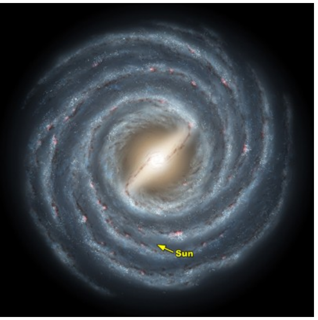
Generalized Stellar Parametrizer with Gaia Photometry Data (GSP-Phot)



copyright: NASA/JPL-Caltech/R. Hurt (SSC)

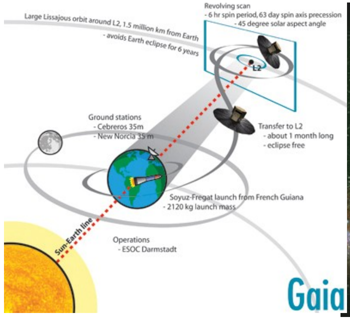
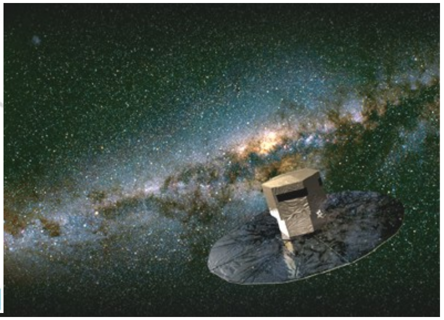


Image credit: ESA



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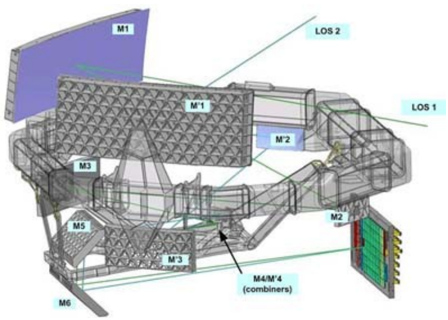


Image credit: EADS Astrium

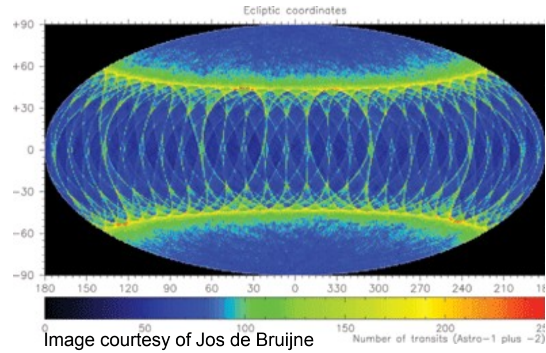


Image courtesy of Jos de Bruijne

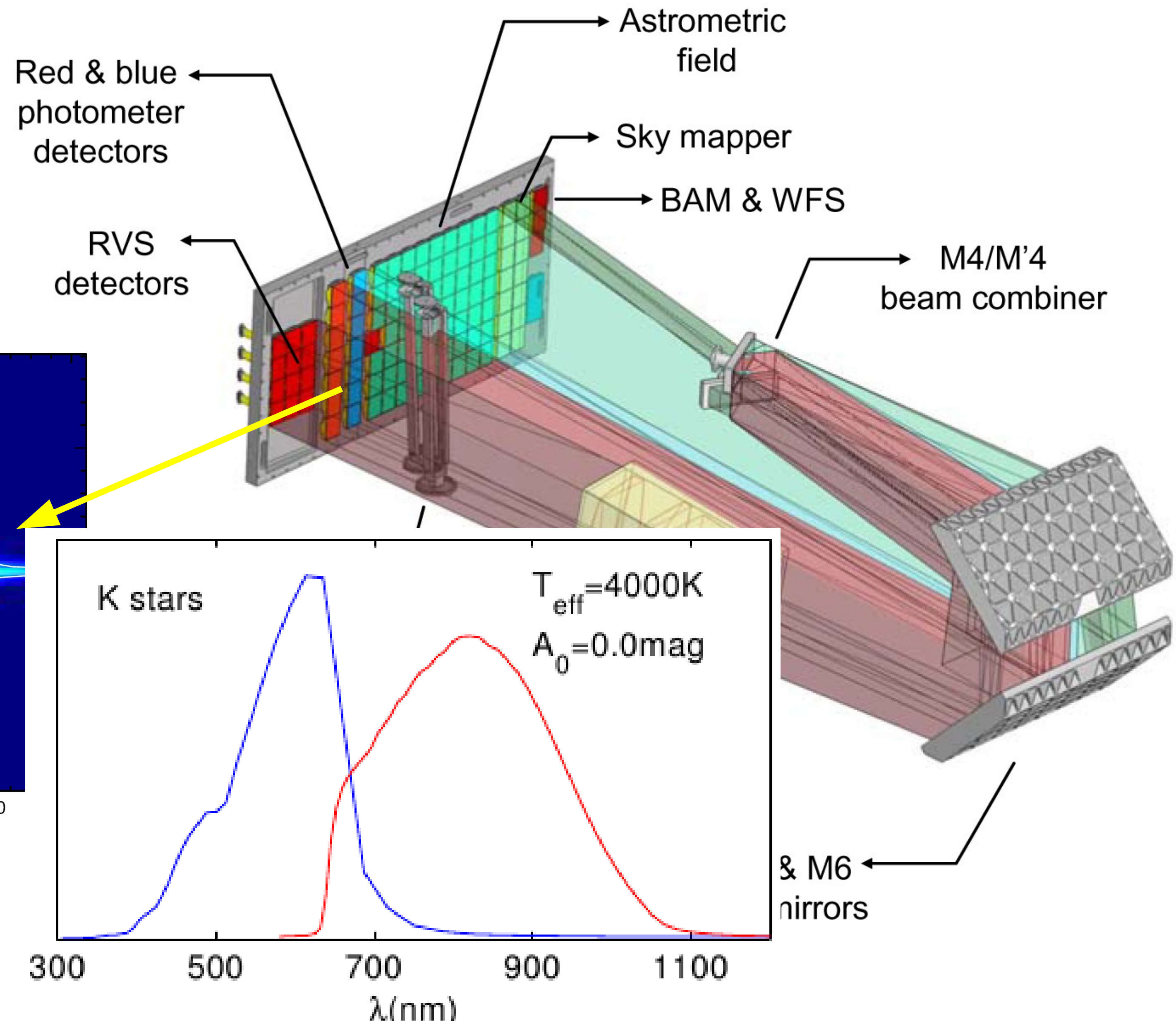
Chao Liu, Coryn Bailer-Jones
Paraskevi Tsalmantza and Kester Smith

Max-Planck-Institut für Astronomie
Heidelberg, Germany

The parametrization problem

- Estimation of the best continuous parameters (generally, probability distribution over the parameters)
  - Astrophysical parameters (AP)
    - Effective temperature(Teff)
    - Metallicity([Fe/H])
    - Surface gravity(logg)
    - Interstellar medium extinction : $A_\lambda = A_0[a(\lambda)+b(\lambda)/R_0]$
- Use as much information as possible
  - BP/RP combined with multi-epoch observations (color)
  - Parallax (distance)
  - G magnitude (brightness)

Gaia data



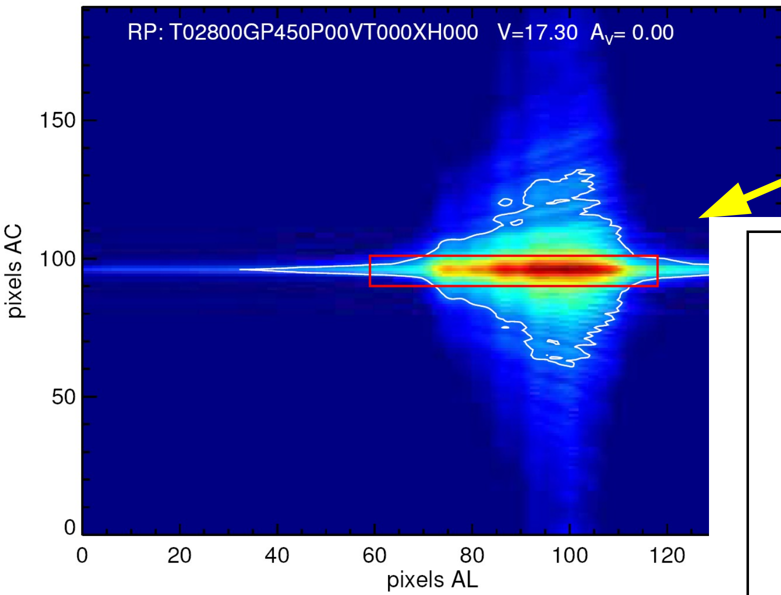
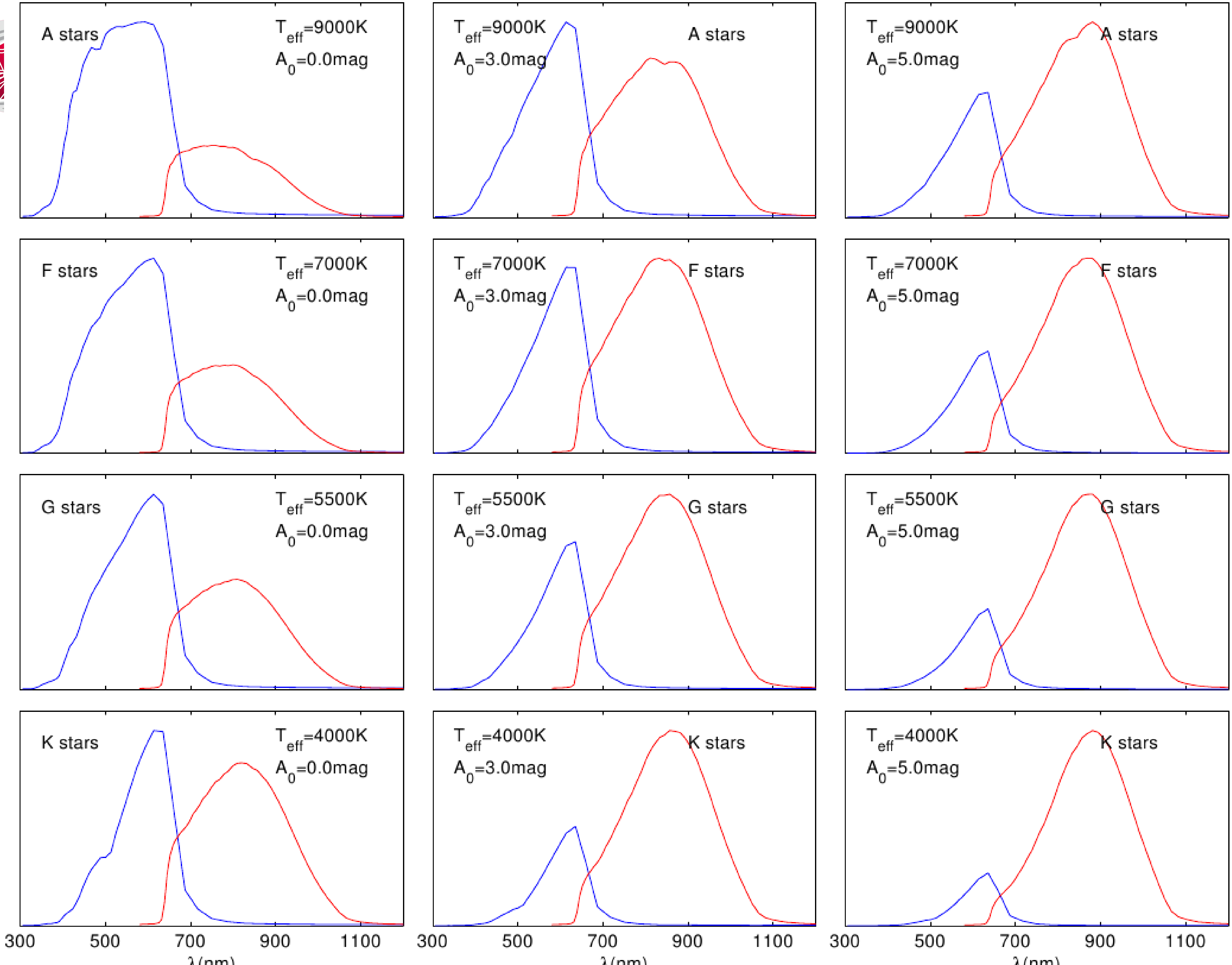
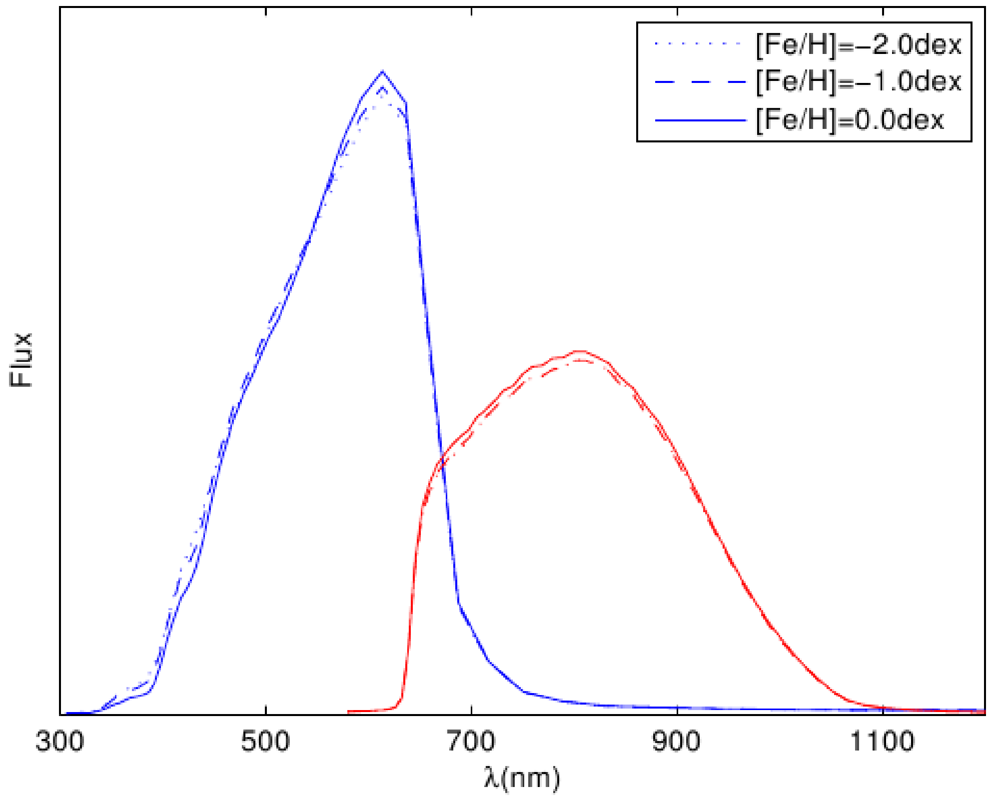


