

The high-dimensional and
multi-modal Bayesian inference code
DIAMONDS

The background graphic consists of a dense, wavy pattern of blue and yellow dots, creating a textured, undulating effect that serves as a backdrop for the text.

Application to Asteroseismology

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Bayesian Statistics

Bayes Theorem

$$\mathbf{D} = \{d_1, d_2, \dots, d_m\}$$

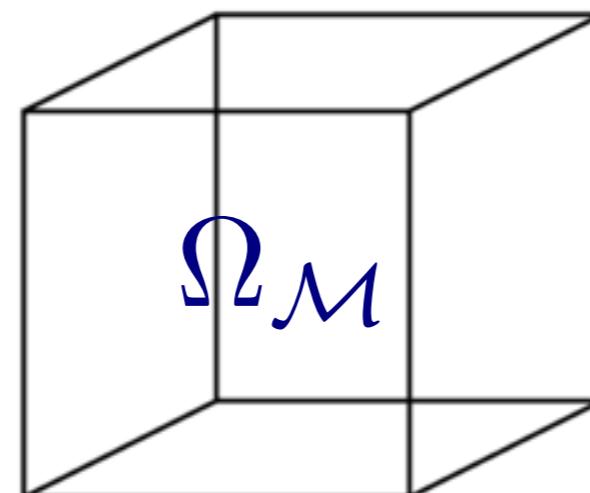
Dataset (observations)

$$\mathcal{M} = \mathcal{M}(\boldsymbol{\theta})$$

Model to be tested

$$\boldsymbol{\theta} = \{\theta_1, \theta_2, \dots, \theta_k\}$$

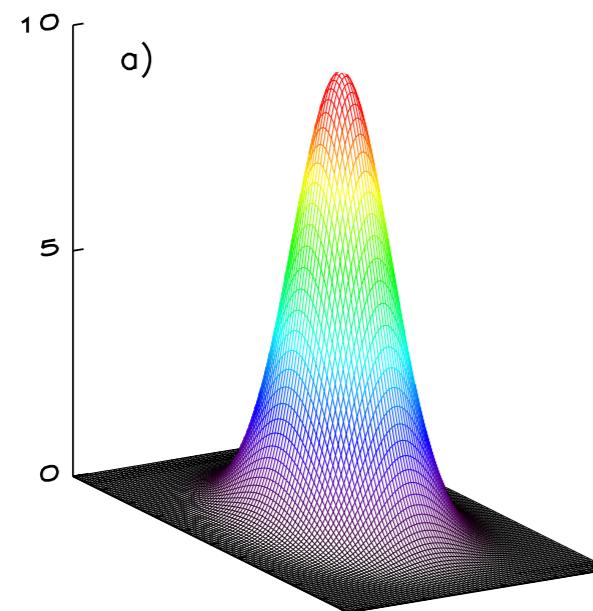
k free parameters (parameter vector)



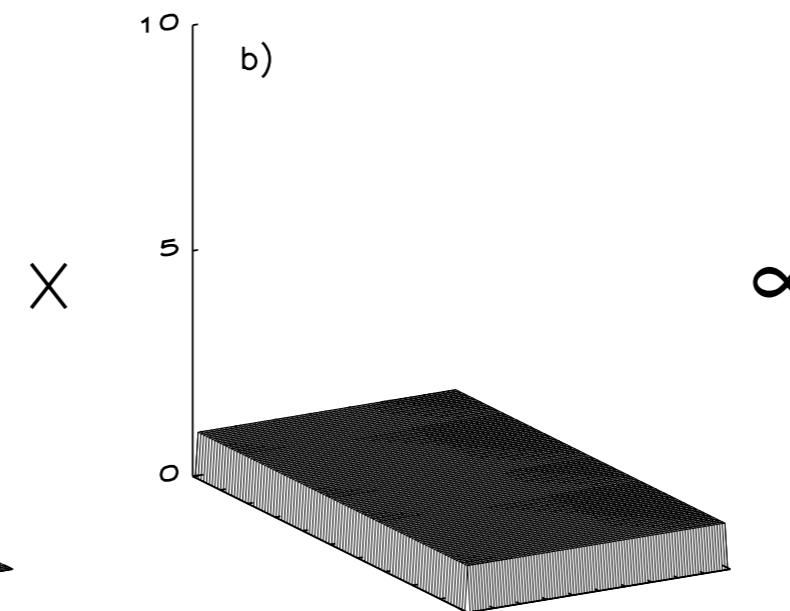
k-dimensional **parameter space** defined by the free parameters

Bayes Theorem

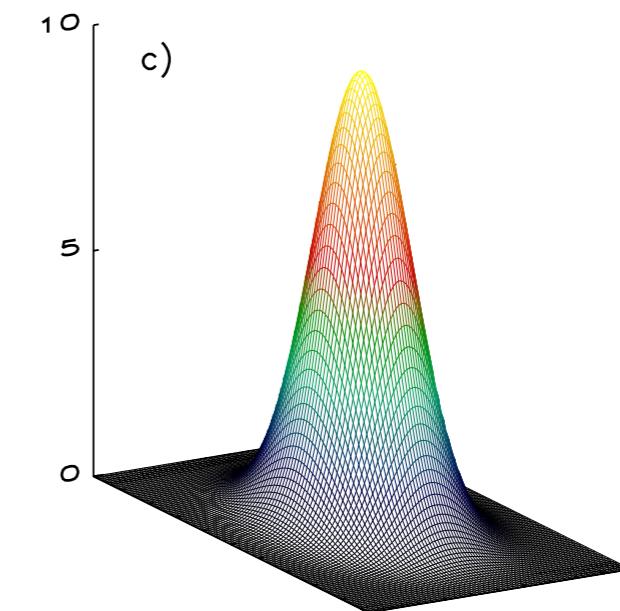
Likelihood



Prior



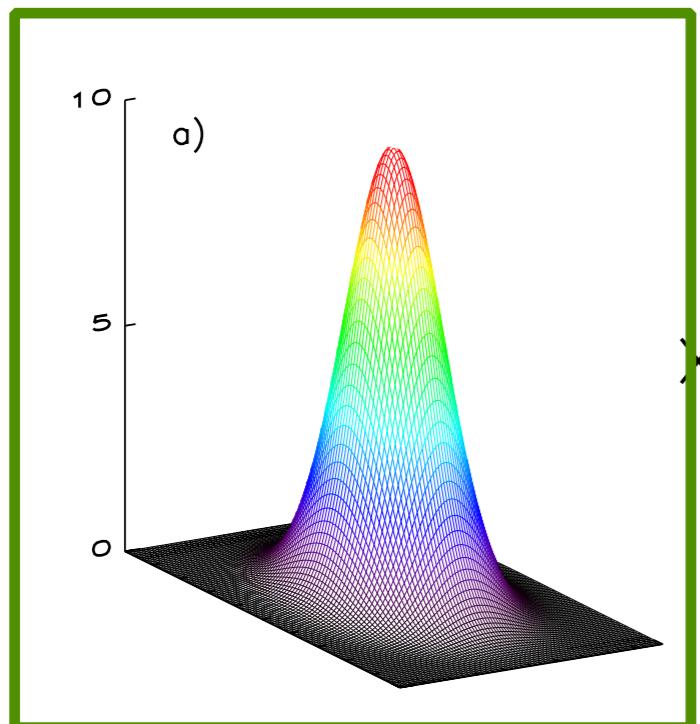
Posterior



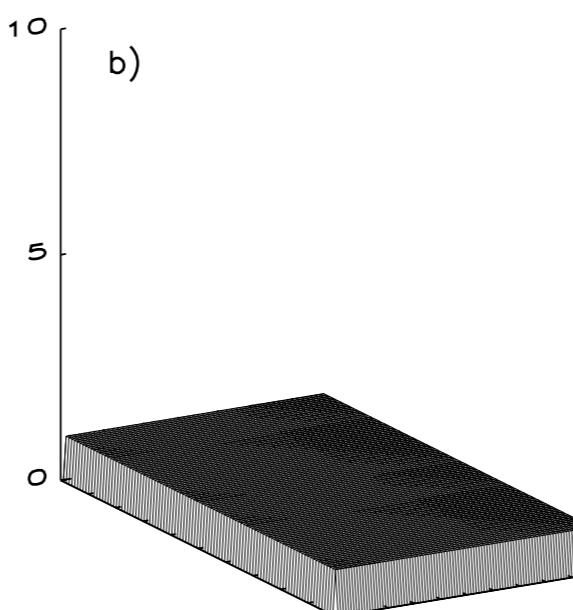
$$p(\theta) = \frac{\mathcal{L}(\theta)\pi(\theta)}{\mathcal{E}}$$

Bayes Theorem

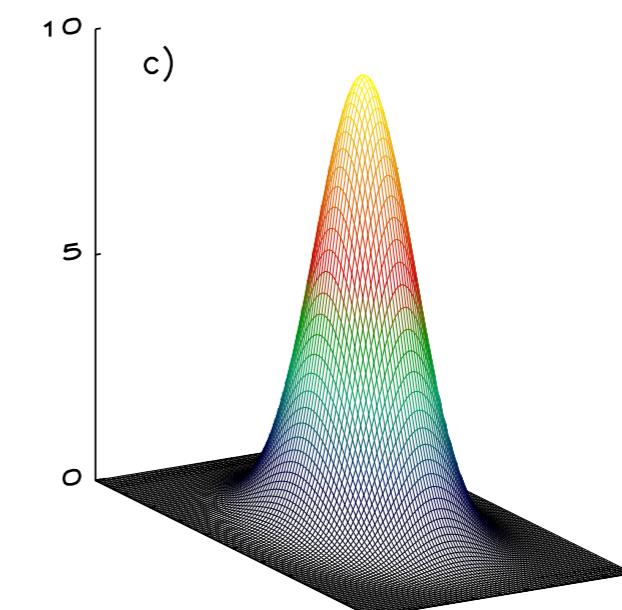
Likelihood



Prior



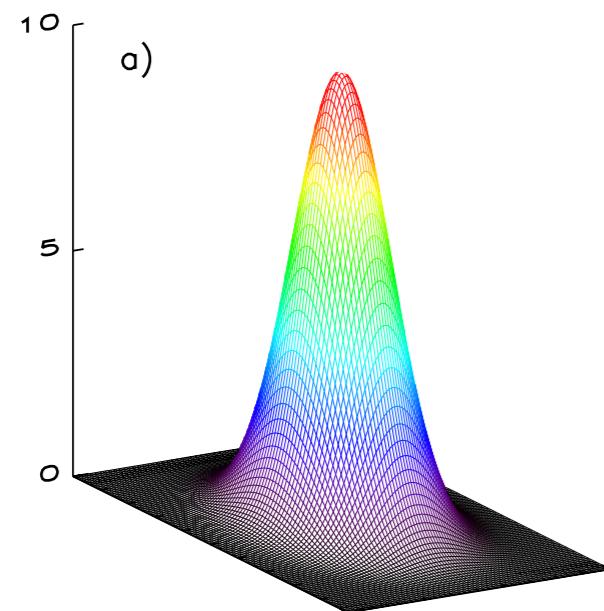
Posterior



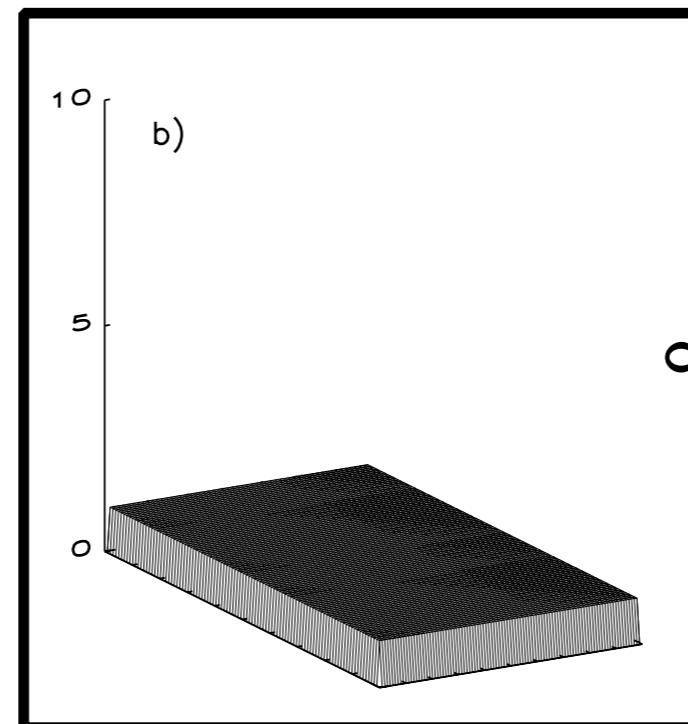
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Bayes Theorem

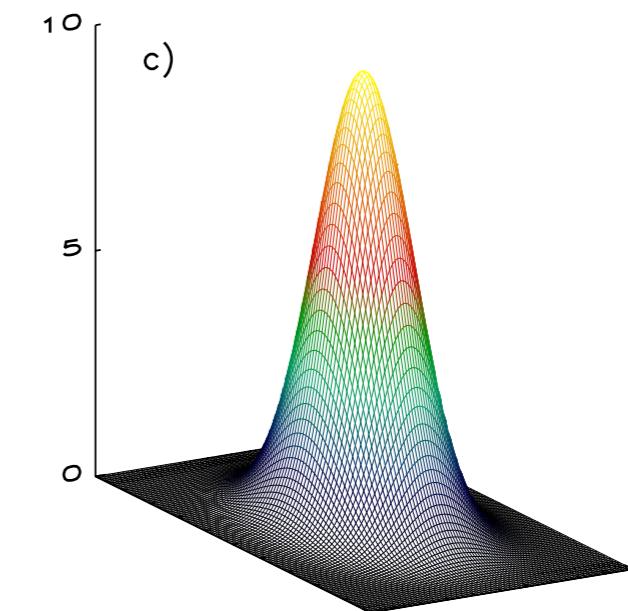
Likelihood



Prior



Posterior



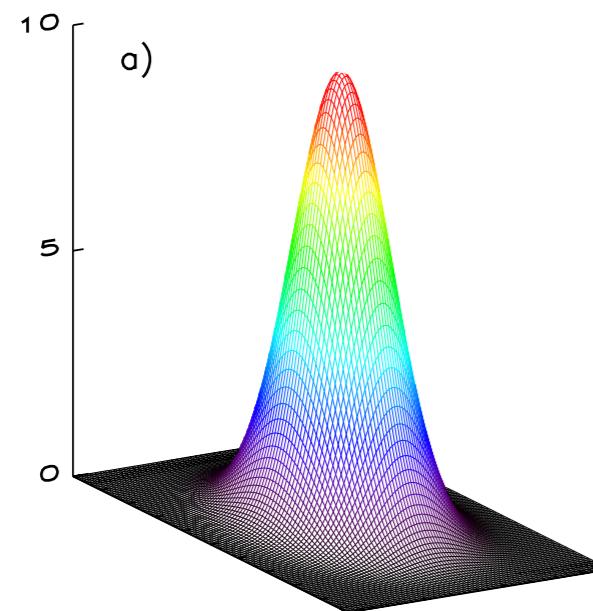
$$p(\theta) = \frac{\mathcal{L}(\theta)\pi(\theta)}{\mathcal{E}}$$

Probability density
function (PDF)

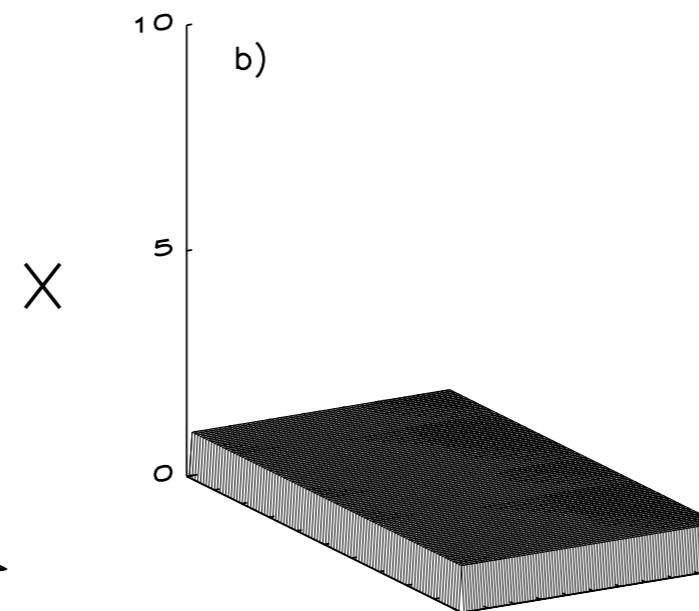
$$\int \pi(\theta) d\theta = 1$$

Bayes Theorem

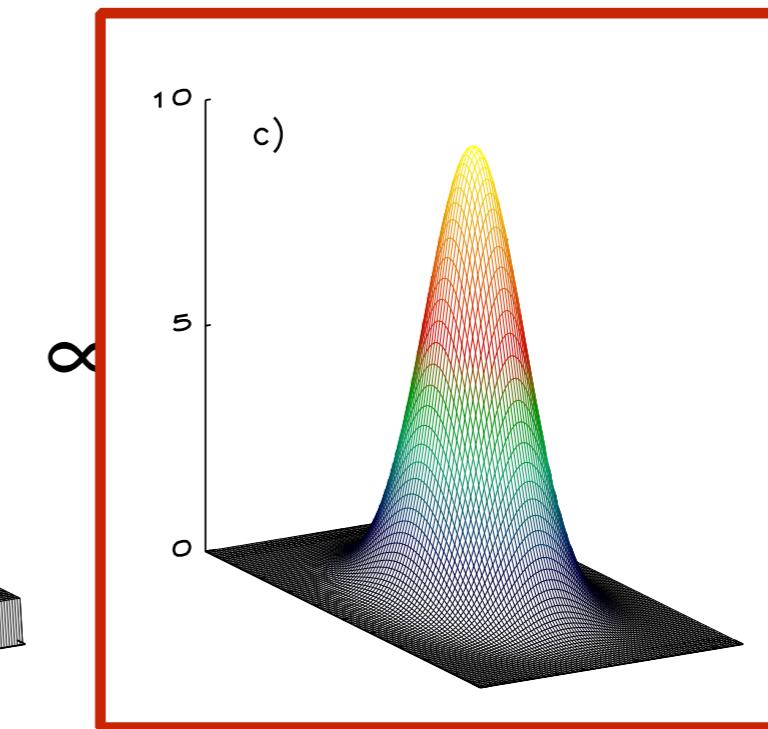
Likelihood



Prior



Posterior



$$p(\theta) = \frac{\mathcal{L}(\theta) \pi(\theta)}{\mathcal{E}}$$

Probability density
function (PDF)

$$\int p(\theta) d\theta = 1$$

Bayesian Inference

- The Bayesian inference of a dataset is divided in two problems:
 - **Parameter Estimation**
Allows to obtain the estimates of all the free parameters and the corresponding error bars
 - **Model comparison**
Provides a way to select the best model to represent the observations among different possible ones

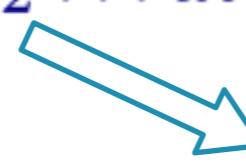
Parameter estimation

- k-dimensional parameter space

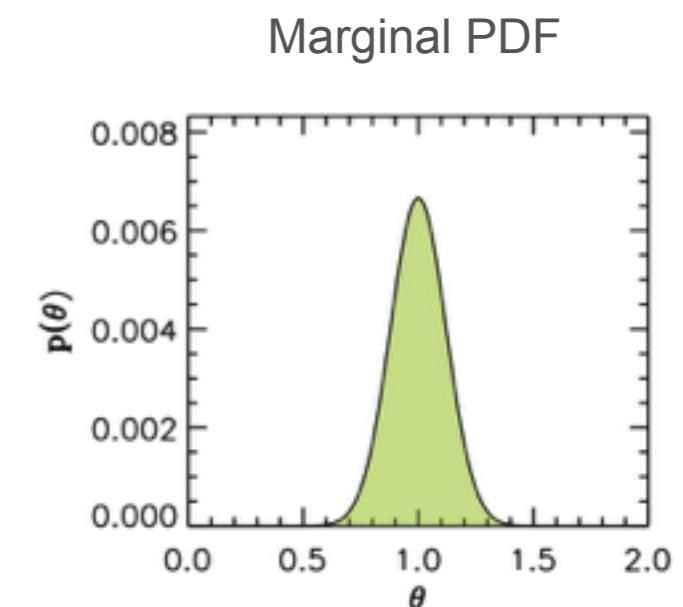
$\boldsymbol{\theta} = \{\theta_1, \theta_2, \dots, \theta_k\}$ k free parameters (parameter vector)

- The posterior PDF is a function of k parameters

$$p(\theta_1) = \int p(\boldsymbol{\theta}) d\theta_2 \dots d\theta_k$$



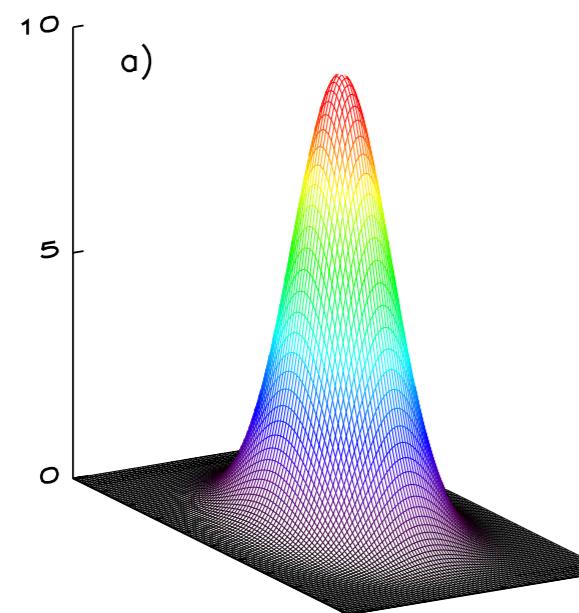
Mean
Mode
Median
Variance
Credible Intervals



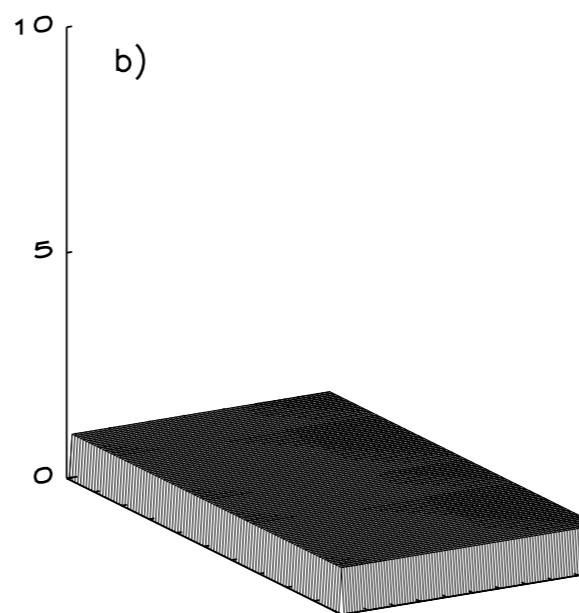
- To obtain the PDF of a single parameter we can marginalize the posterior PDF

Model comparison

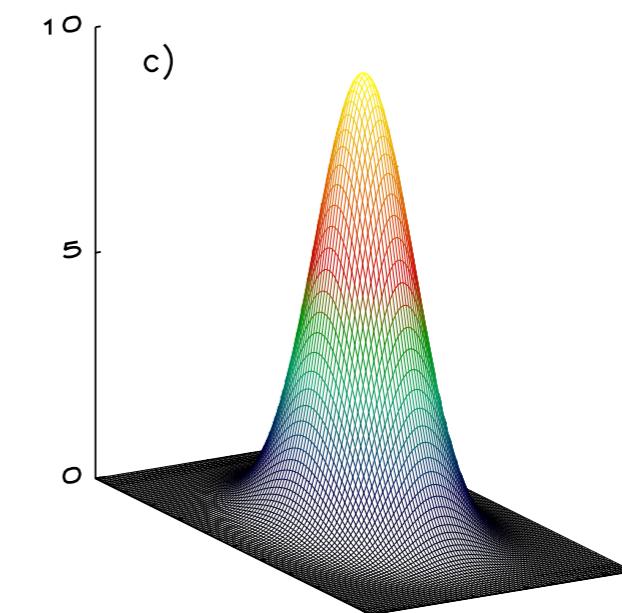
Likelihood



Prior



Posterior

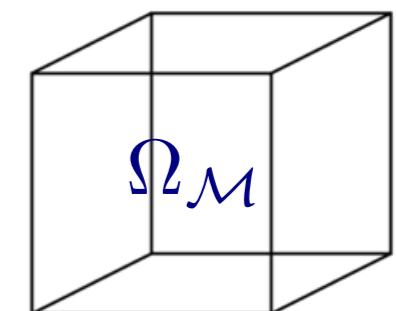


$$p(\theta) = \frac{\mathcal{L}(\theta)\pi(\theta)}{\mathcal{E}}$$

Model comparison

- **Bayesian Evidence** is an a-dimensional quantity given as a k-dimensional integral over the entire parameter space (does not exist in frequentist approach!)

$$\mathcal{E} = \int \mathcal{L}(\boldsymbol{\theta}) \pi(\boldsymbol{\theta}) d\boldsymbol{\theta}$$

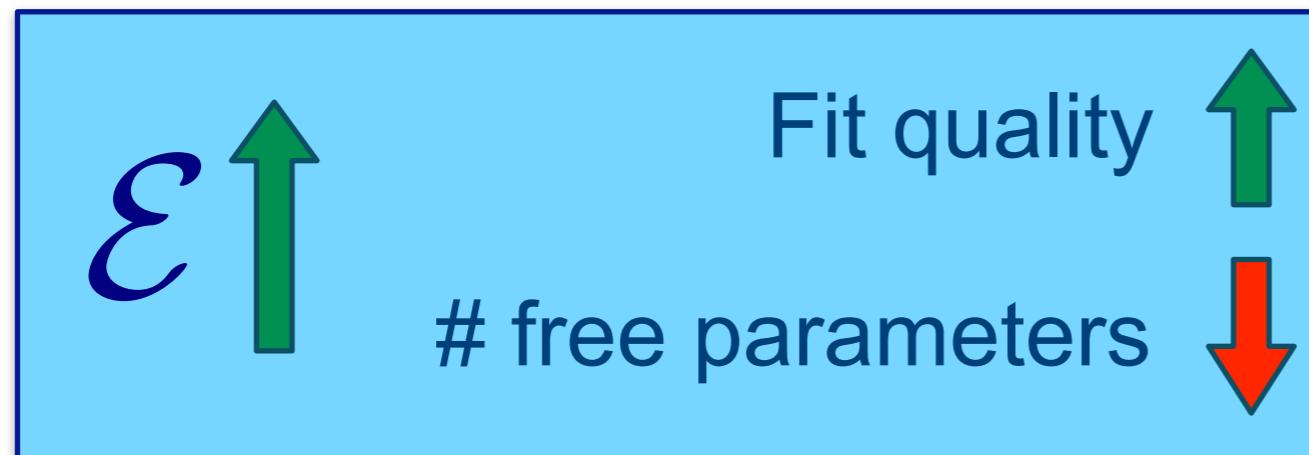
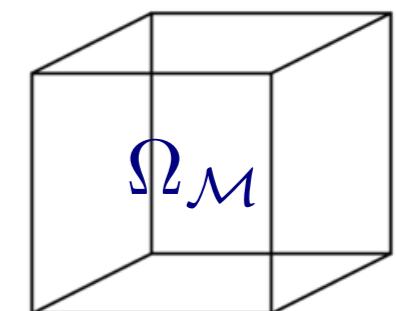


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$$\mathcal{E} = \int \mathcal{L}(\boldsymbol{\theta}) \pi(\boldsymbol{\theta}) d\boldsymbol{\theta}$$



WEIGHT: simple models are preferred (Occam's razor)

Problems

- For $k > 3$ no more analytical solutions to the marginalization problem (hence also the computation of the Bayesian Evidence integral)
- Numerical integration needed but for higher dimensions ($k \sim 20$) is not enough (too approximated)
- Numerical sampling techniques (e.g. **Monte Carlo**) are approximate by definition, so lot of samples are required.
- Sampling algorithm can get stuck into a local maximum and never be able to explore all the parameter space (e.g. Eggbox). Lot of ad-hoc improvements required, depending on the application.
- Computational time and number of samples to be used can be a real problem. Big limitations to complex fitting problems.

