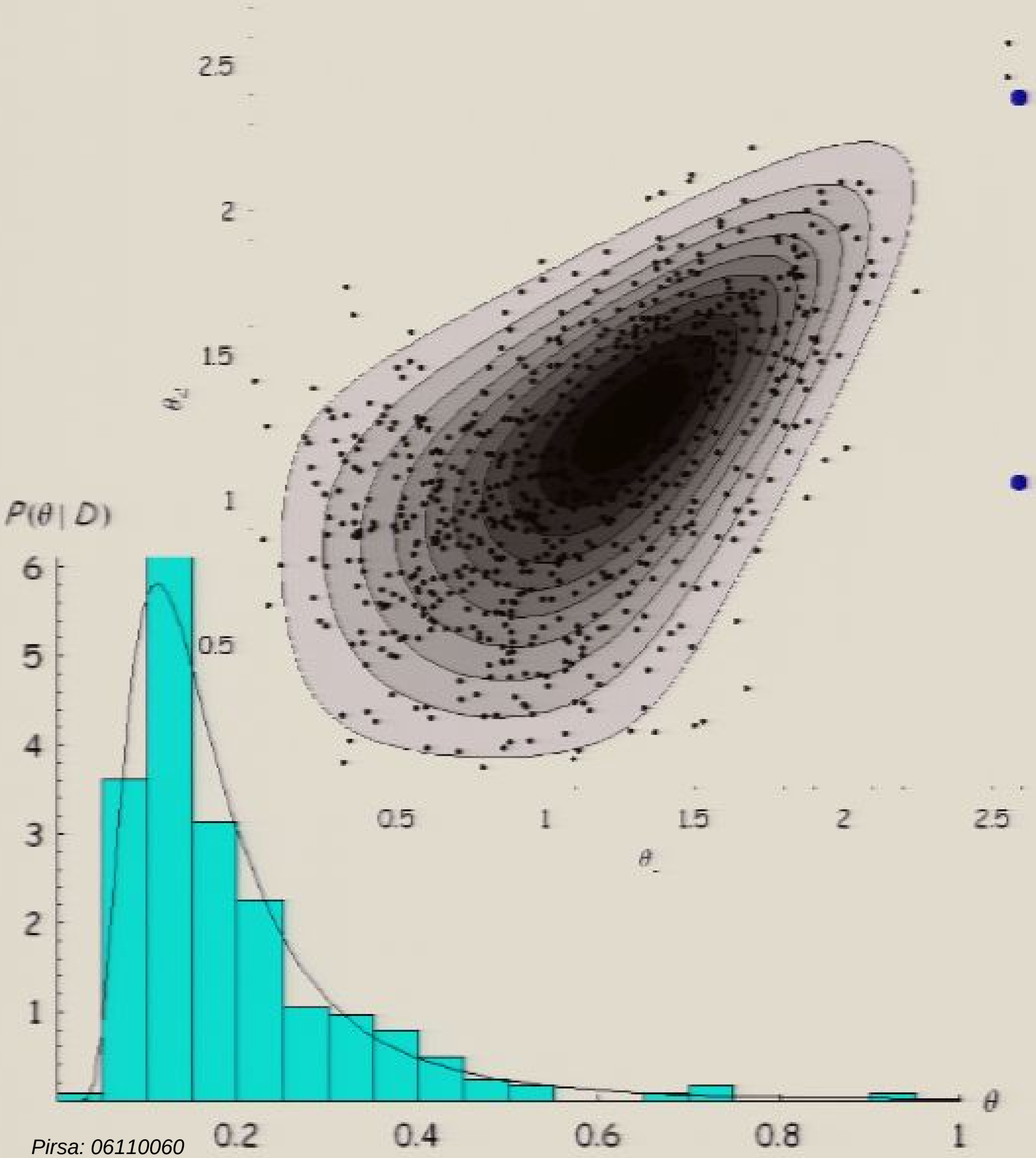
Gibbs Sampling: How?



- Gibbs sampling is a Monte Carlo technique for generating samples from the likelihood/posterior.
- It recovers the results of the full Bayesian approach without brute force evaluation of the likelihood.

(Jewell, Levin Anderson 2004,
Wandelt, Larson, Lakshm. 2004; Eriksen et al. 2(

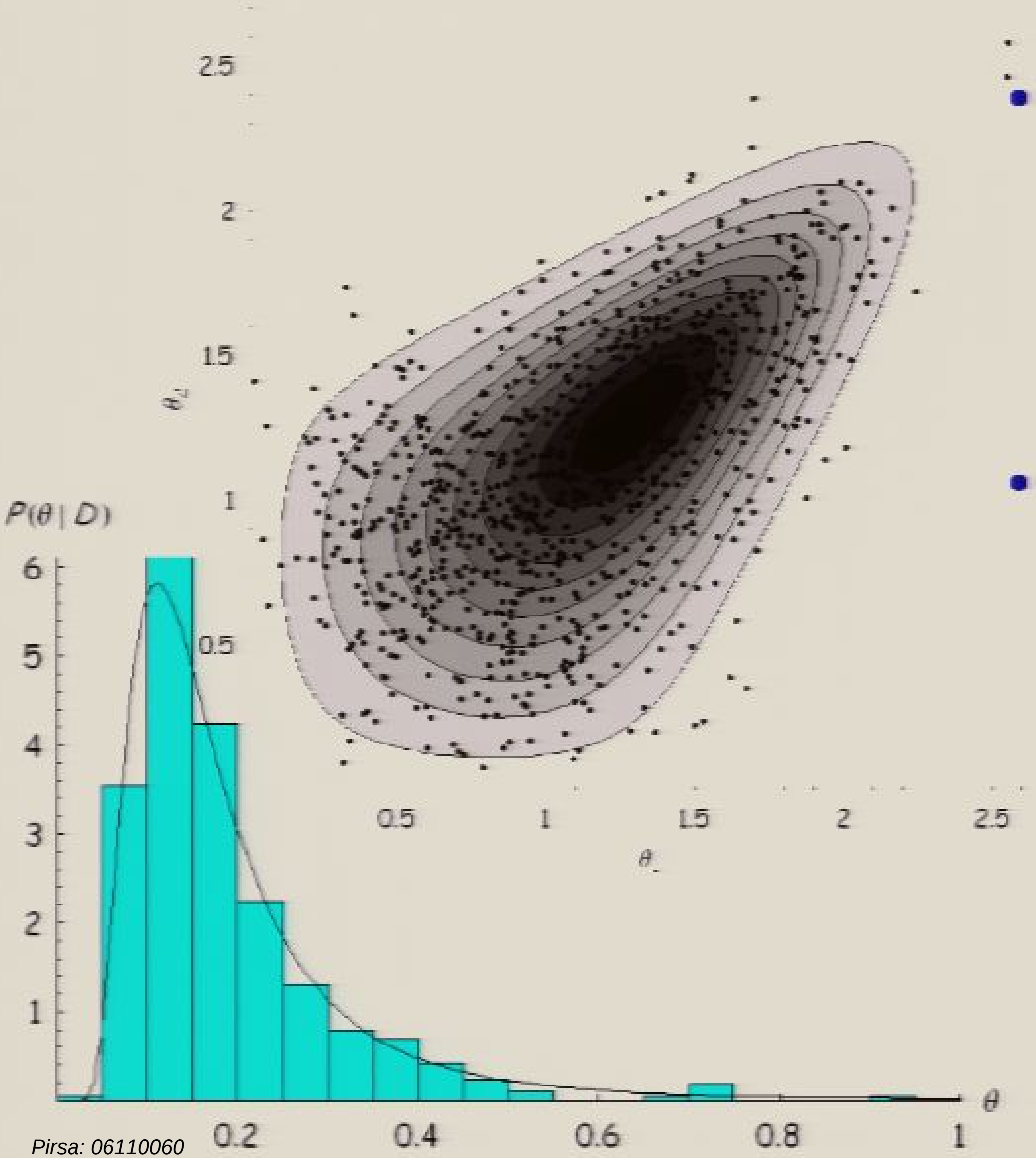
Gibbs Sampling: How?



- Gibbs sampling is a Monte Carlo technique for generating samples from the likelihood/posterior.
- It recovers the results of the full Bayesian approach without brute force evaluation of the likelihood.

(Jewell, Levin Anderson 2004,
Wandelt, Larson, Lakshm. 2004; Eriksen et al. 2(

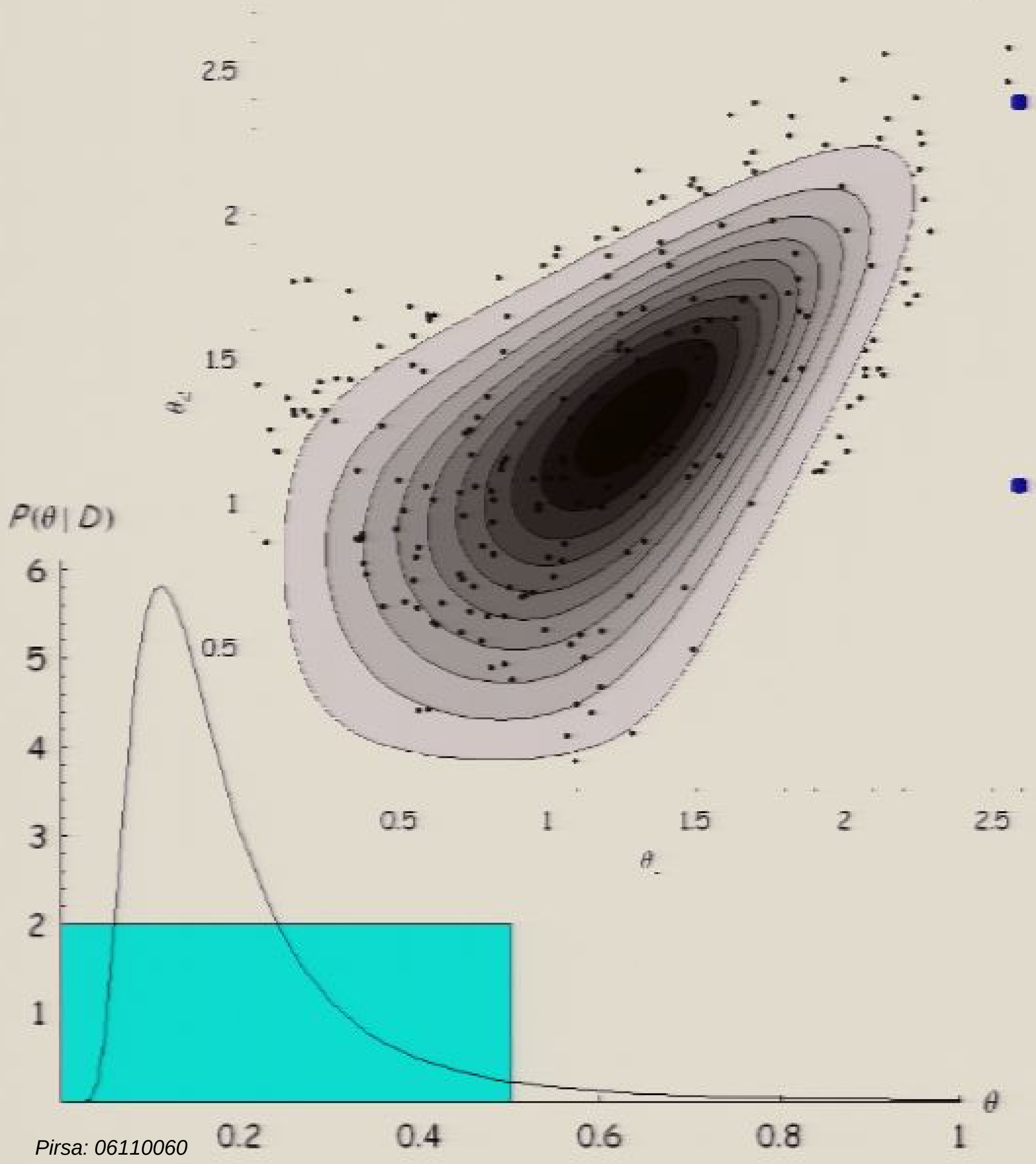
Gibbs Sampling: How?



- Gibbs sampling is a Monte Carlo technique for generating samples from the likelihood/posterior.
- It recovers the results of the full Bayesian approach without brute force evaluation of the likelihood.

(Jewell, Levin Anderson 2004,
Wandelt, Larson, Lakshm. 2004; Eriksen et al. 2(

Gibbs Sampling: How?



- Gibbs sampling is a Monte Carlo technique for generating samples from the likelihood/posterior.
- It recovers the results of the full Bayesian approach without brute force evaluation of the likelihood.

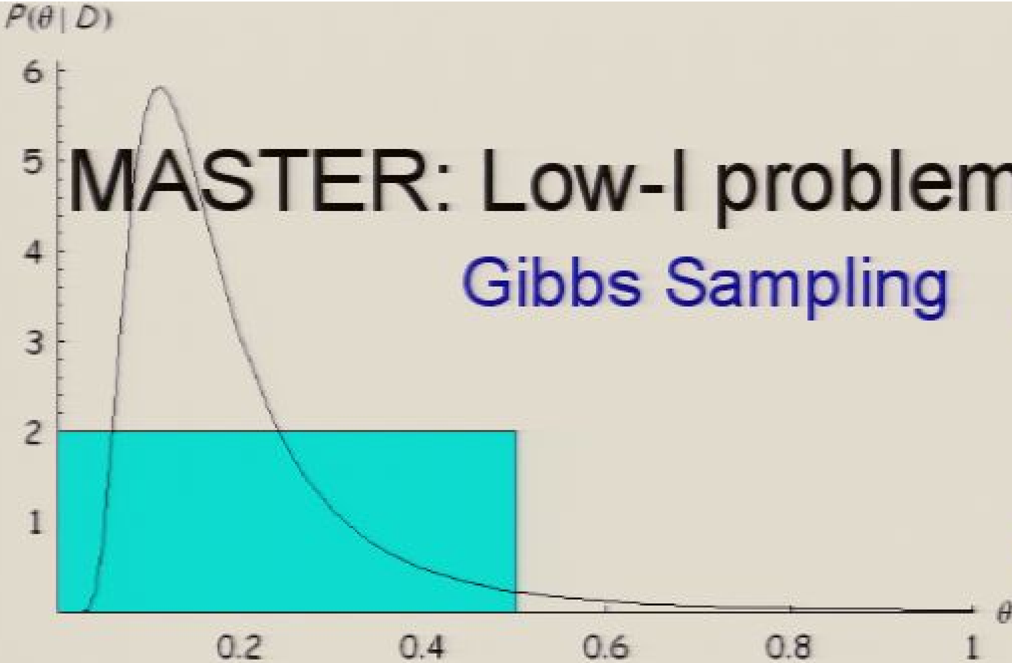
(Jewell, Levin Anderson 2004,
Wandelt, Larson, Lakshm. 2004; Eriksen et al. 2(

Gibbs Sampling: How?

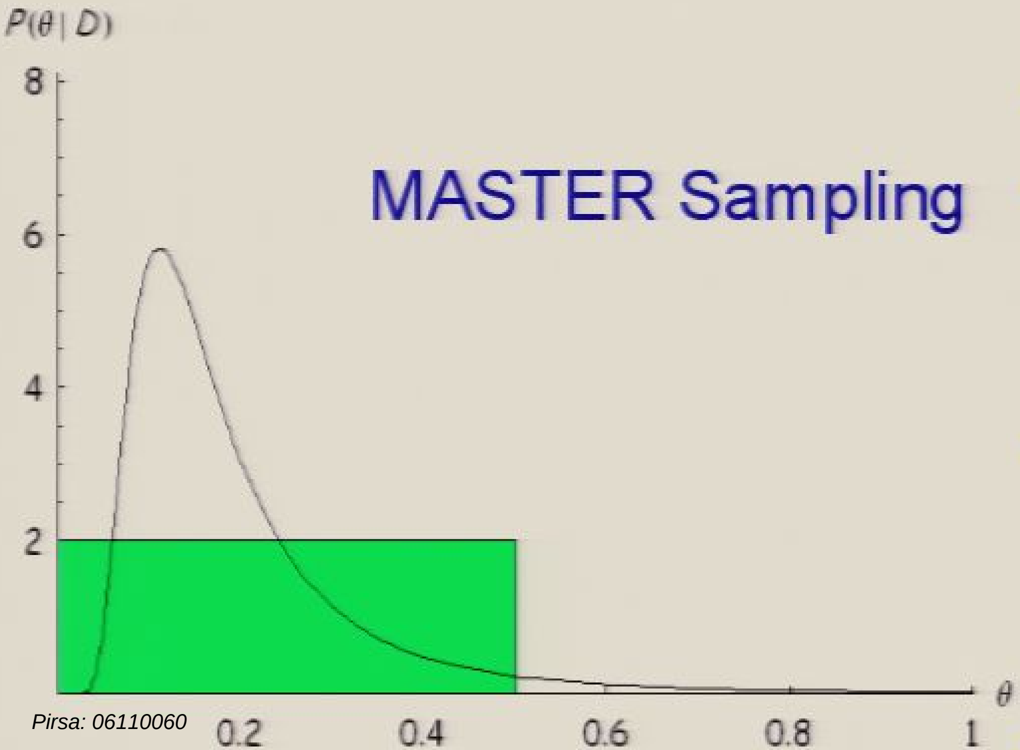
- Gibbs sampling is a Monte Carlo technique for generating samples from the likelihood/posterior.
- It recovers the results of the full Bayesian approach without brute force evaluation of the likelihood.