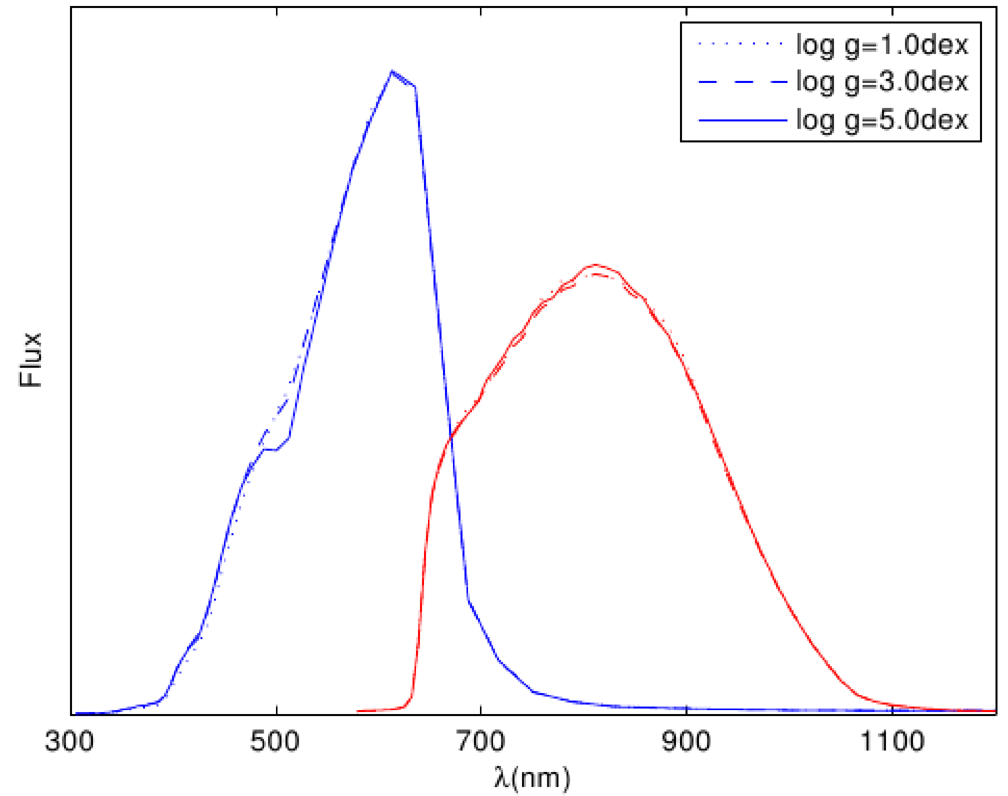
Figure courtesy EADS-Astrium


A stars
F stars
G stars
K stars
T_{eff}=9000K
T_{eff}=7000K
T_{eff}=5500K
T_{eff}=4000K
A_0=0.0mag
A_0=3.0mag
A_0=5.0mag
300
500
700
900
1100
λ(nm)

Strong APs and Weak APs

- Strong APs: Teff, A0
- Weak APs: [Fe/H], logg





Methods of estimation

- Template matching
  - e.g. k-nearest neighbors
  - direct method
  - need a large grid with high dimensions
  - slow and insensitive to weak APs
- Forward model
  - fit the function: spectrum=f(AP)
  - GoF/error estimates
  - difficult to simultaneously fit the strong and weak APs
- Pattern recognition
  - ANN, SVM, etc.
  - flexible and fast
  - but complicated, no natural error estimates

Algorithms used in GSP-Phot

- Support vector regression
- Forward model (ILIUM) (Bailer-Jones 2010)
- Add parallax to a forward model, a Bayesian method (q-method) (Bailer-Jones 2011)

SVM regression

- set up SVM training model for each AP

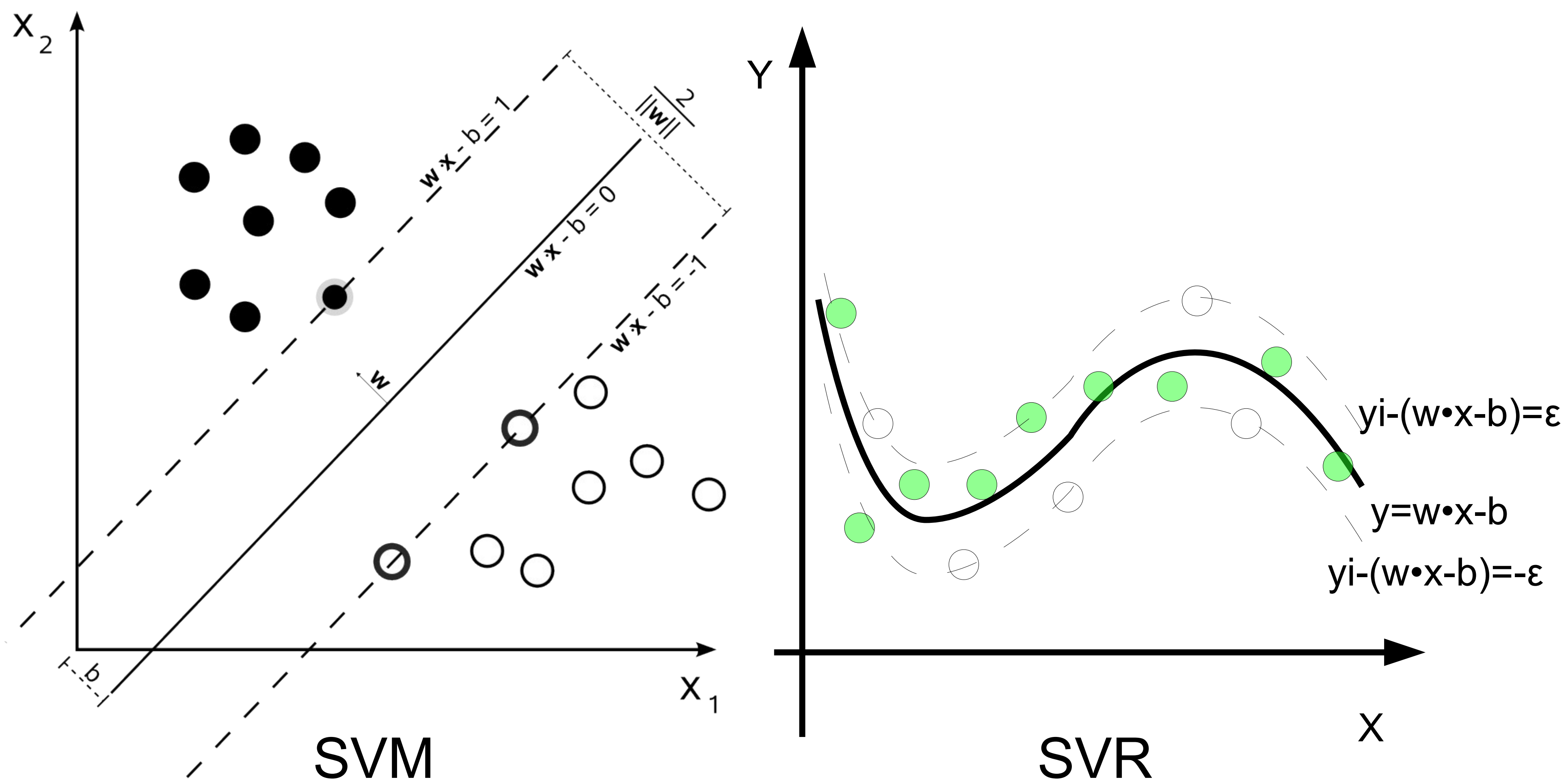
Regression model: $f(x) = w \cdot x + b$

SVR:

$$\text{minimize } \frac{1}{2}\|w\|^2$$
$$\text{subject to } \|y_i - (w \cdot x_i - b)\| \le \varepsilon$$