The basic algorithm

- **Nested Sampling Monte Carlo (NSMC)**

Skilling 2004

- For k free parameters to estimate, Bayesian Evidence is a k -dimensional integral

$$\mathcal{E} = \int \mathcal{L}(\boldsymbol{\theta}) \pi(\boldsymbol{\theta}) d\boldsymbol{\theta}$$

Bayes' Theorem

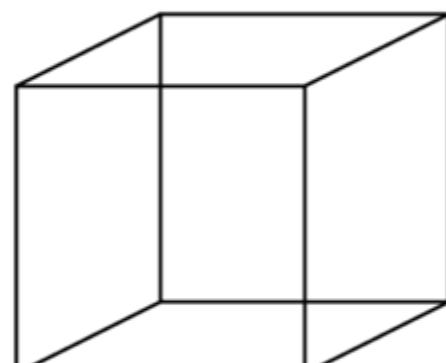
$$p(\boldsymbol{\theta}) = \frac{\mathcal{L}(\boldsymbol{\theta}) \pi(\boldsymbol{\theta})}{\mathcal{E}}$$

- Convert evidence into a one-dimensional integral

$$\mathcal{E} = \int_0^1 \mathcal{L}(X) dX$$

$$dX = \pi(\boldsymbol{\theta}) d\boldsymbol{\theta}$$

small portion of prior
volume (prior mass)

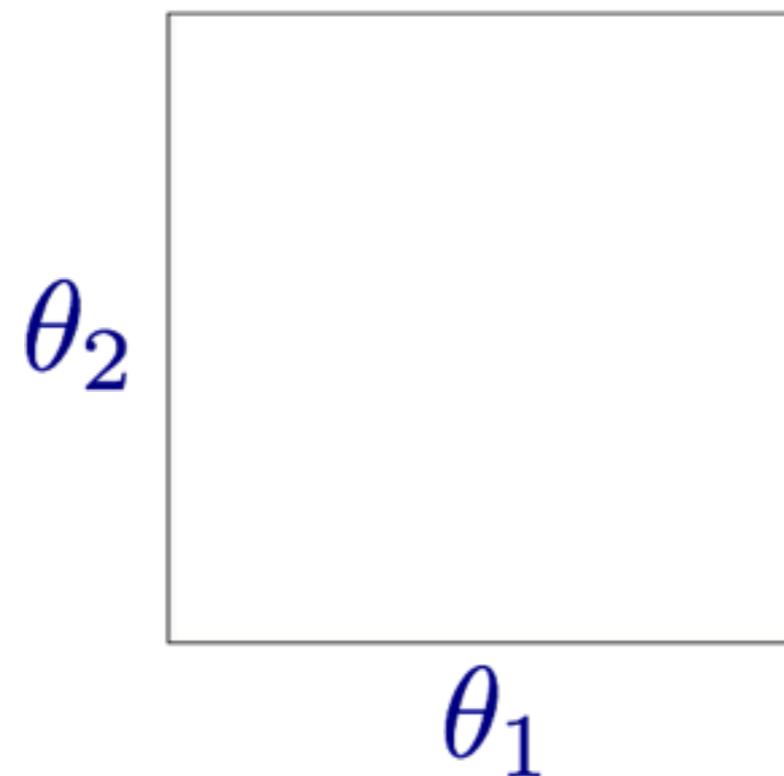


Nested Sampling

in a nutshell...

$$\mathcal{E} = \int_0^1 \mathcal{L}(X) dX$$

Bayesian Evidence

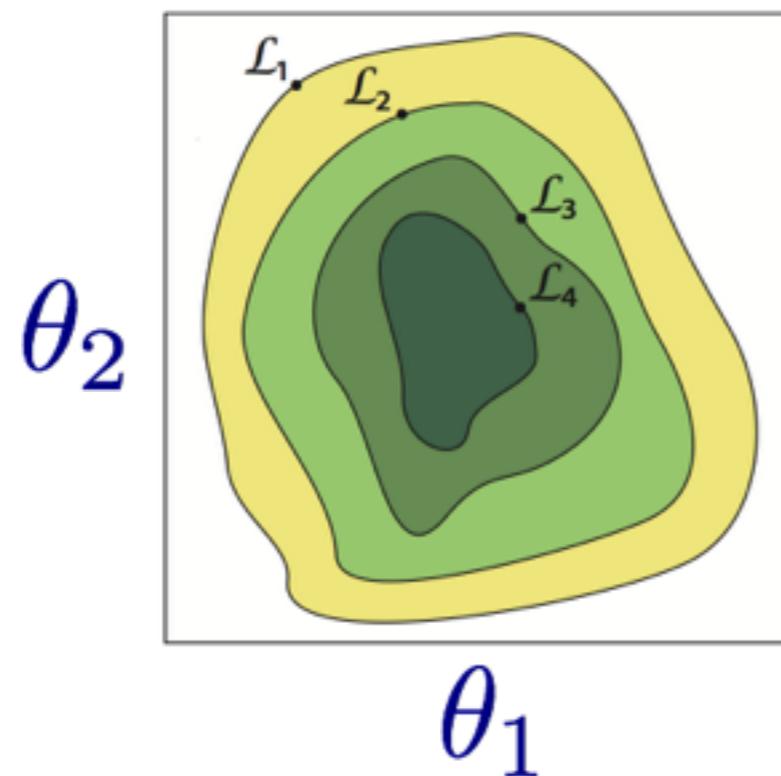


Nested Sampling

in a nutshell...

$$\mathcal{E} = \int_0^1 \mathcal{L}(X) dX$$

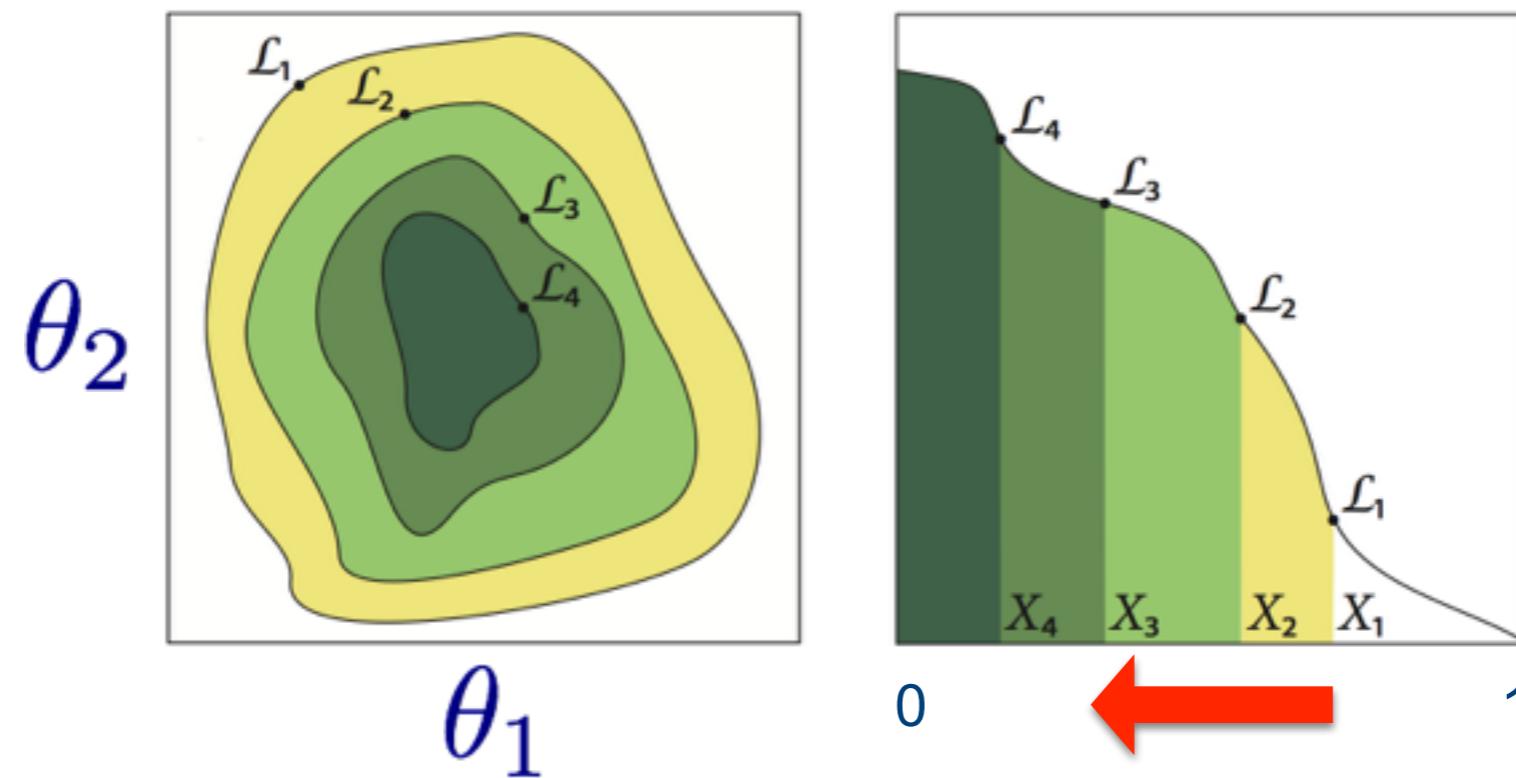
Bayesian Evidence



Nested Sampling

in a nutshell...

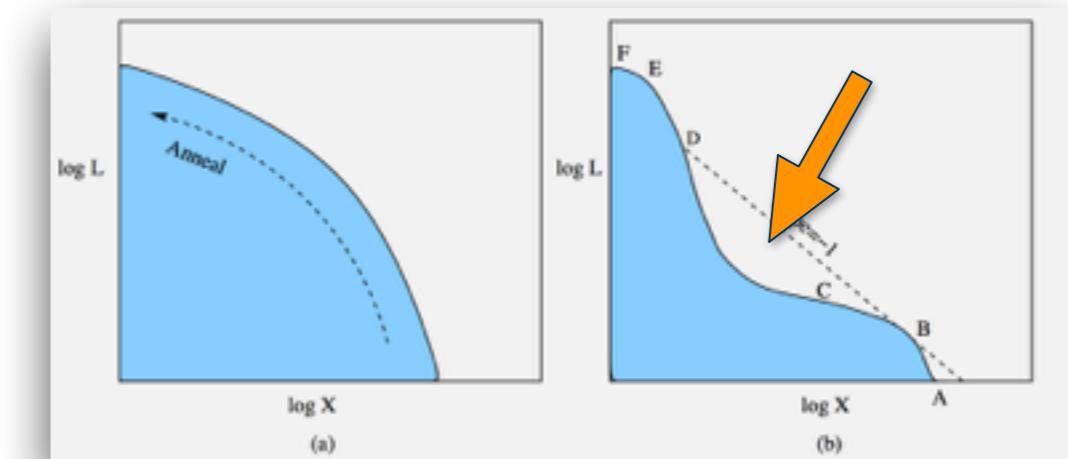
$$\mathcal{E} = \int_0^1 \mathcal{L}(X) dX \quad \xrightarrow{\text{Bayesian Evidence}} \quad \mathcal{E} = \sum_{i=0}^M \mathcal{L}_i \Delta X_i$$



Nested Sampling

in a nutshell...

- **ADVANTAGES** with respect to Markov chain Monte Carlo:
 1. Typically **~100 times fewer** samples than thermodynamic integration to calculate evidence to same accuracy + error bar
 2. **Direct** solution to model comparison problems
 3. No troubles with phase changes in likelihood (**multi modal distributions**)





A&A 571, A71 (2014)
DOI: [10.1051/0004-6361/201424181](https://doi.org/10.1051/0004-6361/201424181)
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**Astronomy
&
Astrophysics**

DIAMONDS: A new Bayesian nested sampling tool[★]

Application to peak bagging of solar-like oscillations

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Received 11 May 2014 / Accepted 8 August 2014

What is DIAMONDS ?

high-DImensional And multi-MOdal NesteD Sampling

Corsaro & De Ridder 2014 A&A, 571, 71



- C++11 code for **inference** problems in a Bayesian framework:
 - Dataset to fit
 - Model to test
 - Estimate the free parameters of the model

What is DIAMONDS ?

high-DImensional And multi-MOdal NesteD Sampling

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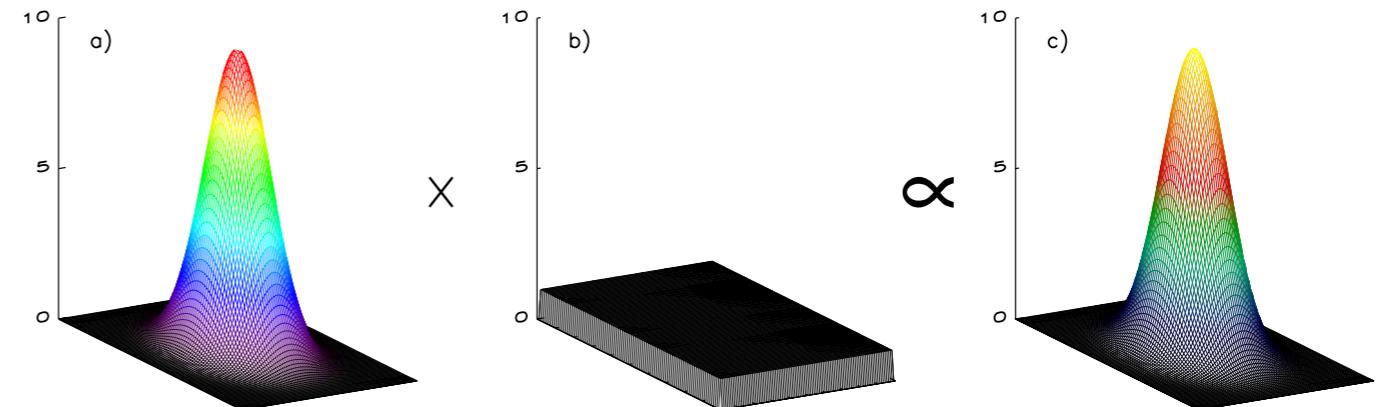


- C++11 code for **inference** problems in a Bayesian framework:
 - Dataset to fit (**Likelihood**)
 - Model to test (**Prior**)
 - Estimate the free parameters of the model (**Posterior**)

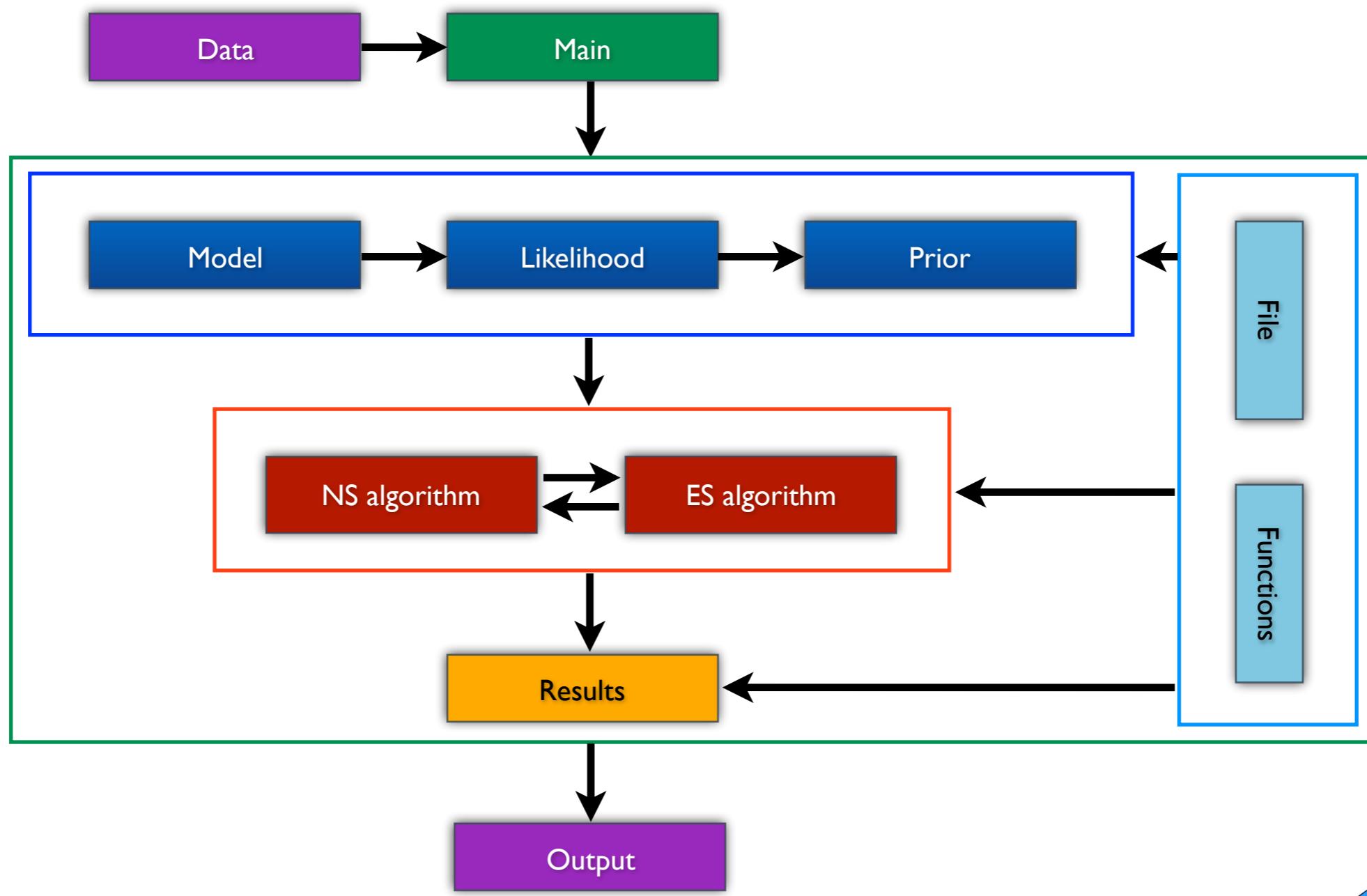
Likelihood **Prior** **Posterior**

Bayes' Theorem

$$p(\theta) = \frac{\mathcal{L}(\theta) \pi(\theta)}{\mathcal{E}}$$

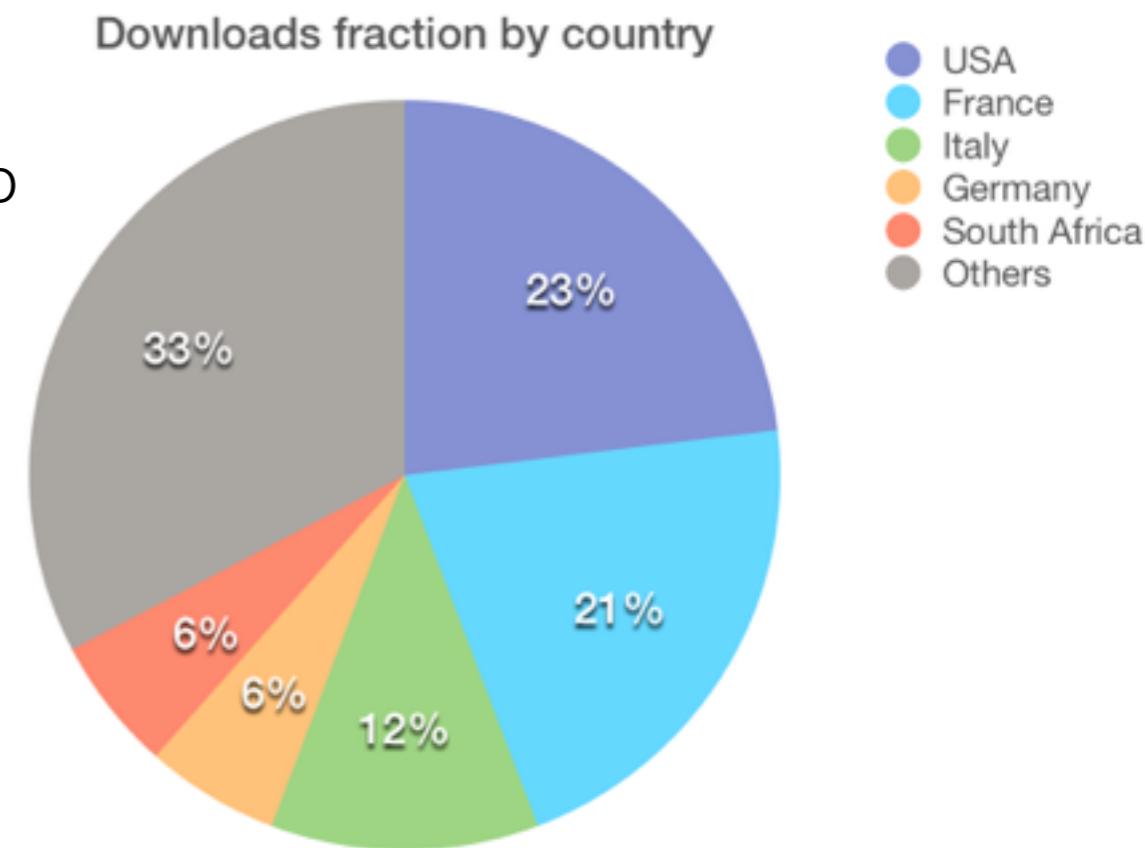


Working scheme



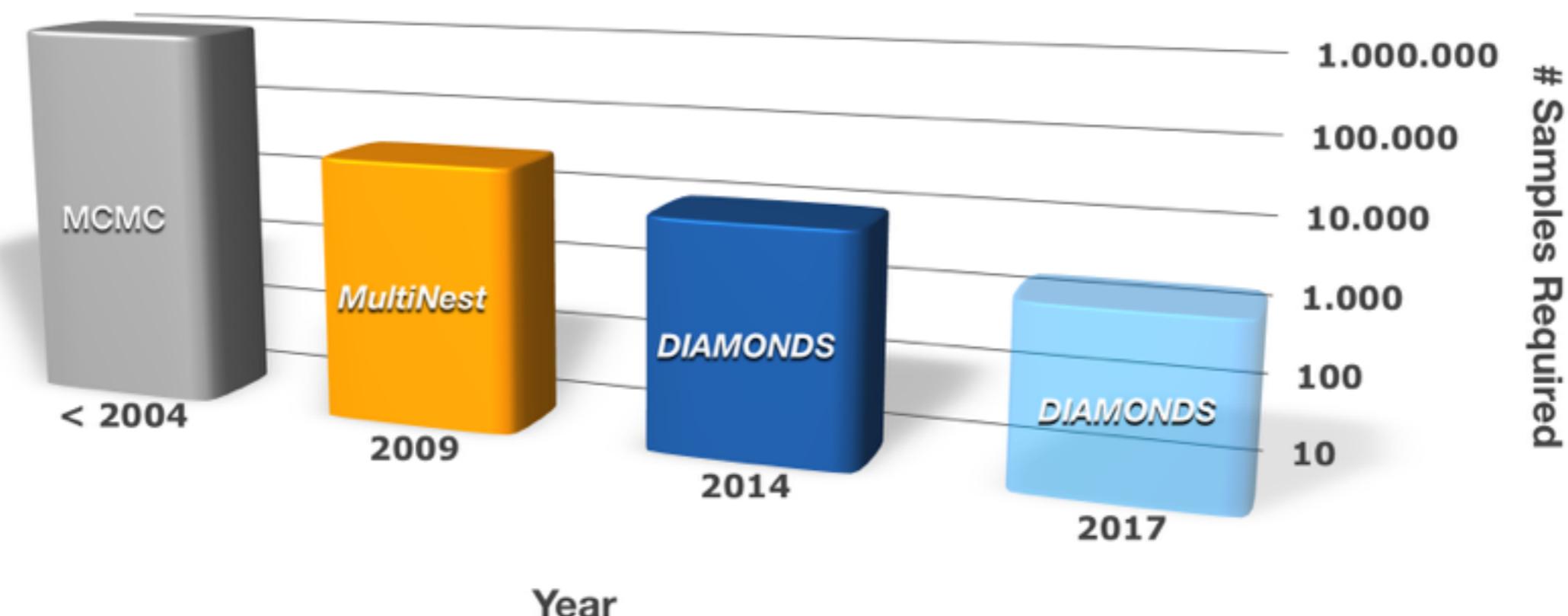
What makes DIAMONDS so appealing? (1)

- Basic core **public** available (now released v. 1.1) with usable demos
- General for **any** application involving Bayesian Inference
- **Bayesian evidence** (essential for model comparison problems) is a direct output
- Very powerful in identifying multiple (degenerate) solutions, also in high-dimensions
- Code implementation is **flexible** and easy to upgrade (replace modules, add new ones)
- Different types of **prior** distributions and **likelihood** functions already provided
- Attracted more than **50 users** from many world's institutions and different fields of physics