(Jewell, Levin Anderson 2004,
Wandelt, Larson, Lakshm. 2004; Eriksen et al. 2(

MASTER: Low-l problems even for Perfect Data



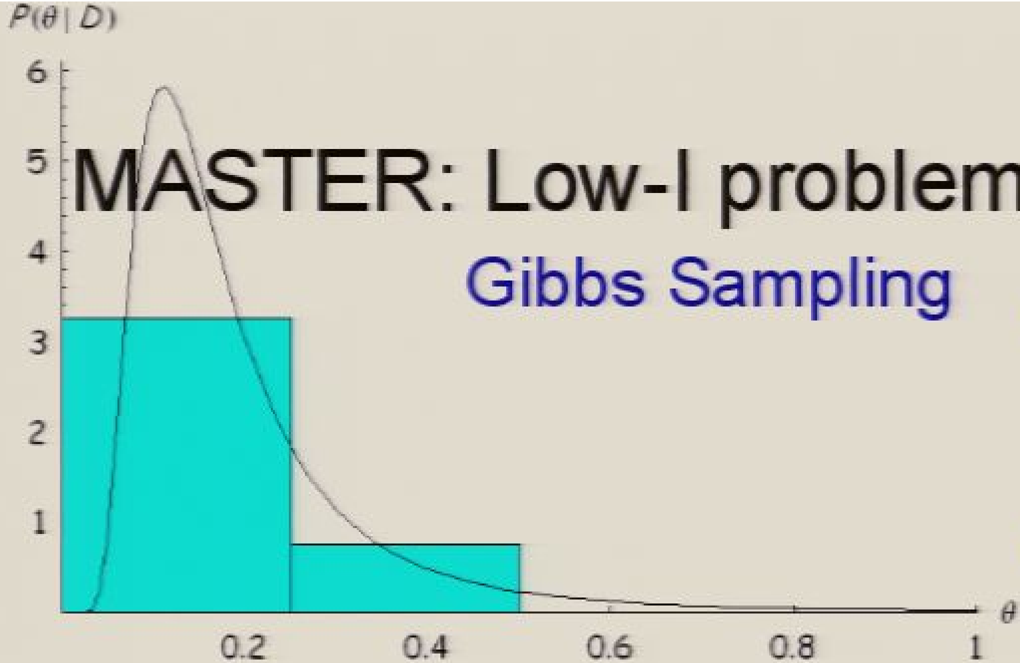
Gibbs Sampling

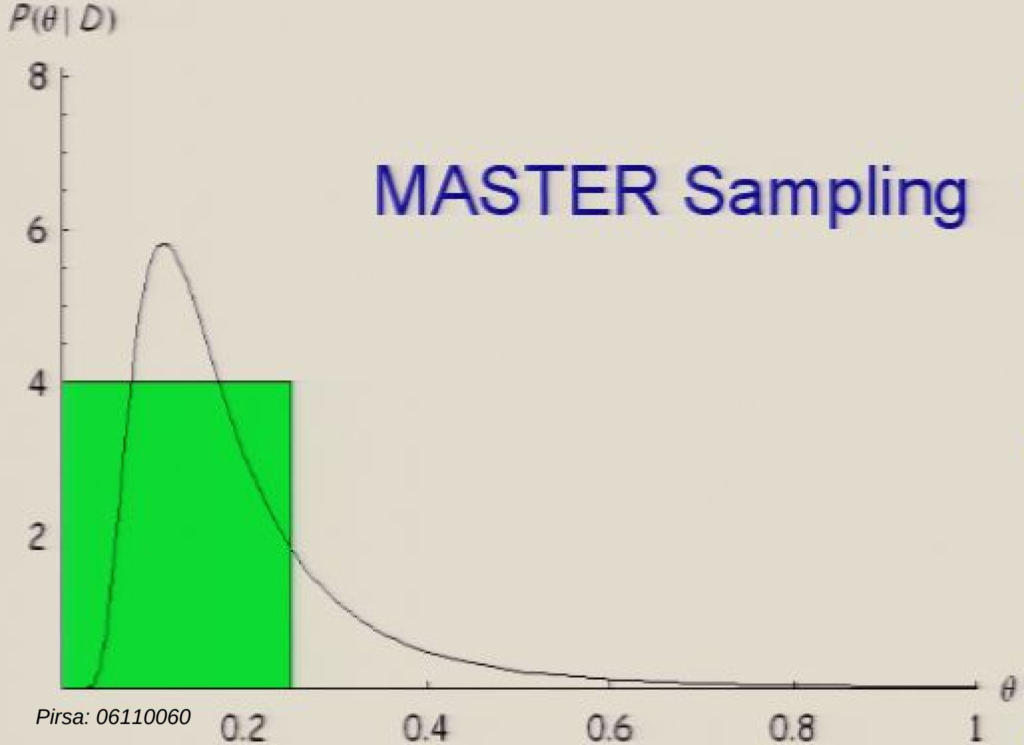


MASTER Sampling

- What do the error bars from a MASTER-like approx. technique mean?
- Here is an example using perfect, all sky data without any noise.
- We focus on $\theta = C_4$.
- In both cases, the solid line shows the actual likelihood for C_ℓ at $\ell=4$.
- The samples are obtained using Gibbs sampling and by “regular” Monte Carlo, like MASTER.
- MASTER is *neither frequentist*

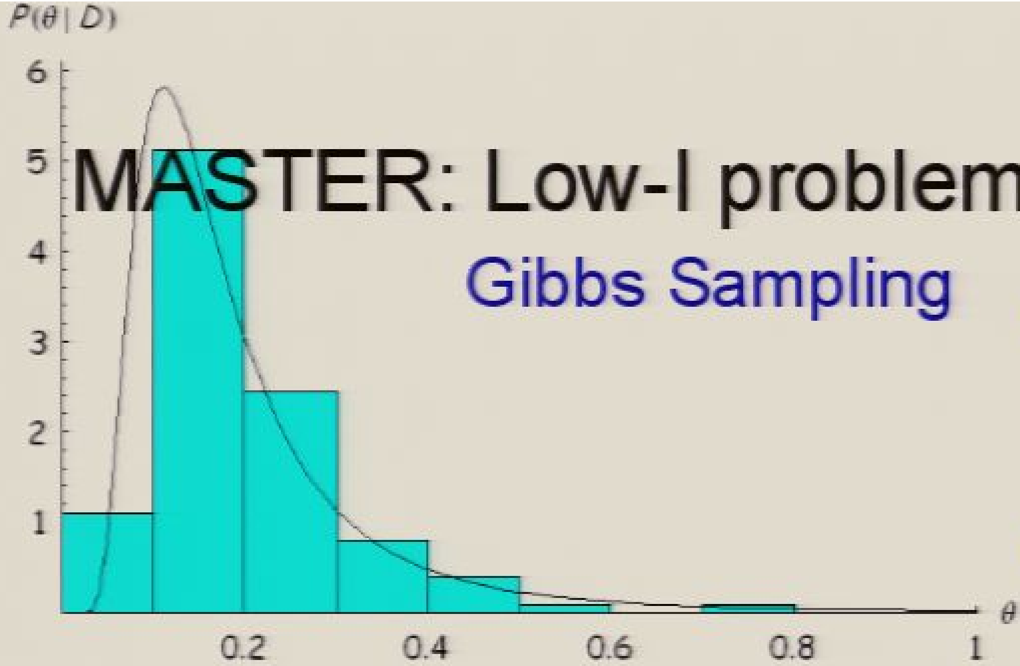
MASTER: Low-l problems even for Perfect Data

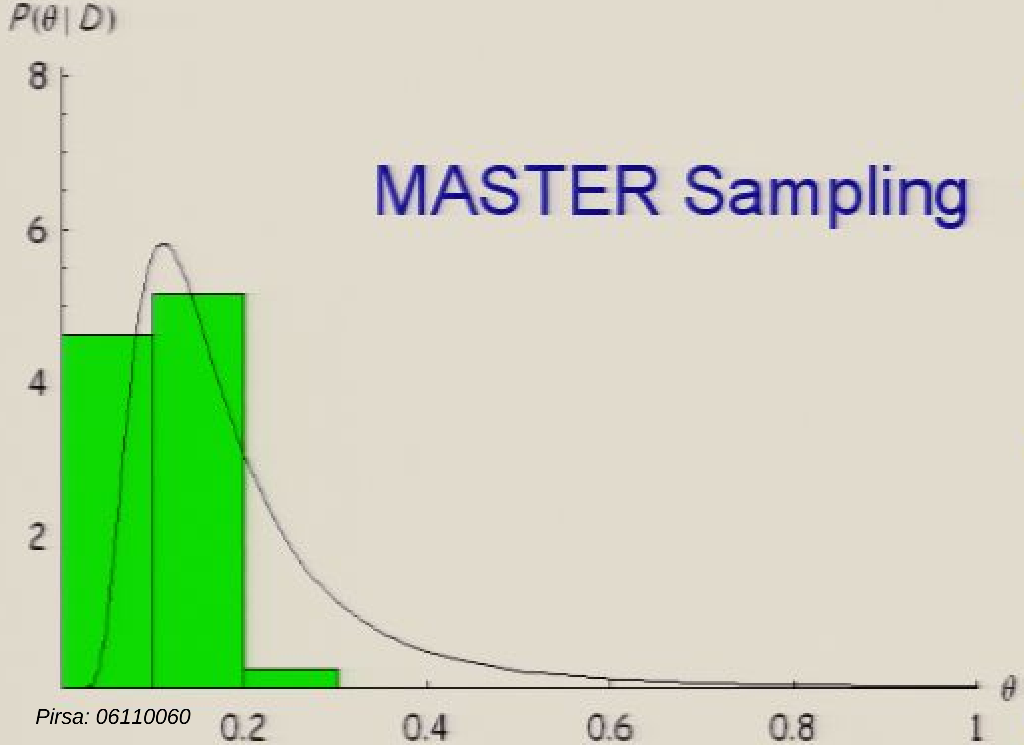




- What do the error bars from a MASTER-like approx. technique mean?
- Here is an example using perfect, all sky data without any noise.
- We focus on $\theta = C_4$.
- In both cases, the solid line shows the actual likelihood for C_ℓ at ℓ=4.
- The samples are obtained using Gibbs sampling and by "regular" Monte Carlo, like MASTER.
- MASTER is *neither frequentist*

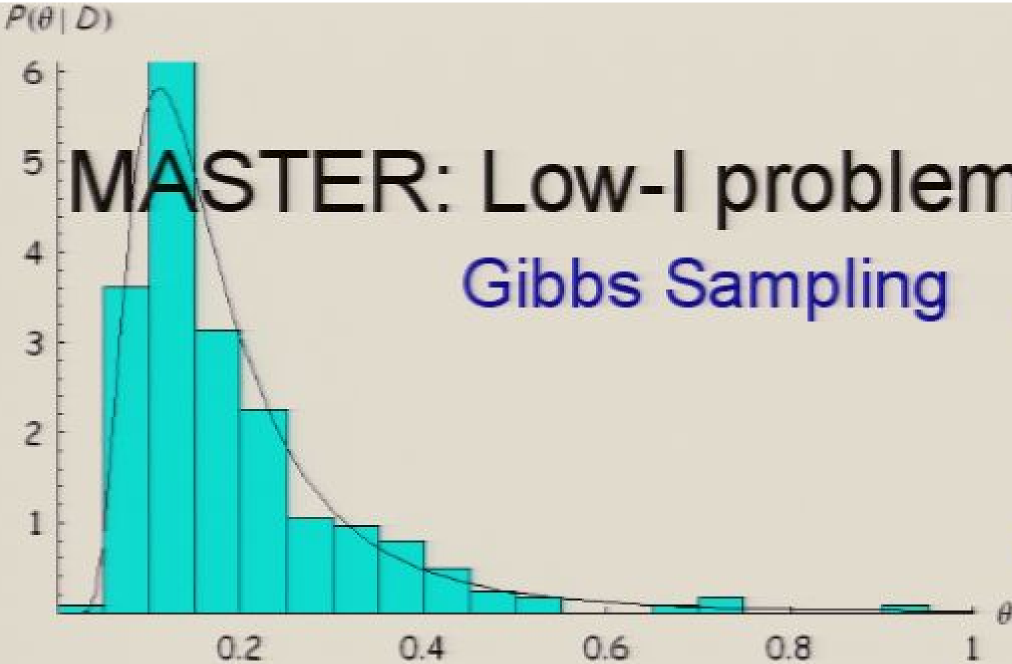
MASTER: Low-l problems even for Perfect Data

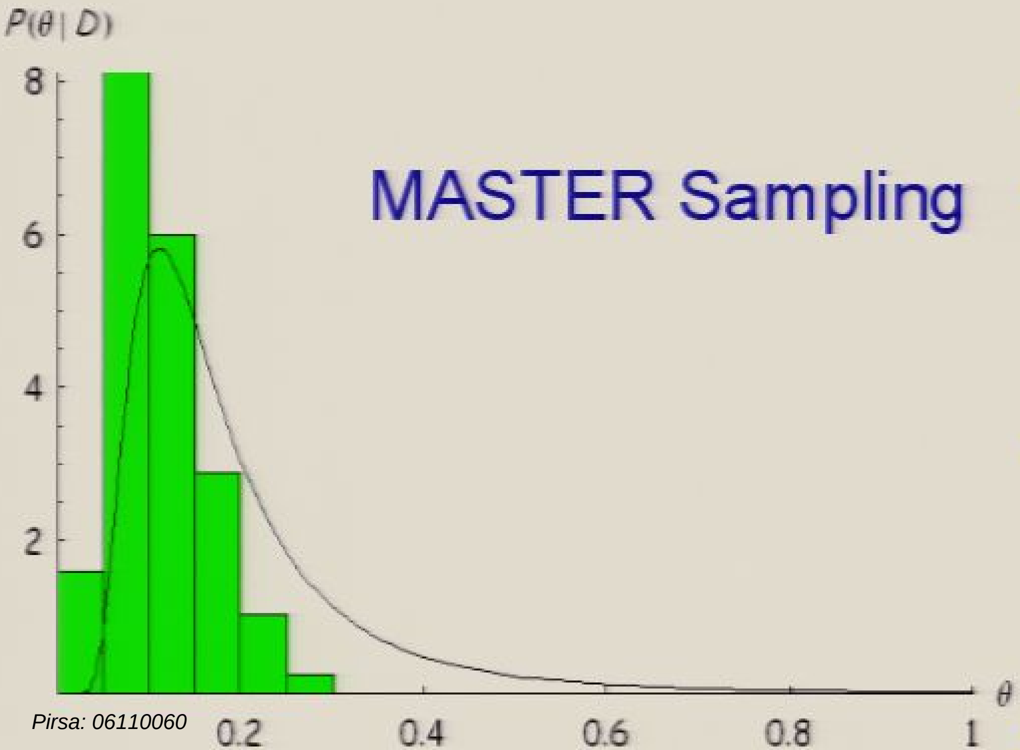




- What do the error bars from a MASTER-like approx. technique mean?
- Here is an example using perfect, all sky data without any noise.
- We focus on $\theta = C_4$.
- In both cases, the solid line shows the actual likelihood for C_ℓ at ℓ=4.
- The samples are obtained using Gibbs sampling and by "regular" Monte Carlo, like MASTER.
- MASTER is *neither frequentist*