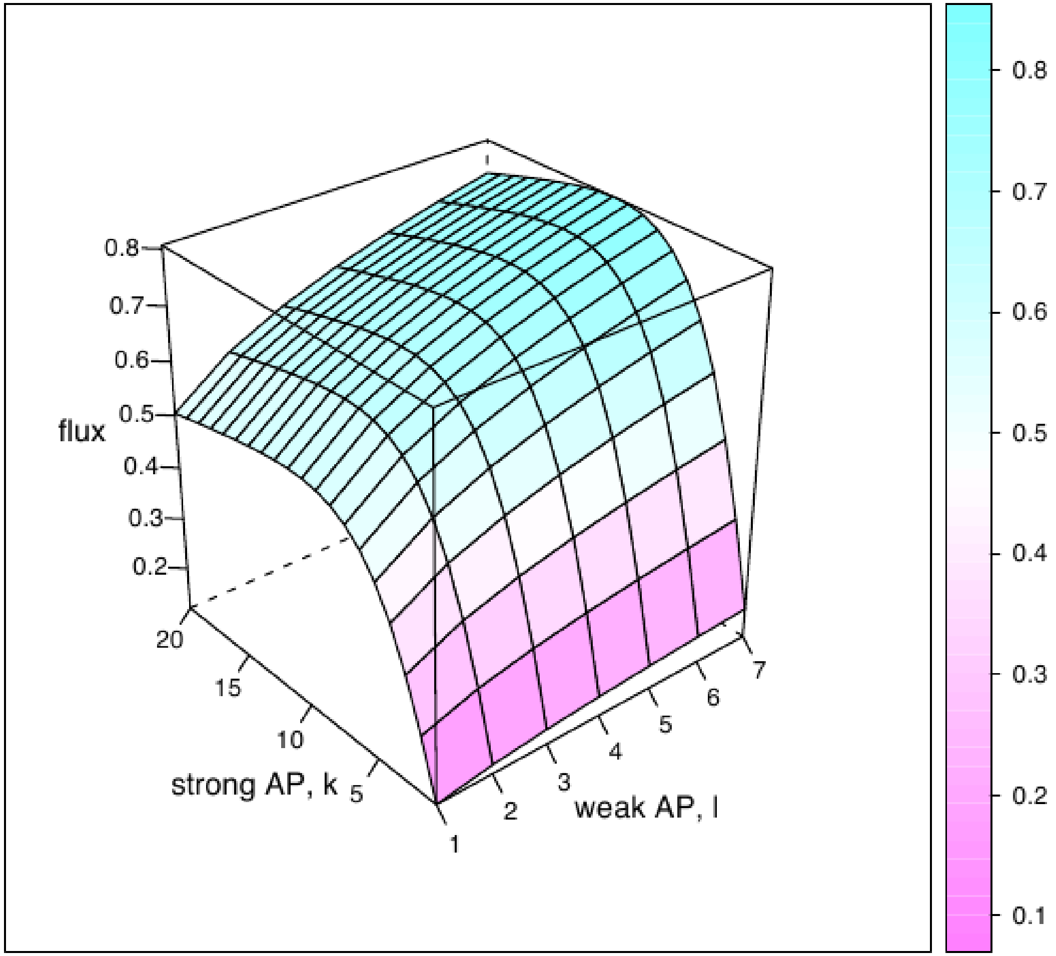
$$\text{minimize } \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}(\xi_i + \xi_i^*)$$
$$\text{subject to } \begin{cases} y_i - w \cdot x_i - b \le \varepsilon + \xi_i \\ w \cdot x_i + b - y_i \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0 \end{cases}$$

Support vector regression



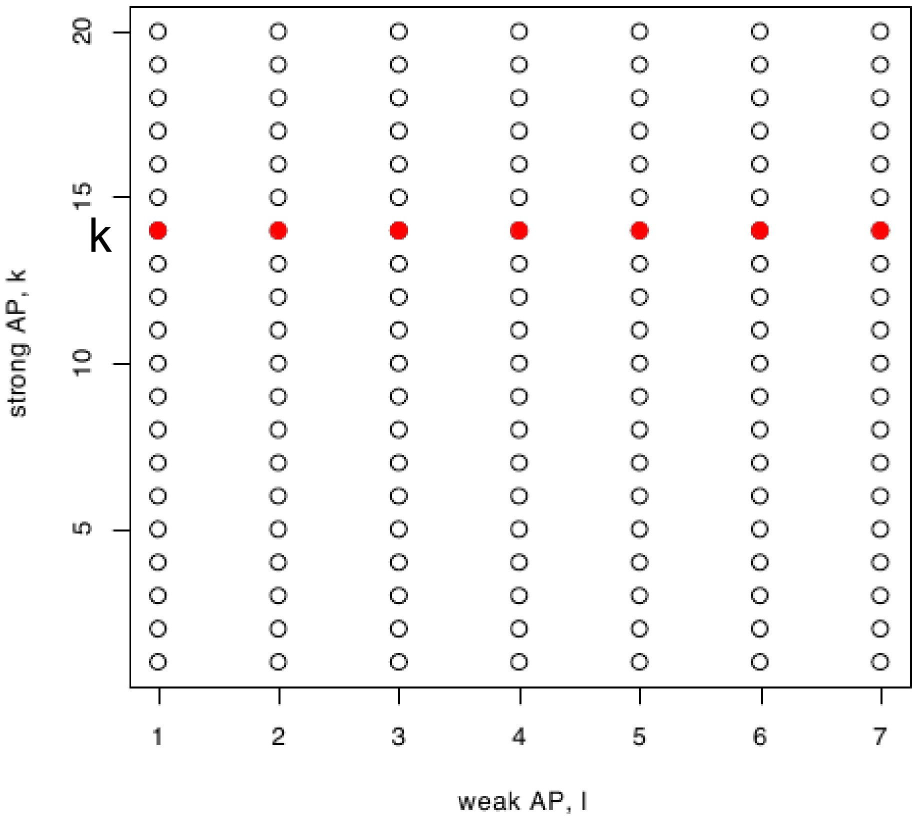
Forward model---ILIUM

- spectrum: p_i
- APs: ϕ_j
- $p_i = f_i(\phi)$
- sensitivity matrix S,
  $$s_{ij} = \partial p_i / \partial \phi_j$$
- Iteratively find the best fitted Φ from the AP grid spanned
  AP-flux surface
- Given Φ, how to determine the p from the forward model grid?