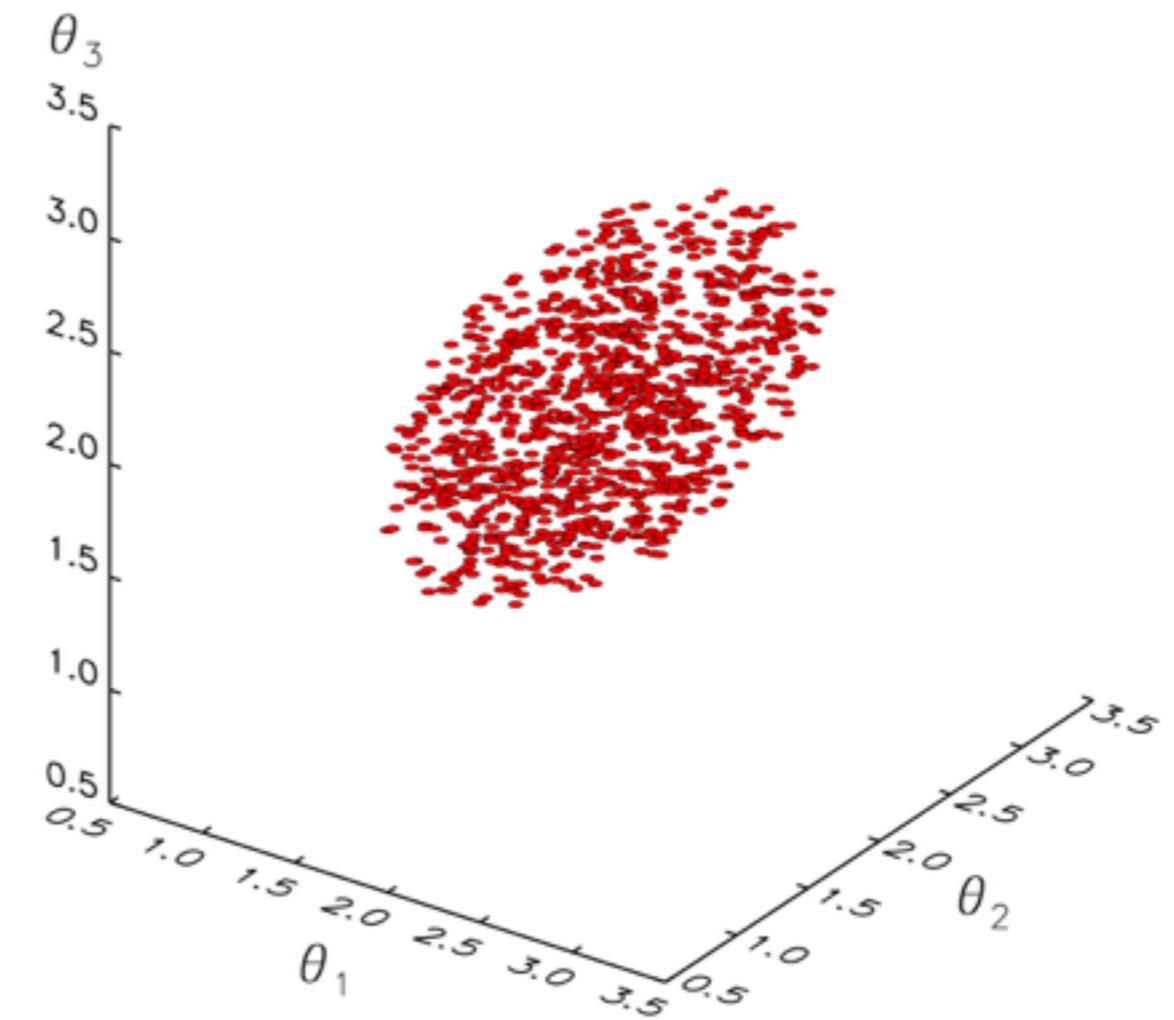
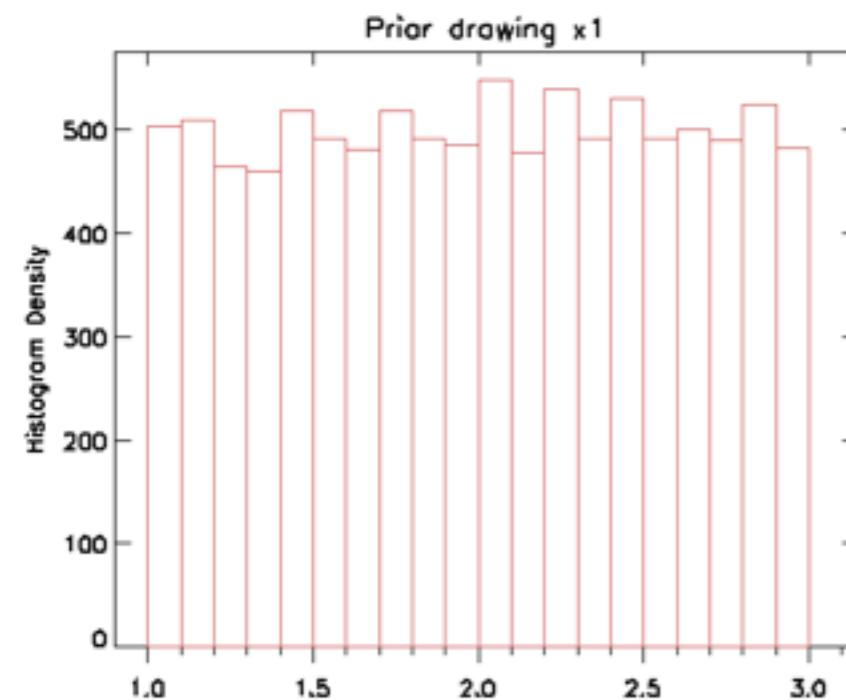
What makes **DIAMONDS** so appealing? (2)

- **Overtakes** other existing MCMC, NSMC codes (e.g. MultiNest, POLYCHORD)
- Foreseen upgrade with full multi-core parallelization by early 2017 (v. 2.0)



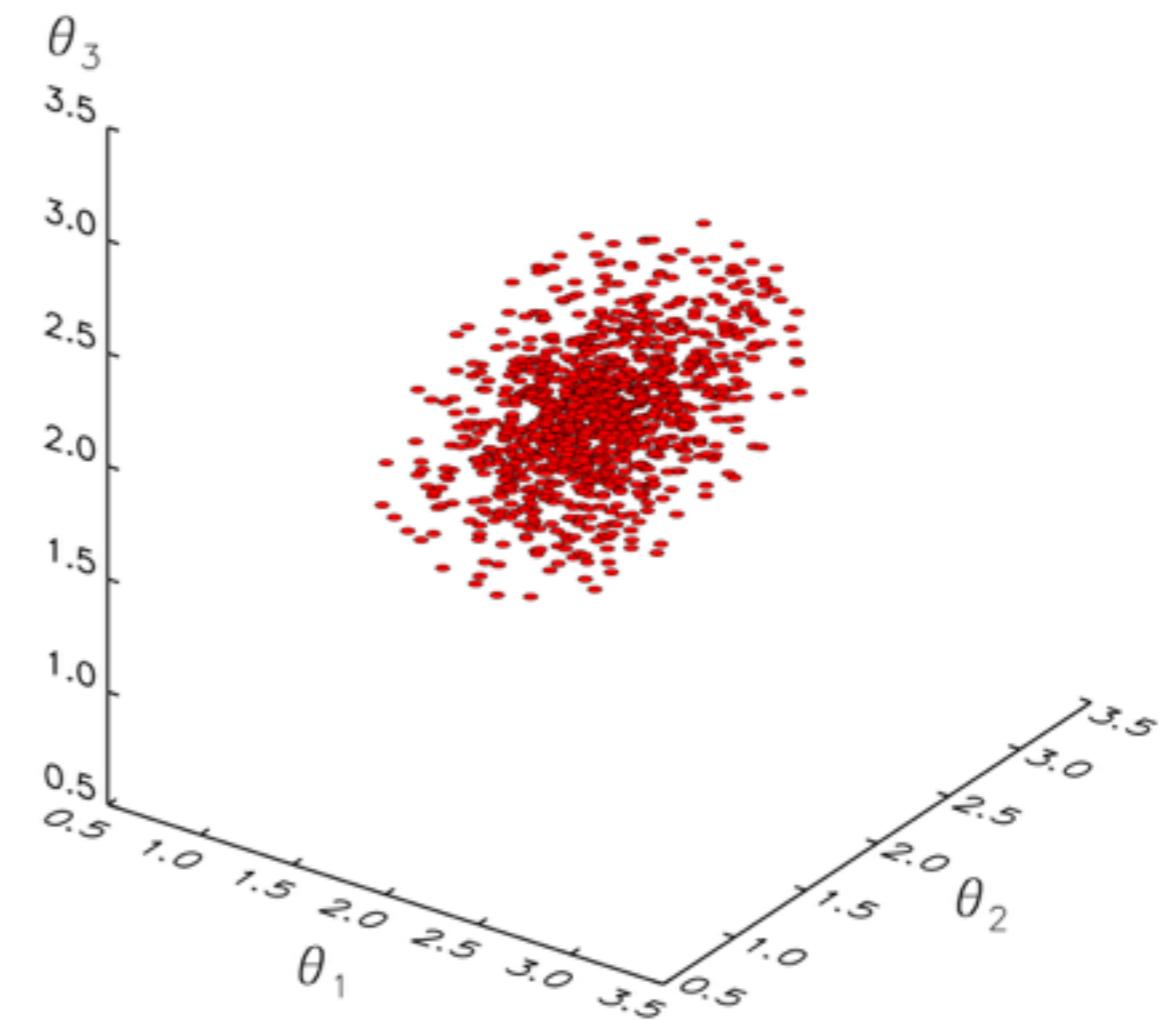
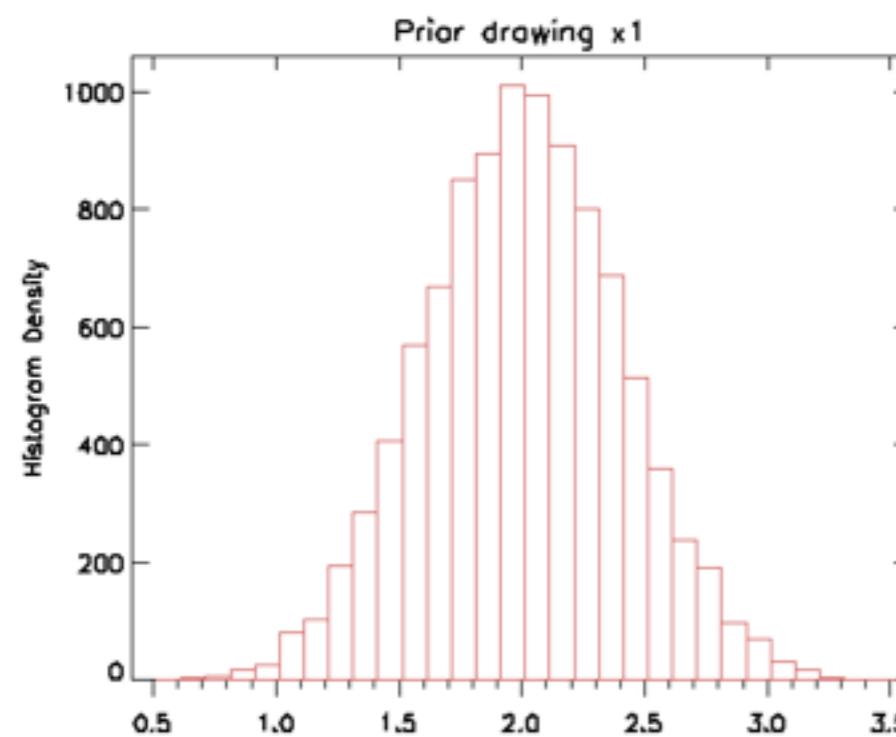
Prior distributions

Uniform

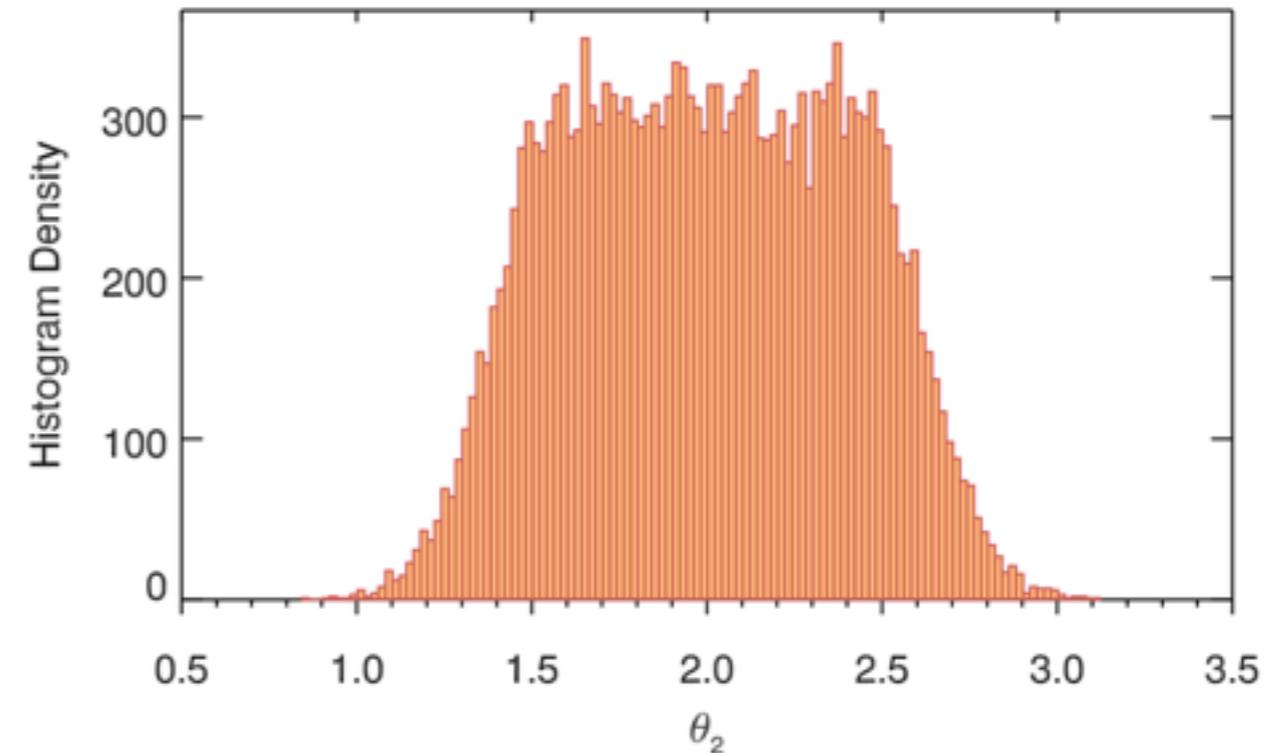
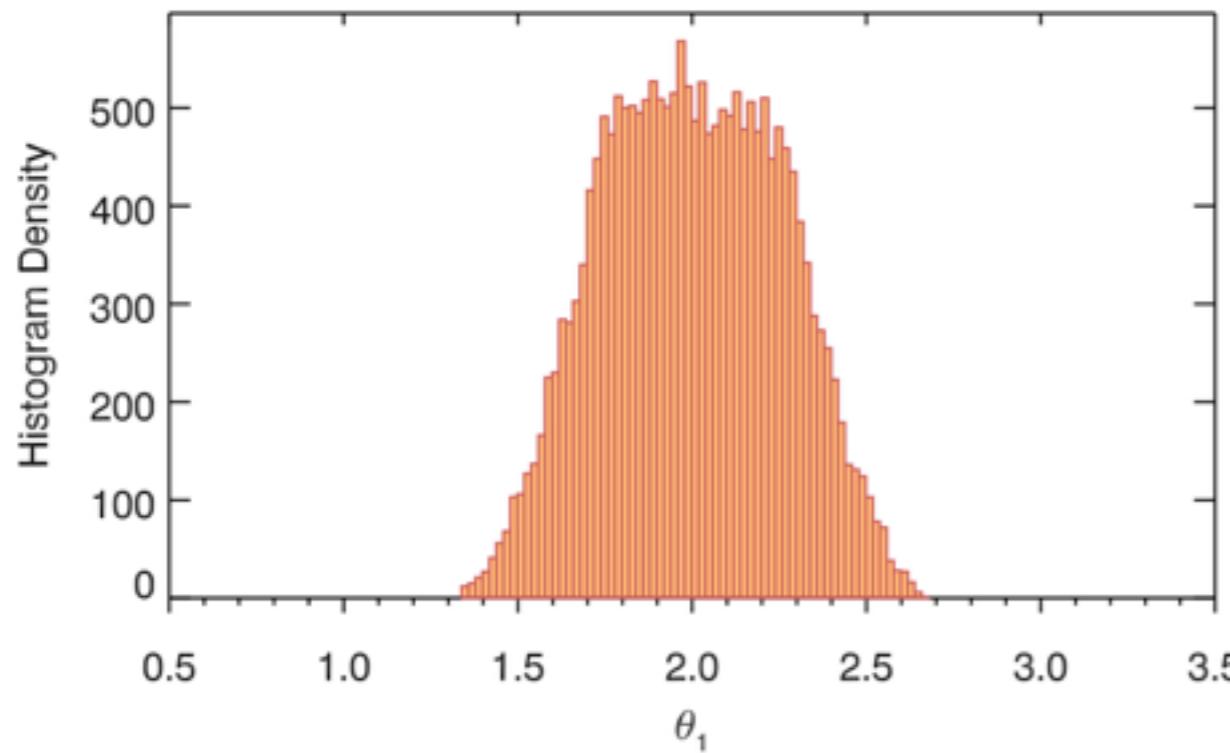