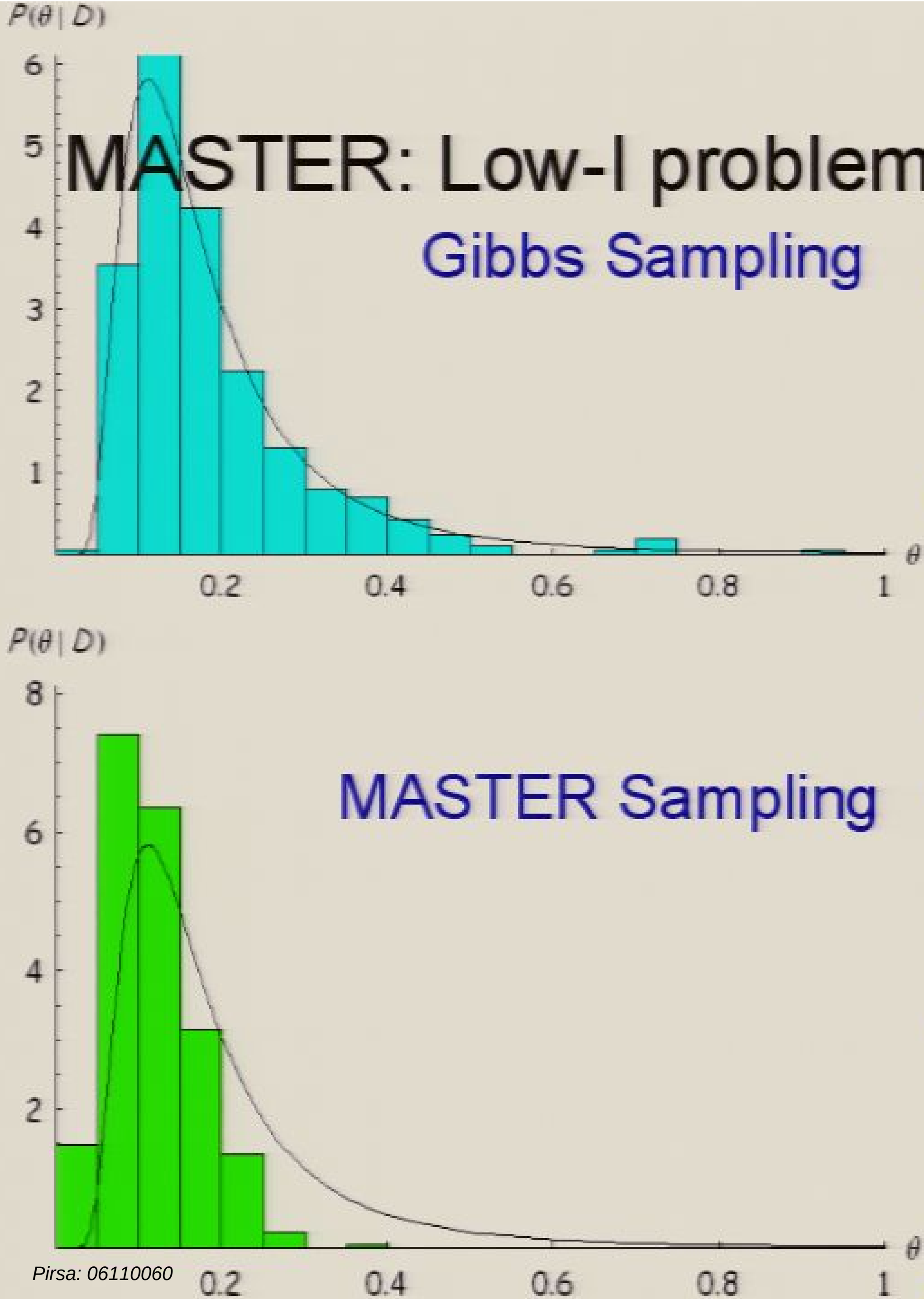
MASTER: Low-l problems even for Perfect Data





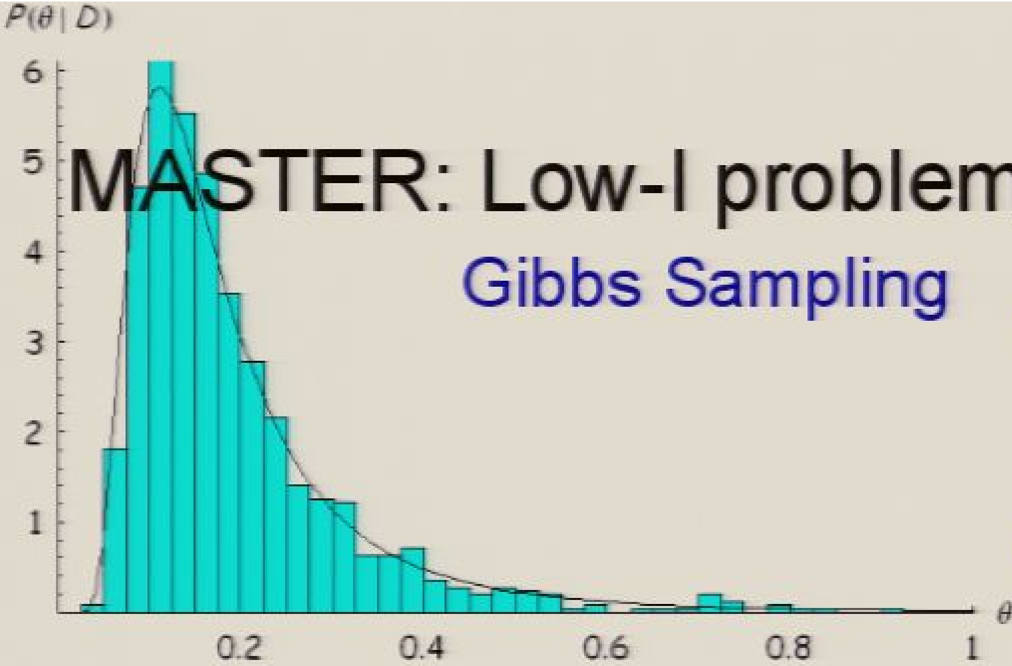
- What do the error bars from a MASTER-like approx. technique mean?
- Here is an example using perfect, all sky data without any noise.
- We focus on $\theta = C_4$.
- In both cases, the solid line shows the actual likelihood for C_ℓ at $\ell=4$.
- The samples are obtained using Gibbs sampling and by "regular" Monte Carlo, like MASTER.
- MASTER is *neither frequentist*

MASTER: Low-l problems even for Perfect Data

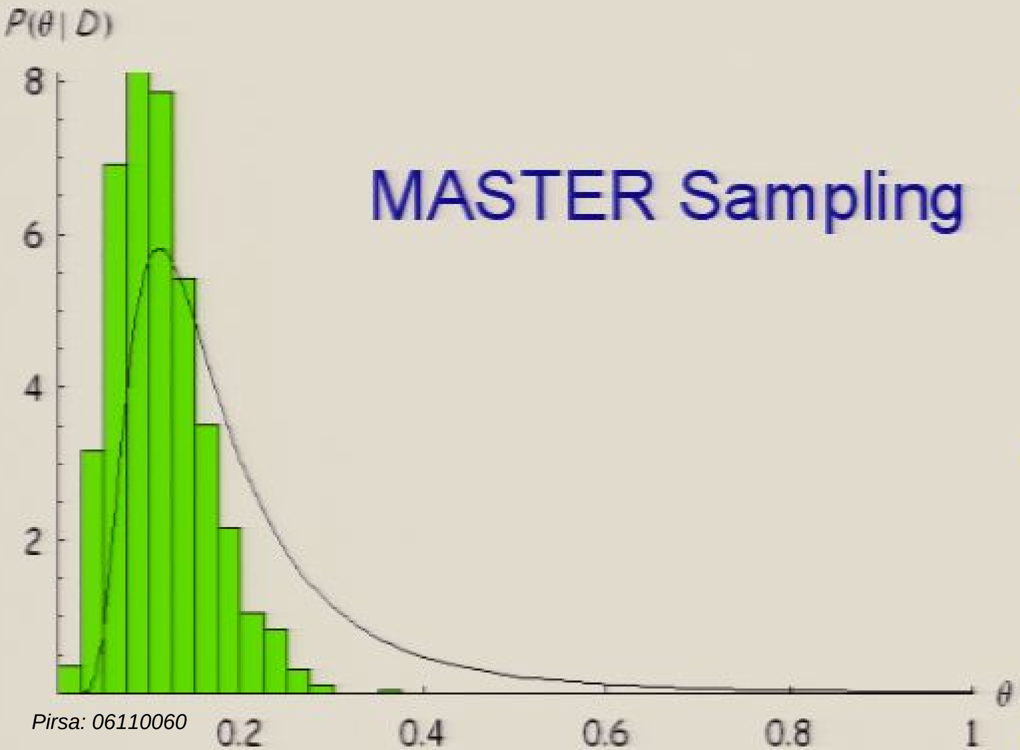


- What do the error bars from a MASTER-like approx. technique mean?
- Here is an example using perfect, all sky data without any noise.
- We focus on $\theta = C_4$.
- In both cases, the solid line shows the actual likelihood for C_ℓ at ℓ=4.
- The samples are obtained using Gibbs sampling and by "regular" Monte Carlo, like MASTER.
- MASTER is *neither frequentist*

MASTER: Low-l problems even for Perfect Data



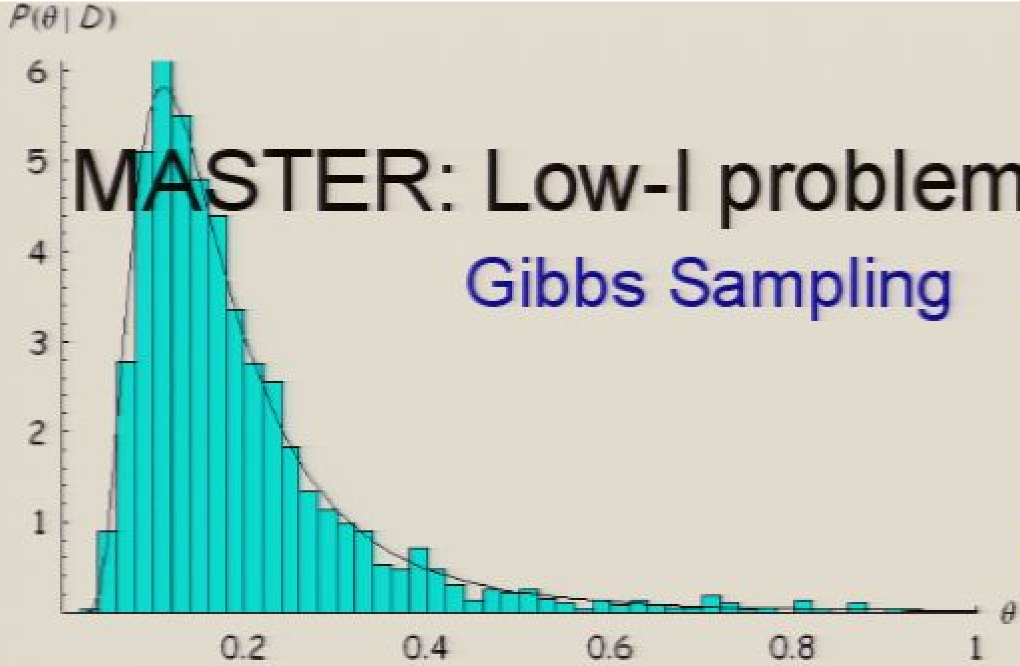
Gibbs Sampling

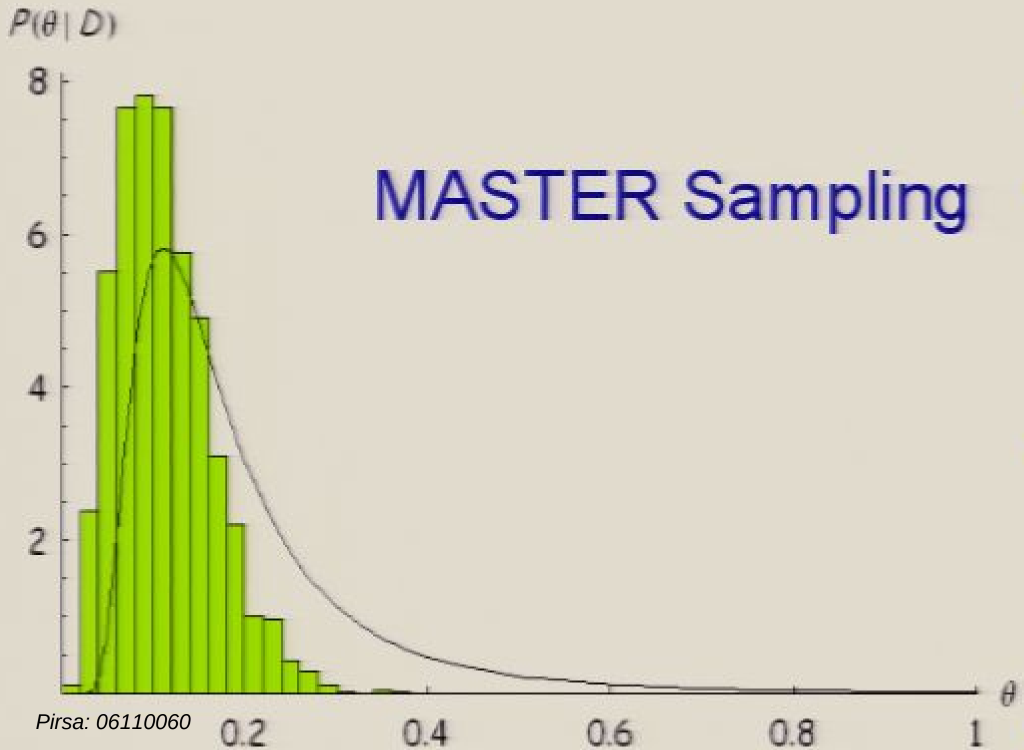


MASTER Sampling

- What do the error bars from a MASTER-like approx. technique mean?
- Here is an example using perfect, all sky data without any noise.
- We focus on $\theta = C_4$.
- In both cases, the solid line shows the actual likelihood for C_ℓ at $\ell=4$.
- The samples are obtained using Gibbs sampling and by "regular" Monte Carlo, like MASTER.
- MASTER is *neither frequentist*

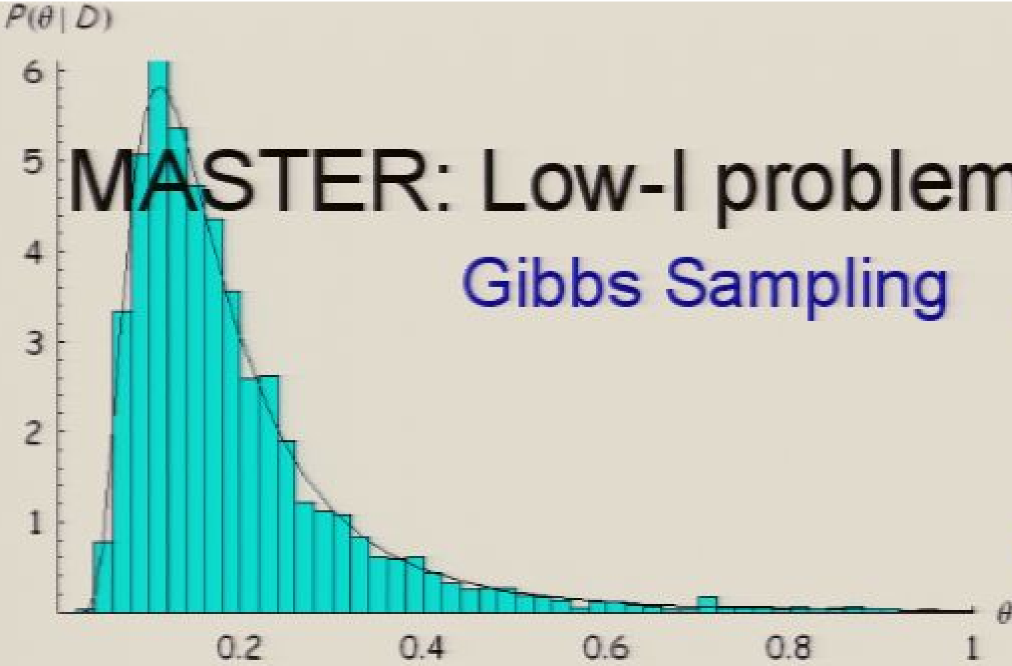
MASTER: Low-l problems even for Perfect Data