Bailer-Jones 2010

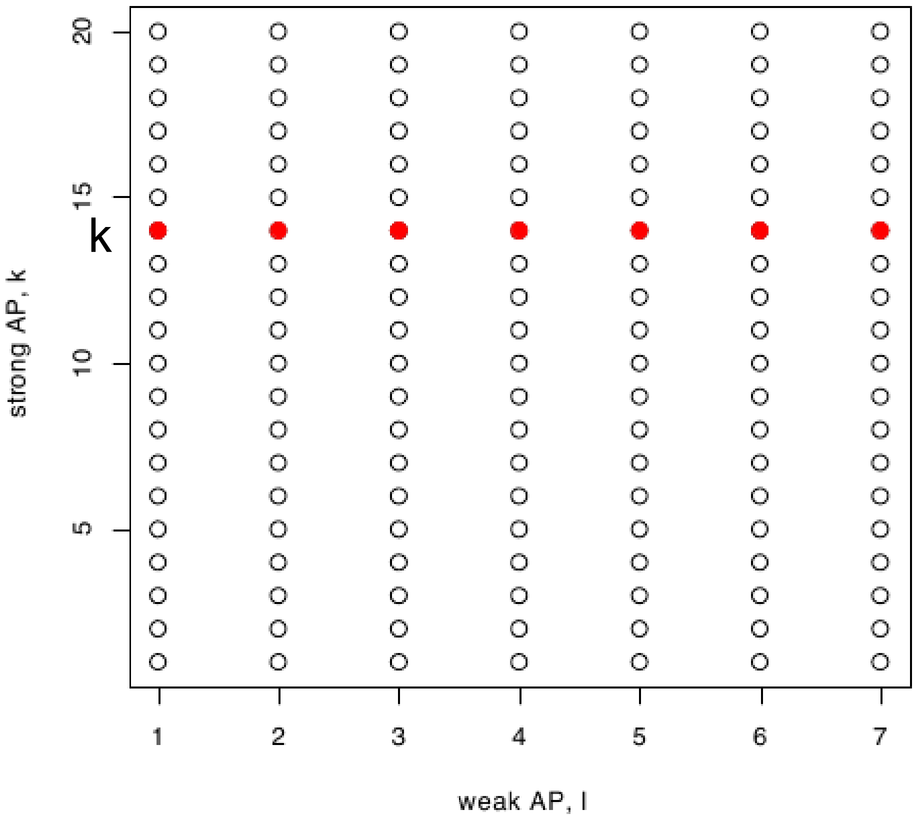
Forward model---ILIUM

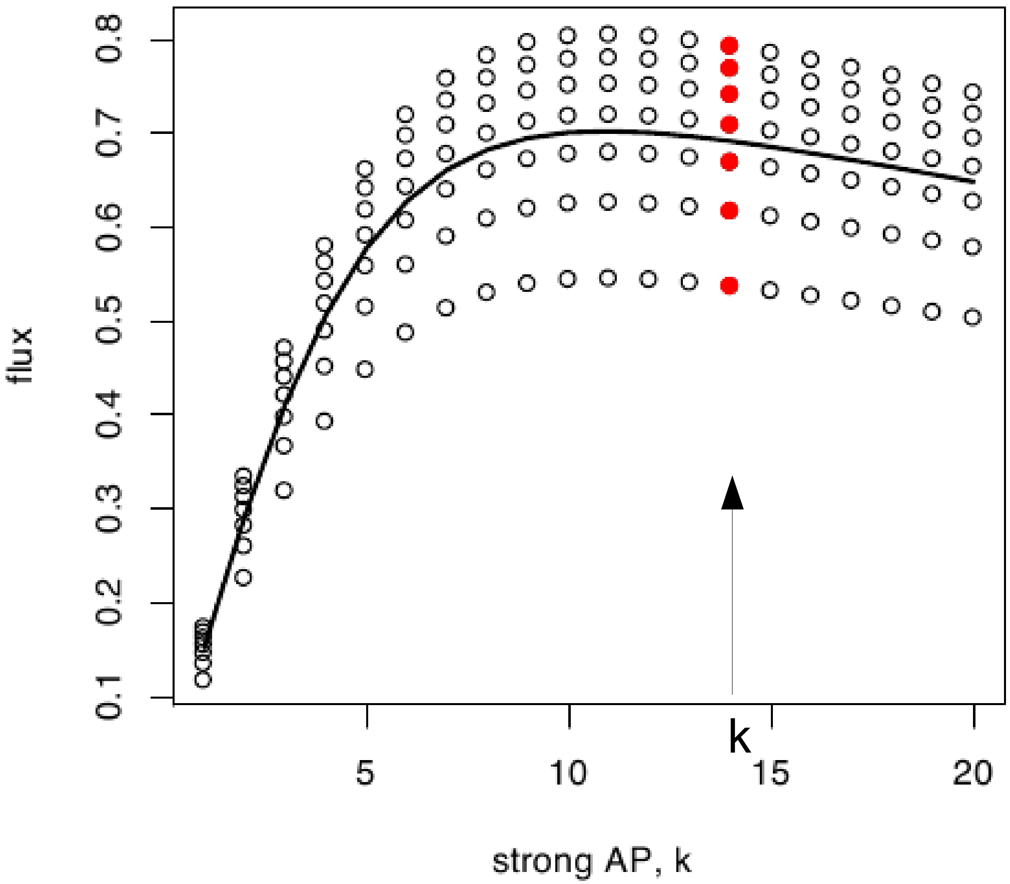


Bailer-Jones 2010

Forward model---ILIUM

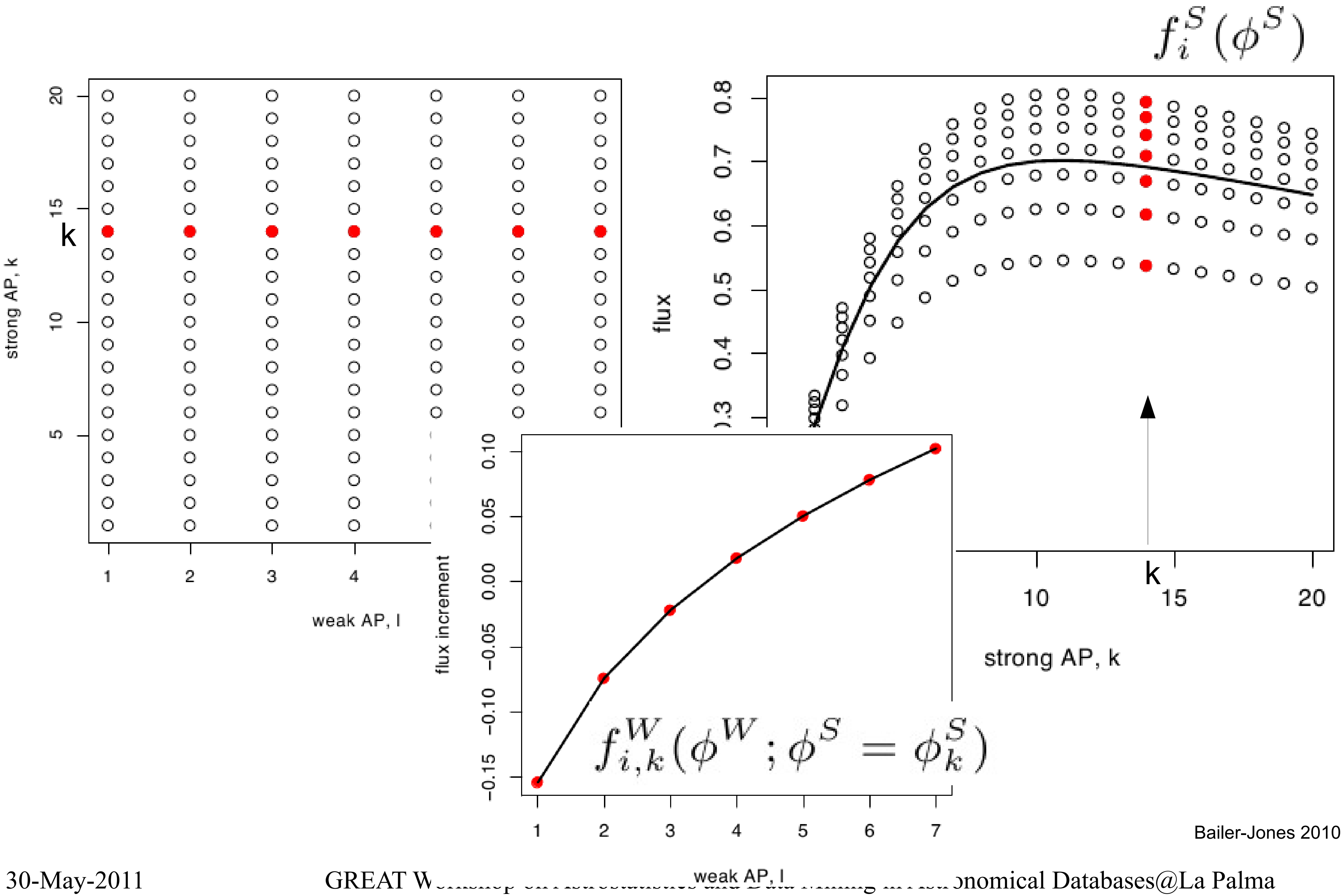
$$f_i^S(\phi^S)$$





Bailer-Jones 2010

Forward model---ILIUM

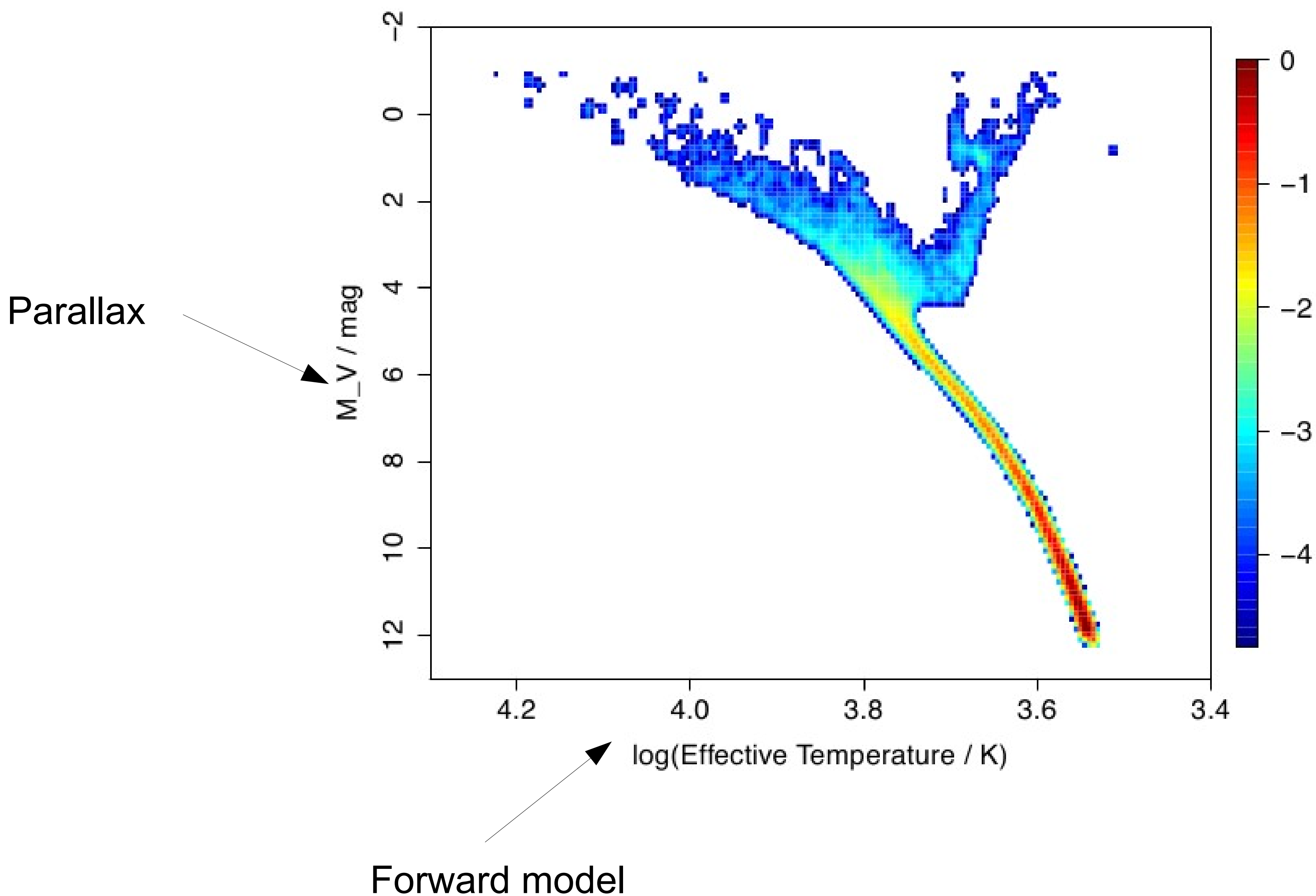


Bailer-Jones 2010

Forward model---ILIUM

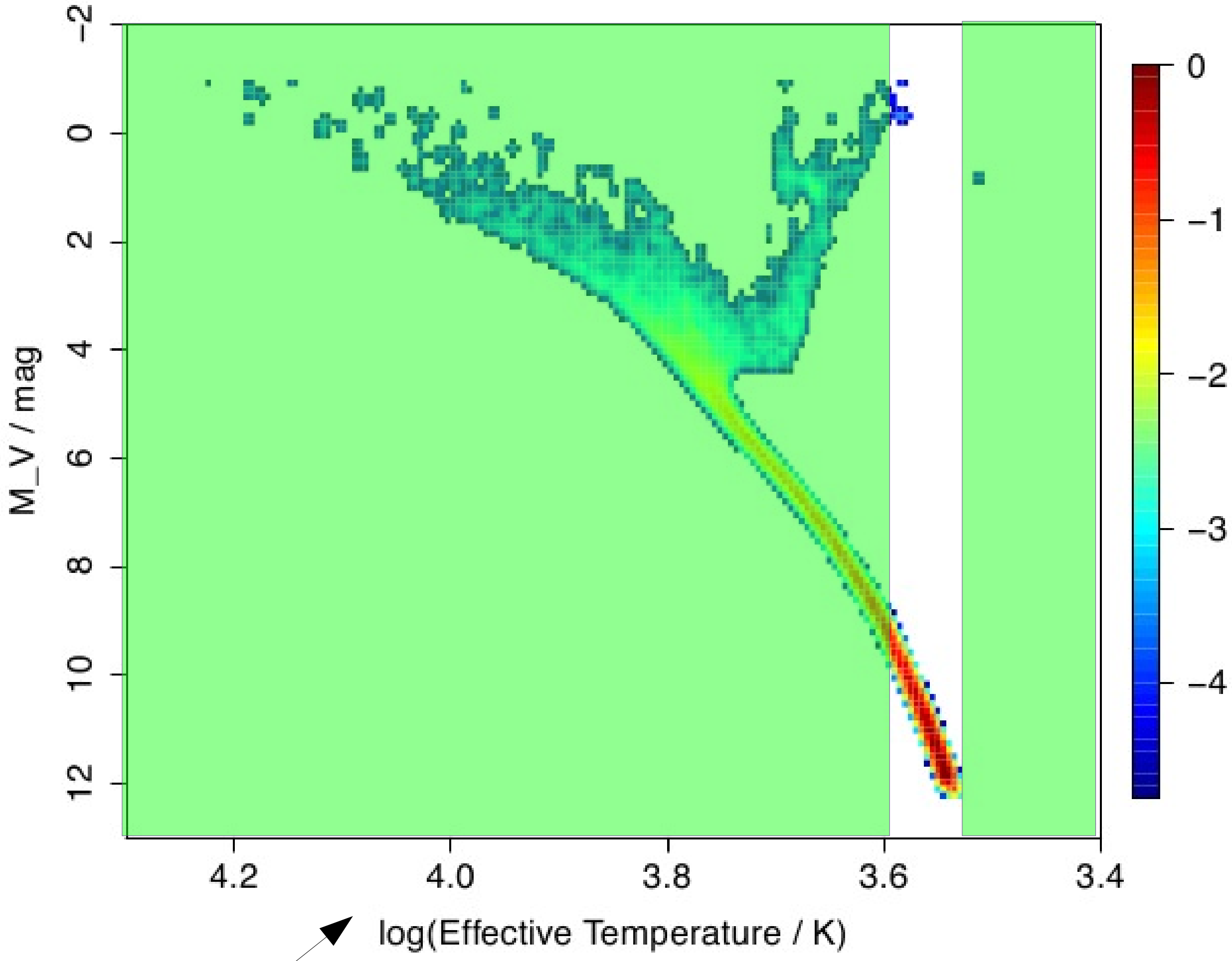
- Forward model:
  - evaluate $f_i^S(\phi^S)$ over weak APs
  - select weak component: find ϕ_k^S, the nearest neighbour in grid to ϕ^S
  - evaluate $f_{i,k}^W(\phi^W; \phi^S = \phi_k^S)$
  - $f_i(\phi^S, \phi^W) = f_i^S(\phi^S) + f_{i,k}^W(\phi^W; \phi^S = \phi_k^S)$

parallax+forward model (q-method)



parallax+forward model (q-method)

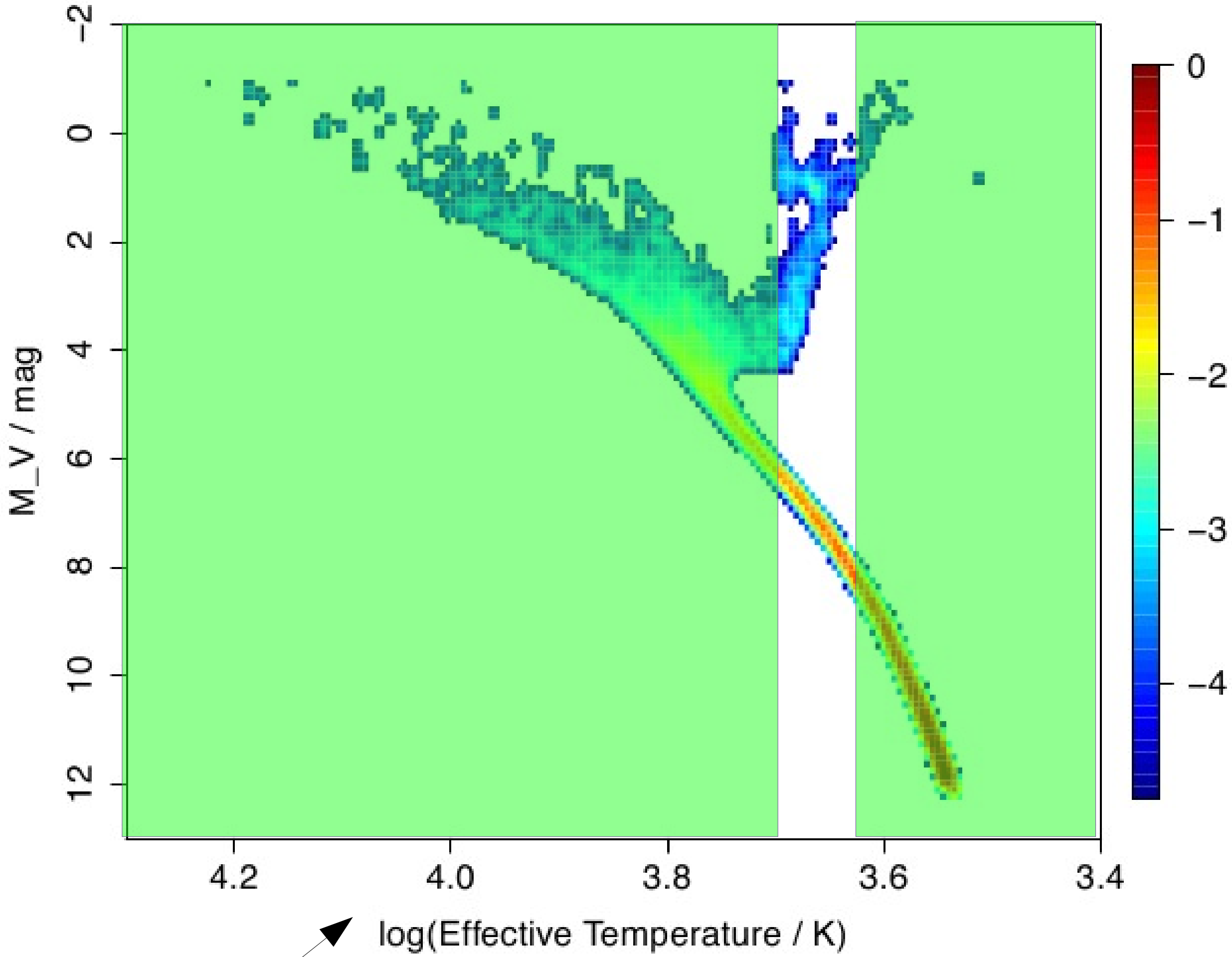
Parallax



Forward model

parallax+forward model (q-method)