Prior distributions

Gaussian



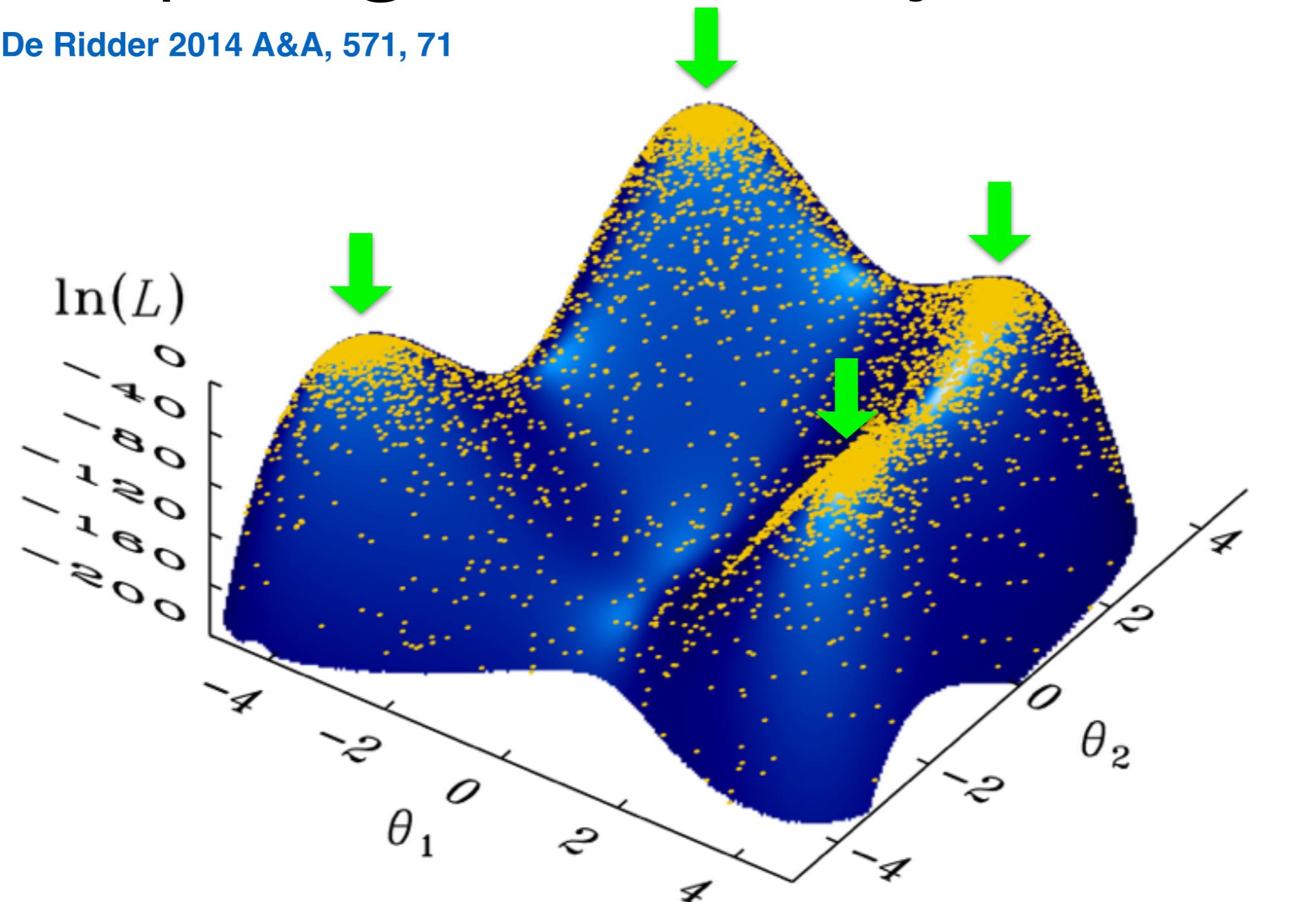
Prior distributions



Super Gaussian

Sampling efficiency demos

Corsaro & De Ridder 2014 A&A, 571, 71

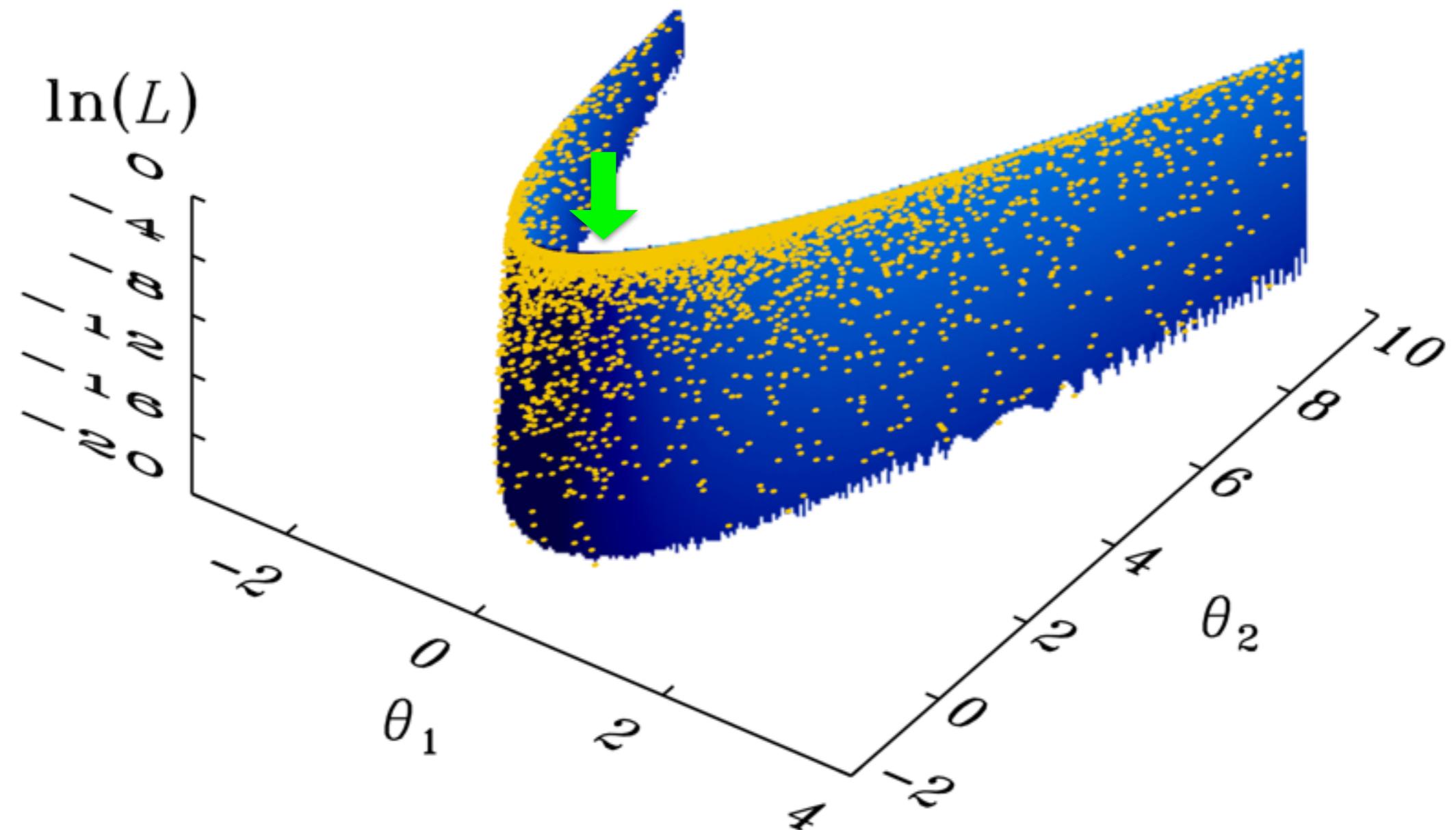


Himmelblau's Function

$N = 8485$ Samples

Sampling efficiency demos

Corsaro & De Ridder 2014 A&A, 571, 71

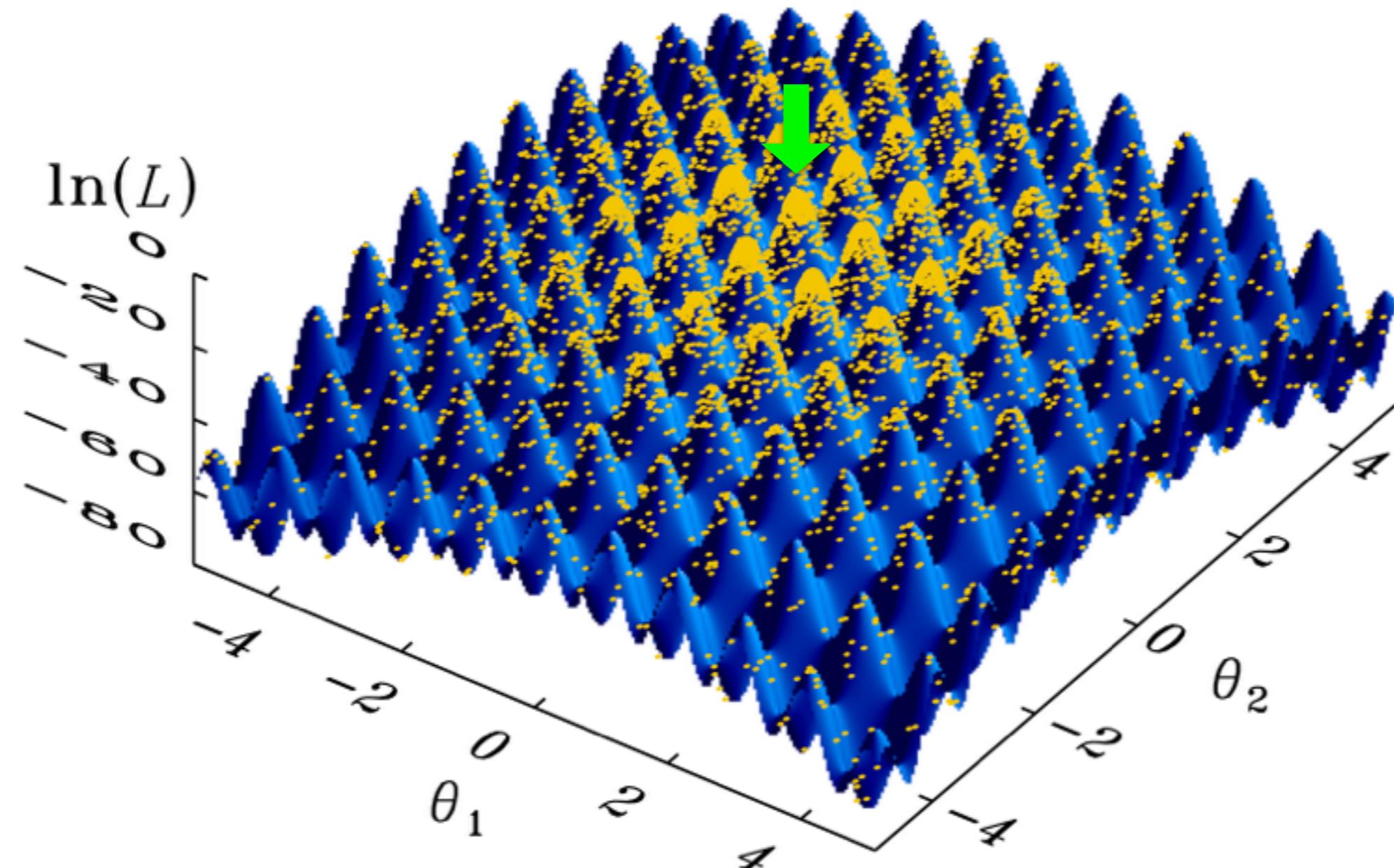


Rosenbrock's Function

N = 8558 Samples

Sampling efficiency demos

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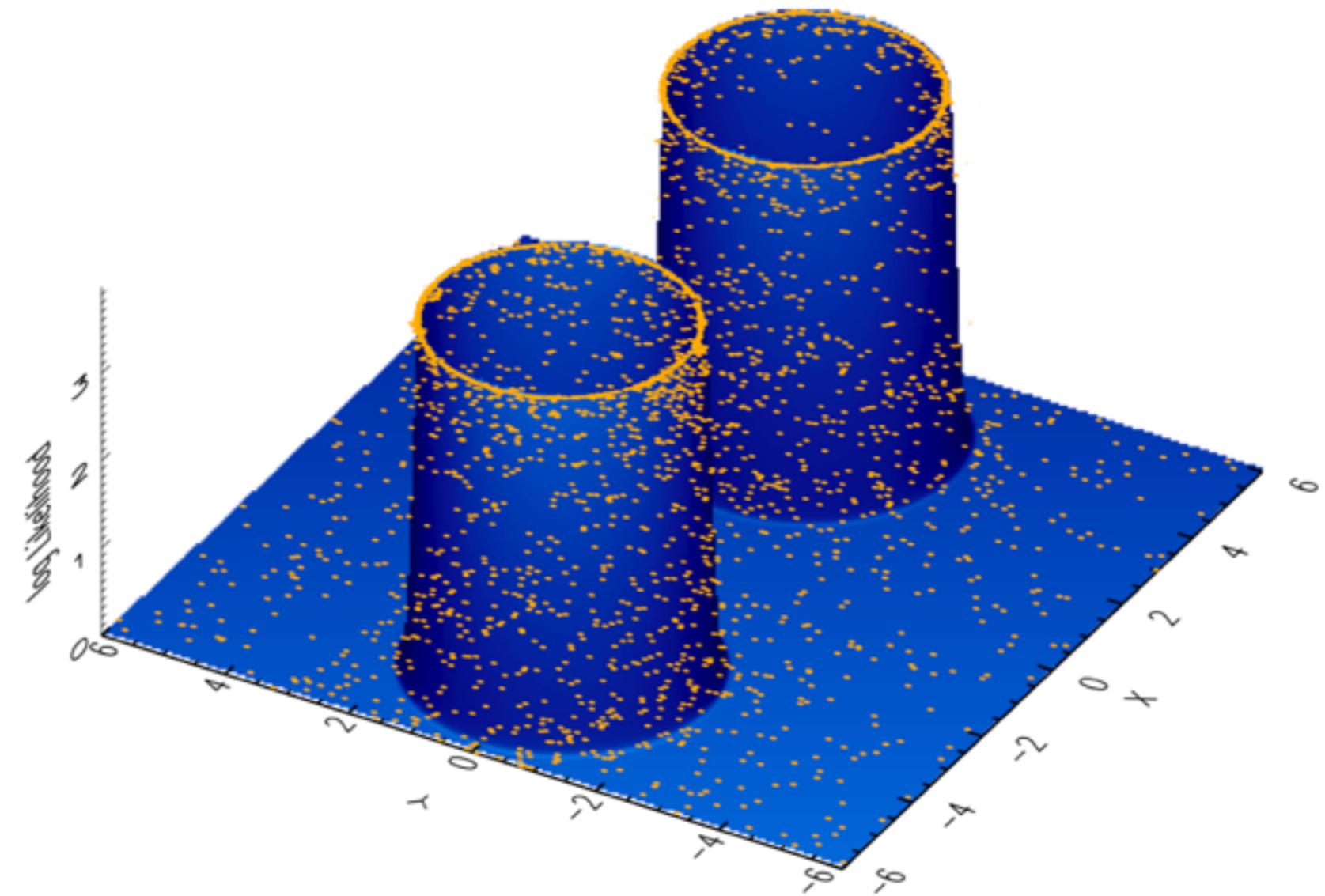
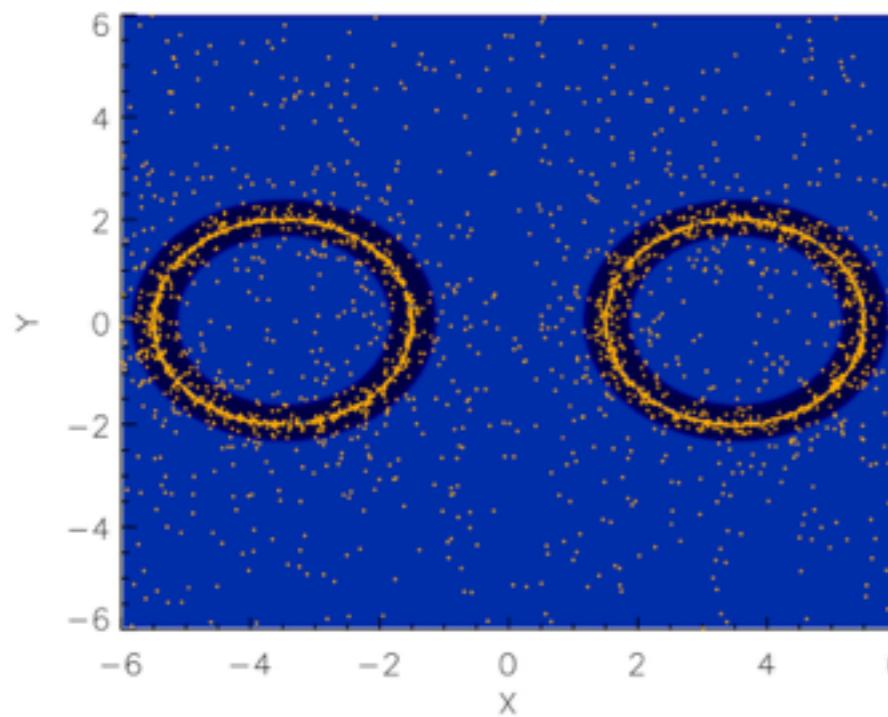


Rastrigin's Function

$N = 10648$ Samples

Sampling efficiency demos

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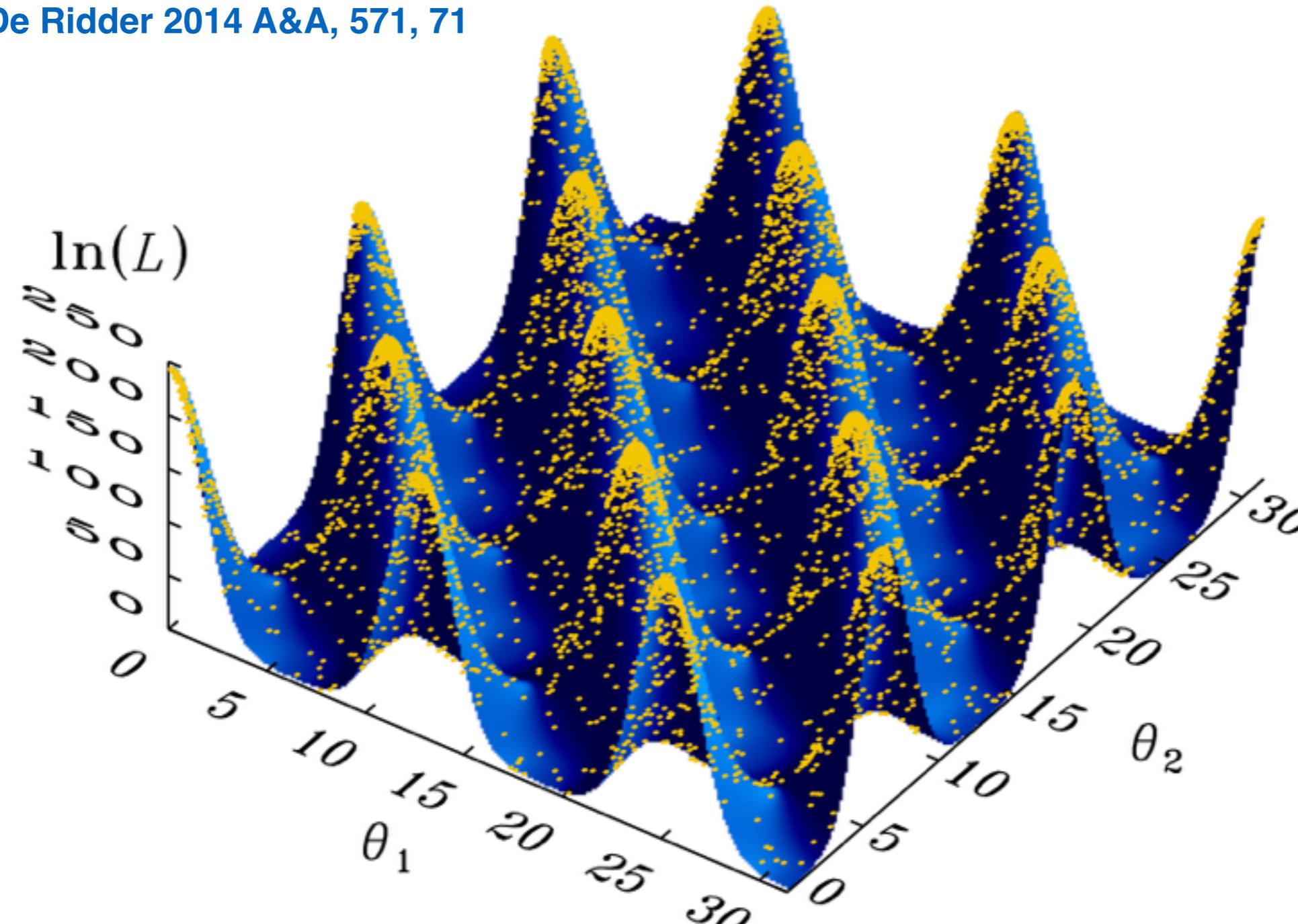


Gaussian Shell Function

N = 3100 Samples

Sampling efficiency demos

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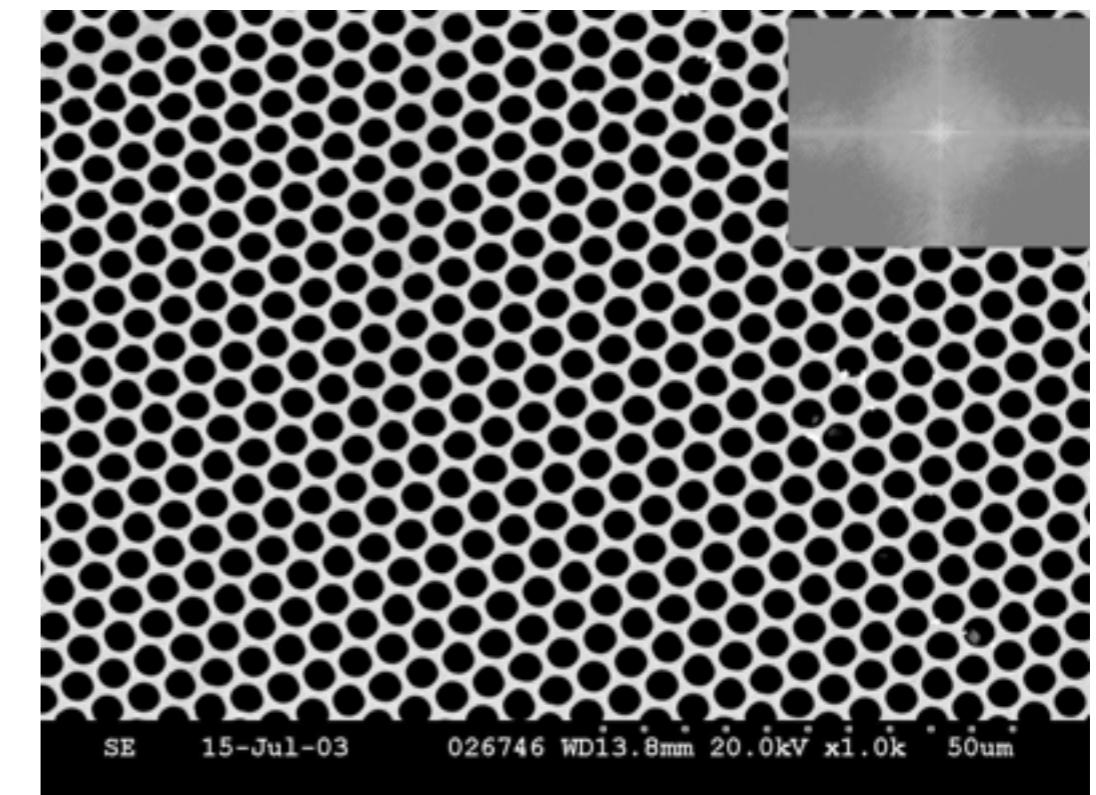
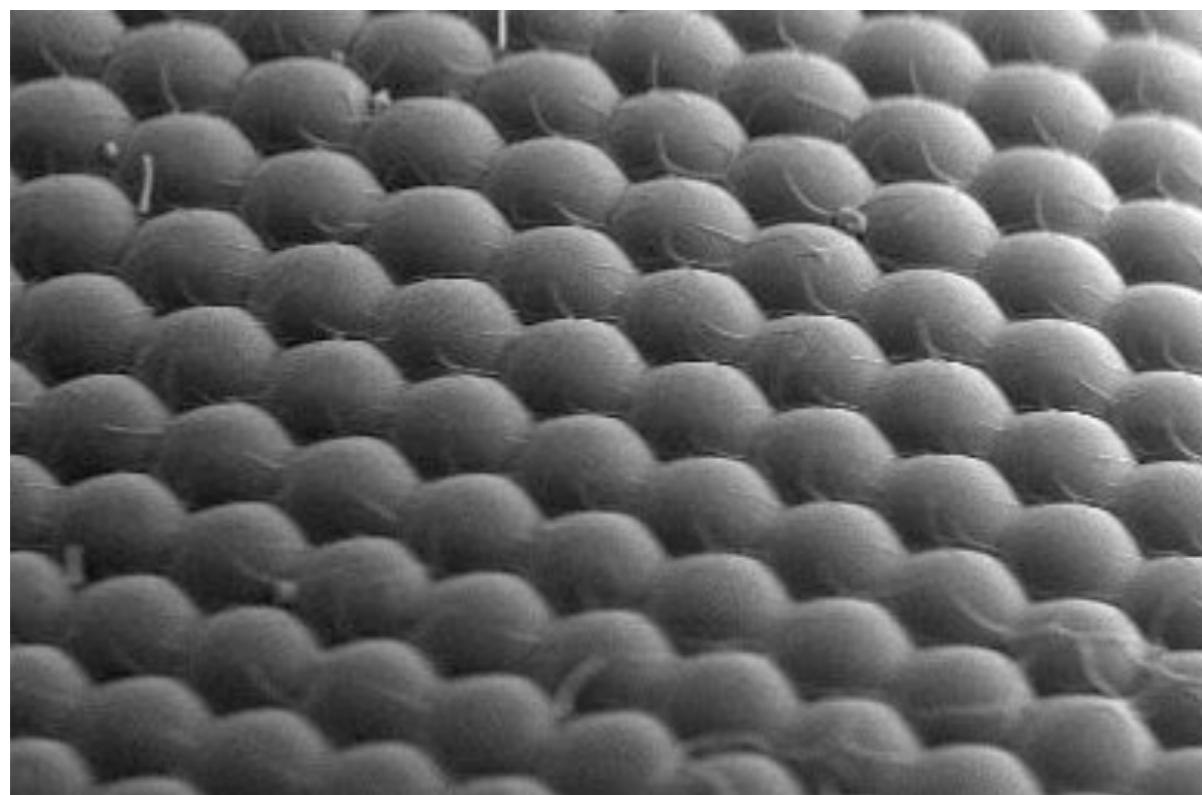


Eggbox Function

$N = 8207$ Samples

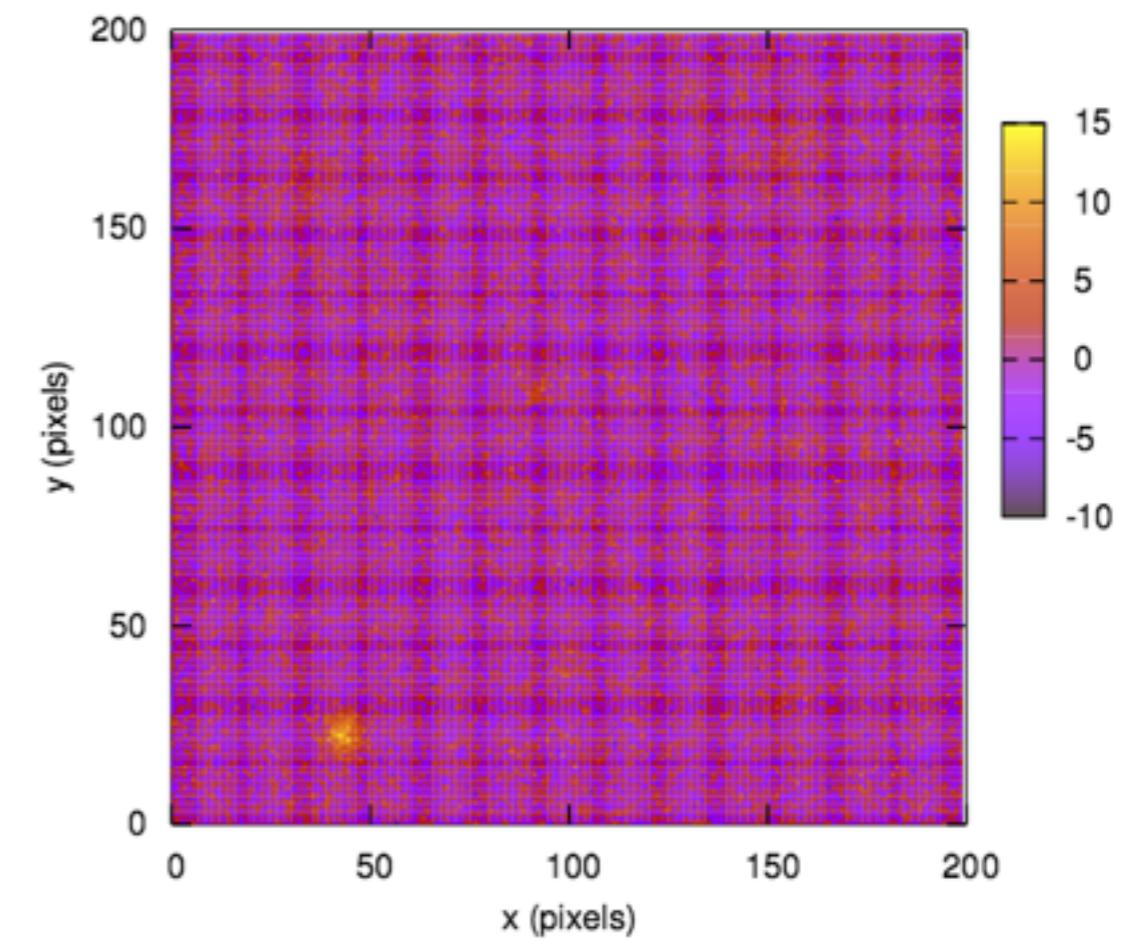
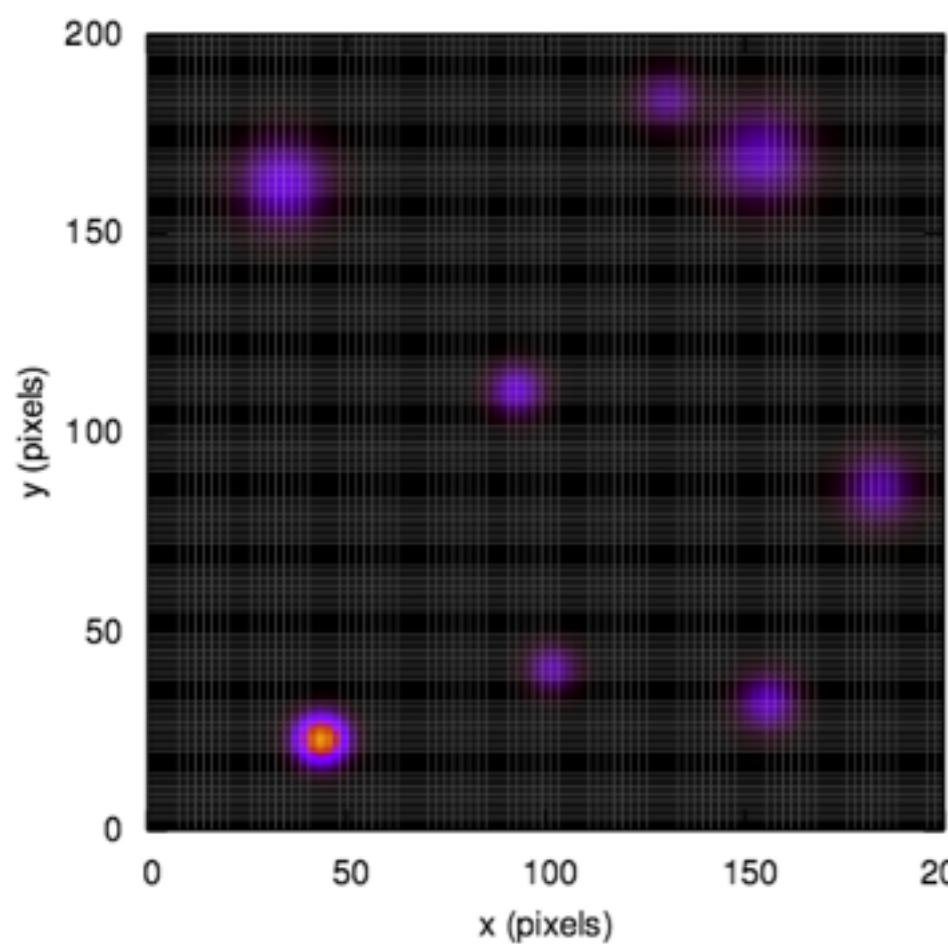
Examples for real applications

Scanning Electron Microscopy (SEM)
e.g. detecting the position of individual atoms



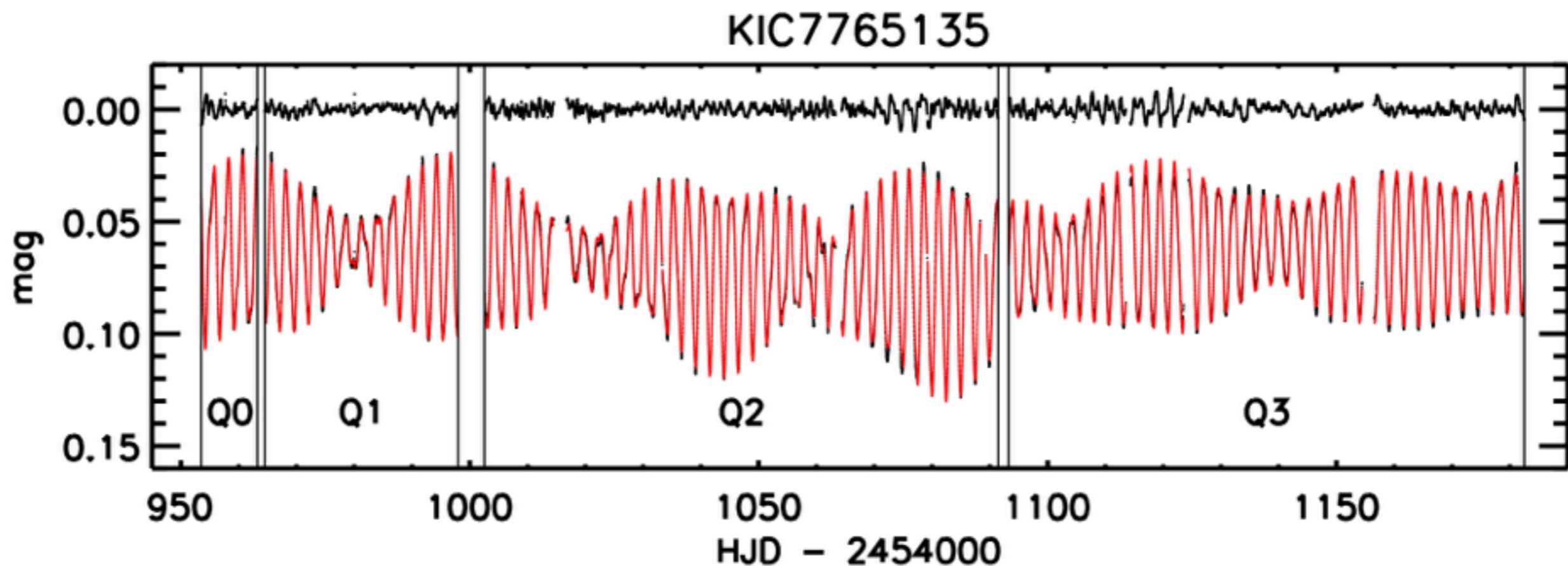
Examples for real applications

Detecting signal from a noisy background
e.g. detecting SZ effect in CBR maps



Examples for real applications

Fitting very complex time-series shapes
e.g. spot modeling for differential rotation in active stars



Asteroseismology

Why do we need **DIAMONDS?**

1. Tackling **high-dimensional** and/or **multi-modal** fitting problems at high speed (otherwise very difficult, if not impossible, to solve with standard methods and available computational power)
2. Easy and direct solution to model comparison problems

For example?

Asteroseismology!

but also...

**exoplanetary science, solar physics,
cosmology, high-energy physics, etc.**

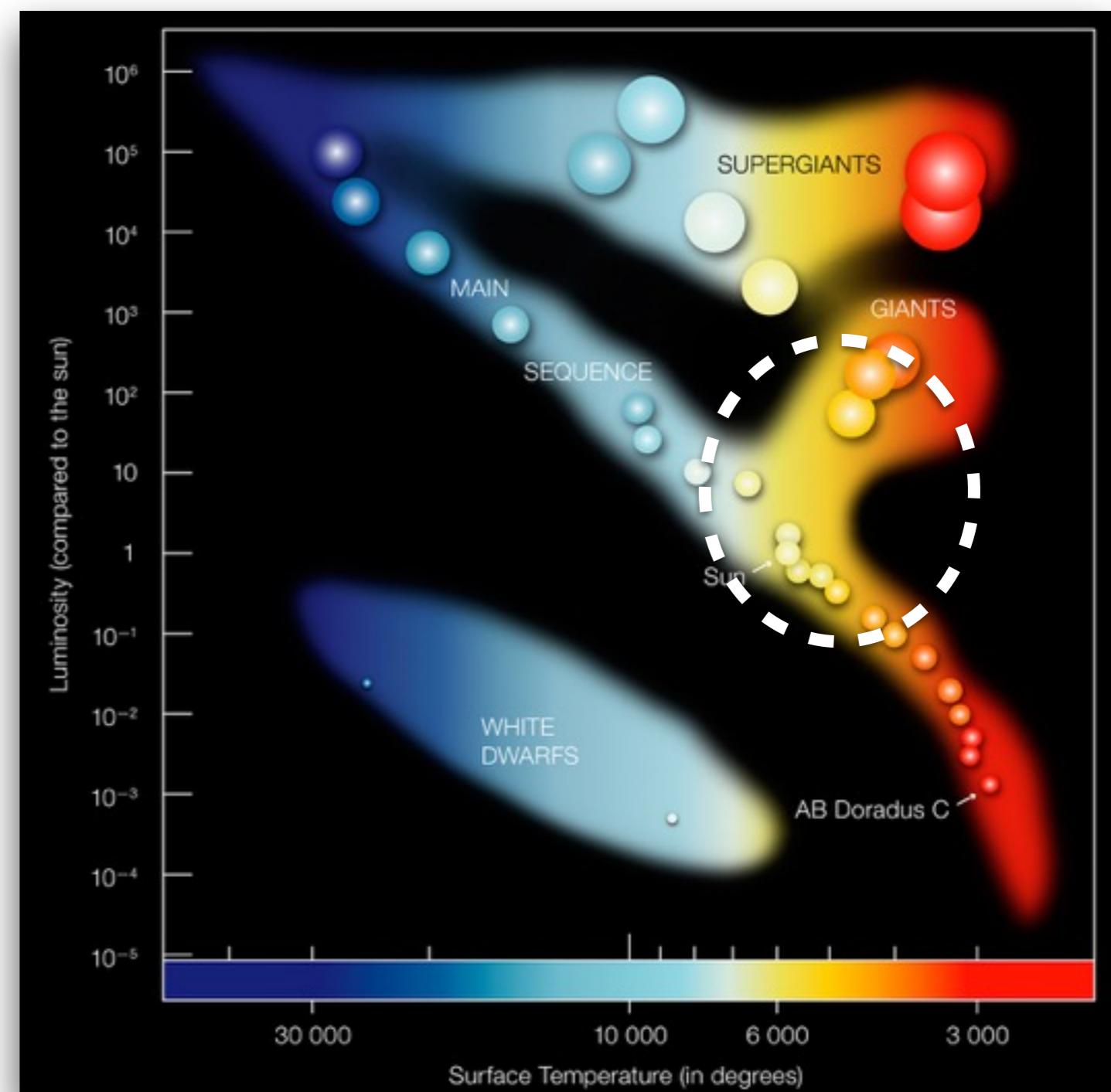
What is Asteroseismology?