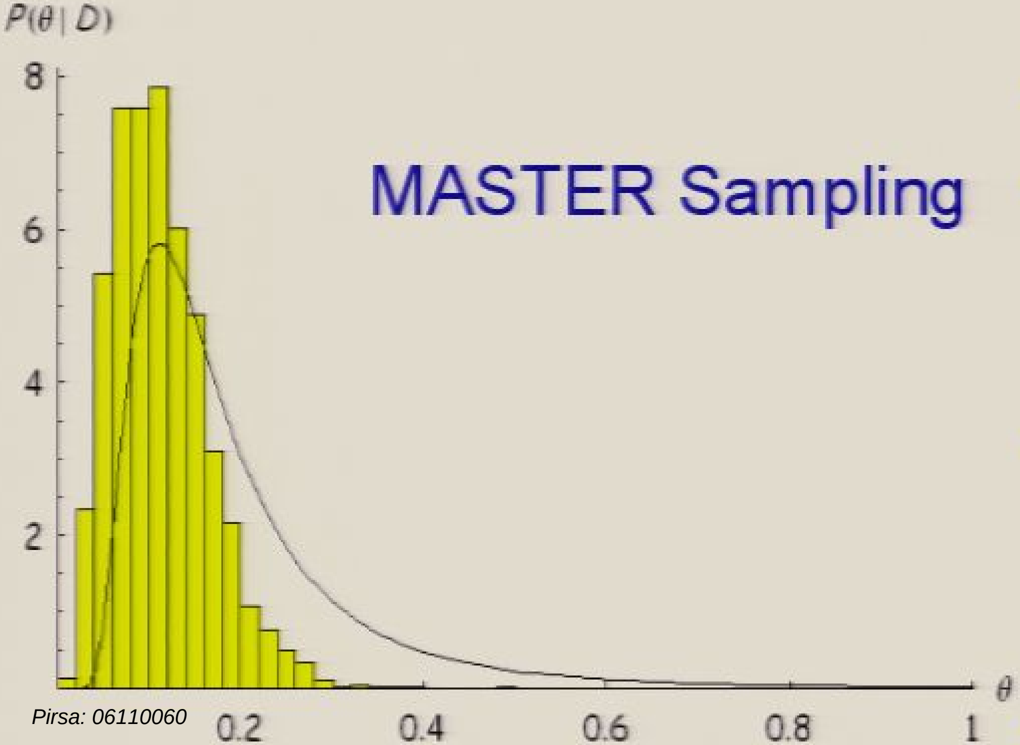




- What do the error bars from a MASTER-like approx. technique mean?
- Here is an example using perfect, all sky data without any noise.
- We focus on $\theta = C_4$.
- In both cases, the solid line shows the actual likelihood for C_ℓ at $\ell=4$.
- The samples are obtained using Gibbs sampling and by "regular" Monte Carlo, like MASTER.
- MASTER is *neither frequentist*

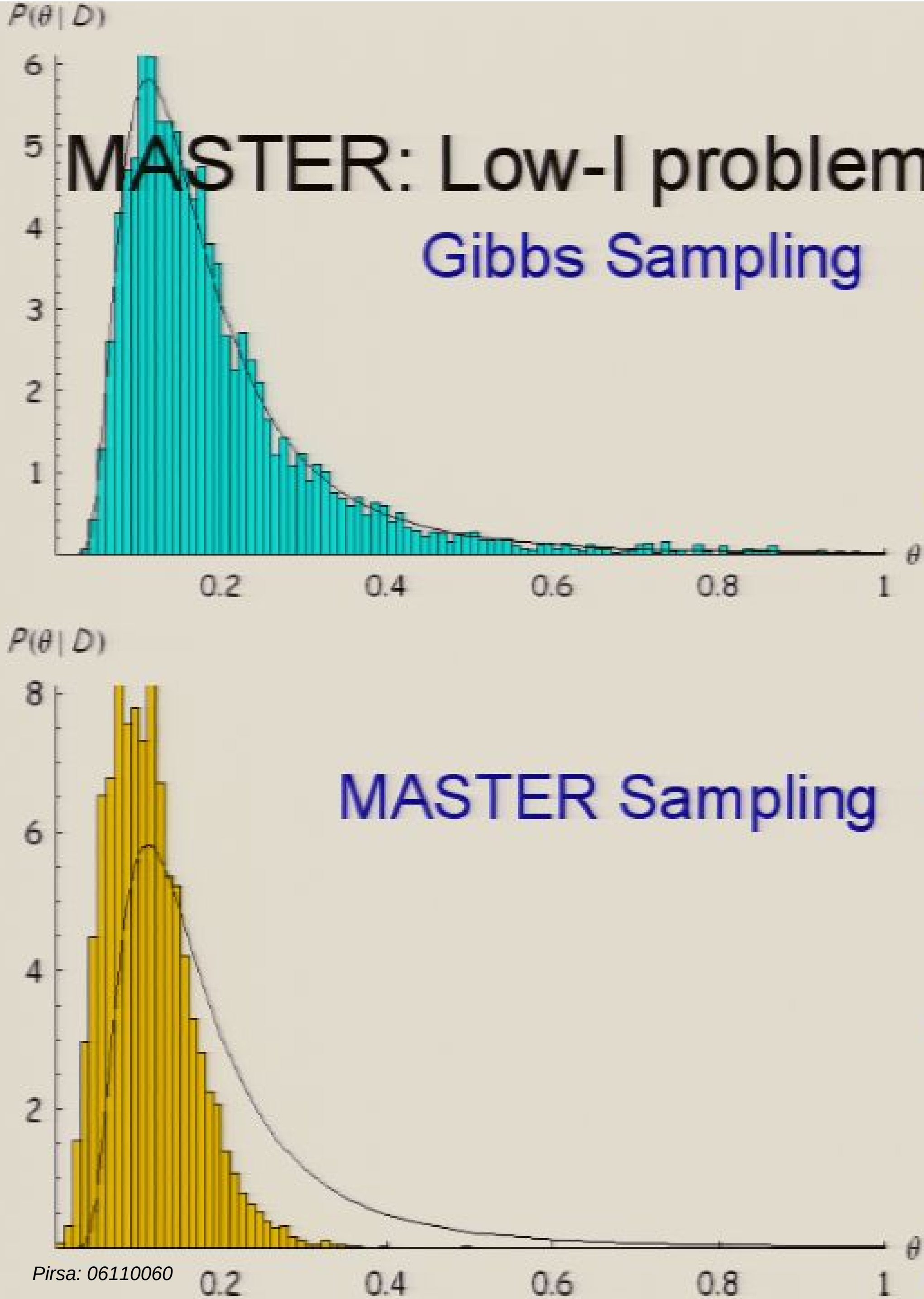
MASTER: Low-l problems even for Perfect Data





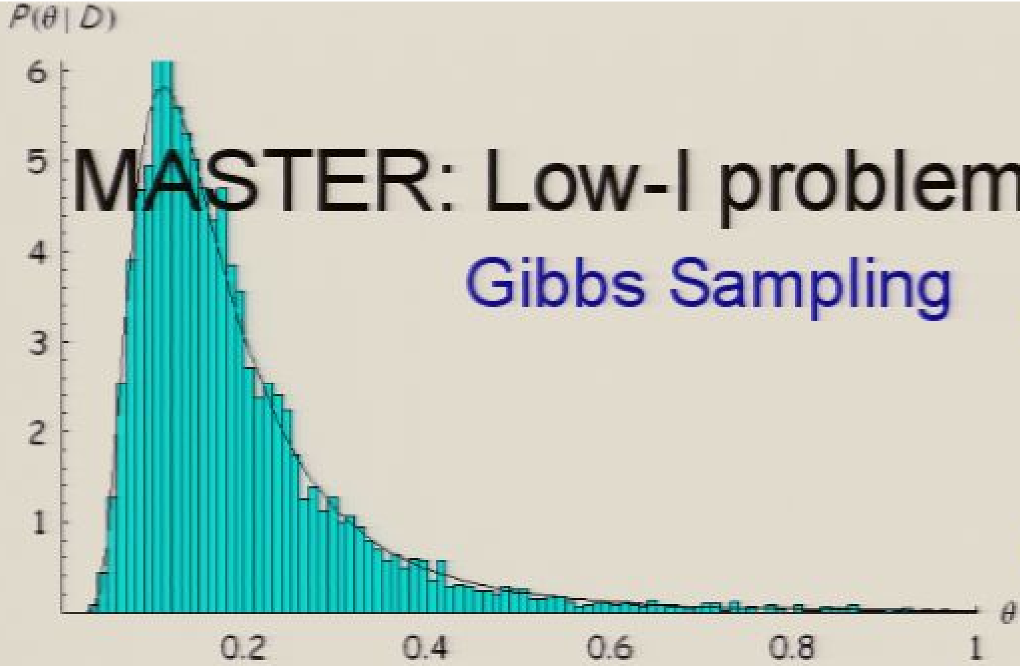
- What do the error bars from a MASTER-like approx. technique mean?
- Here is an example using perfect, all sky data without any noise.
- We focus on $\theta = C_4$.
- In both cases, the solid line shows the actual likelihood for C_ℓ at ℓ=4.
- The samples are obtained using Gibbs sampling and by "regular" Monte Carlo, like MASTER.
- MASTER is *neither frequentist*

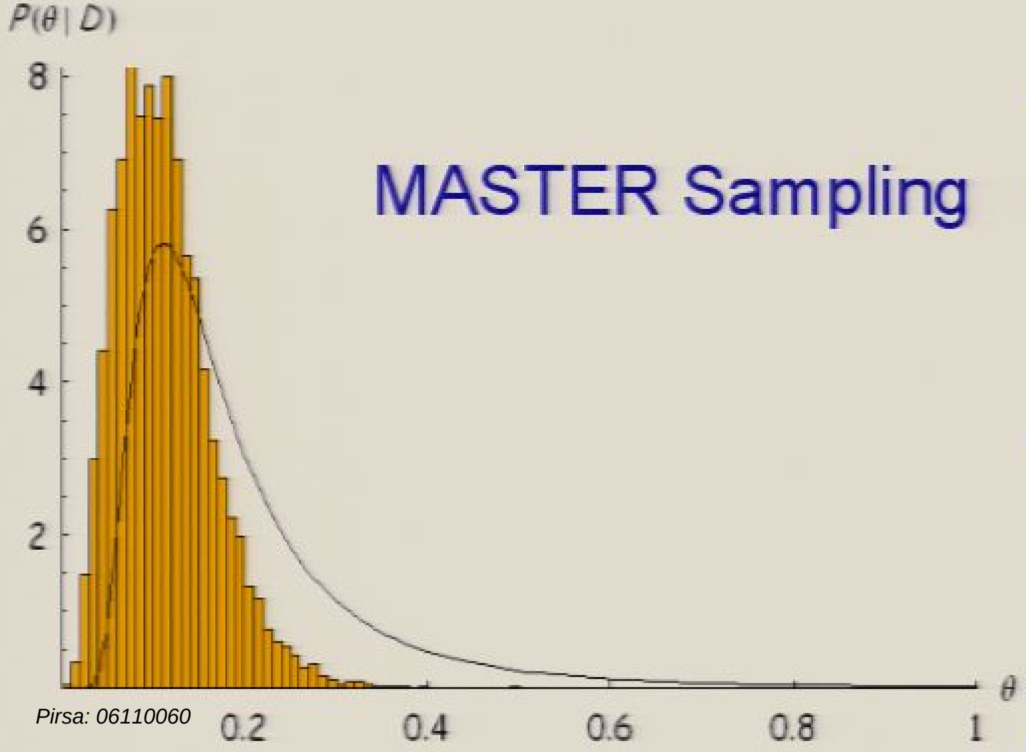
MASTER: Low-l problems even for Perfect Data



- What do the error bars from a MASTER-like approx. technique mean?
- Here is an example using perfect, all sky data without any noise.
- We focus on $\theta = C_4$.
- In both cases, the solid line shows the actual likelihood for C_ℓ at ℓ=4.
- The samples are obtained using Gibbs sampling and by "regular" Monte Carlo, like MASTER.
- MASTER is *neither frequentist*

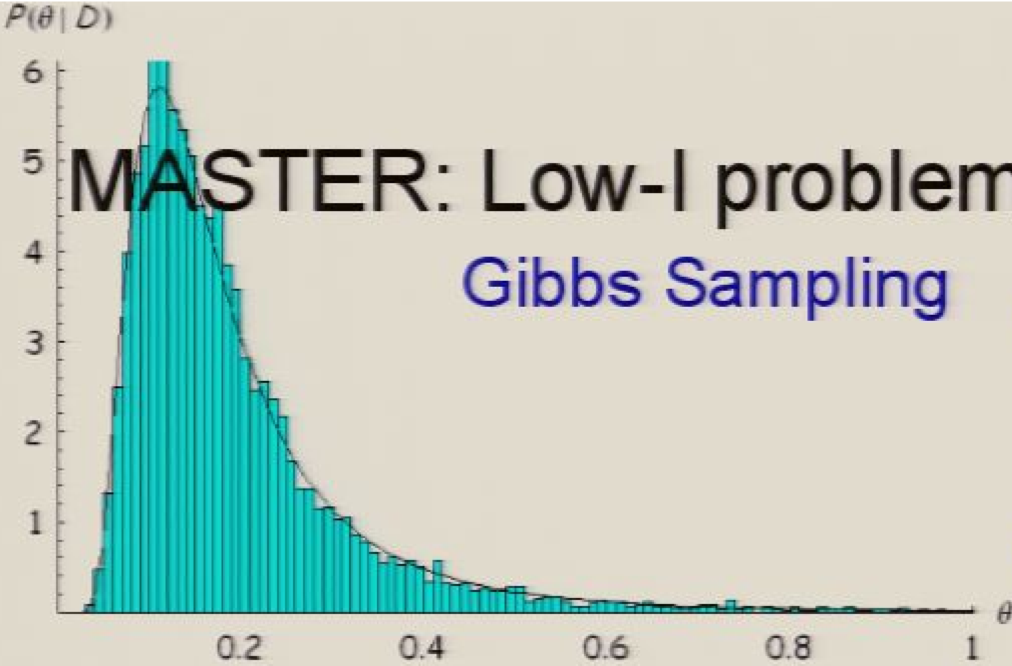
MASTER: Low-l problems even for Perfect Data