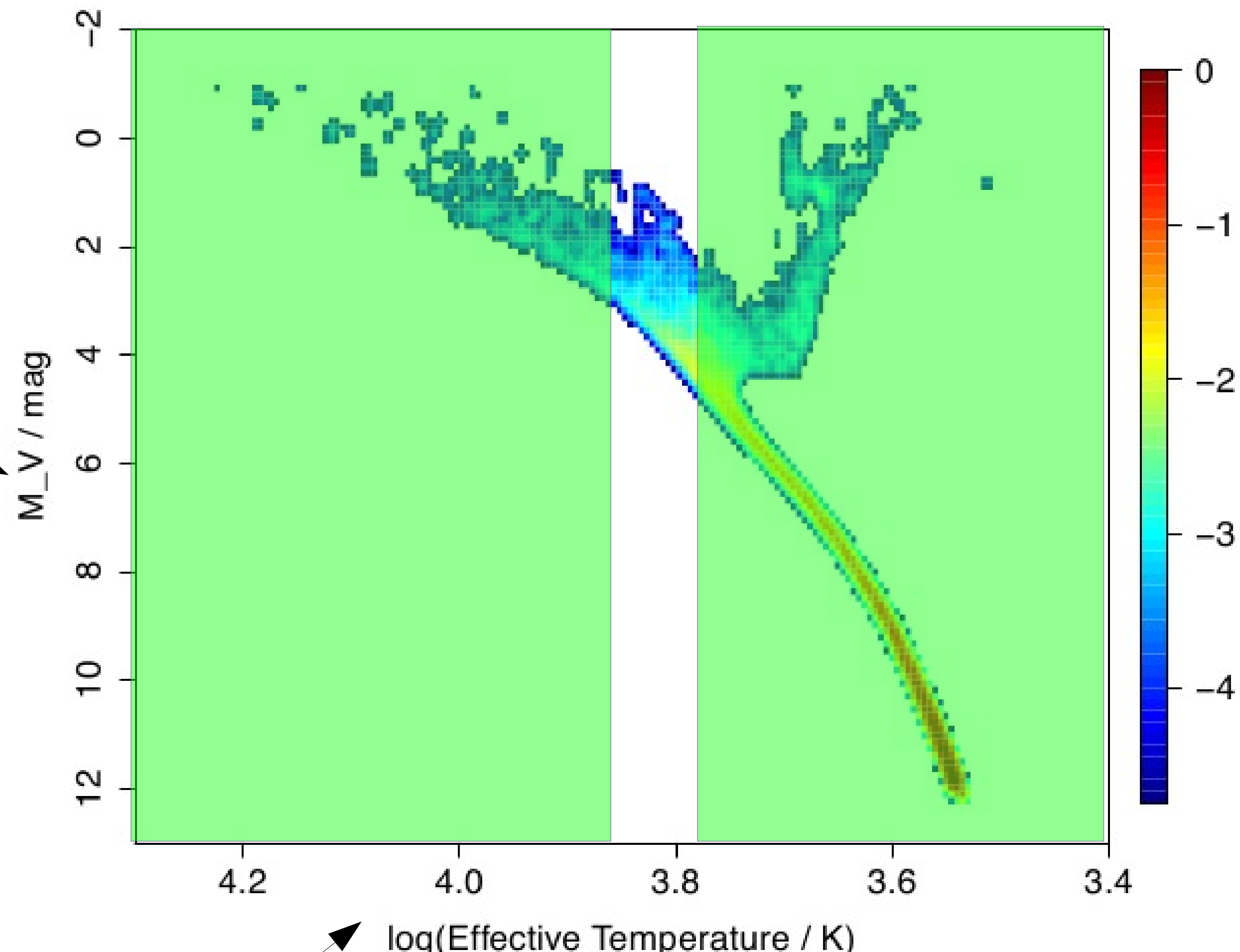
Parallax



Forward model

parallax+forward model (q-method)

Parallax



Forward model

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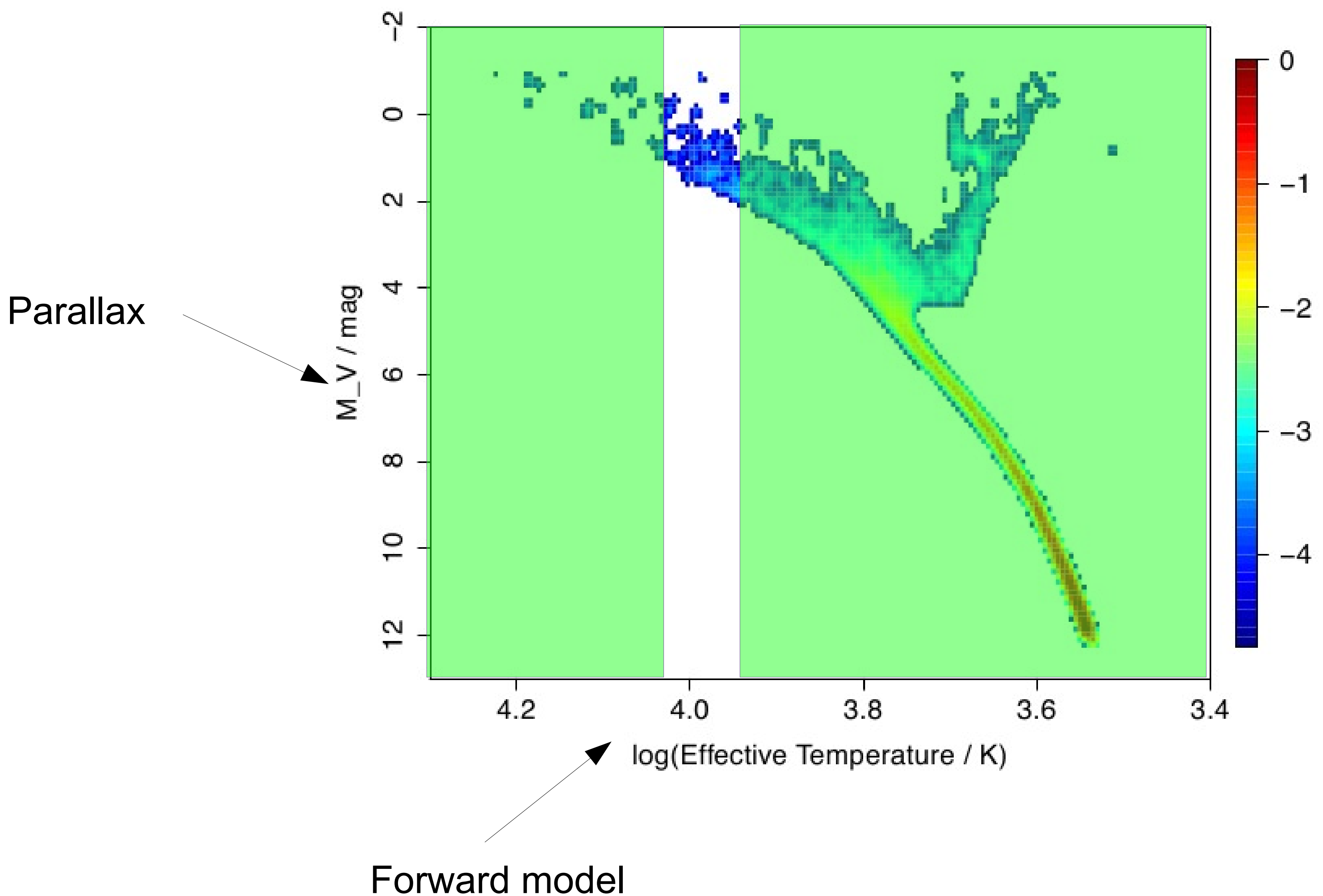