The analysis of stellar oscillations to probe stellar structure, dynamics, and evolution

- The **most powerful** available approach to look inside the stars!
- Our main example: **the Sun** (helioseismology)
- Many stars oscillate similarly to the Sun (**solar-like**): about **40,000 known to date** and growing every year

Solar-like oscillators

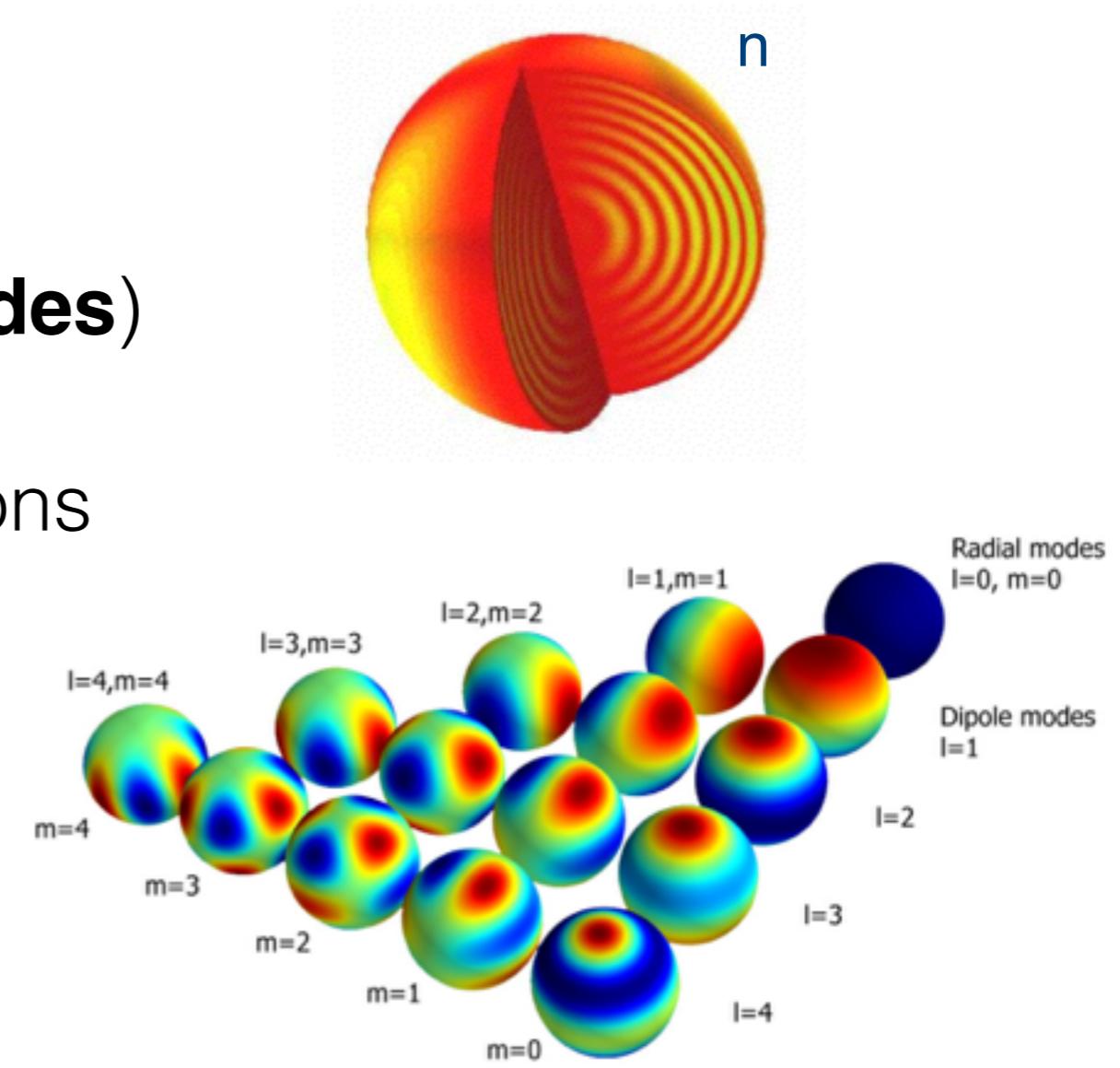
- Spectral types F-K, can be observed at galactic scale distances (up to about 10 kpc)
- The most common, hence constitute a statistically useful sample for population studies
- Often host Earth-sized planets and offer extended habitability zones, hence crucial to study the conditions for life
- Cover all epochs of star formation in the different regions of the Galaxy (thin and thick disks, and the halo)
- Show narrow spectral lines that provide more accurate and precise element abundances than for other stars.



Solar-like oscillations

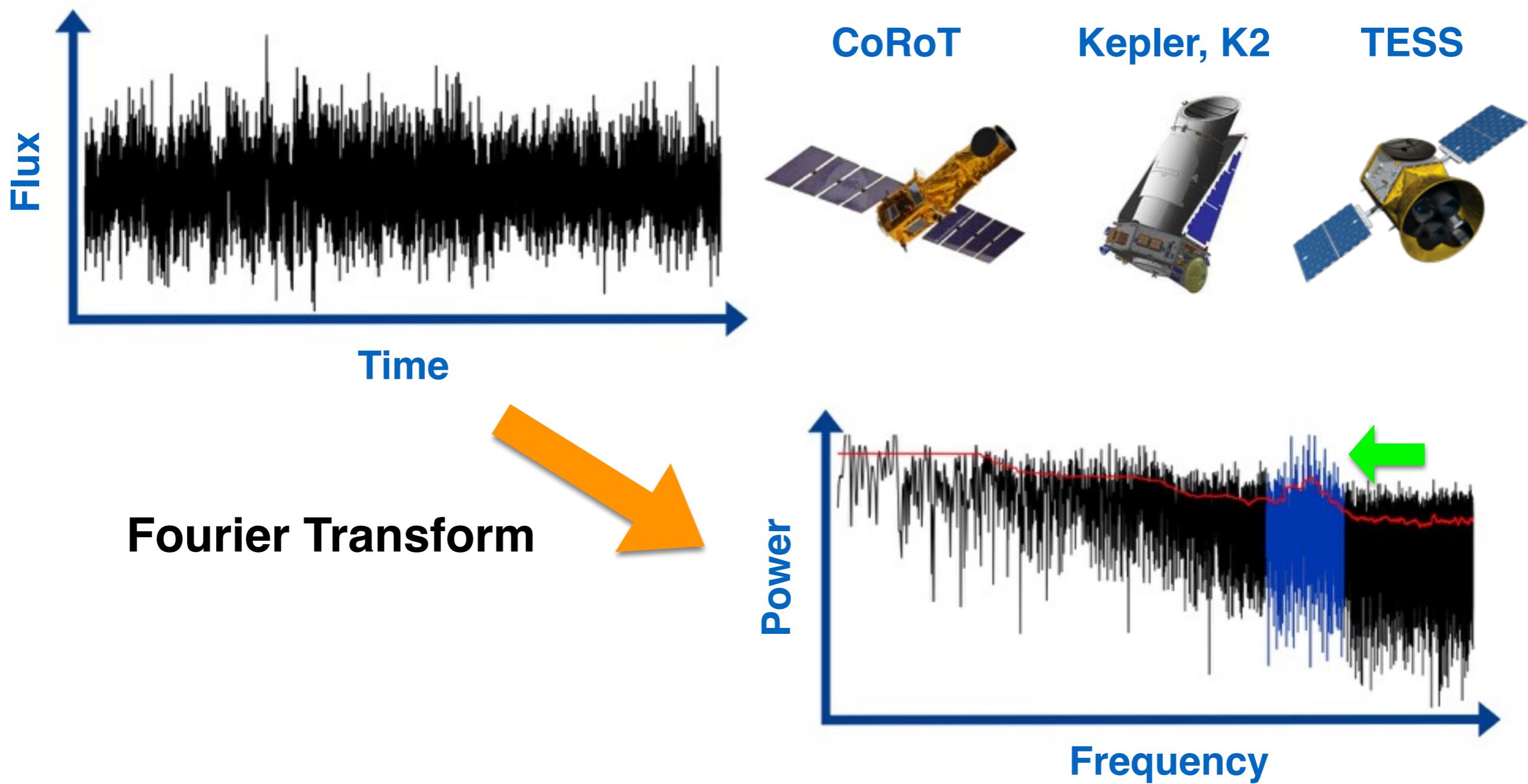
- Acoustic waves from surface convection in low- and intermediate-mass stars (***p modes***)
- Produce tiny brightness variations (**10^{-6} - 10^{-3} mag**)
- Each oscillation mode can be identified by three quantum numbers

$$\nu_{n,l,m}$$

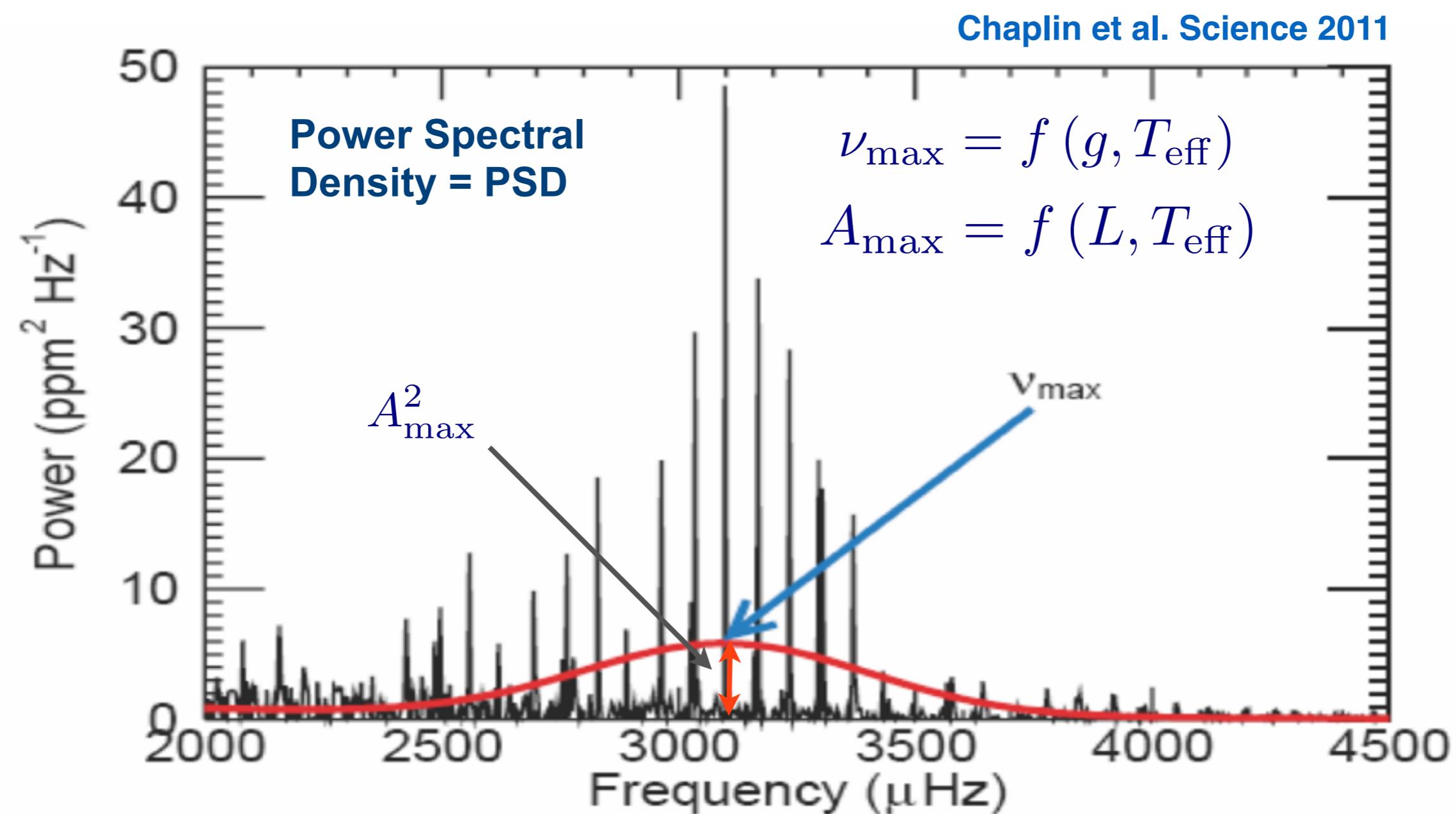


Beck & Kallinger S&W 2013

Time-series analysis

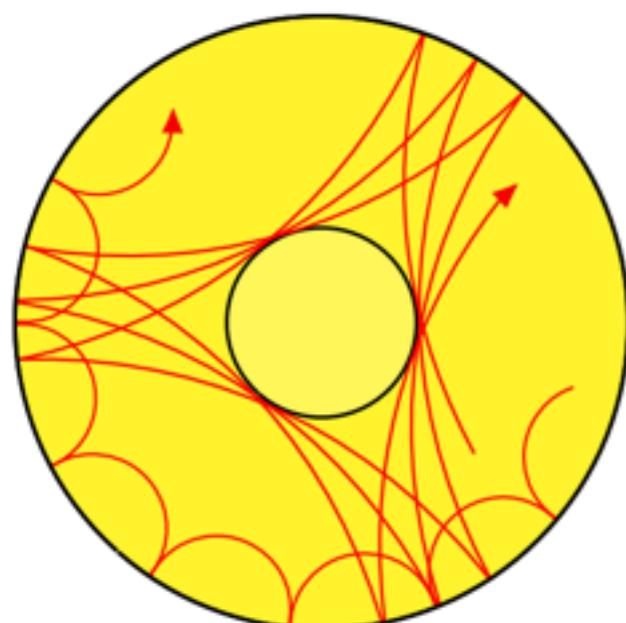


Global parameters

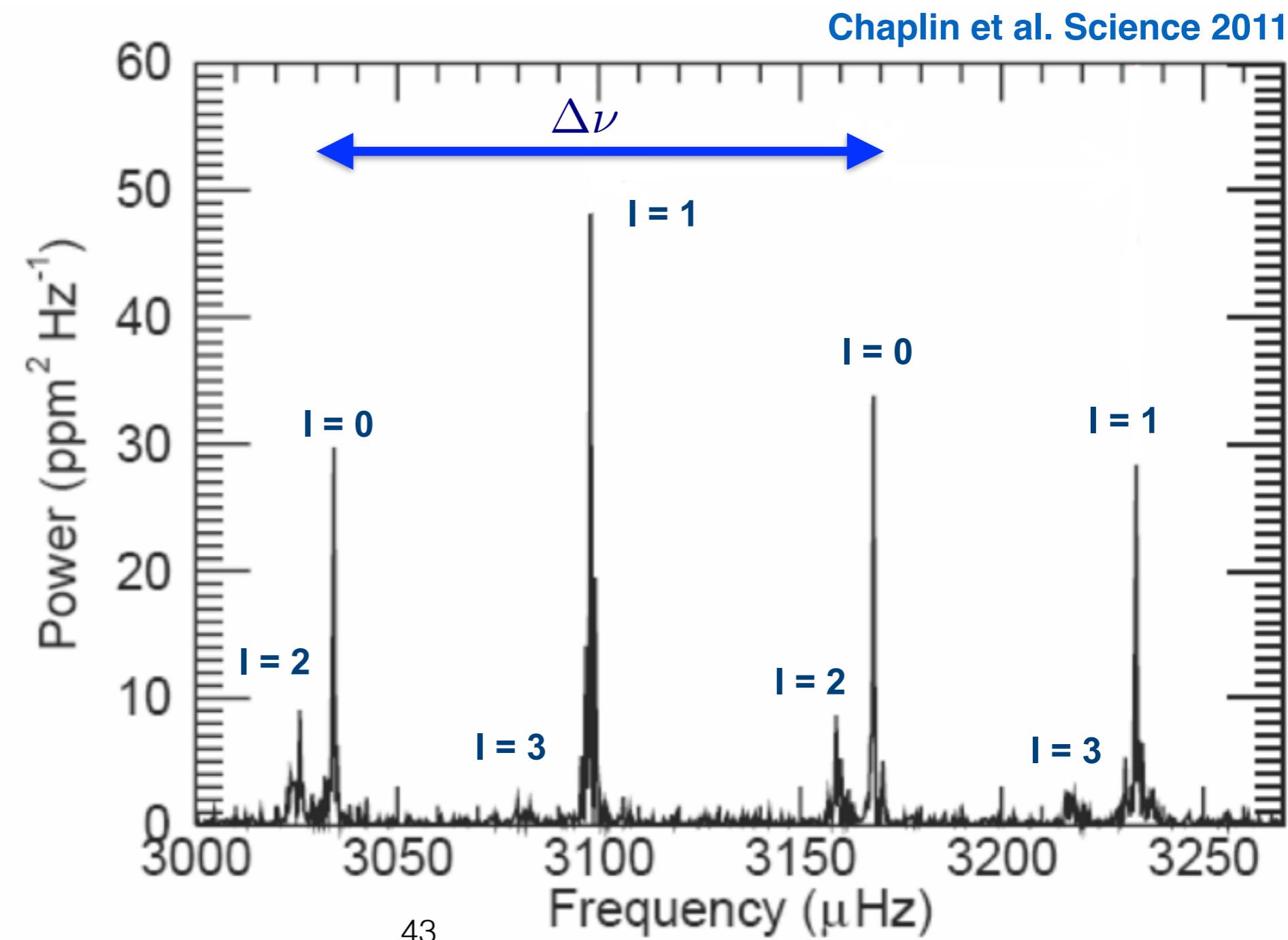


Global parameters

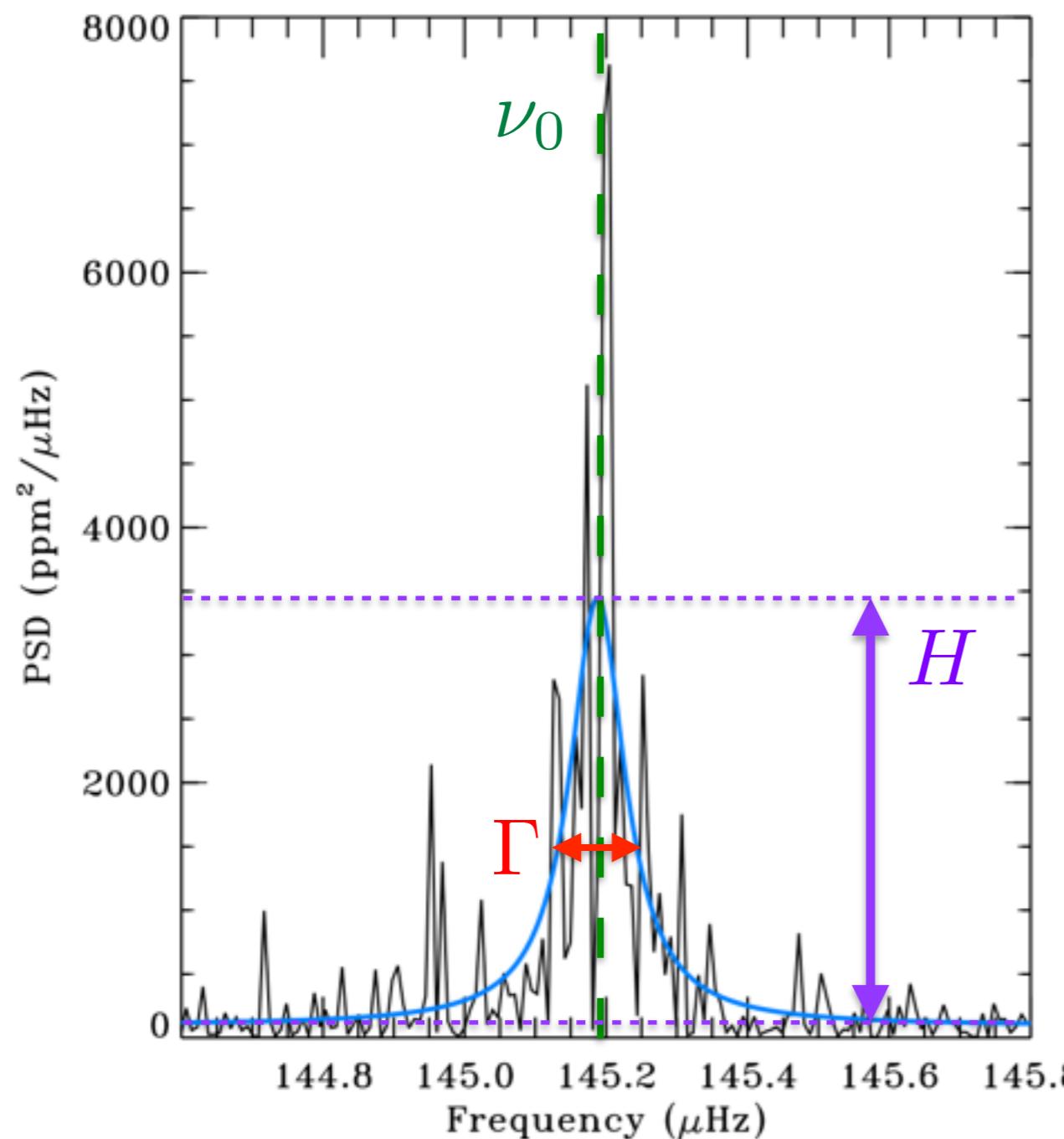
$$\Delta\nu \propto \bar{\rho}$$



Age, A_{\max}
 $\nu_{\max}, \Delta\nu$



Fine-structure of p modes



Damped oscillation

$\nu_{n,1,m}$

Lorentzian profile

$$T_{\text{obs}} \gg \tau$$

$$\Gamma \propto \tau^{-1}$$

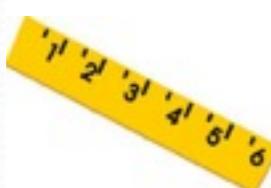
$$A^2 = \pi H \Gamma$$

ν_0, Γ, A

Why do we need this?

Constrain and understand to the best level possible
+ Spectroscopy

Physical Properties & Internal Structure



Mass, Radius to few percent precision

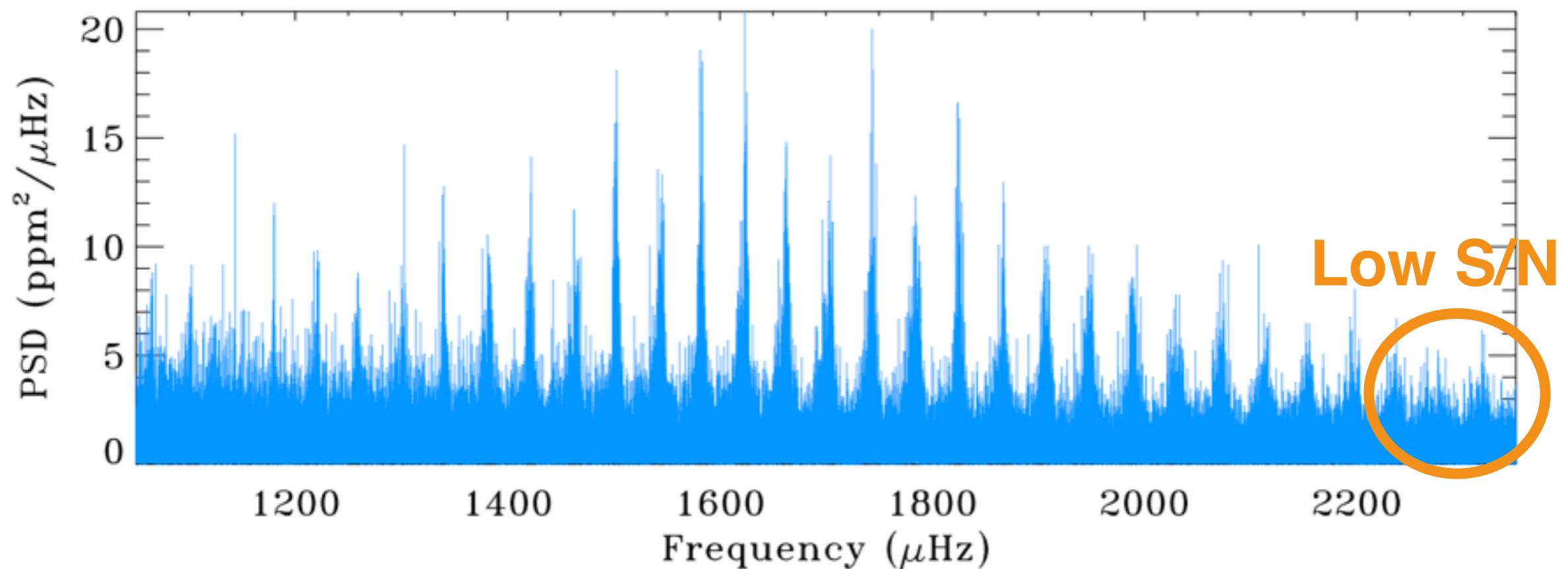


Position of BCZ, Hell zone
Evolutionary stage



Metallicity effect

Problems



- **Problem 1:** big dataset + fitting numerous oscillation modes (peaks) per star (can be more than 100)
- **Problem 2:** testing if a peak is real or not (noise)