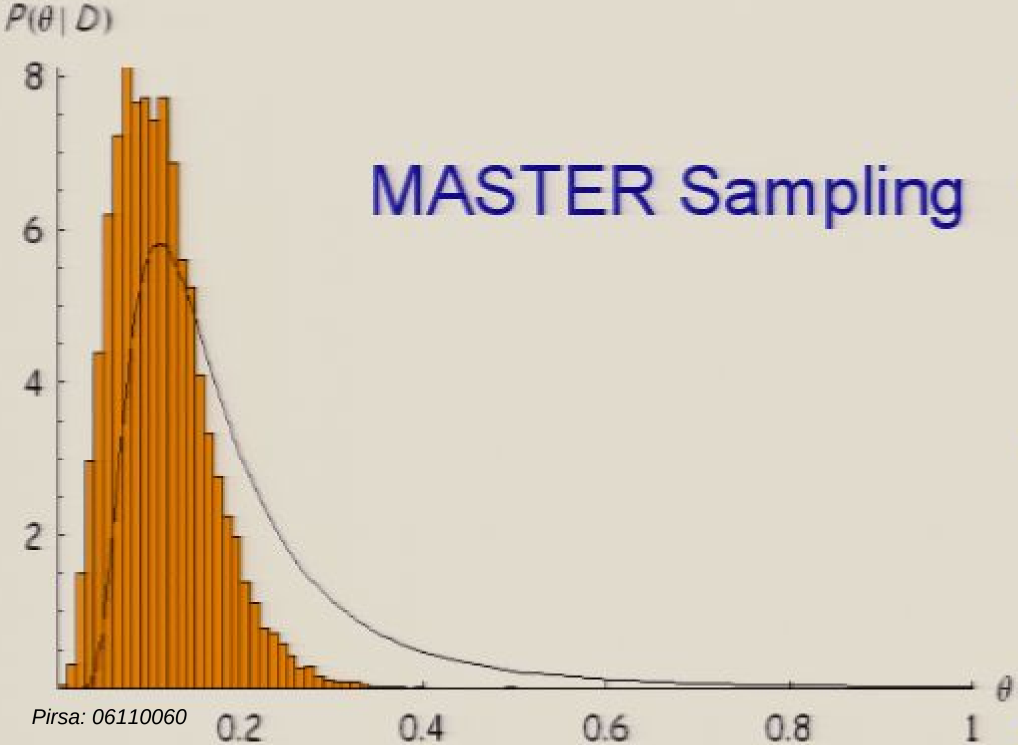


- What do the error bars from a MASTER-like approx. technique mean?
- Here is an example using perfect, all sky data without any noise.
- We focus on $\theta = C_4$.
- In both cases, the solid line shows the actual likelihood for C_ℓ at $\ell=4$.
- The samples are obtained using Gibbs sampling and by "regular" Monte Carlo, like MASTER.
- MASTER is *neither frequentist*

MASTER: Low-l problems even for Perfect Data



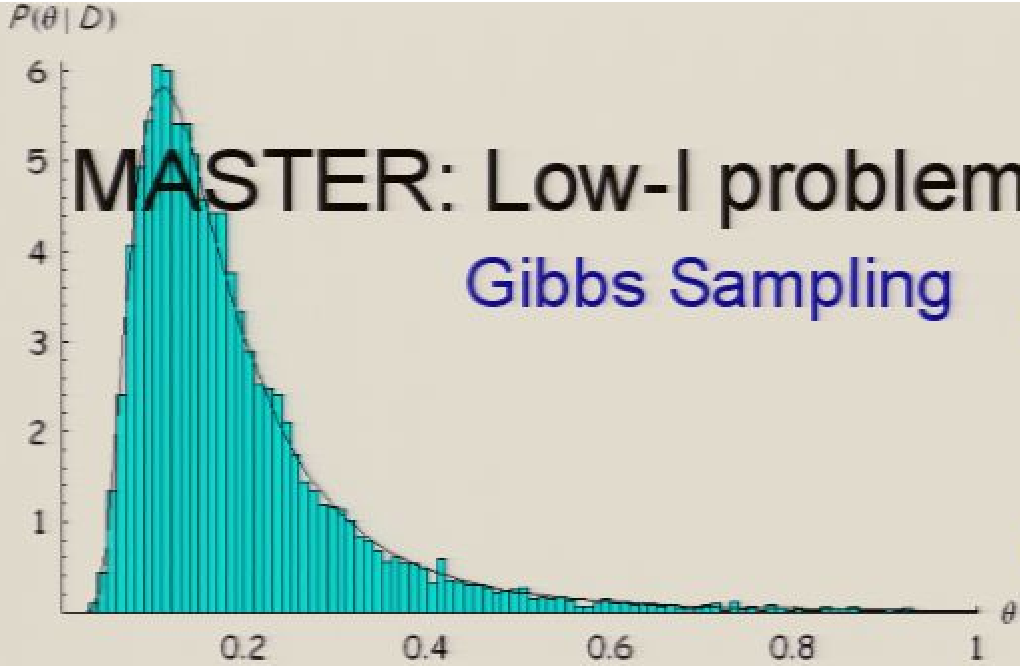
Gibbs Sampling

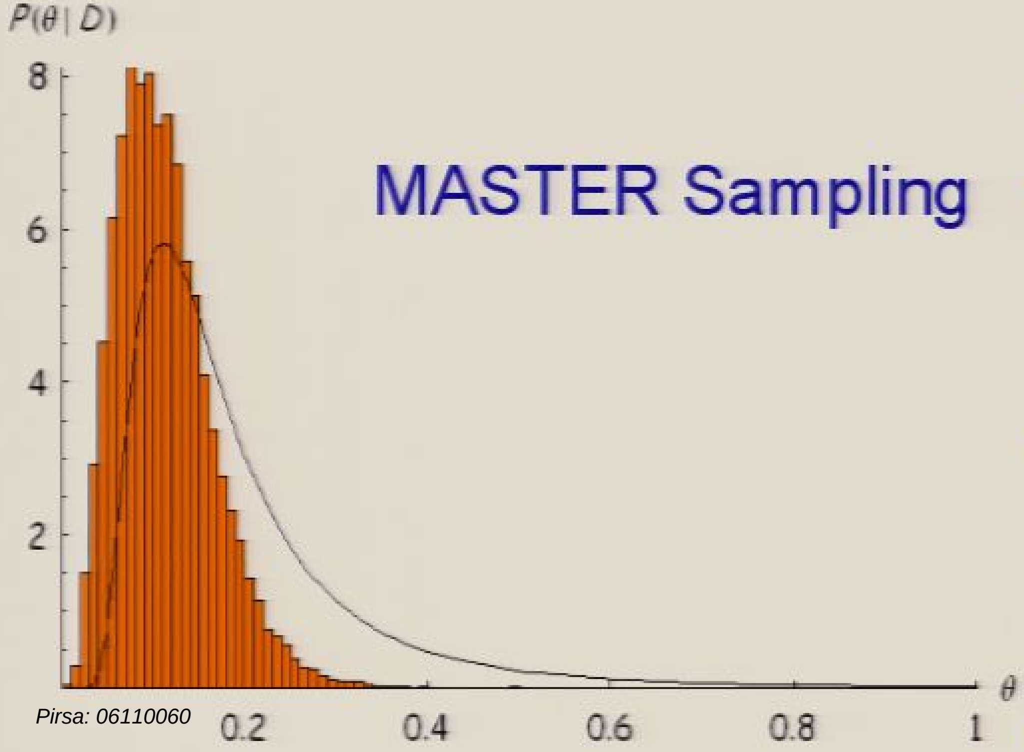


MASTER Sampling

- What do the error bars from a MASTER-like approx. technique mean?
- Here is an example using perfect, all sky data without any noise.
- We focus on $\theta = C_4$.
- In both cases, the solid line shows the actual likelihood for C_ℓ at $\ell=4$.
- The samples are obtained using Gibbs sampling and by “regular” Monte Carlo, like MASTER.
- MASTER is *neither frequentist*

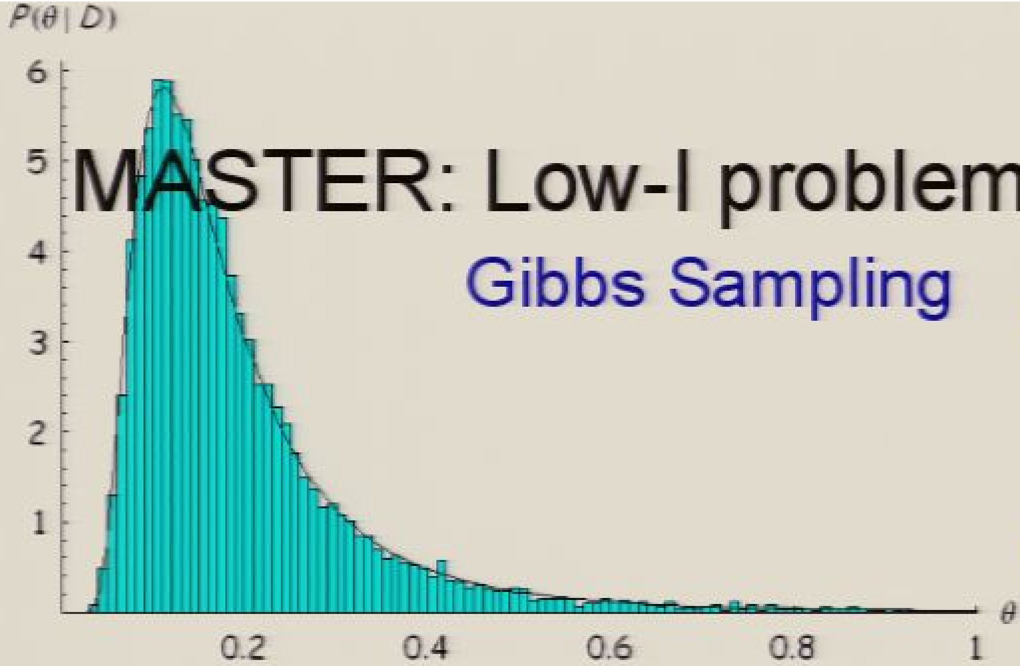
MASTER: Low-l problems even for Perfect Data

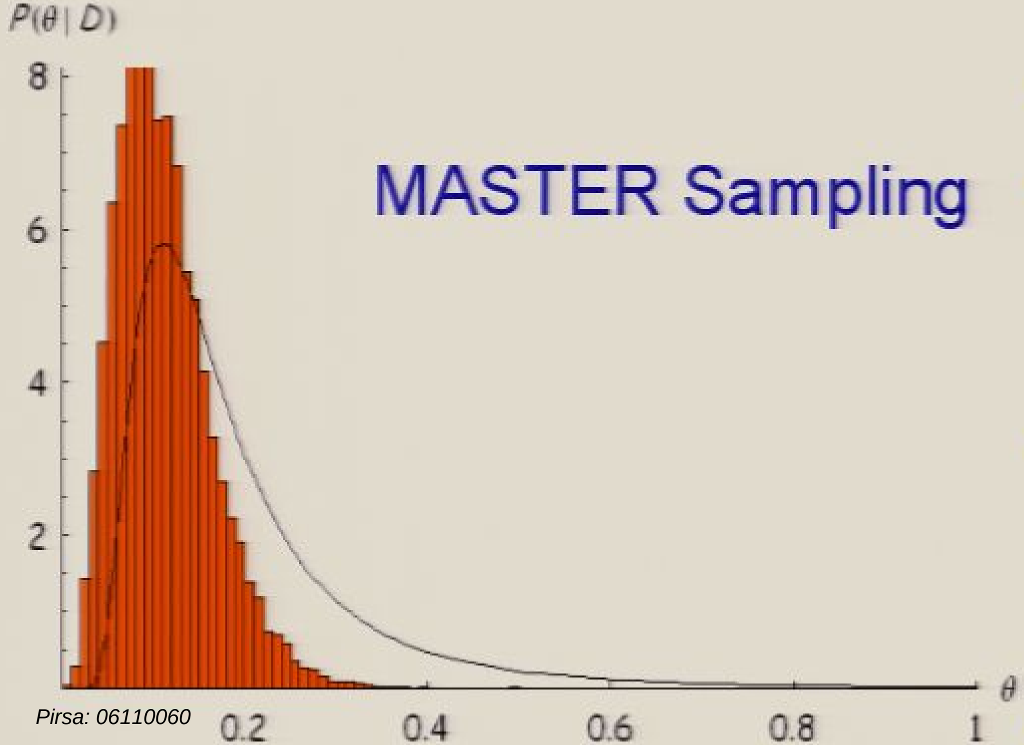




- What do the error bars from a MASTER-like approx. technique mean?
- Here is an example using perfect, all sky data without any noise.
- We focus on $\theta = C_4$.
- In both cases, the solid line shows the actual likelihood for C_ℓ at ℓ=4.
- The samples are obtained using Gibbs sampling and by "regular" Monte Carlo, like MASTER.
- MASTER is *neither frequentist*

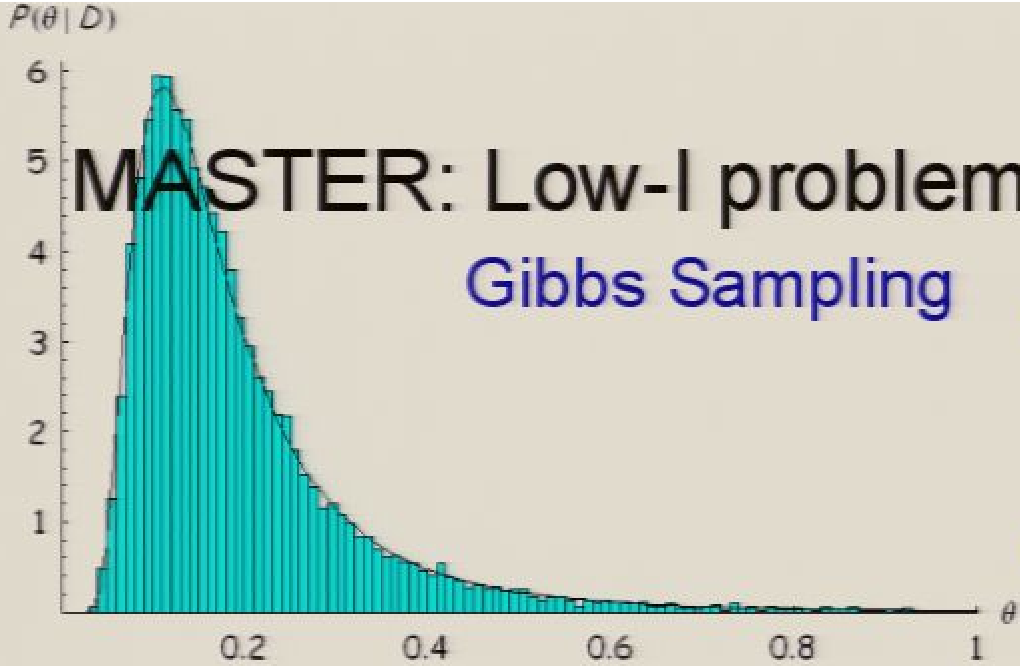
MASTER: Low-l problems even for Perfect Data



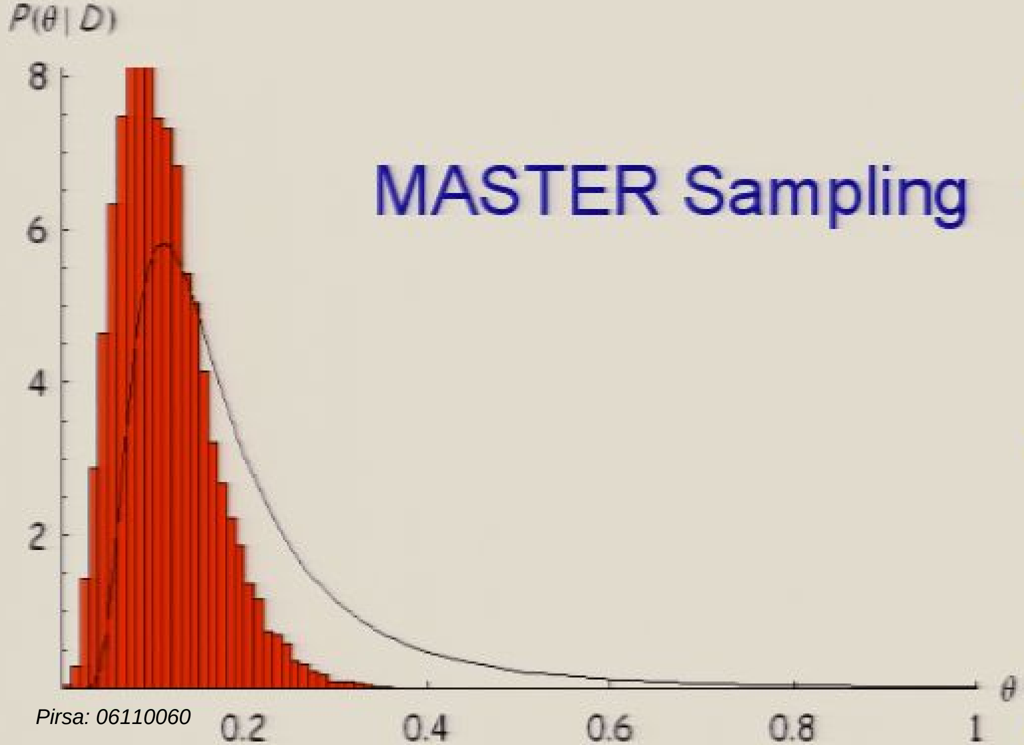


- What do the error bars from a MASTER-like approx. technique mean?
- Here is an example using perfect, all sky data without any noise.
- We focus on $\theta = C_4$.
- In both cases, the solid line shows the actual likelihood for C_ℓ at ℓ=4.
- The samples are obtained using Gibbs sampling and by “regular” Monte Carlo, like MASTER.
- MASTER is *neither frequentist*