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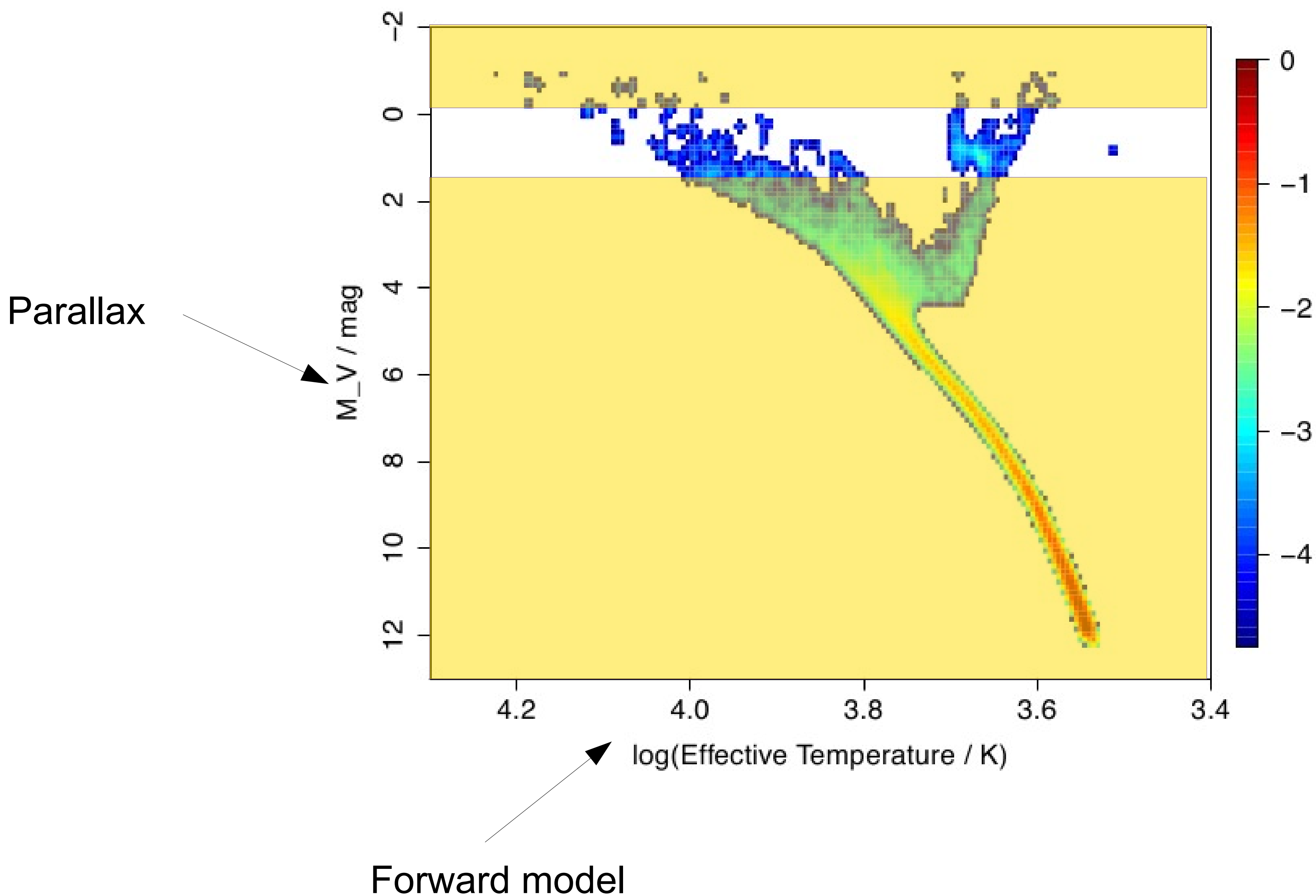
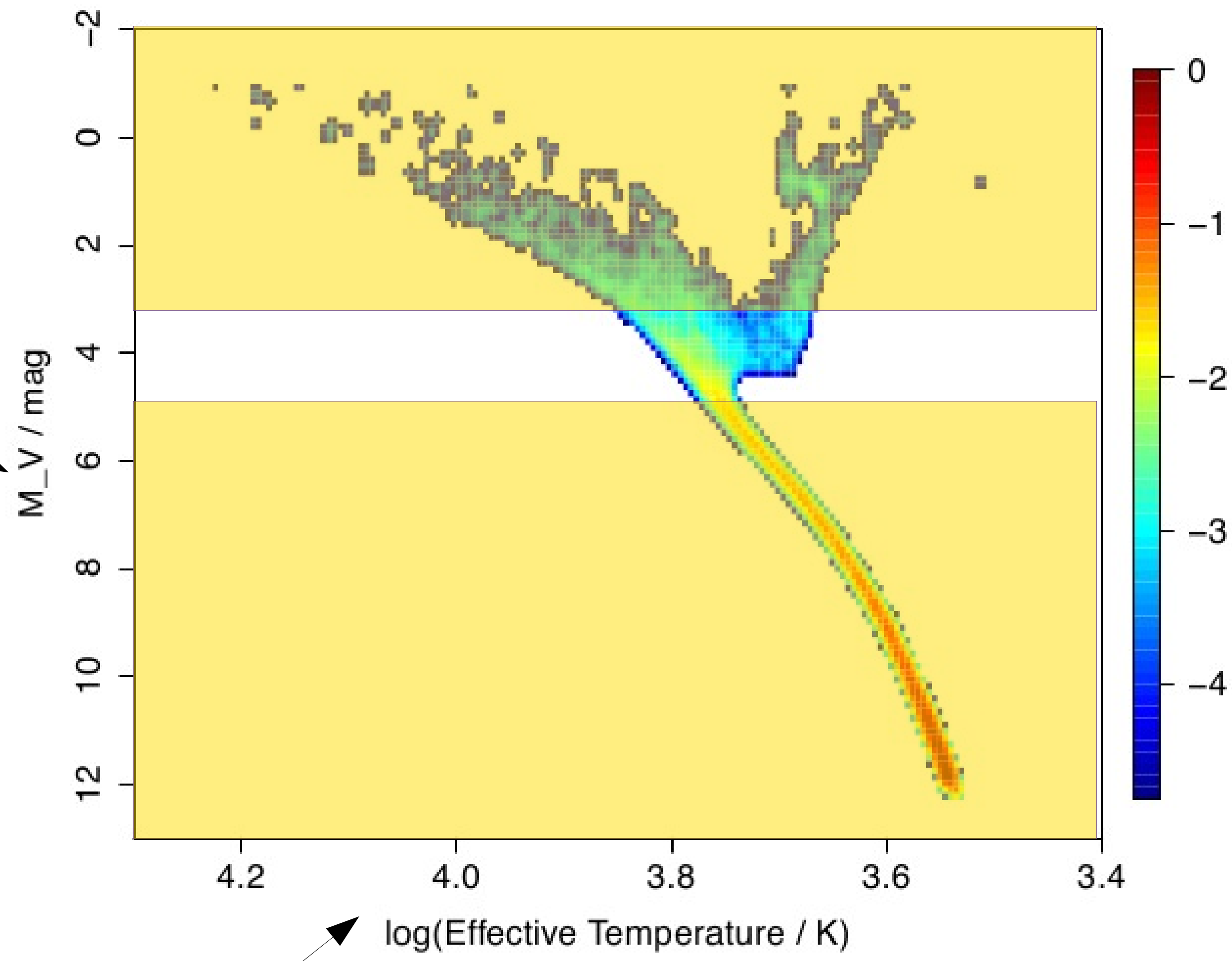


parallax+forward model (q-method)

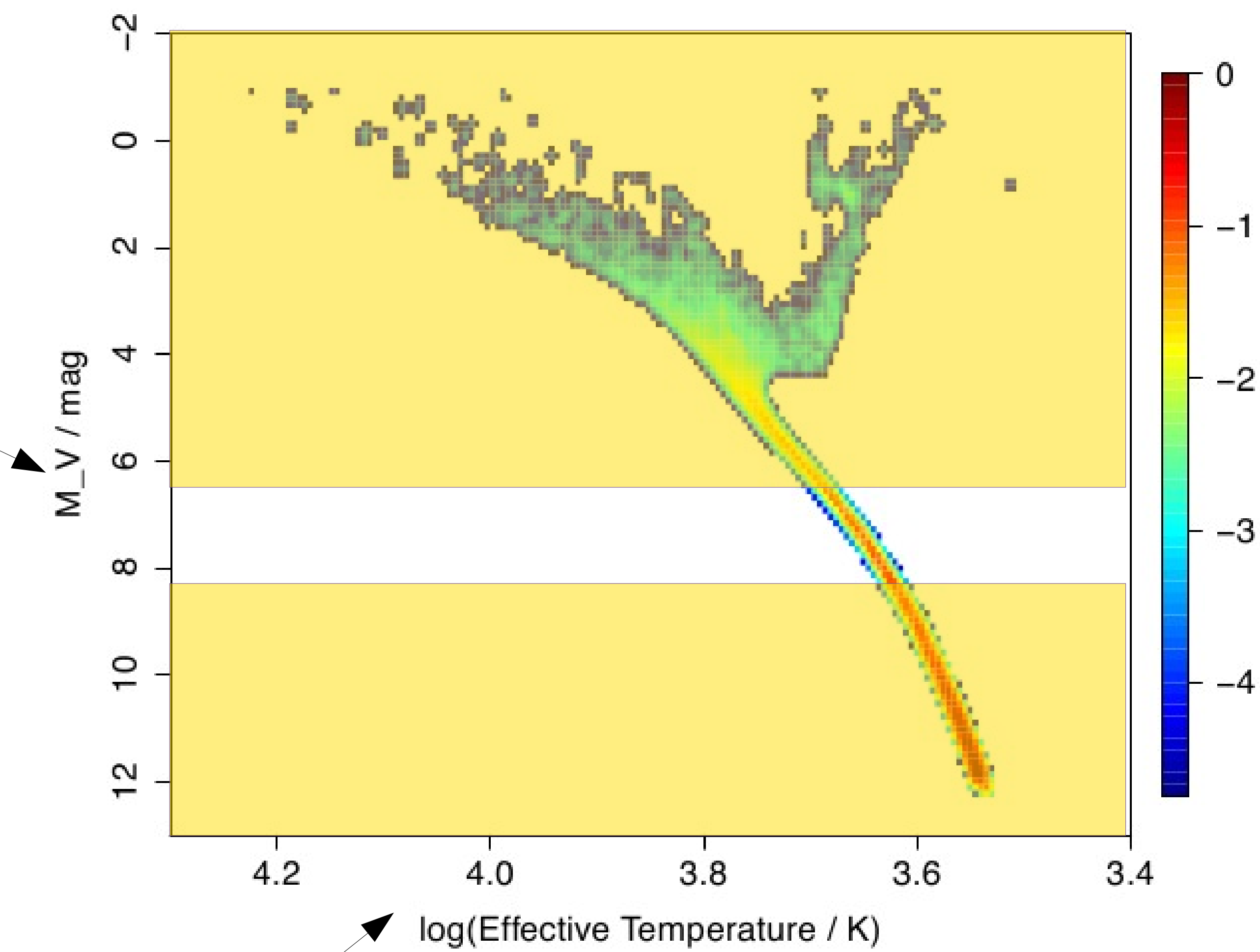
Parallax



Forward model

parallax+forward model (q-method)

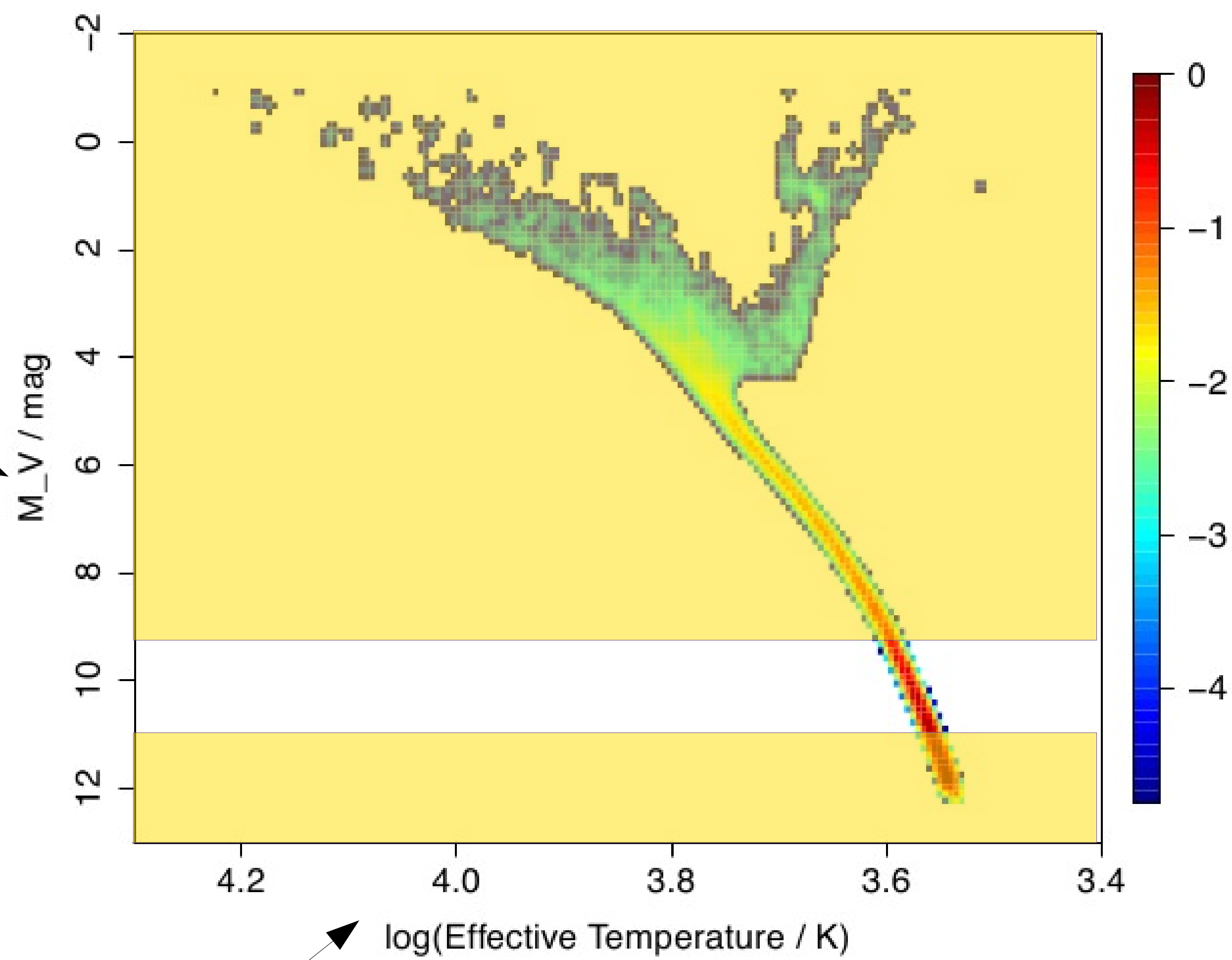
Parallax



Forward model

parallax+forward model (q-method)