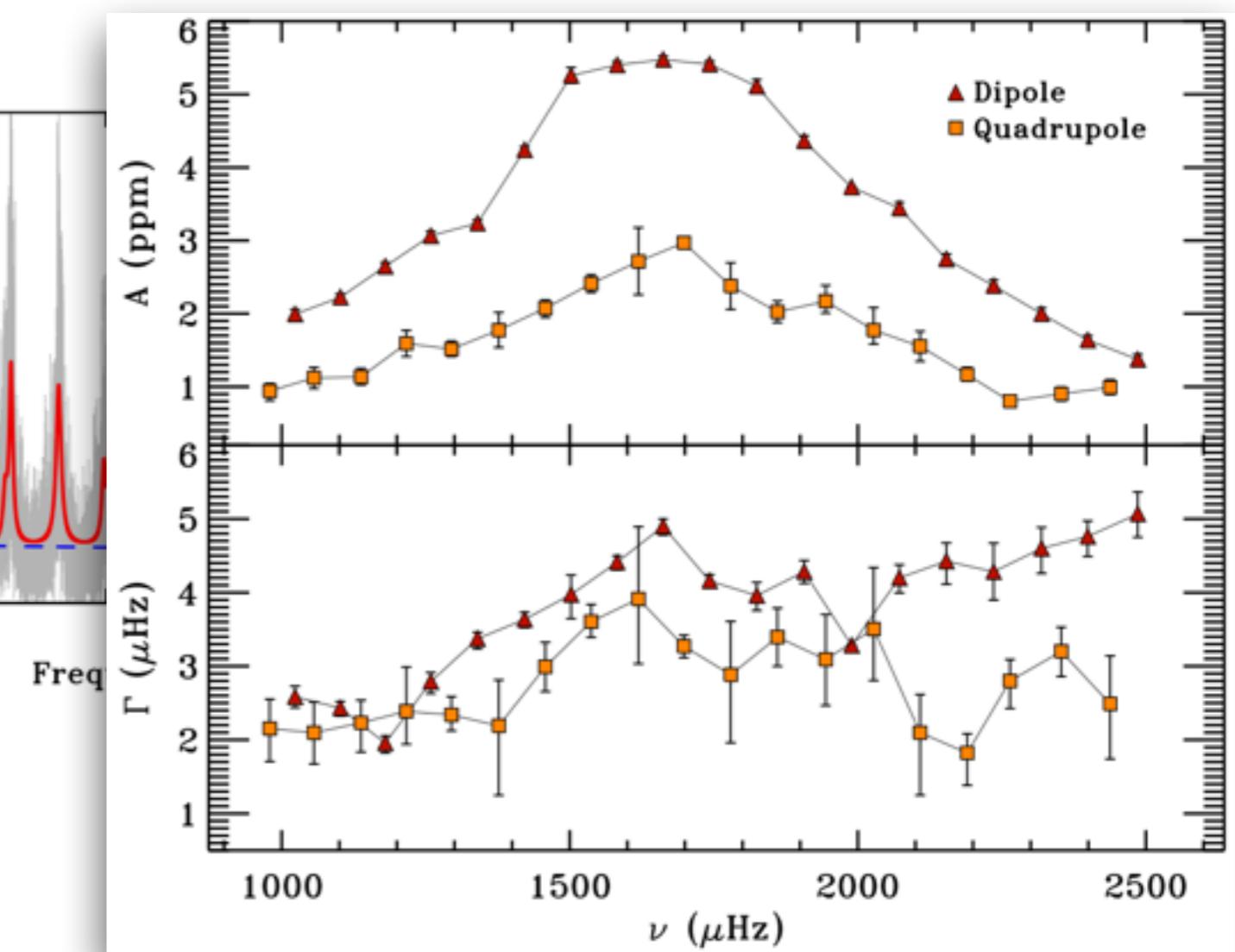
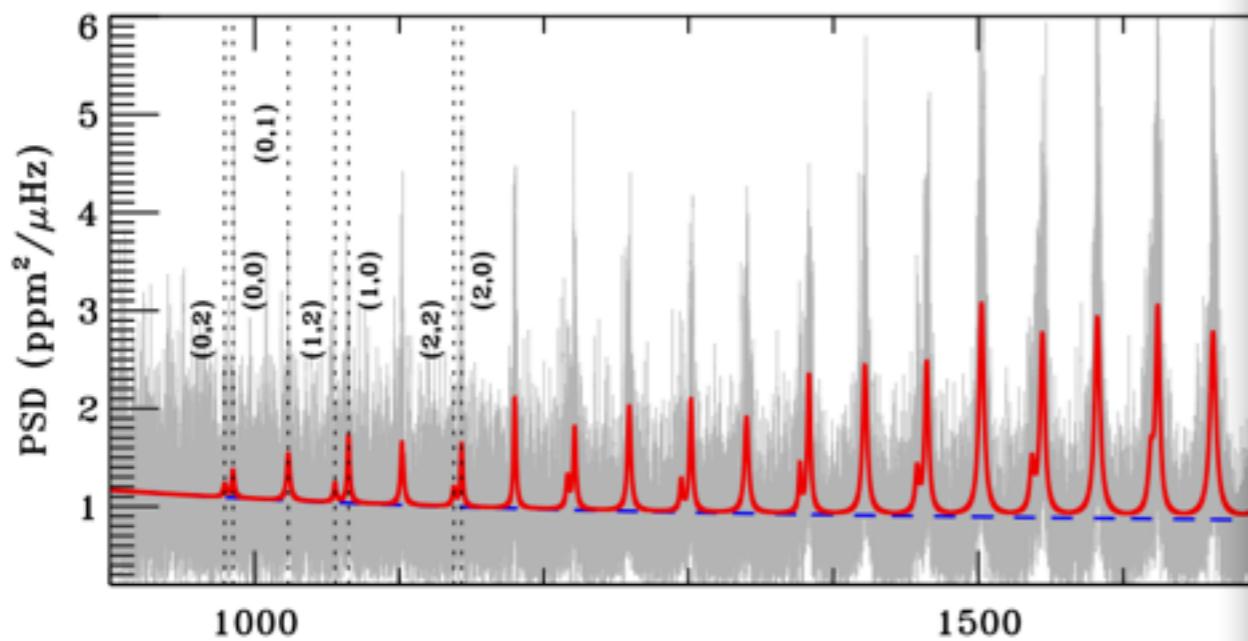
Problem 1

Solving a high-dimensional fitting problem

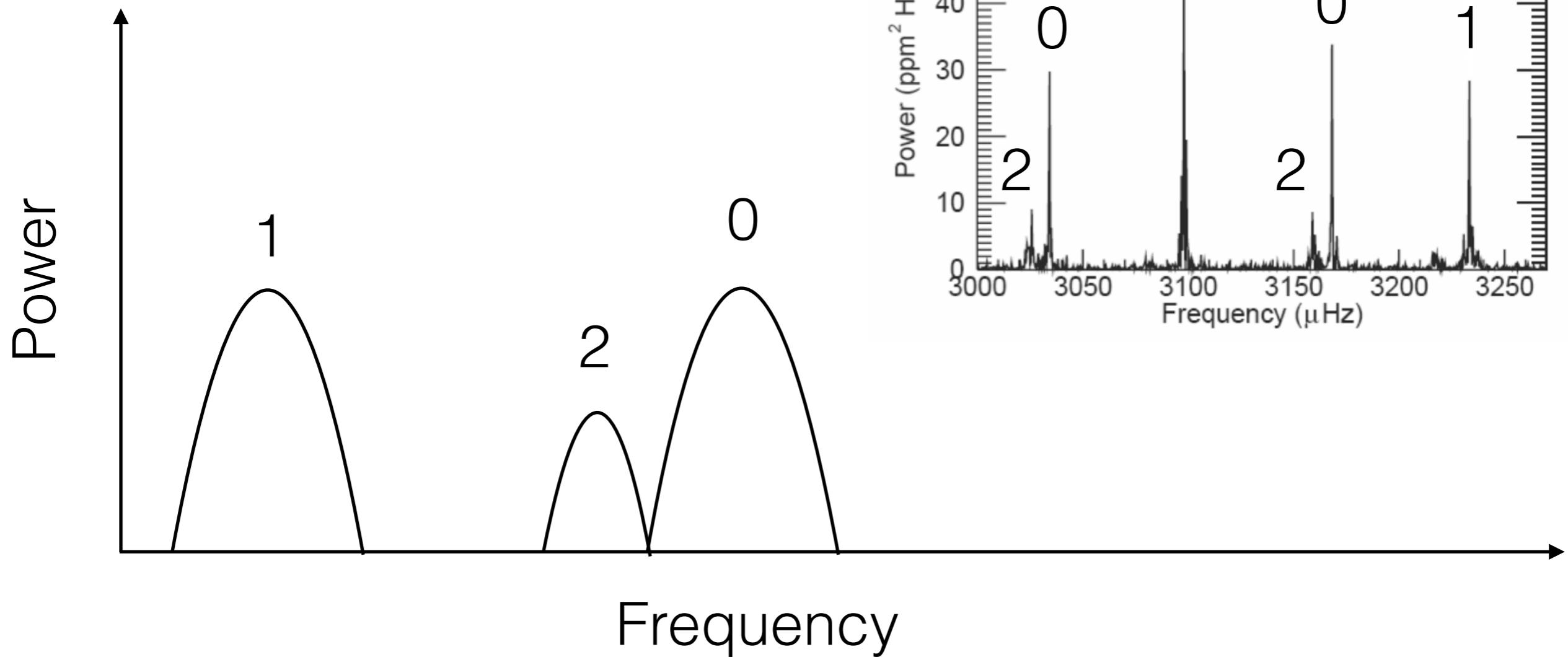
High-dimensional Model

About 180 free parameters!
Computational time increases a lot

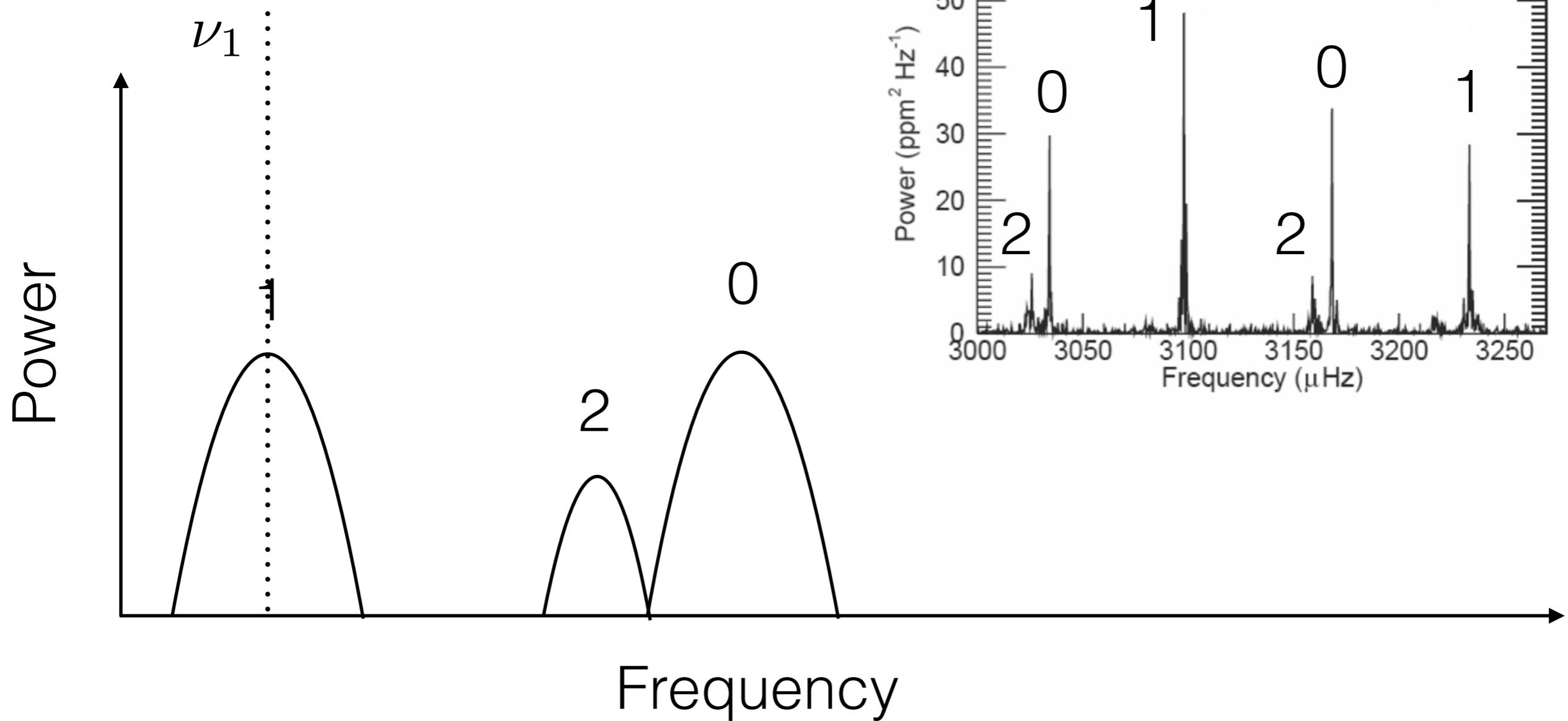
KIC 9139163



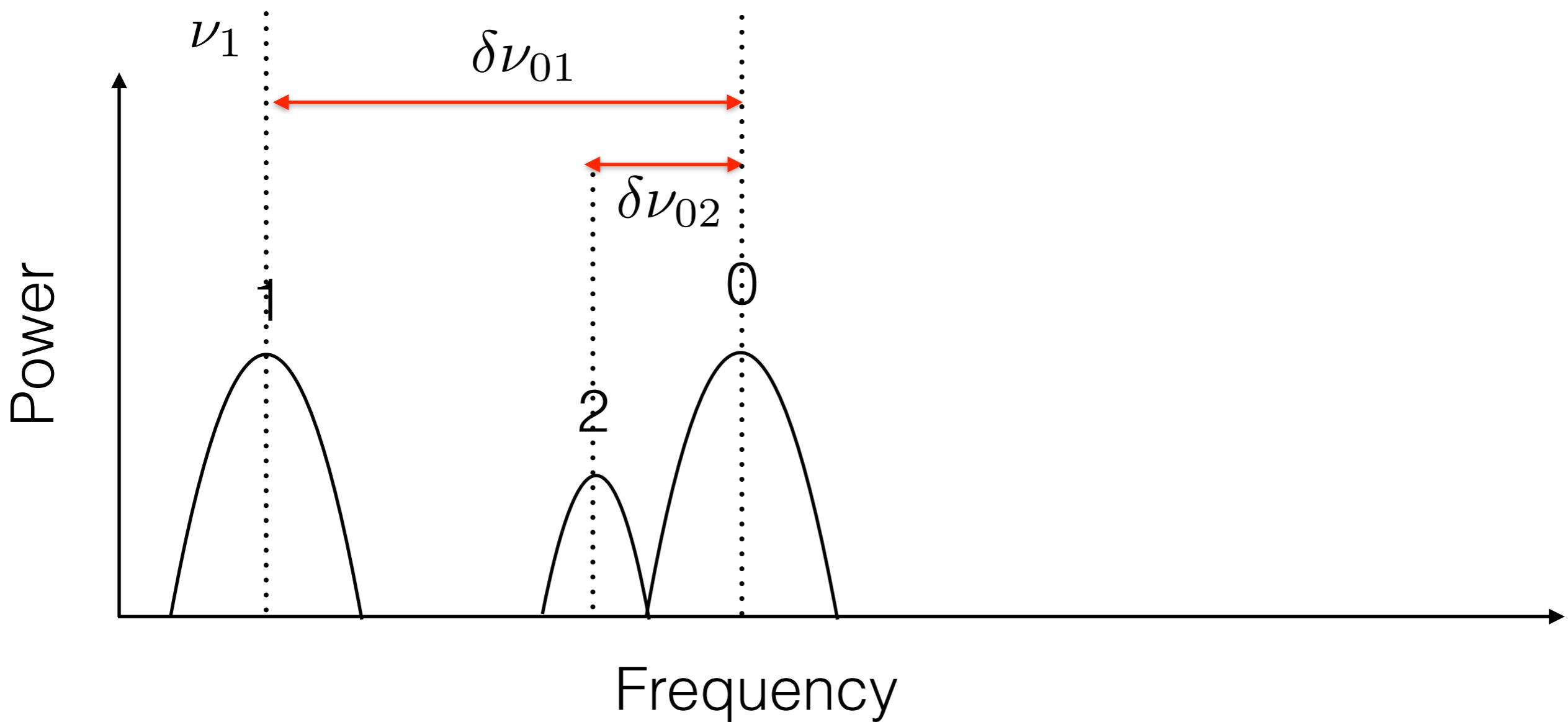
Multi-modal Model



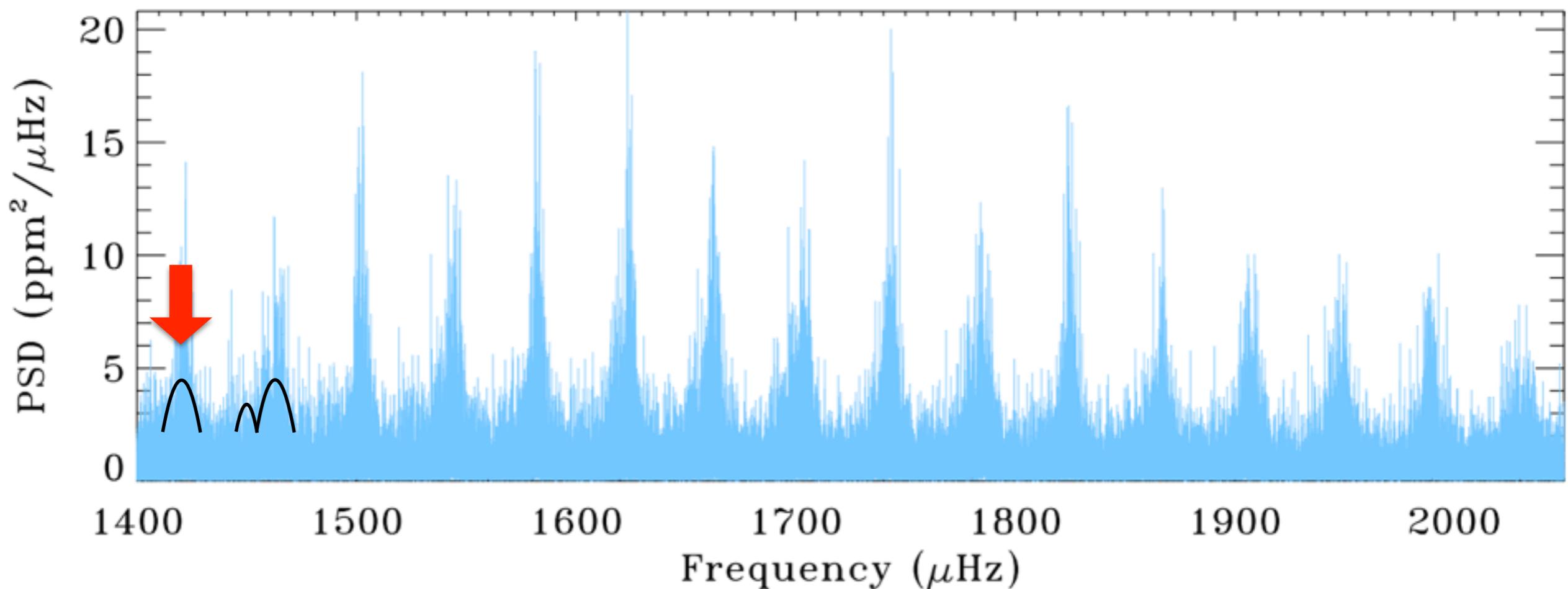
Multi-modal Model



Multi-modal Model



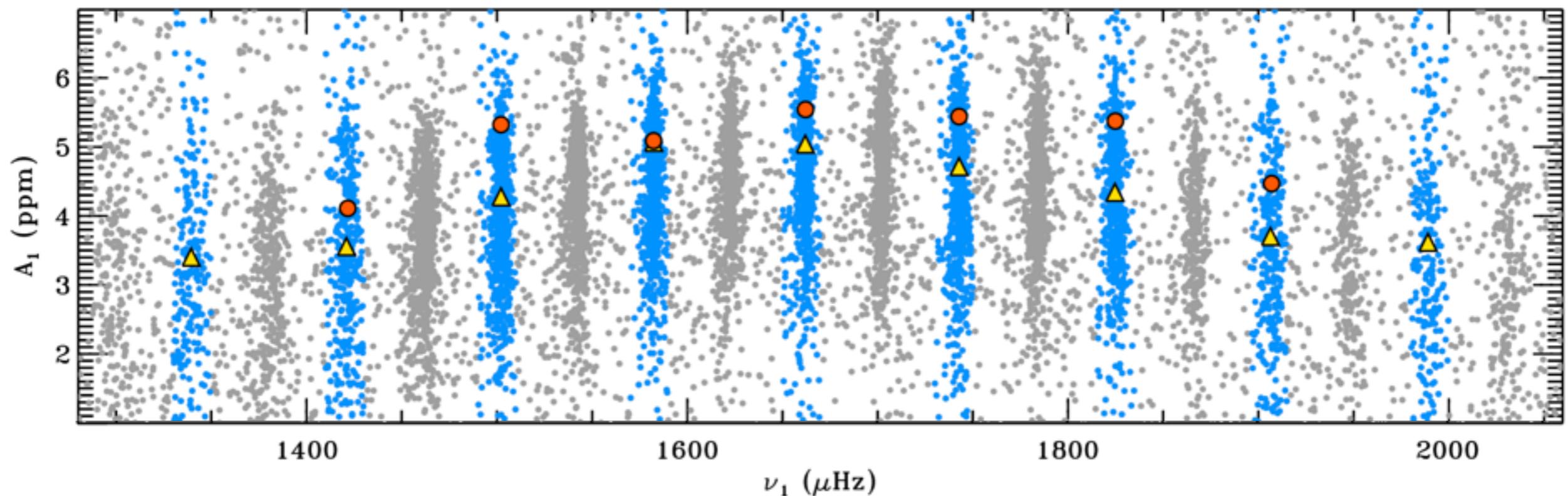
Multi-modal Model



Results

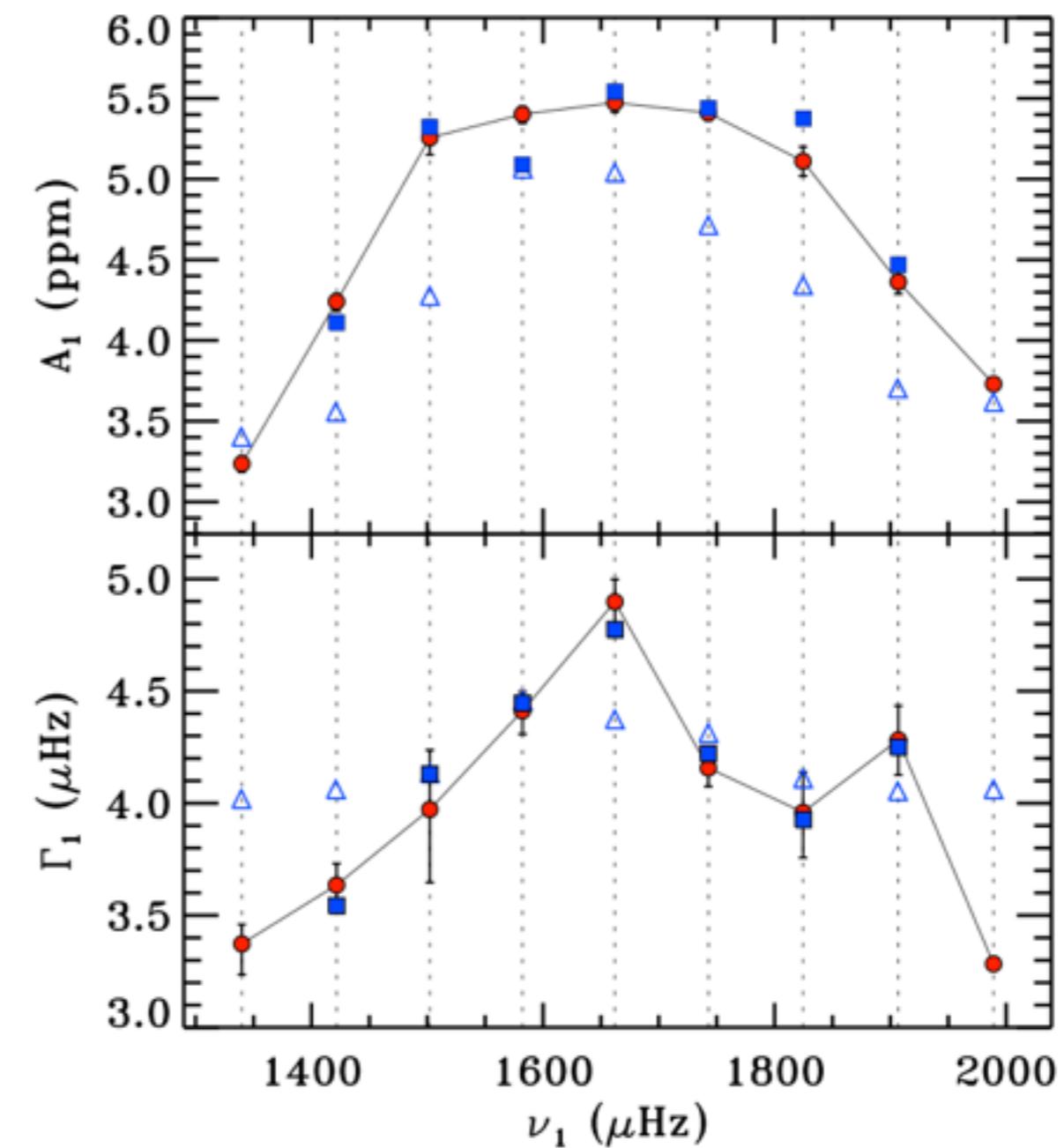
Multi-modal inference problem on 9 consecutive radial orders (27 peaks)

Only 9 free parameters!