MASTER: Low-l problems even for Perfect Data



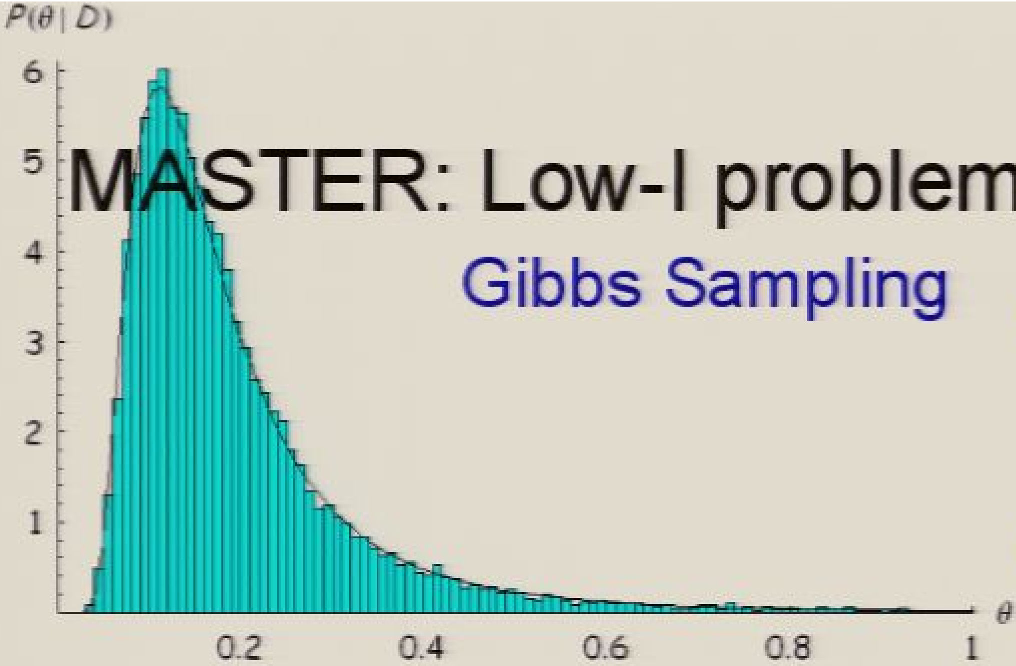
Gibbs Sampling

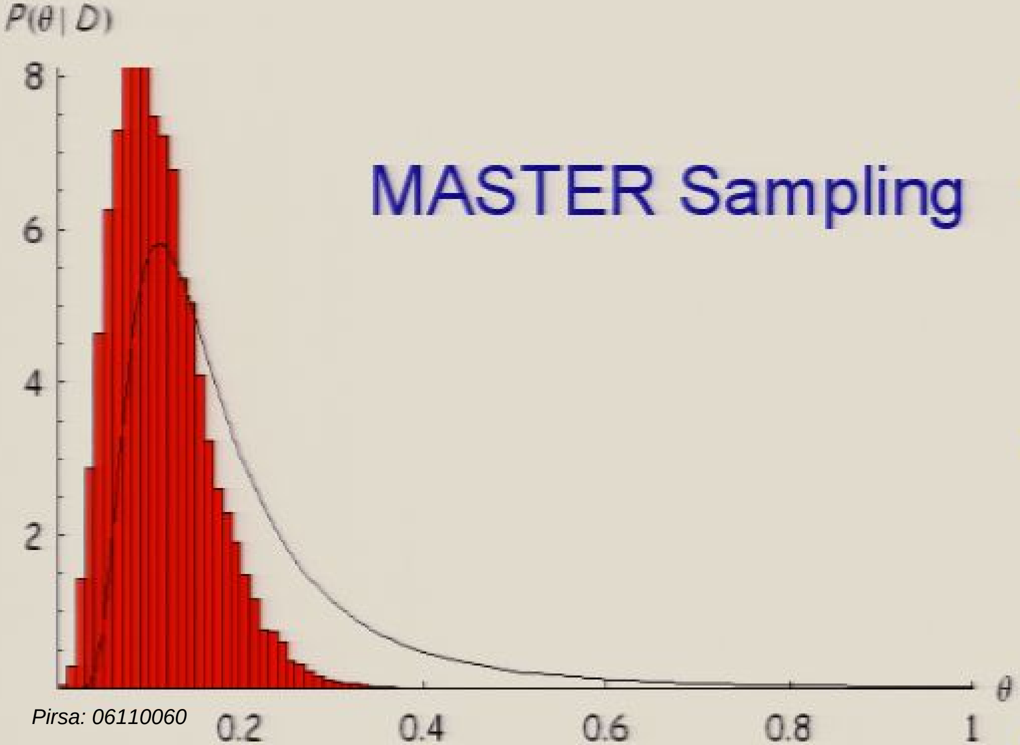


MASTER Sampling

- What do the error bars from a MASTER-like approx. technique mean?
- Here is an example using perfect, all sky data without any noise.
- We focus on $\theta = C_4$.
- In both cases, the solid line shows the actual likelihood for C_ℓ at $\ell=4$.
- The samples are obtained using Gibbs sampling and by "regular" Monte Carlo, like MASTER.
- MASTER is *neither frequentist*

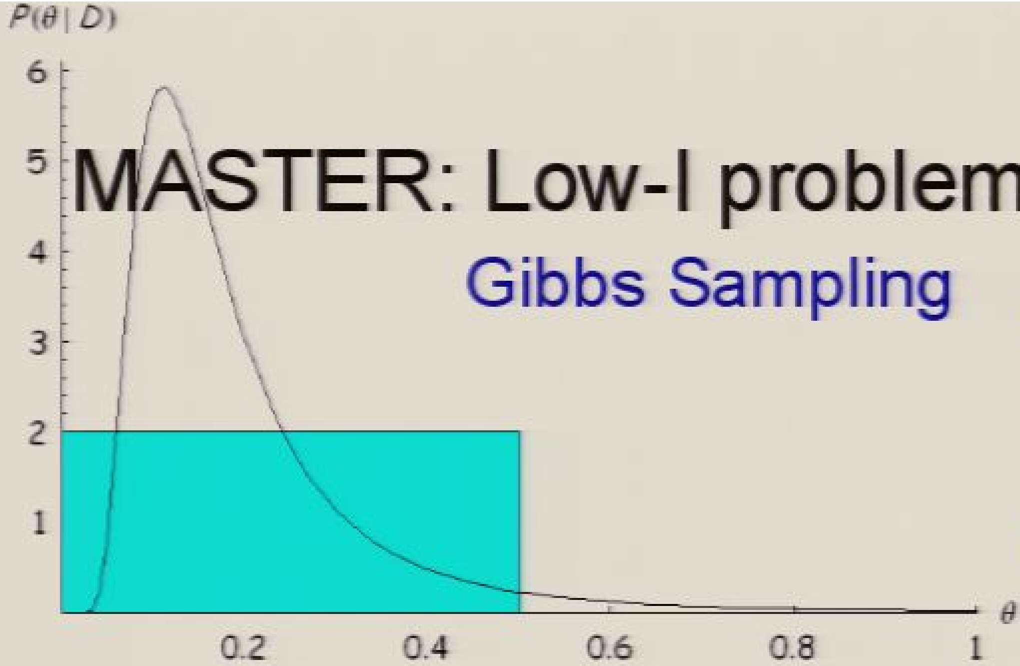
MASTER: Low-l problems even for Perfect Data



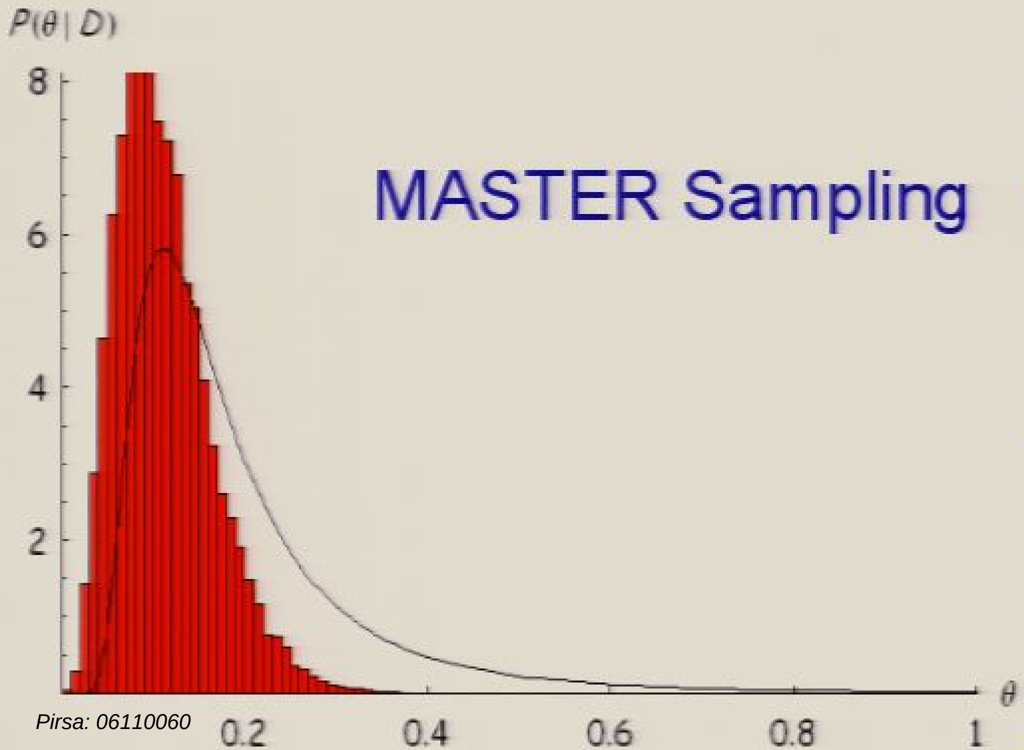


- What do the error bars from a MASTER-like approx. technique mean?
- Here is an example using perfect, all sky data without any noise.
- We focus on $\theta = C_4$.
- In both cases, the solid line shows the actual likelihood for C_ℓ at ℓ=4.
- The samples are obtained using Gibbs sampling and by "regular" Monte Carlo, like MASTER.
- MASTER is *neither frequentist*

MASTER: Low-l problems even for Perfect Data



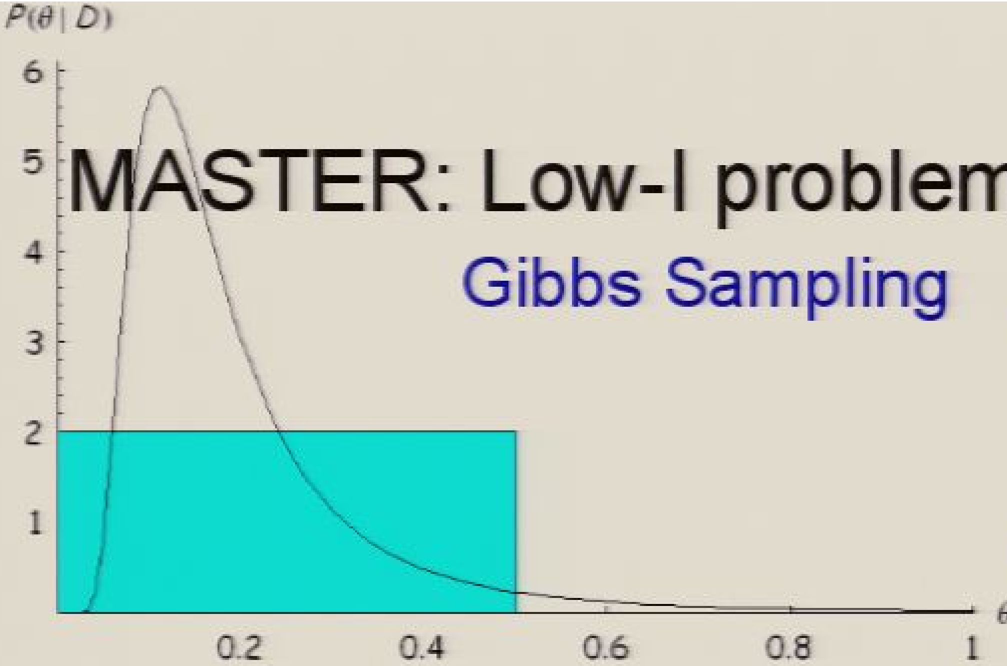
Gibbs Sampling



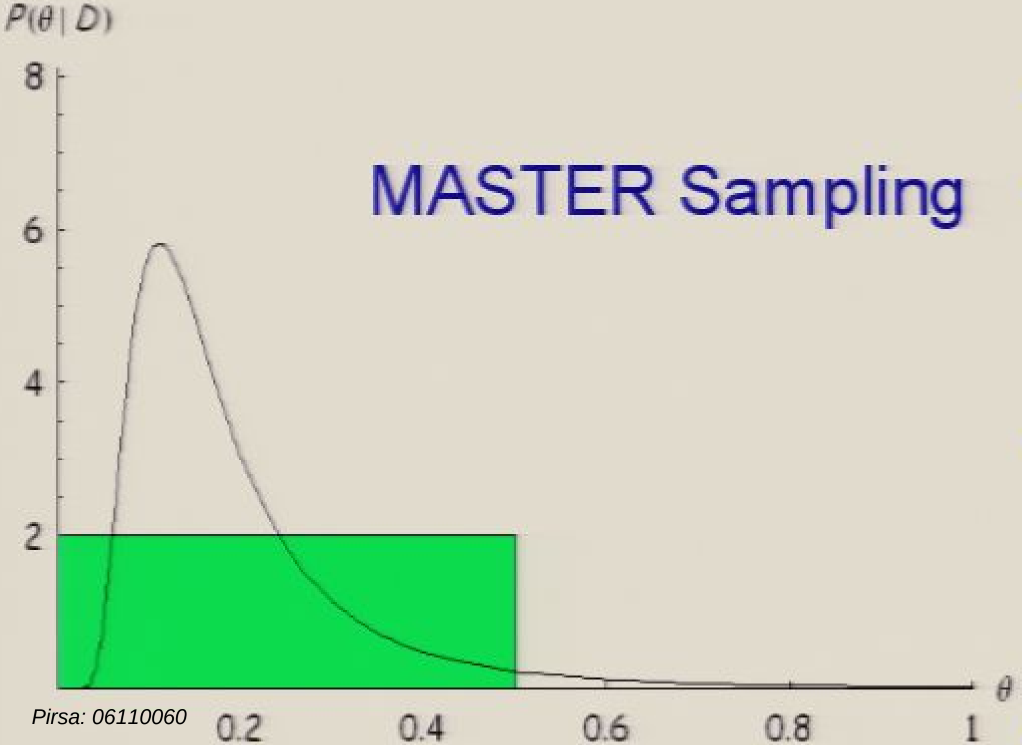
MASTER Sampling

- What do the error bars from a MASTER-like approx. technique mean?
- Here is an example using perfect, all sky data without any noise.
- We focus on $\theta = C_4$.
- In both cases, the solid line shows the actual likelihood for C_ℓ at $\ell=4$.
- The samples are obtained using Gibbs sampling and by “regular” Monte Carlo, like MASTER.
- MASTER is *neither frequentist*

MASTER: Low-l problems even for Perfect Data



Gibbs Sampling



MASTER Sampling

- What do the error bars from a MASTER-like approx. technique mean?
- Here is an example using perfect, all sky data without any noise.
- We focus on $\theta = C_4$.
- In both cases, the solid line shows the actual likelihood for C_ℓ at ℓ=4.
- The samples are obtained using Gibbs sampling and by “regular” Monte Carlo, like MASTER.
- MASTER is *neither frequentist*

The Team (alphabetical by institution)