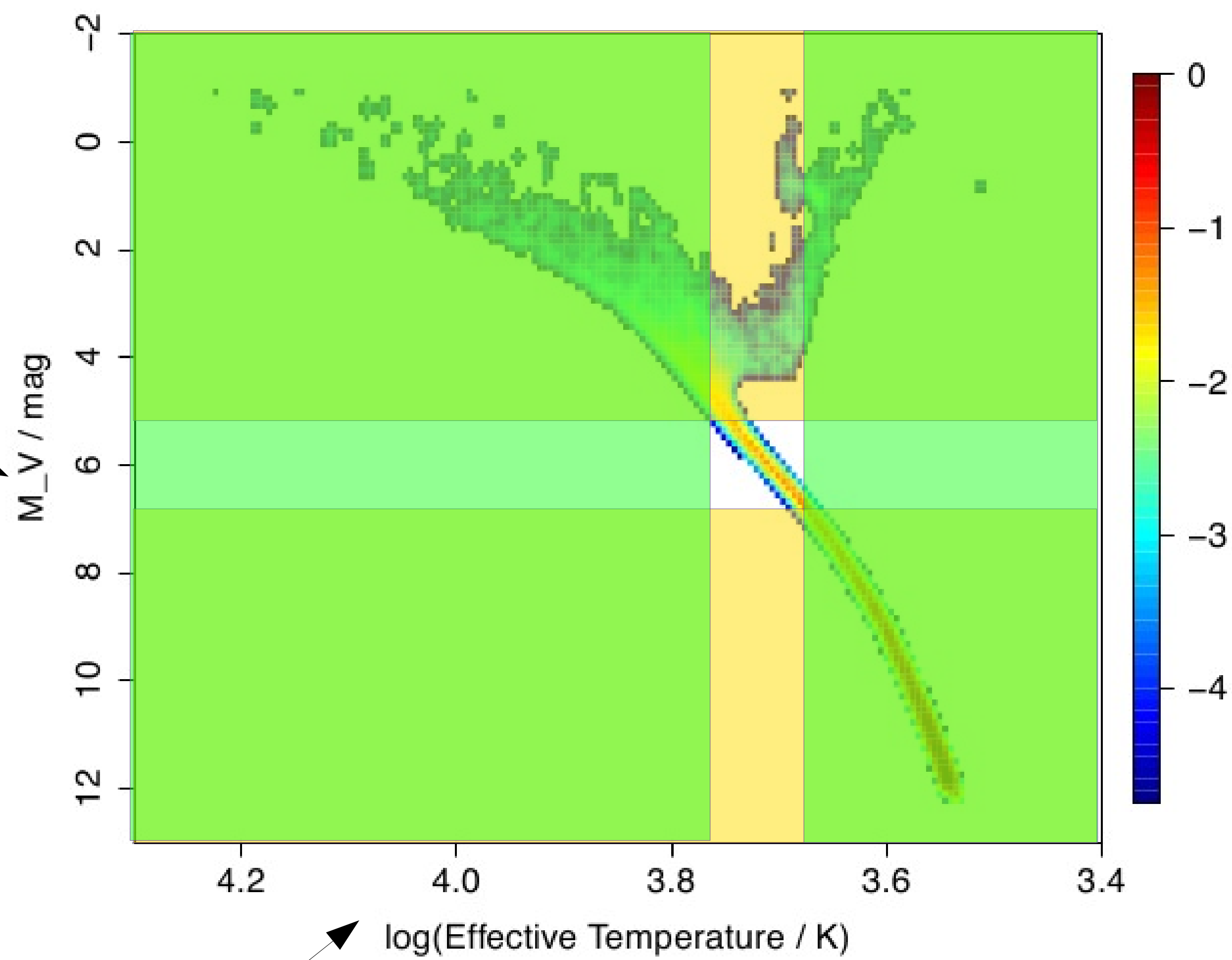
Parallax



Forward model

Parallax+forward model (q-method)

Parallax



Forward model

Use Beyasian theorem

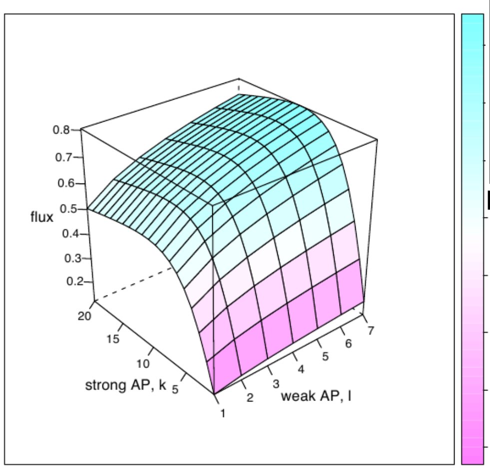
$$V + 5\log\varpi = M_V + A_V - 5$$

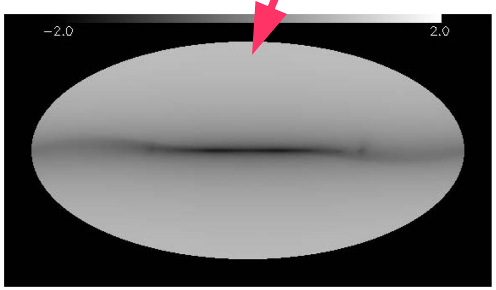
$$q \equiv V + 5\log\varpi\,.$$

$$P(A_0, T|p, q) = \quad (15)$$

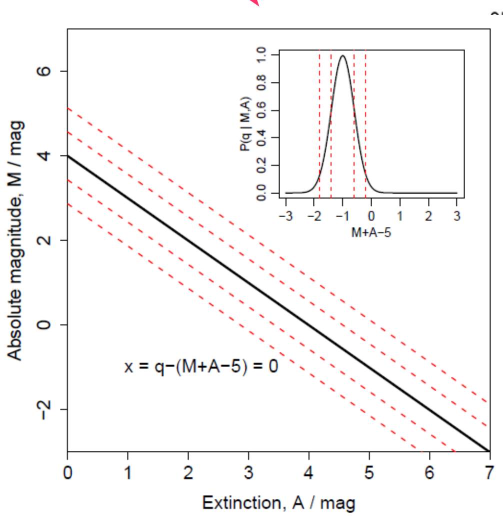
$$\underbrace{P(p|A_0,T)}_{\text{likelihood}}\;\underbrace{\frac{P(A_0)}{P(p,q)}}_{\text{priors}}\;\underbrace{\int_{M_V}\underbrace{P(q|M_V,A_0,T)}_{q\text{ constraint}}\,\underbrace{P(M_V,T)}_{\text{HRD prior}}\,dM_V}_{\text{HRD/q factor}}$$

Forward model



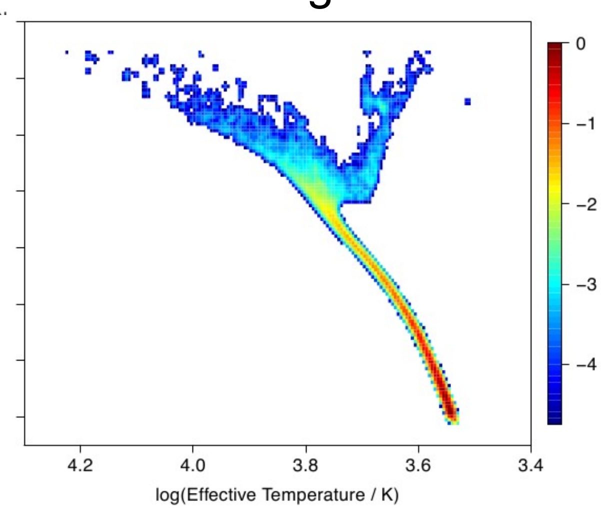


Drimmal et al. 2003



Bailer-Jones 2011

HR diagram

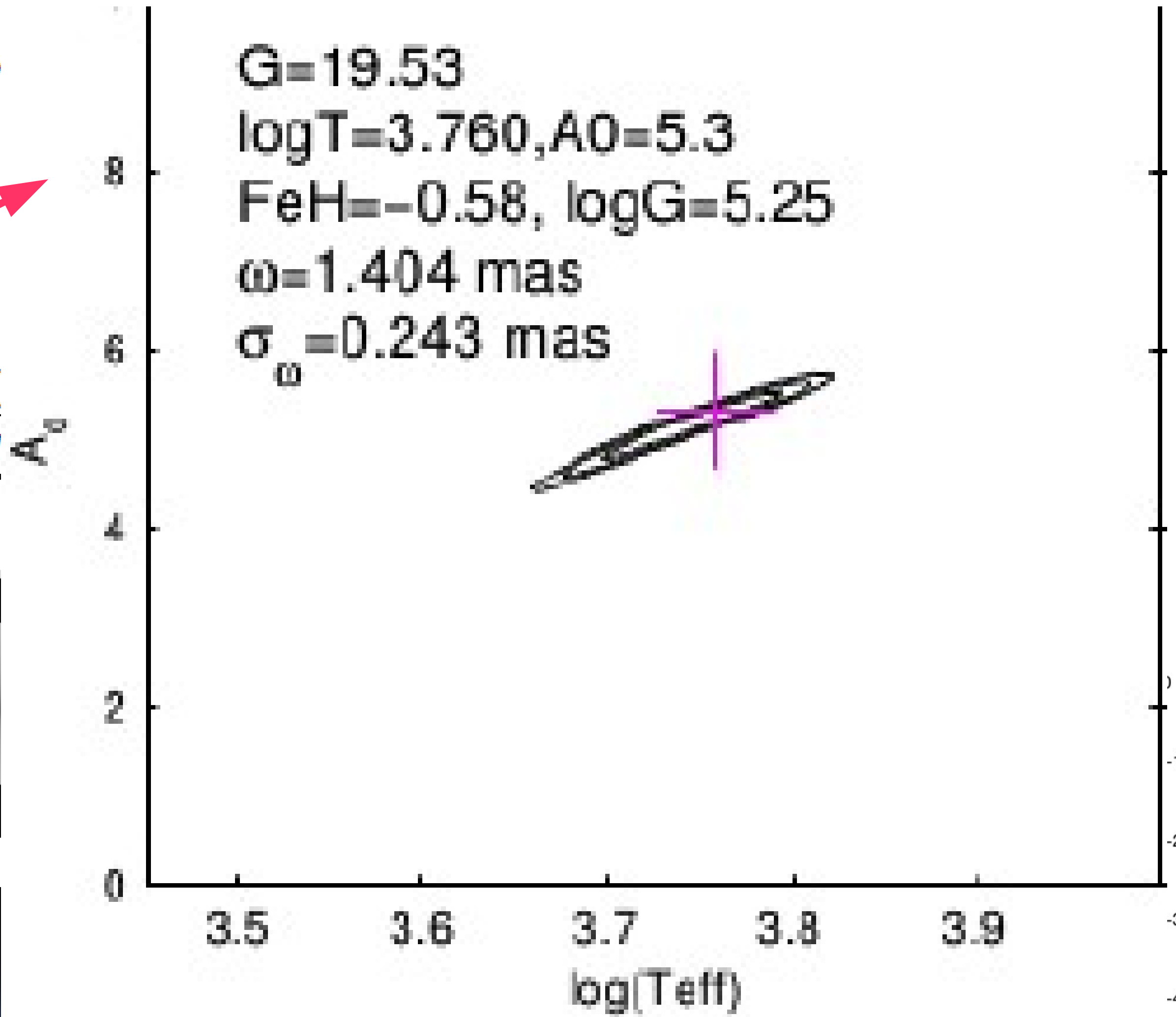


Use Beyasian theorem

$$V + 5\log\varpi = M_V$$

$$q \equiv V + 5\log\varpi \,.$$

$$P(A_0, T|p, q) = \underbrace{P(p|A_0, T)}_{\text{likelihood}} \underbrace{\frac{P(A_0 \ldots}{P(p, q \ldots}}_{\text{priors}}$$