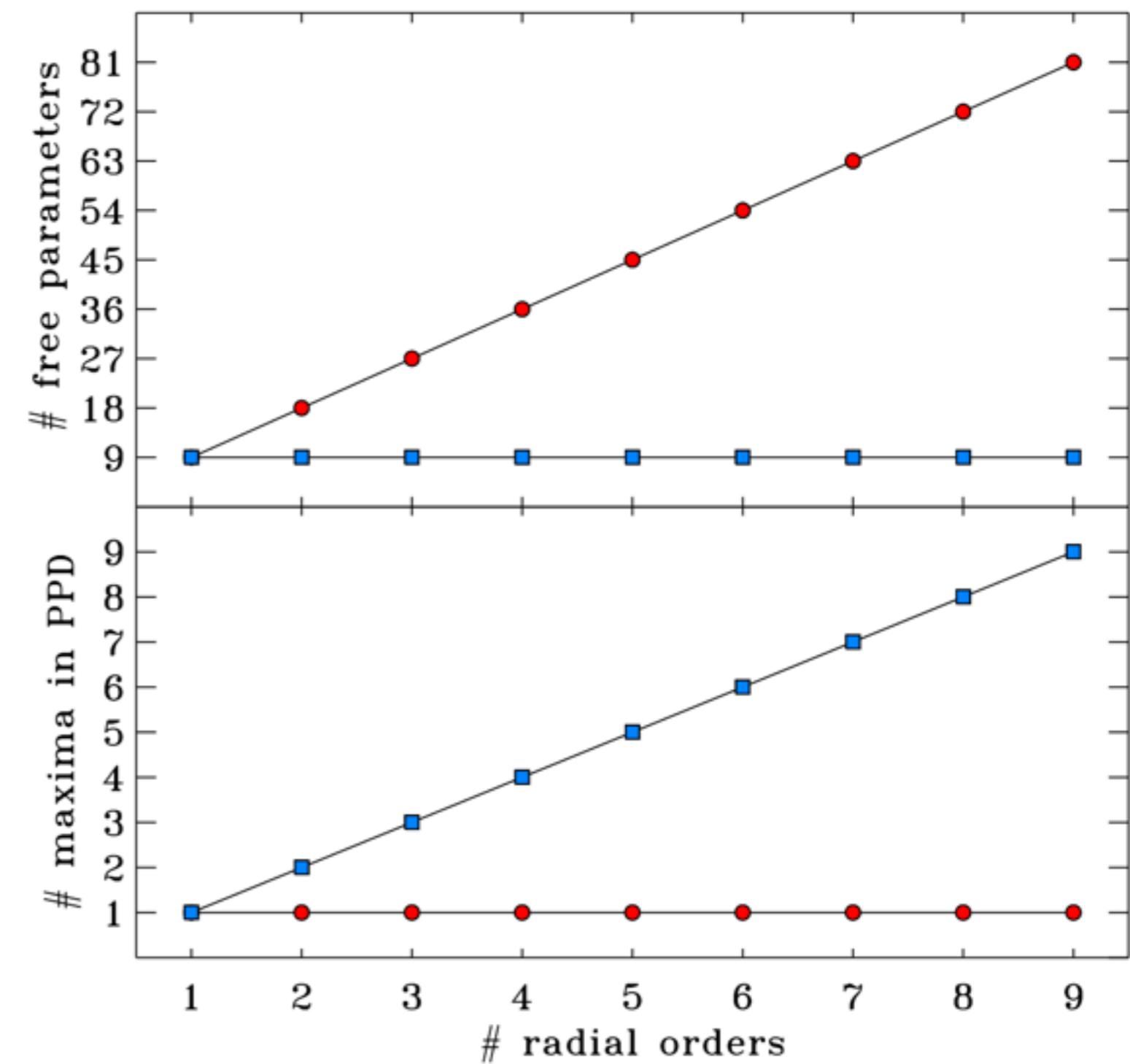
Comparison

Red: uni-modal fit
Blue: multi-modal fit



Comparison

Red: uni-modal fit
Blue: multi-modal fit



Problem 2

Test the significance of an oscillation peak

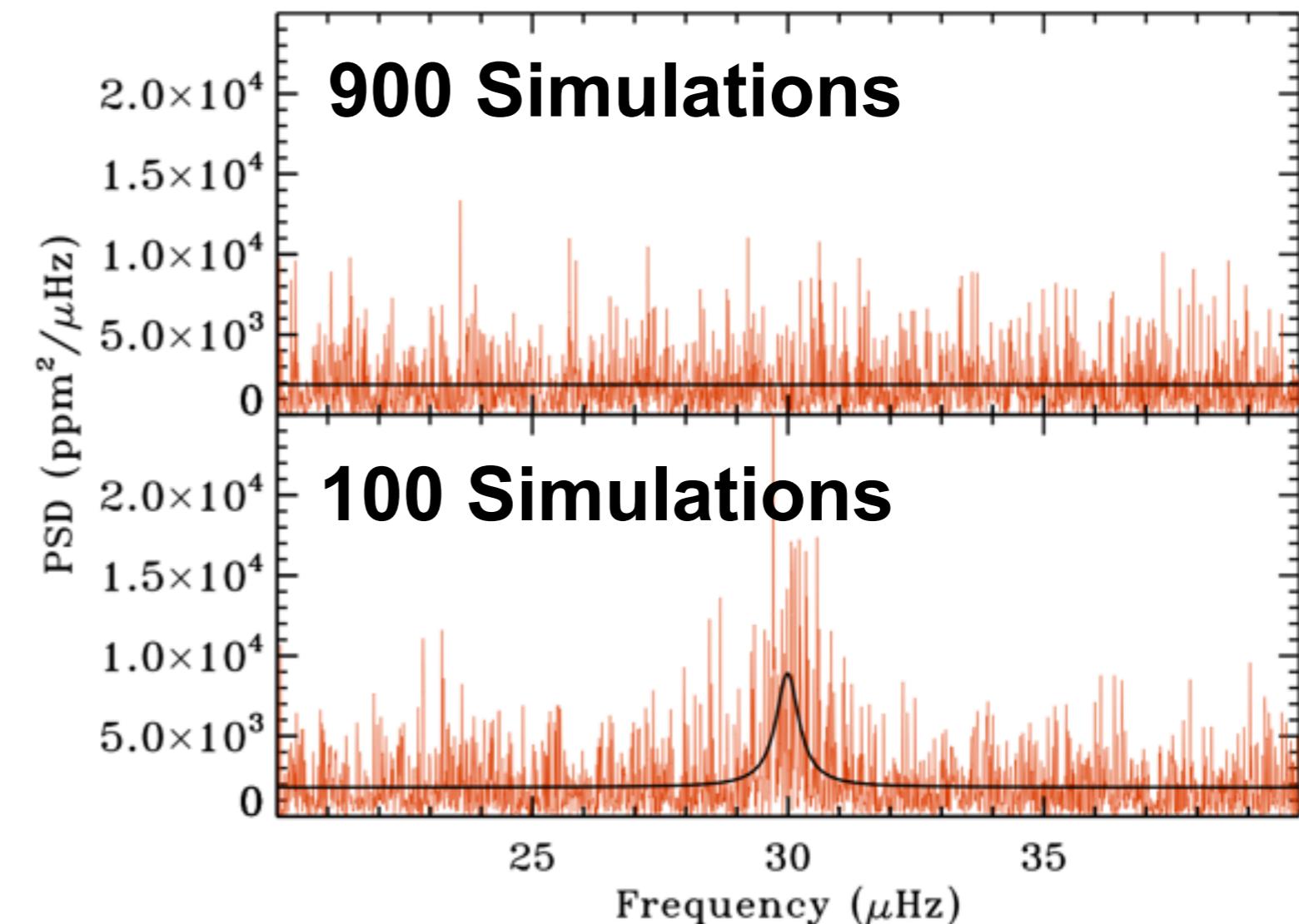
Peak Significance Criterion

- Simulations test
- **1000** artificial chunks of PSD
- Blind search for those with a peak

Bayes' factor

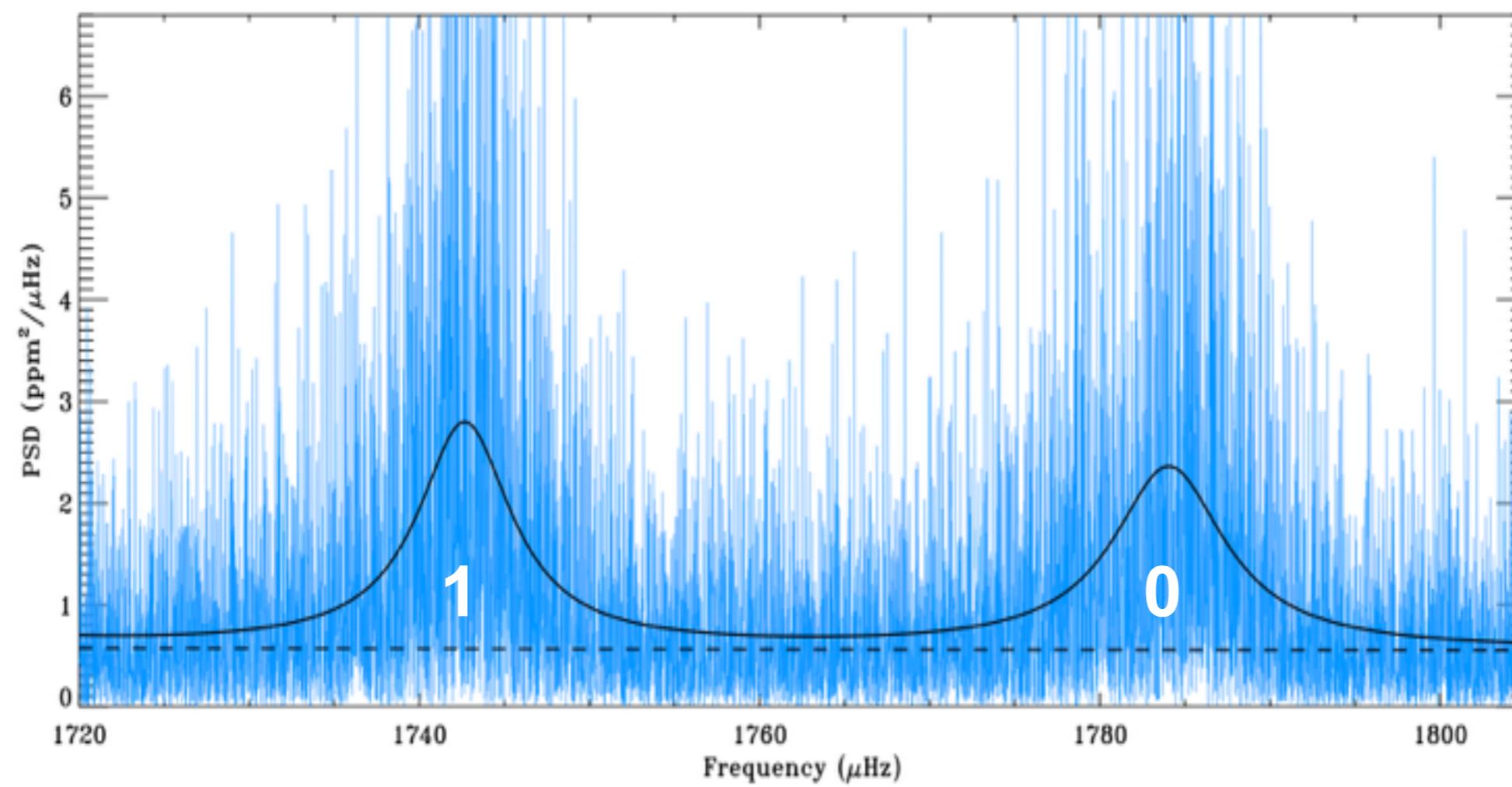
$$B_{yes,no} = \frac{\mathcal{E}_{yes}}{\mathcal{E}_{no}}$$

$$B_{yes,no} \sim 150$$



All peaks found!

Peak significance



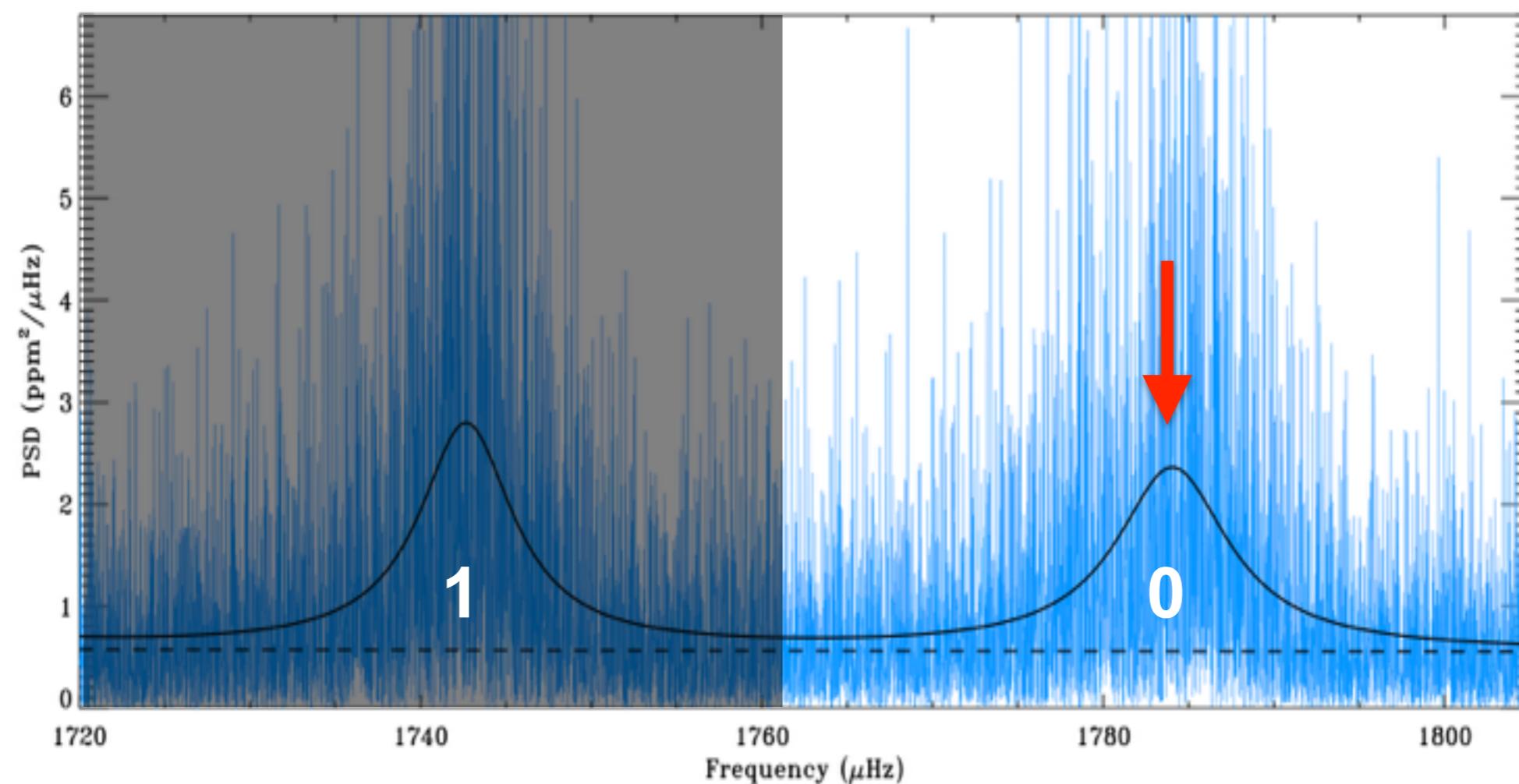
Peak significance

$\mathcal{M}_{\ell=0}$

Only $\ell = 0$

$\mathcal{E}_{\ell=0}$

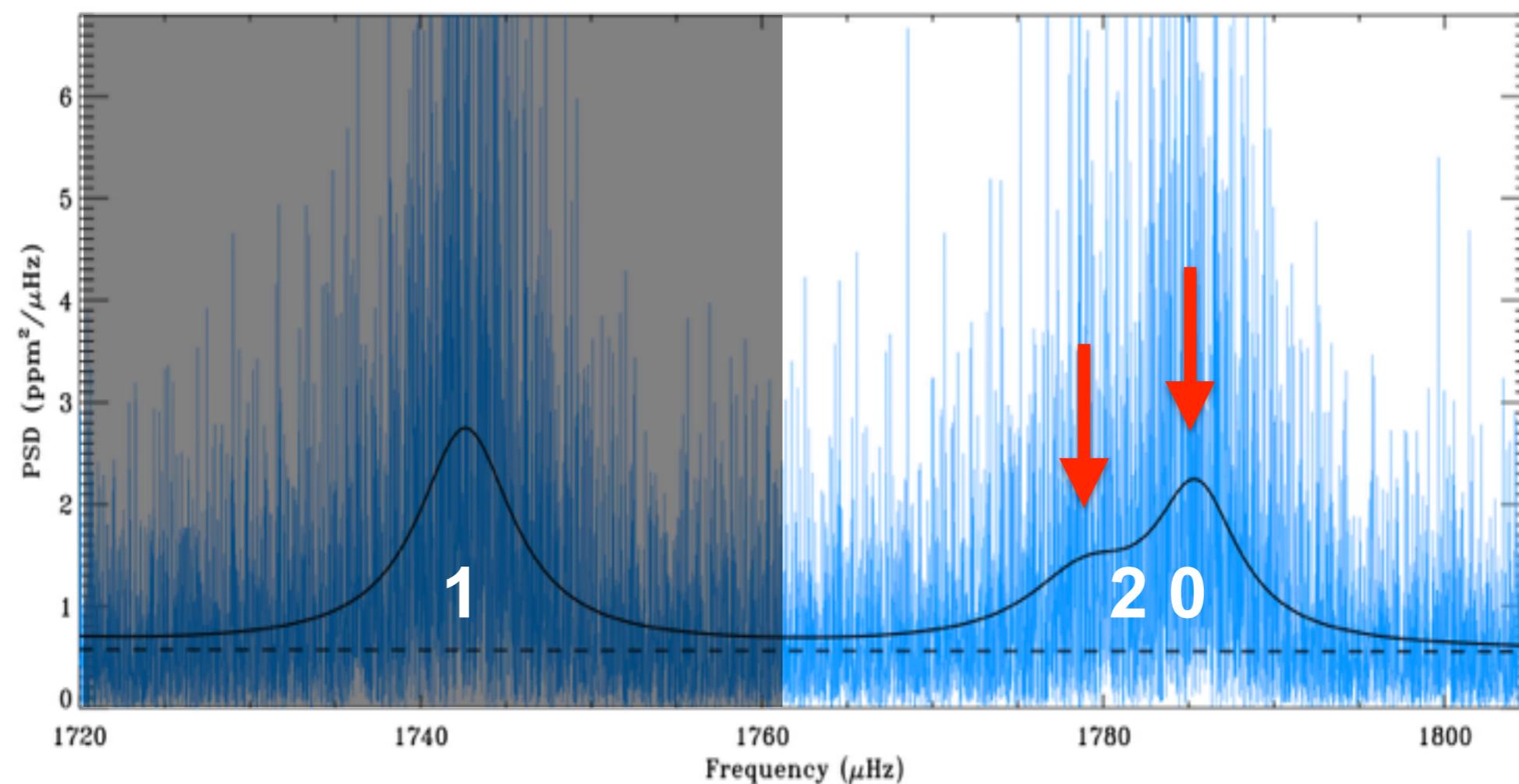
Bayesian Evidence



Peak significance

$\mathcal{M}_{\ell=2}$ **Both $\ell = 2$ and $\ell = 0$**

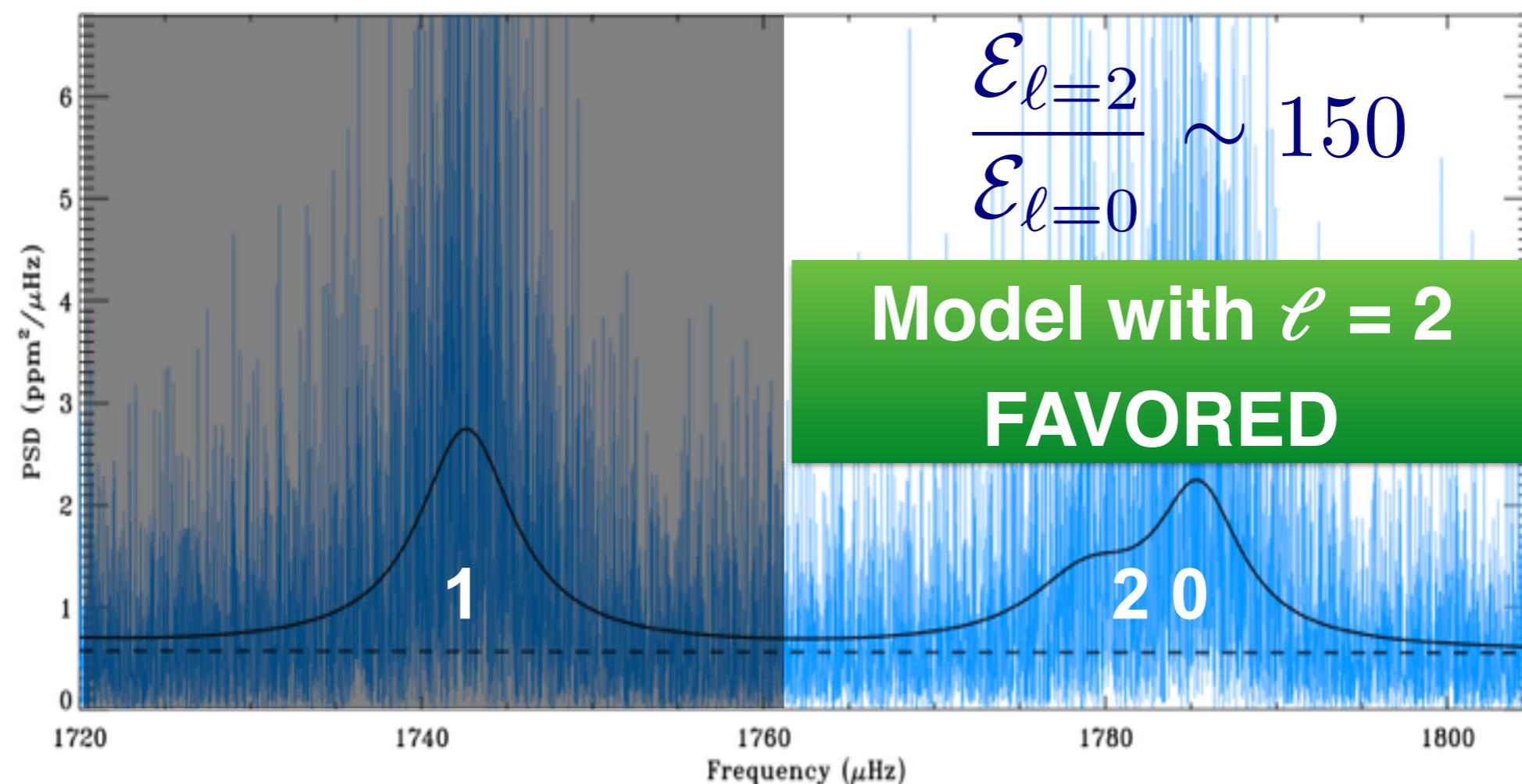
$\mathcal{E}_{\ell=2}$ **Bayesian Evidence**



Peak significance

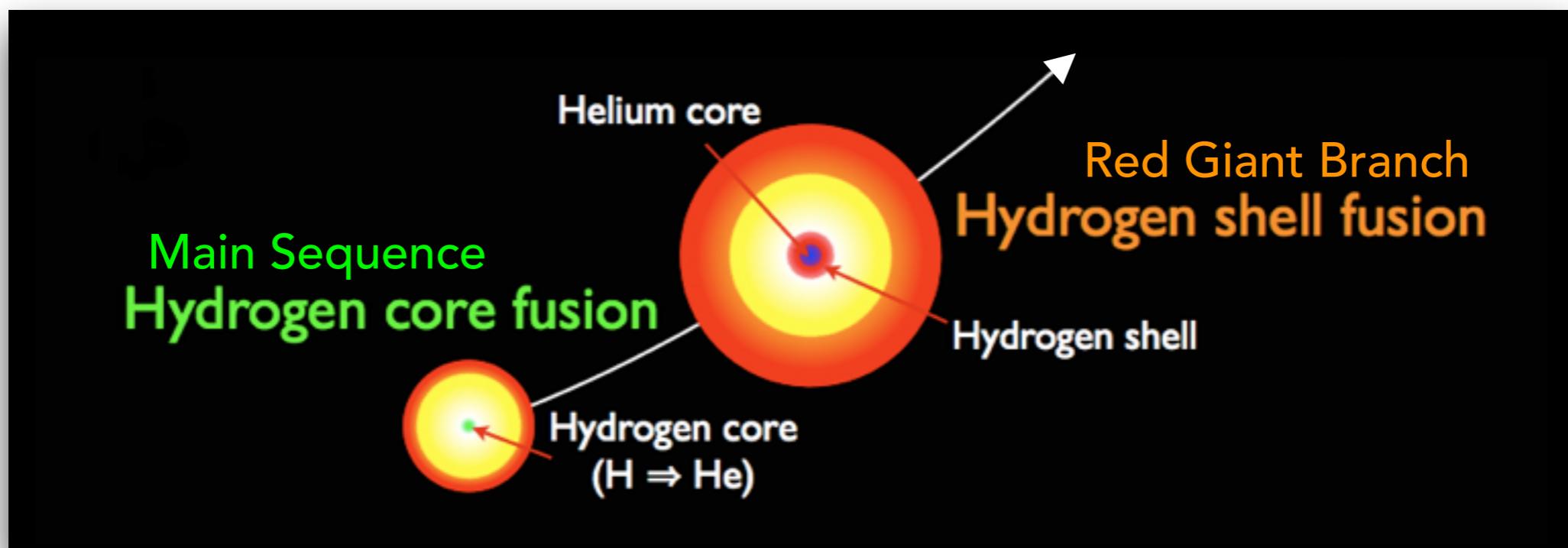
$\mathcal{M}_{\ell=2}$ **Both $\ell = 2$ and $\ell = 0$**

$\mathcal{E}_{\ell=2}$ **Bayesian Evidence**



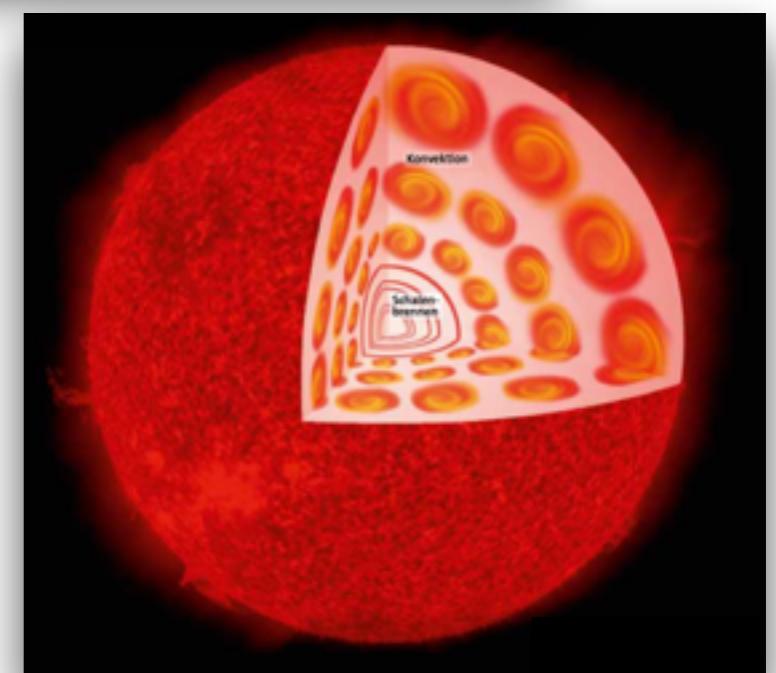
Oscillations in red giant stars

RGB oscillations

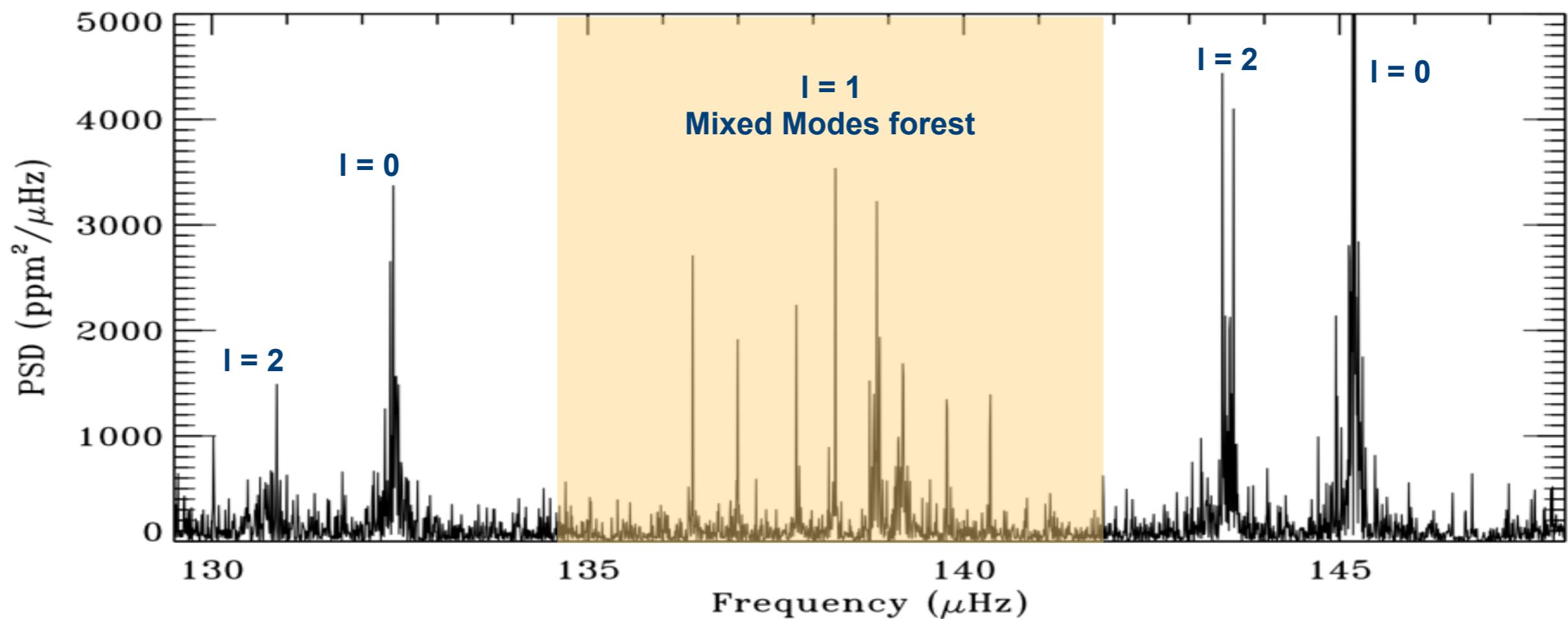


© Thomas Kallinger

p modes couple with gravity modes (g modes) from radiative interior (mixed modes)



RGB oscillations



Many oscillation modes per star (up to about 100)!