- IUCAA, IIT Kanpur
  - Tarun Souradeep and students (IUCAA, IIT Kanpur)
- JPL/Caltech
  - Jeff Jewell
  - Ian O'Dwyer
  - Krzysztof Górski
- Max Planck Institut für Astrophysik
  - Anthony Banday
- University of California at Davis
  - Lloyd Knox
  - J. Dick
- University of Illinois at Urbana-Champaign
  - Ben Wandelt
  - Greg Huey
  - David Larson
- University of Oslo
  - Hans-Kristian Eriksen
  - Frode Hansen

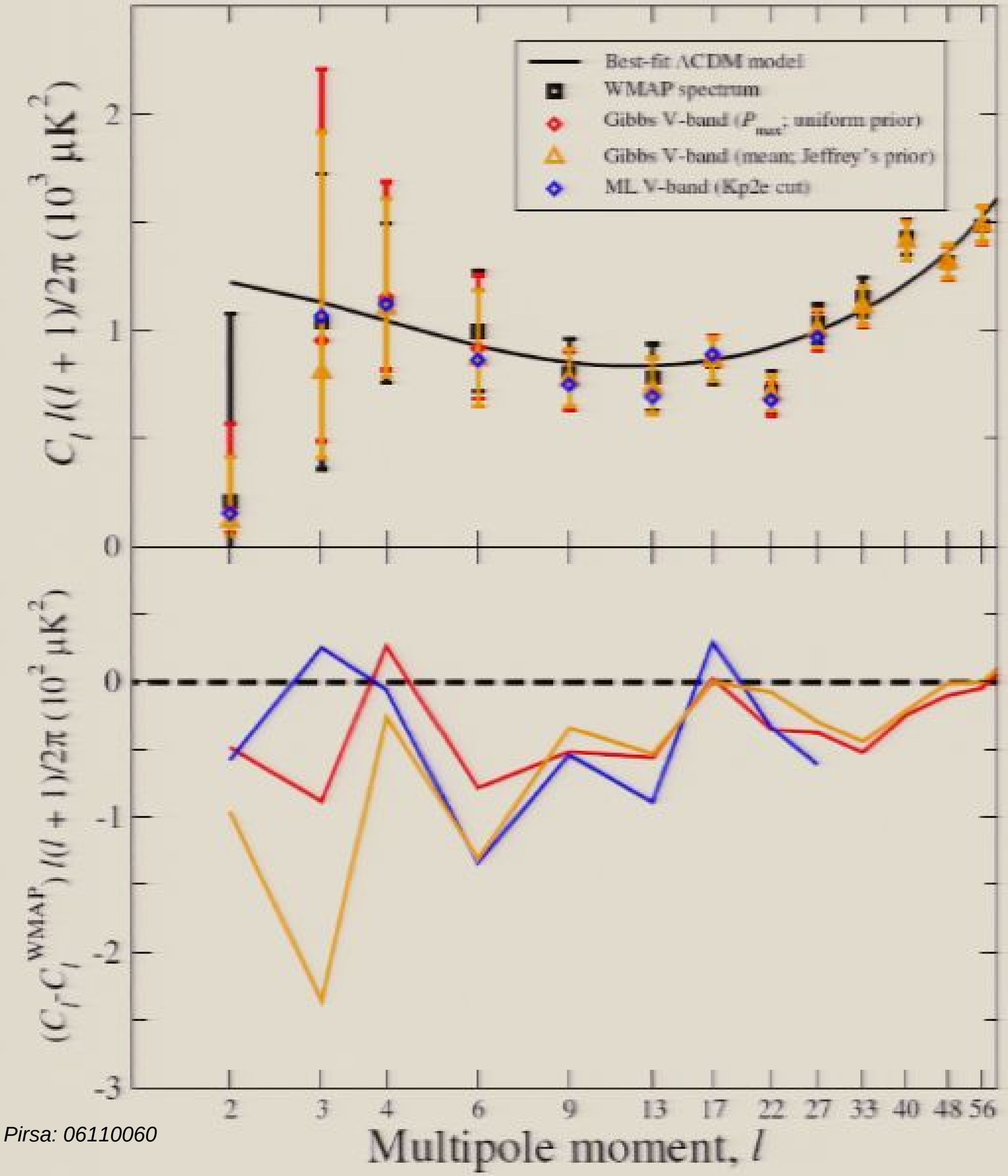
Eriksen et al., ApJ in press, astro-ph/0606088

WMAP re-analysis

- Cross-checking approach adopted throughout
- 5 different research groups (JPL, Illinois, Oslo, "India," Davis)
- 4 different analysis methods
  - Gibbs sampling (2 versions of priors)
  - Maximum likelihood
  - Metropolis Hastings exploration of exact low-l likelihood
  - MASTER (two different foreground treatments)
- This approach allows us to check for not just for systematic differences in the analysis but also various other errors (data handling etc...)

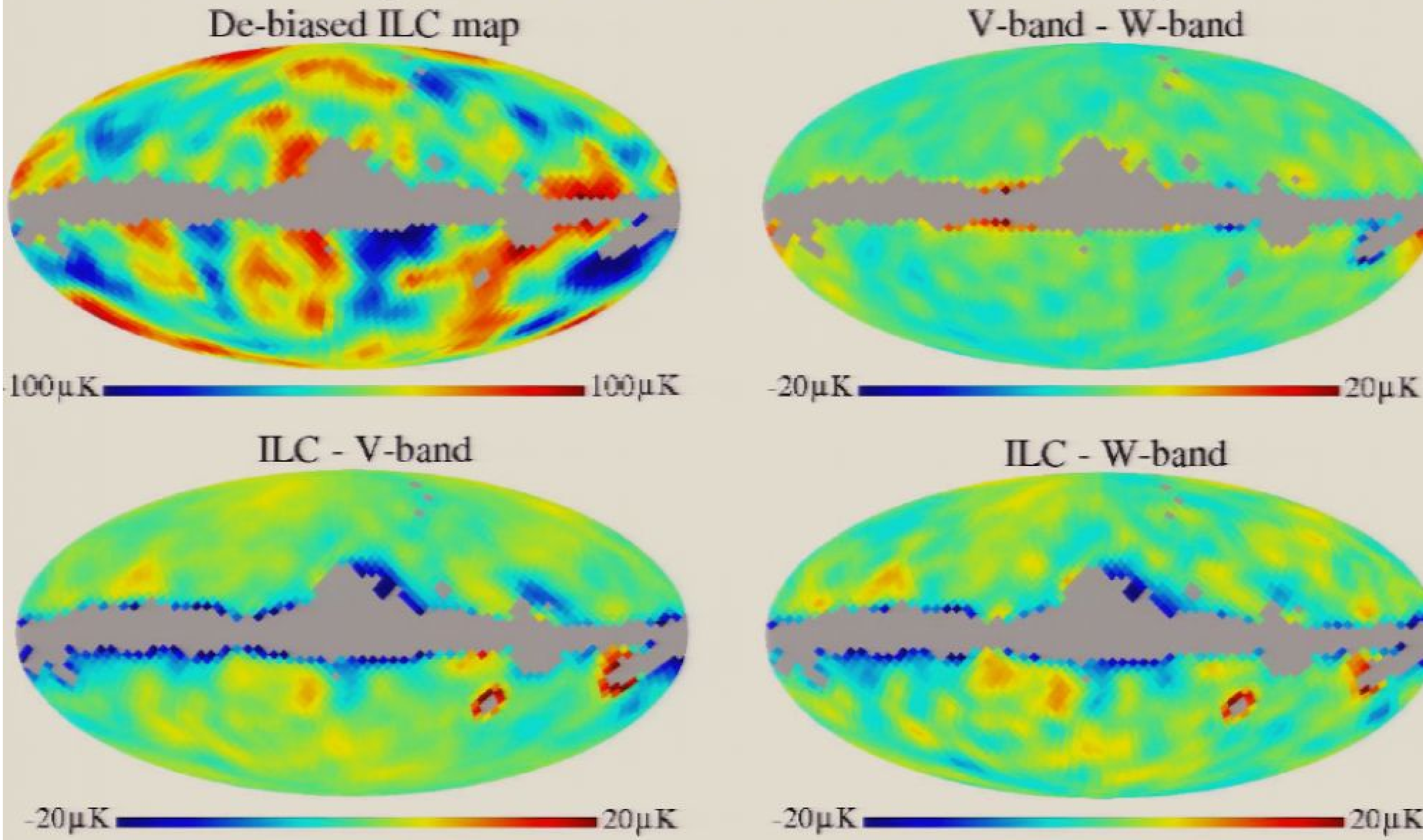
Eriksen et al., ApJ in press, astro-ph/060

Results of low l analysis

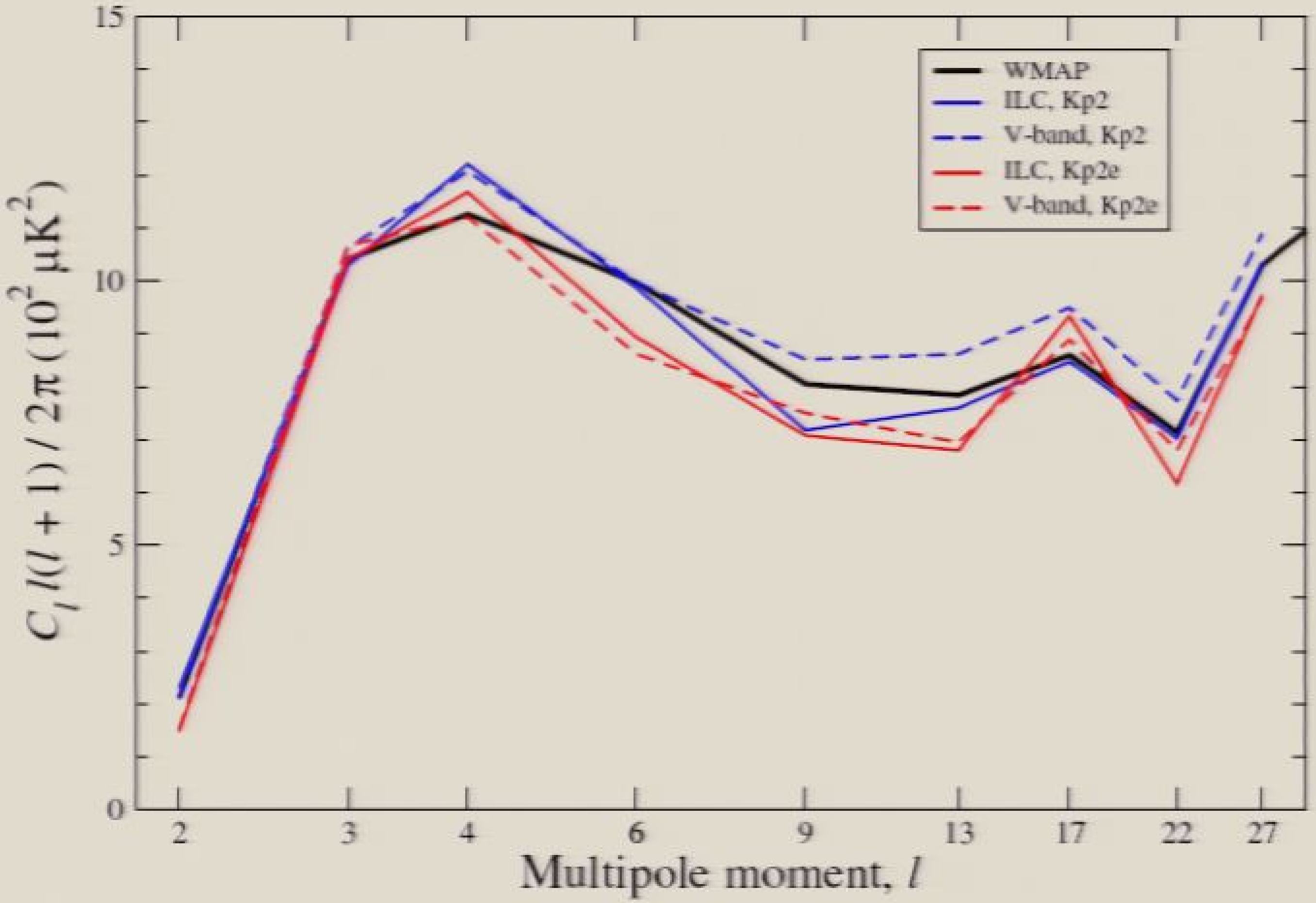


- First result: very good agreement l by l for all methods.
- Second look: the small offset compared to WMAP spectrum is correlated across l.
- These correlated deviations can int

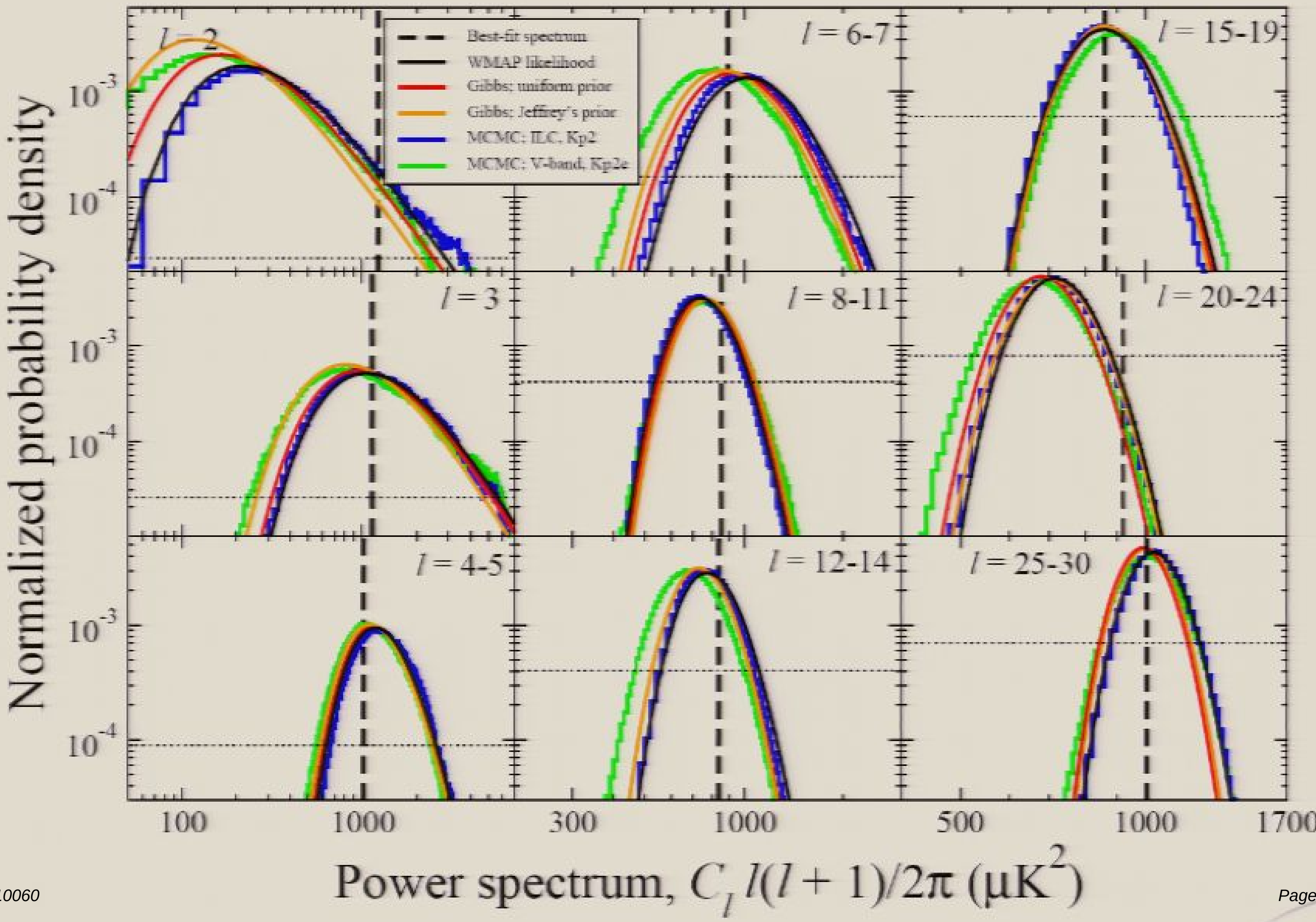
Masking issues in the WMAP3 analysis



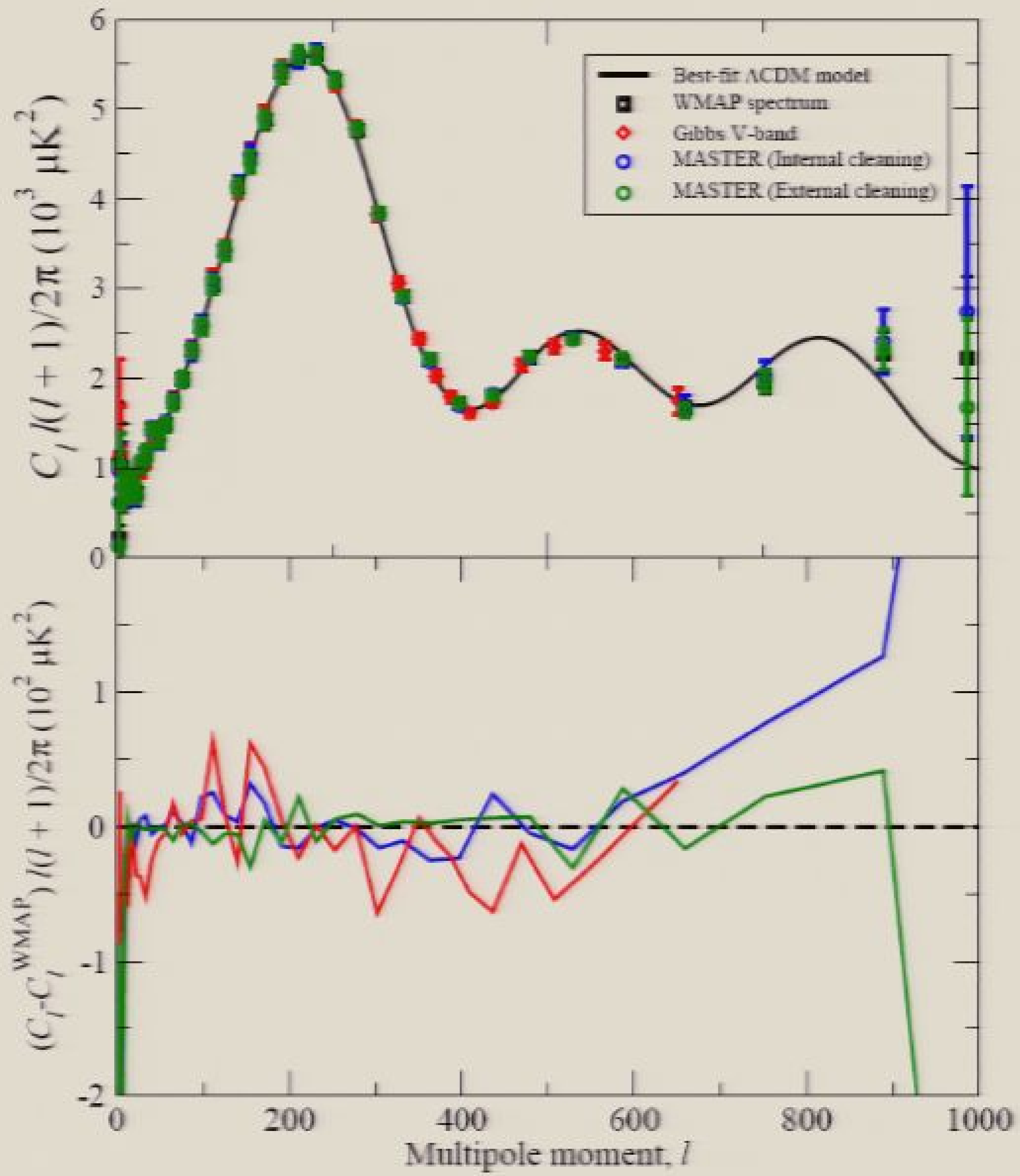
Masking effects on low l power spectrum estimates



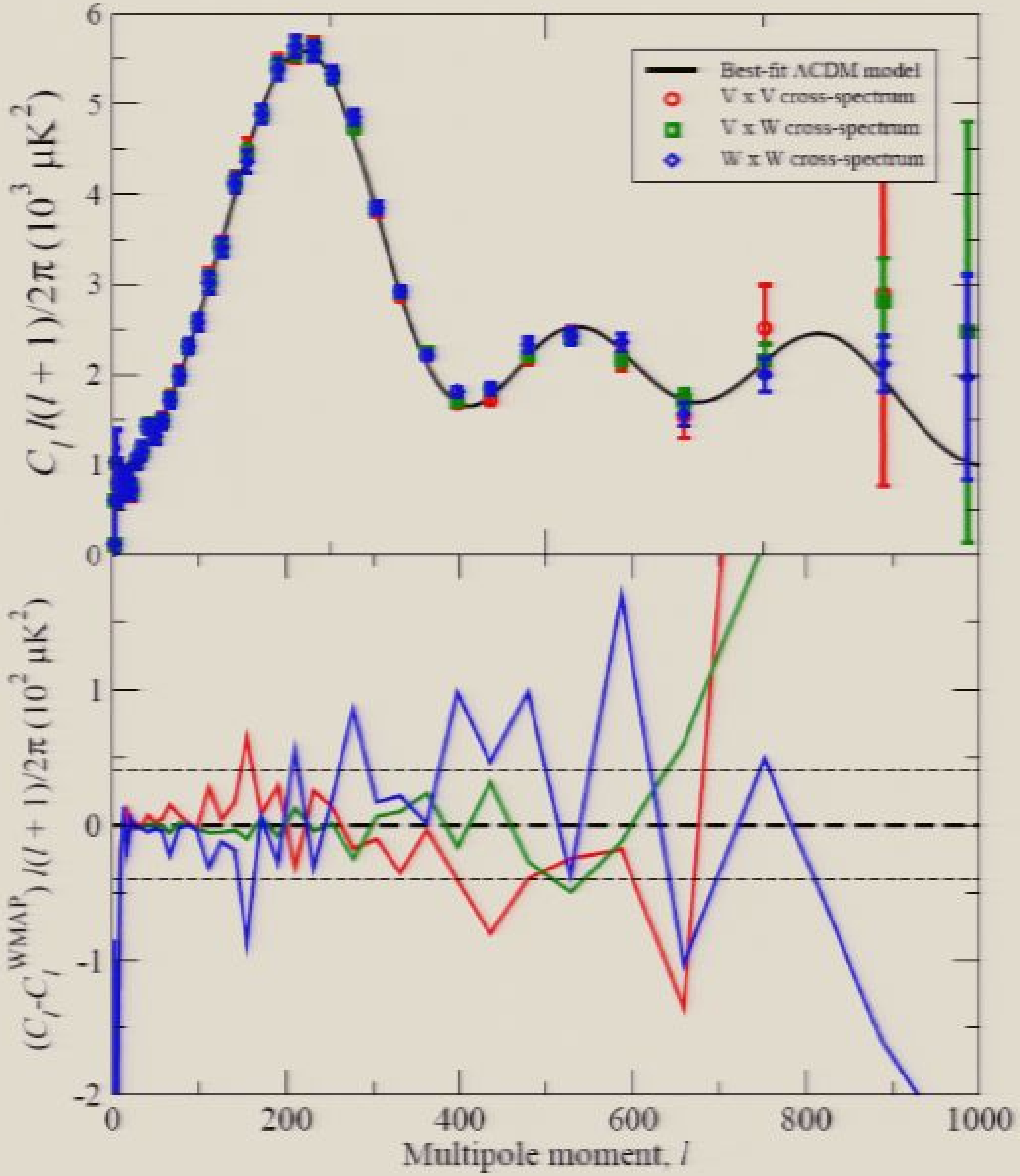
Low l likelihoods and posteriors for C_l



High resolution (all-scale) analysis

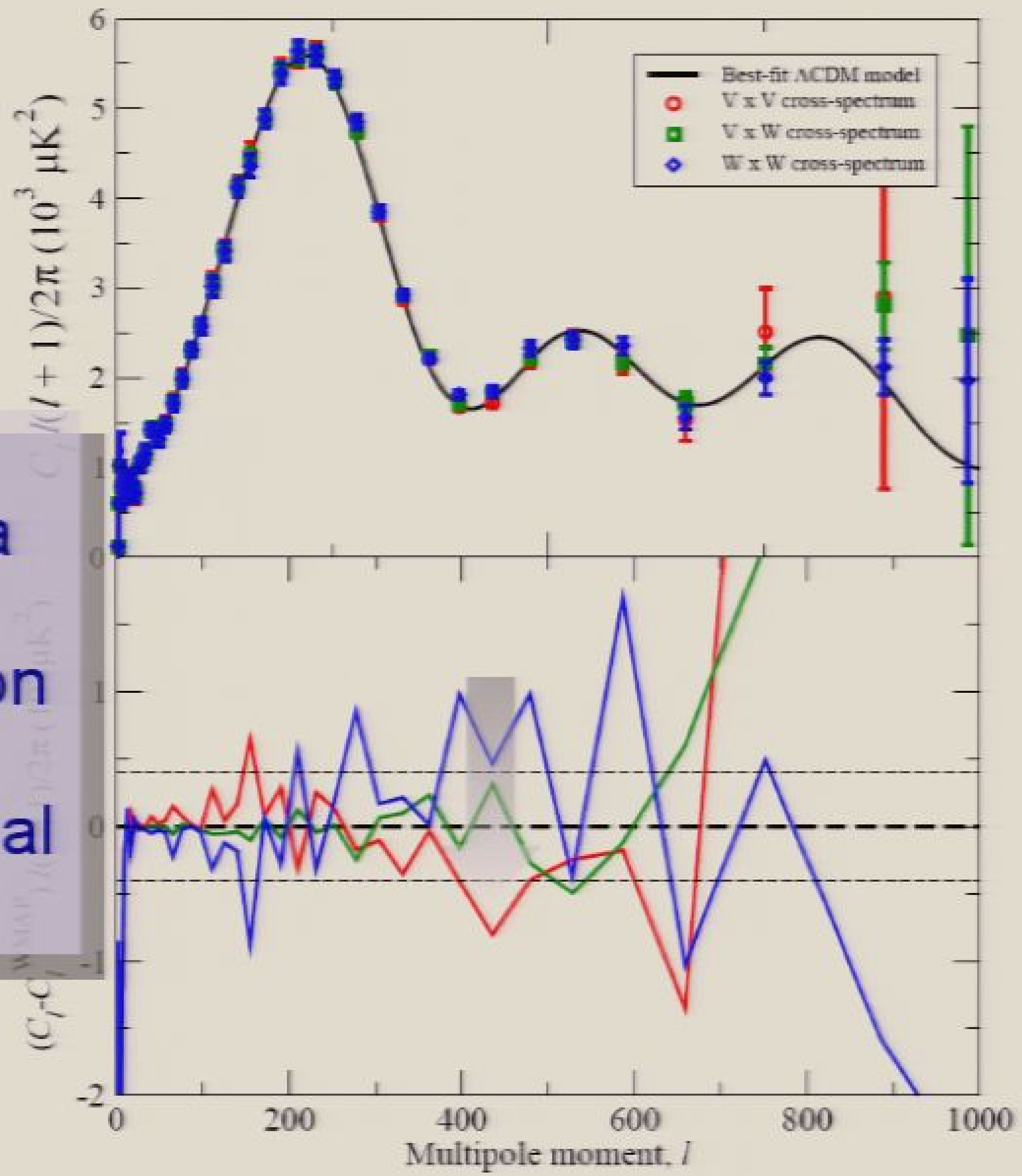


MASTER for Individual Frequency Combinations



Band shows error estimate due to beam asymmetries

MASTER for Individual Frequency Combinations

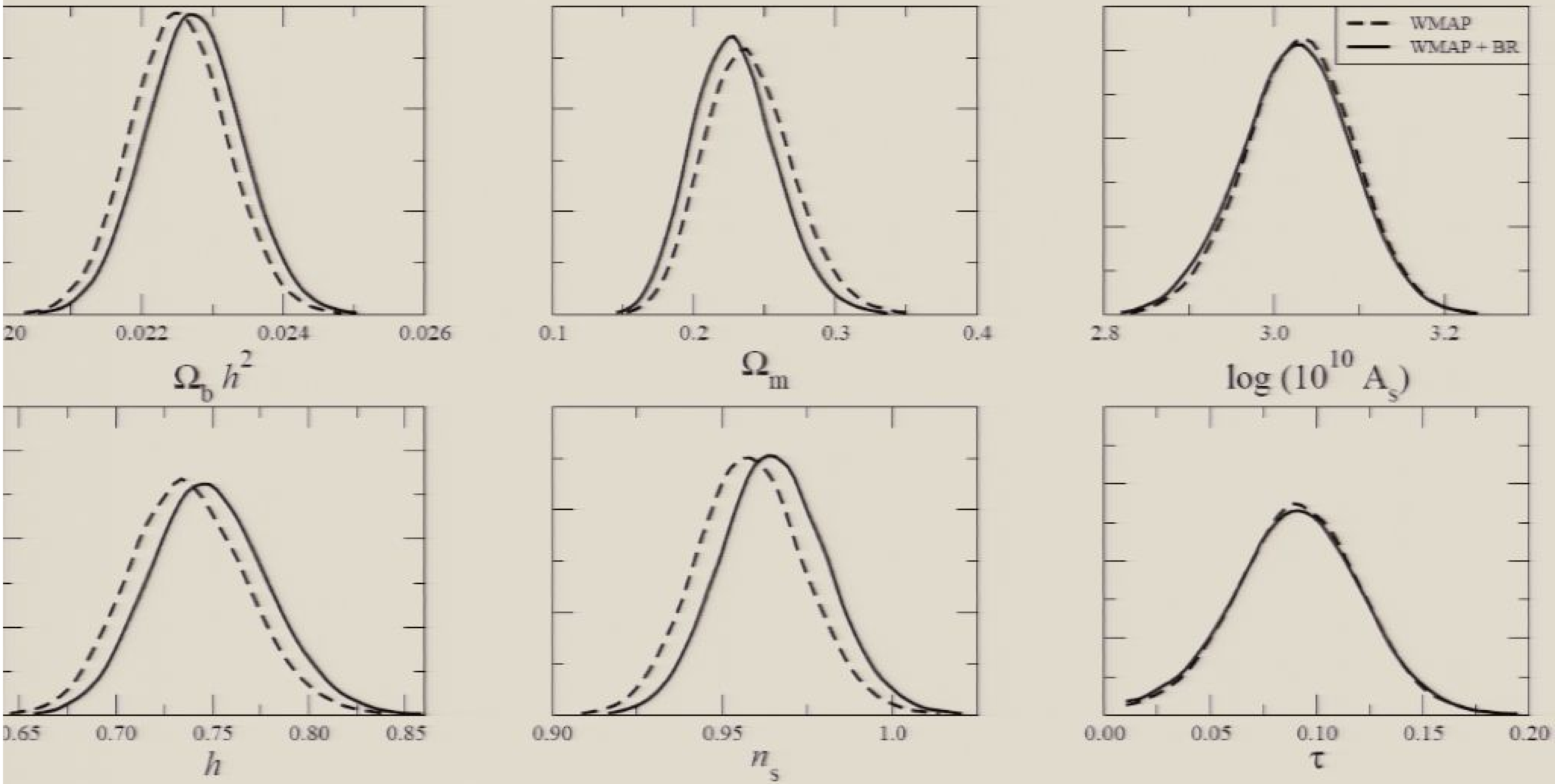


This effect is consistent with a different point source population

Huffenberger et al 2006

Band shows error estimate due to beam asymmetries

Cosmological implications



Conclusions

- Statistically rigorous analysis of the CMB is now feasible using Bayesian sampling techniques (Gibbs sampling).
- Pseudo-C_ℓ techniques are very convenient, but the error bars are "special," especially at low l. This is dangerous when S/N is ~1.
- The WMAP 3-year power spectrum contains a low-l bias, at l around 30
- The WMAP 3-year data power spectrum also contains a bias at high l (400-600) which is consistent with overcorrection for point sources
- The net result of these biases is reduced evidence for $n_s < 1$:
  - The exact low-l likelihood reduces significance from 2.7σ to 2.3σ
  - A new high l point source correction (Huffenberger et al) further reduces the significance to 2σ.
- The new version of the WMAP3 likelihood code on LAMBDA gives results consistent with these conclusions.