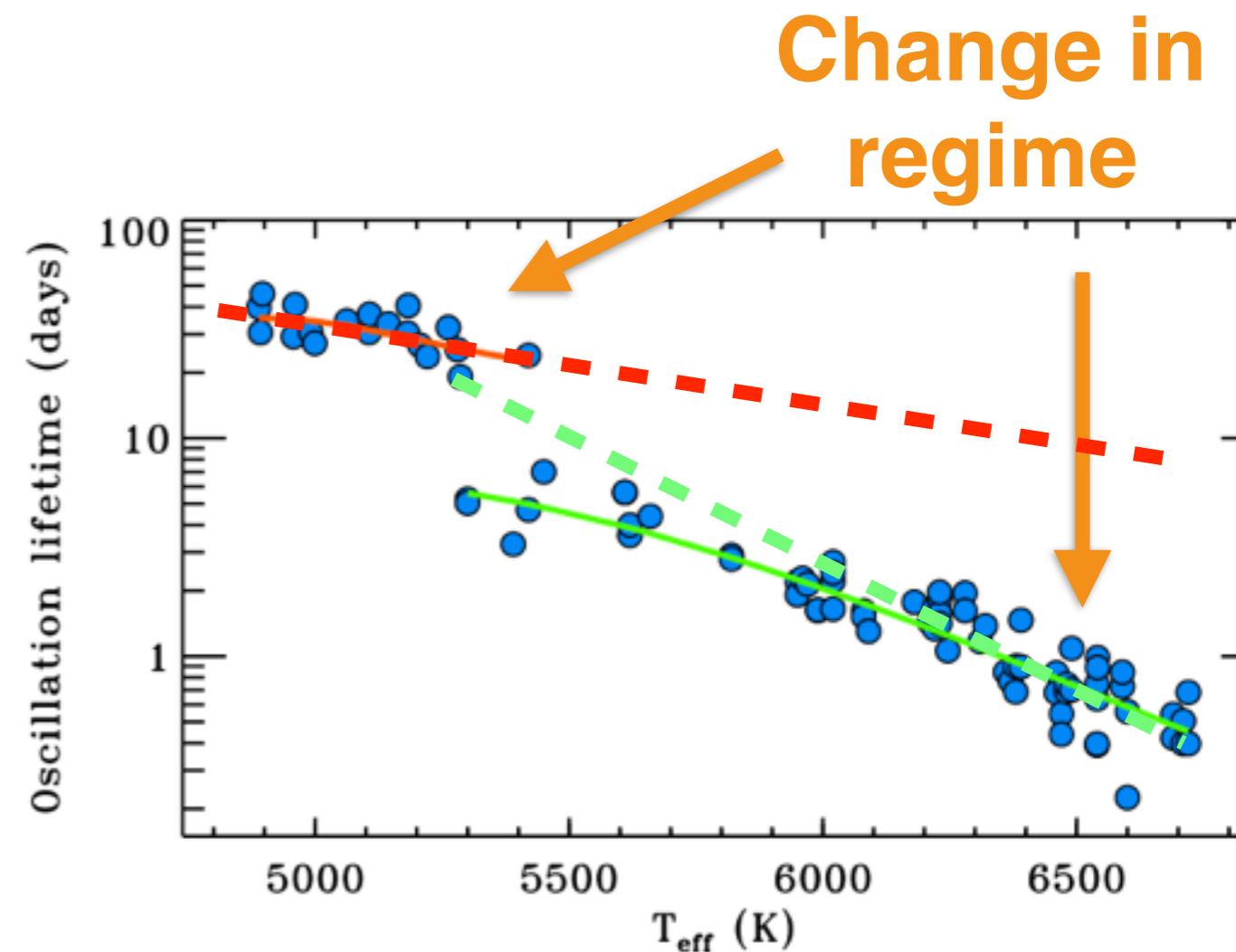
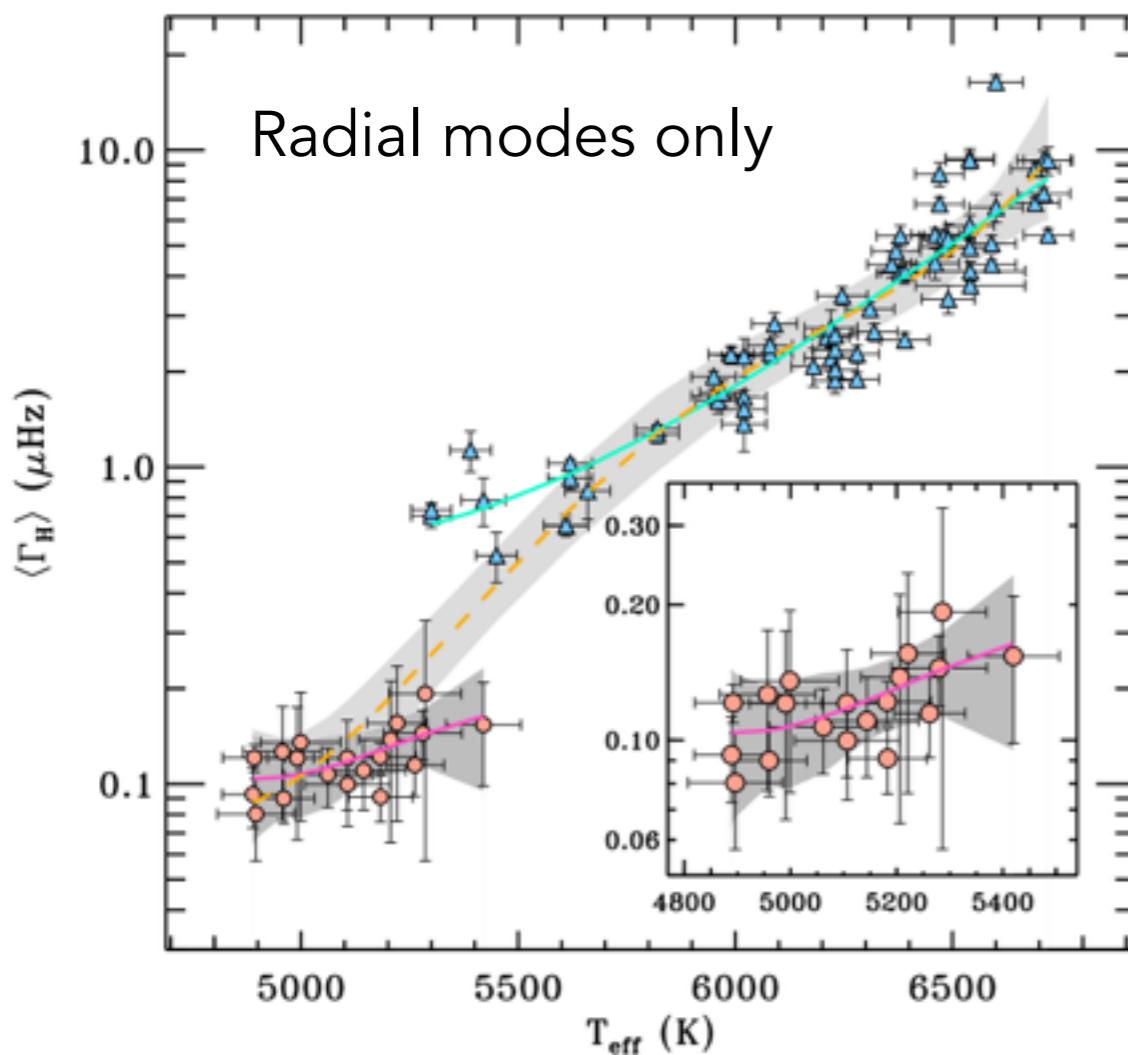
Results on 19 RGB stars

Corsaro, De Ridder, García 2015 A&A, 579, 83

- **1618** oscillation modes extracted
- **612** peaks tested (38%) with Bayesian model comparison
- **380** peaks detected (62% of tested peaks)
- Internal rotation detected in **14** stars

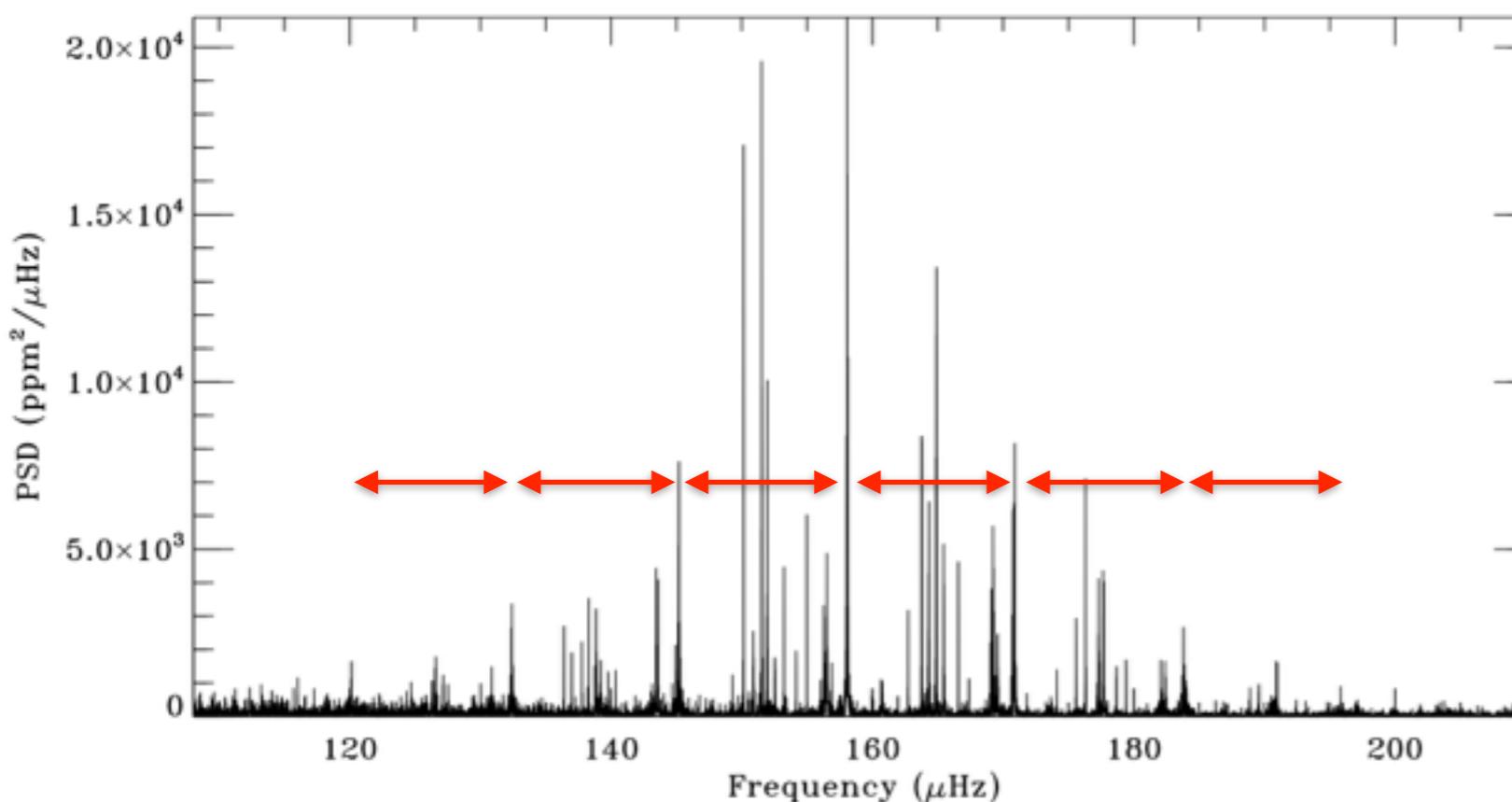
Mode lifetimes

Corsaro, De Ridder, García 2015 A&A, 579, 83

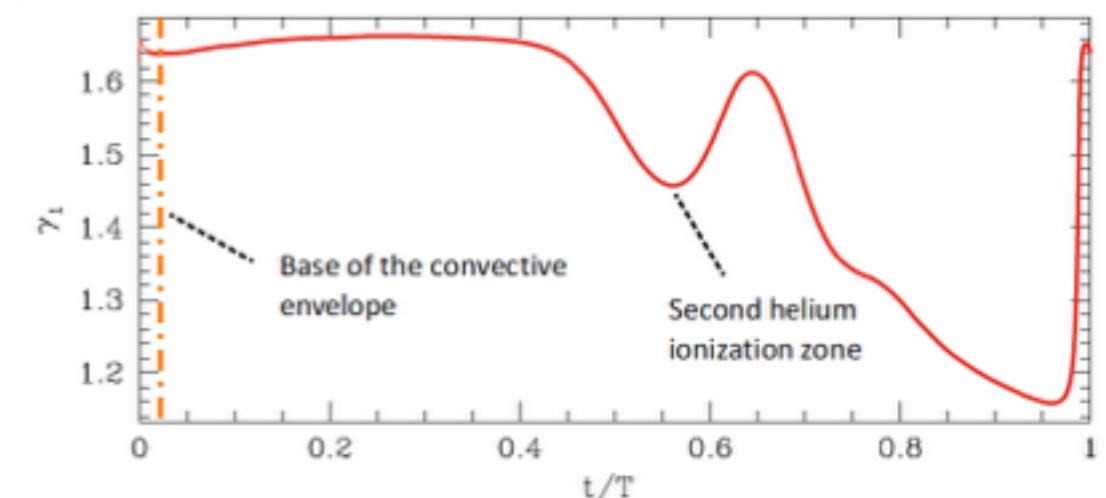


Acoustic glitches

Corsaro, De Ridder, García 2015 A&A, 578, 76

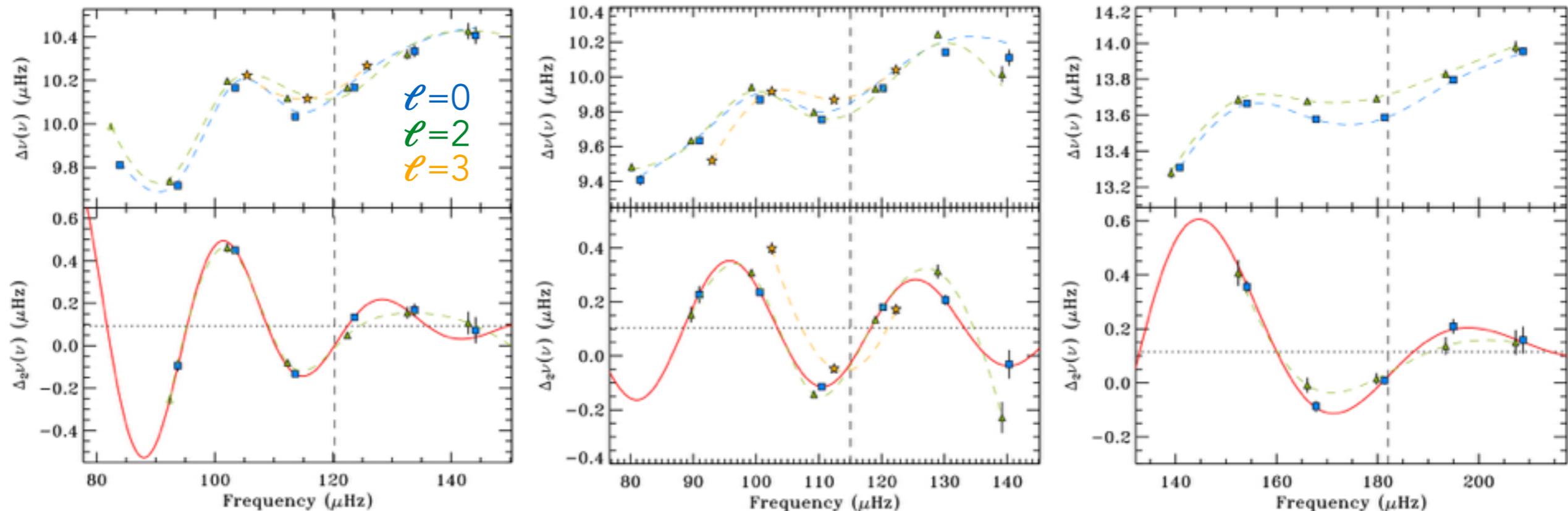


Regions of sharp
structure variation
inside the star induce
oscillatory behavior in
the mode frequencies



Signature of Hell zone

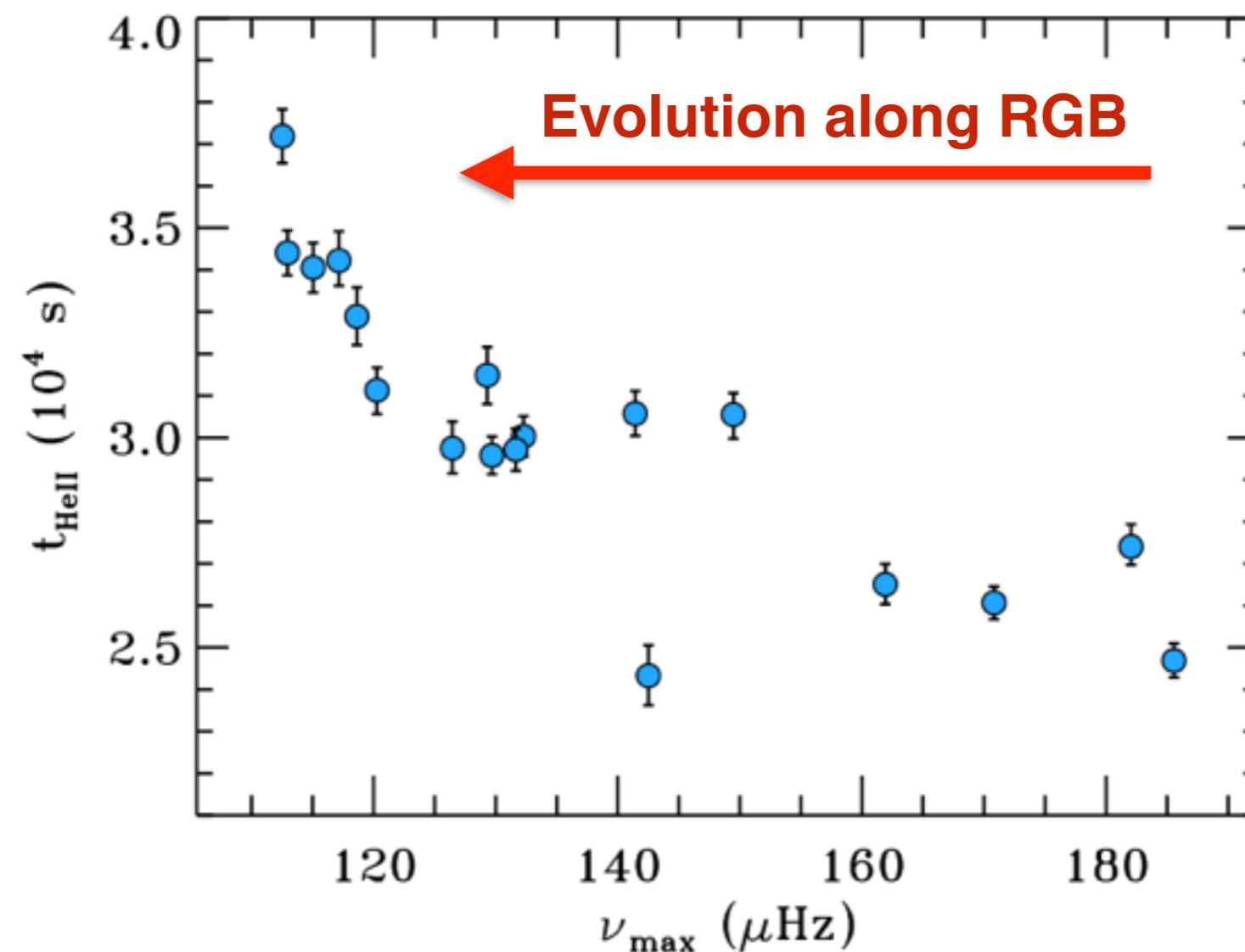
Corsaro, De Ridder, García 2015 A&A, 578, 76



- The position of Hell zone is constrained up to 2% precision!
- Amplitudes up to 6%, can give estimate of He abundance in convective envelope

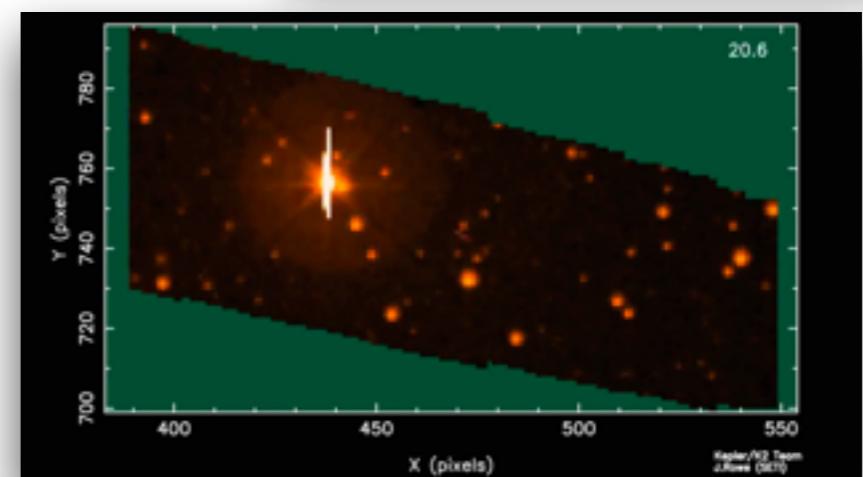
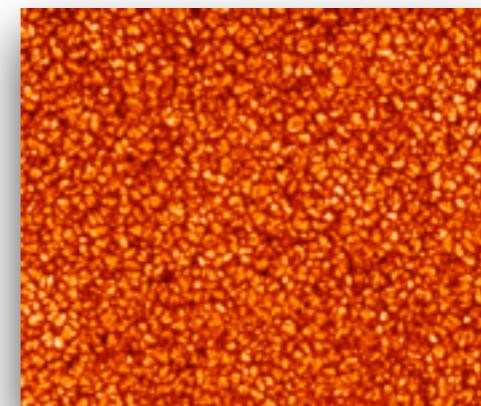
Evolution of Hell zone

Corsaro, De Ridder, García 2015 A&A, 578, 76



Ongoing research

- Analysis of granulation and oscillation properties of the Sun with GOLF & VIRGO + correlation with magnetic activity
- Full characterization of red giant stars in NASA Kepler open clusters NGC 6791, NGC 6811, NGC 6819
- Analysis of solar oscillations reflected from Neptune's atmosphere, observed by K2



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The DIAMONDS code

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User Guide Manual

Publications

Events

Statistics

Logo

Institute of Astronomy → Software Products → The DIAMONDS code

The DIAMONDS code

- Authors
- Description
- Working Scheme

The DIAMONDS Bayesian Software logo, identical to the one at the top of the page.

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<https://fys.kuleuven.be/ster/Software/Diamonds/>

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The screenshot shows the KU Leuven Institute of Astronomy website. The top navigation bar includes links for Contact, Who's who, Organisational chart, Libraries, and Toledo. The main menu has categories for EDUCATION, RESEARCH, ADMISSIONS, and LIFE. On the left, a sidebar menu lists: The DIAMONDS code (selected), Releases, Download, Package Content, Installation Guide, User Guide Manual (with a red arrow pointing to it), Publications, Events, Statistics, and Logo.

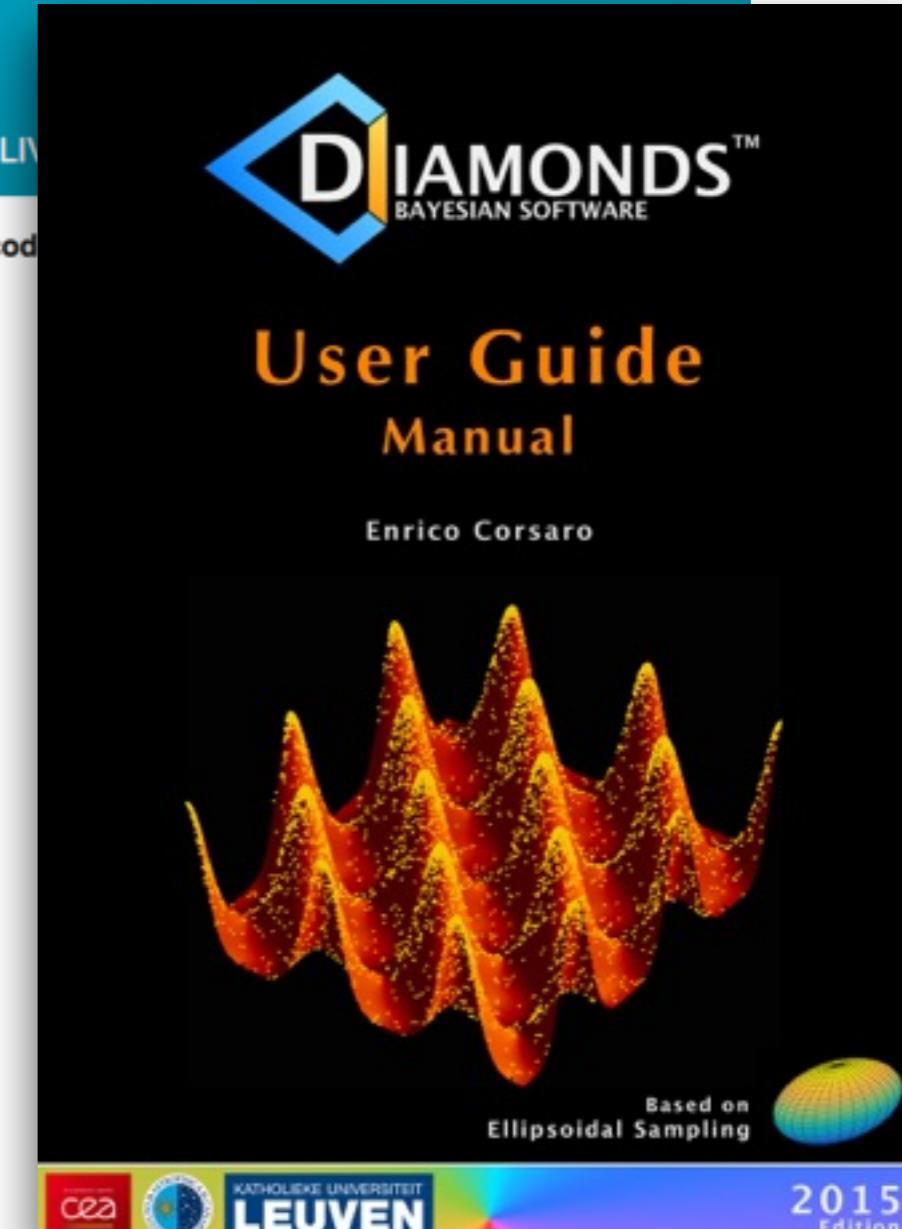
The DIAMONDS code

- Authors
- Description
- Working Scheme

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The cover of the "User Guide Manual" for DIAMONDS Bayesian Software, authored by Enrico Corsaro. The cover features a black background with a 3D surface plot of a multi-peaked distribution in orange and yellow. Text on the cover includes "DIAMONDS™ BAYESIAN SOFTWARE", "User Guide Manual", "Enrico Corsaro", "Based on Ellipsoidal Sampling", and "2015 Edition". Logos for CEA and KU Leuven are also present.

<https://fys.kuleuven.be/ster/Software/Diamonds/>

Thank you!