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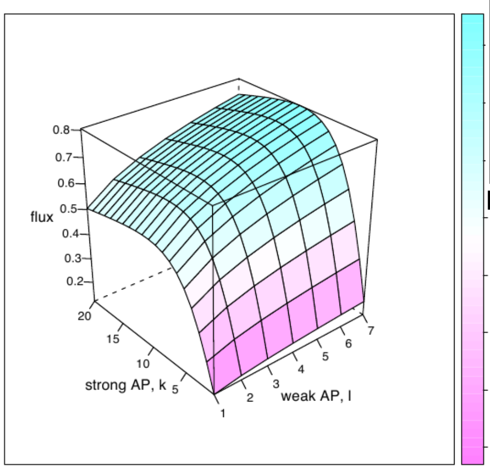
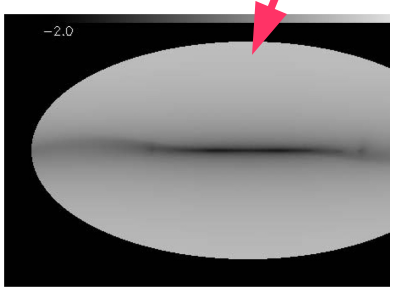
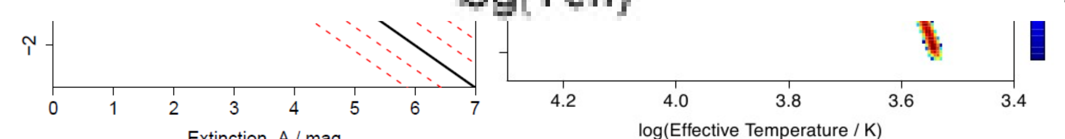




Drimmal et al. 2003

Basardo Model

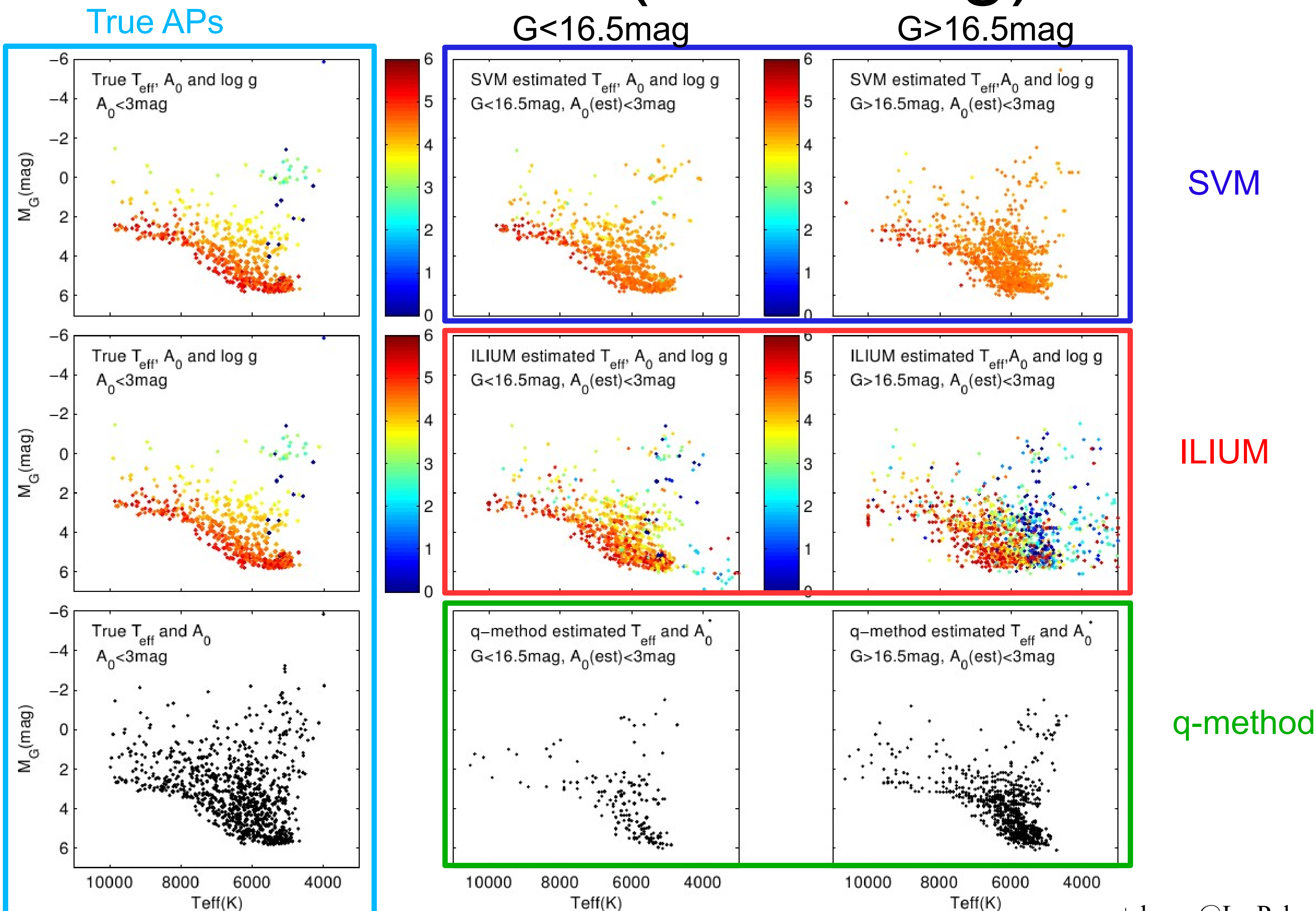


Bailer-Jones 2011

Test with Simulated data

- Simulated Gaia data from synthetic library
  - Phoenix library: $3000<T_{eff}<10000$
  - True APs are known in the simulated data for comparison

Results (A0<3mag)



Analysis

- Spectral types
  - A stars: 7500-10000 K
  - F stars: 6000-7500 K
  - G stars: 5250-6000 K
  - K stars: 3750-5250 K
- Brightness
  - G<16.5 mag
  - G>16.5 mag

gaia

SVM

G<16.5mag

AP residual	All stars	A stars	F stars	G stars	K stars
$< \lvert Teff(true) - Teff(est) \rvert >$	71	111	65	53	117
$< \lvert A0(true) - A0(est) \rvert >$	0.05	0.05	0.03	0.04	0.13
$< \lvert FeH(true) - FeH(est) \rvert >$	0.33	0.65	0.35	0.23	0.32
$< \lvert LogG(true) - LogG(est) \rvert >$	0.39	0.23	0.27	0.43	0.90

G<16.5mag

AP residual	All stars	A stars	F stars	G stars	K stars
$< \lvert Teff(true) - Teff(est) \rvert >$	265	426	226	226	392
$< \lvert A0(true) - A0(est) \rvert >$	0.14	0.16	0.11	0.14	0.30
$< \lvert FeH(true) - FeH(est) \rvert >$	0.51	0.71	0.51	0.41	0.58
$< \lvert LogG(true) - LogG(est) \rvert >$	0.47	0.35	0.33	0.51	1.02

SVM

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ILIUM

G<16.5mag

AP residual	All stars	A stars	F stars	G stars	K stars
$< \|Teff(true) - Teff(est)\| >$	363	483	419	279	291
$< \|A0(true) - A0(est)\| >$	0.25	0.18	0.29	0.21	0.24
$< \|FeH(true) - FeH(est)\| >$	0.35	0.78	0.29	0.32	0.29
$< \|LogG(true) - LogG(est)\| >$	0.61	0.49	0.59	0.62	0.77

G<16.5mag

AP residual	All stars	A stars	F stars	G stars	K stars
$< \|Teff(true) - Teff(est)\| >$	753	971	803	640	706
$< \|A0(true) - A0(est)\| >$	0.47	0.41	0.48	0.45	0.55
$< \|FeH(true) - FeH(est)\| >$	0.75	1.24	0.68	0.70	0.74
$< \|LogG(true) - LogG(est)\| >$	1.45	0.99	1.40	1.65	1.51

gaia

SVM

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$< \|LogG(true) - LogG(est)\| >$	1.45	0.99	1.40	1.65	1.51

SVM

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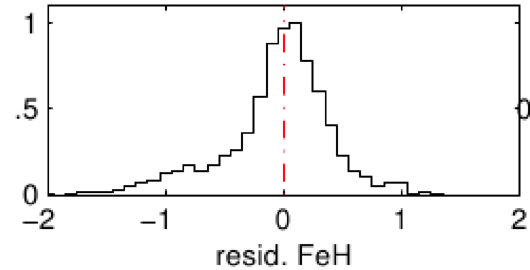

ILIUM

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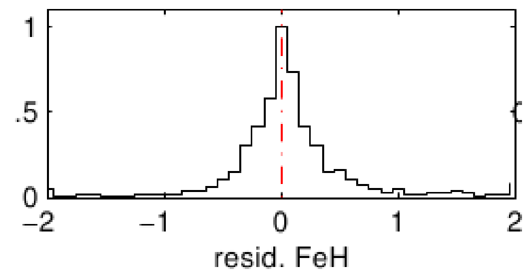
G<16.5mag

AP residual	All stars	A stars	F stars	G stars	K stars
$<\|Teff(true)-Teff(est)\|>$	753	971	803	640	706
$<\|A0(true)-A0(est)\|>$	0.47	0.41	0.48	0.45	0.55
$<\|FeH(true)-FeH(est)\|>$	0.75	1.24	0.68	0.70	0.74
$<\|LogG(true)-LogG(est)\|>$	1.45	0.99	1.40	1.65	1.51



gaia

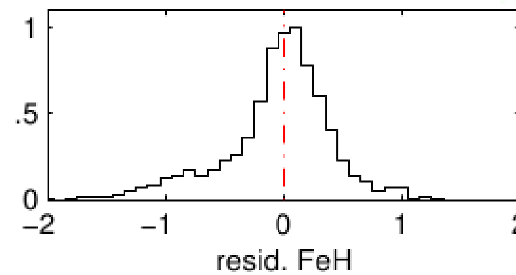
SVM

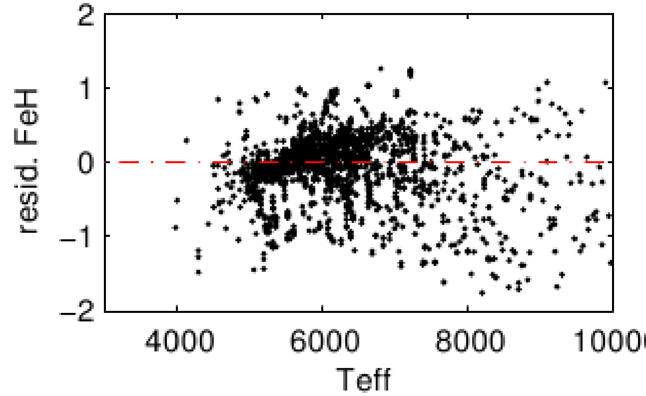
G<16.5mag

AP residual	All stars	A stars	F stars	G stars	K stars
$<\|Teff(true)-Teff(est)\|>$	71	111	65	53	117
$<\|A0(true)-A0(est)\|>$	0.05	0.05	0.03	0.04	0.13
$<\|FeH(true)-FeH(est)\|>$	0.33	0.65	0.35	0.23	0.32
$<\|LogG(true)-LogG(est)\|>$	0.39	0.23	0.27	0.43	0.90

G<16.5mag

AP residual	All stars	A stars	F stars	G stars	K stars
$<\|Teff(true)-Teff(est)\|>$	265	426	226	226	392
$<\|A0(true)-A0(est)\|>$	0.14	0.16	0.11	0.14	0.30
$<\|FeH(true)-FeH(est)\|>$	0.51	0.71	0.51	0.41	0.58
$<\|LogG(true)-LogG(est)\|>$	0.47	0.35	0.33	0.51	1.02





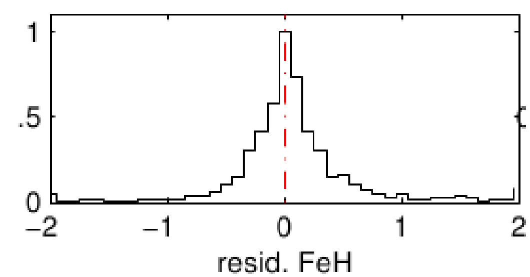
ILIUM

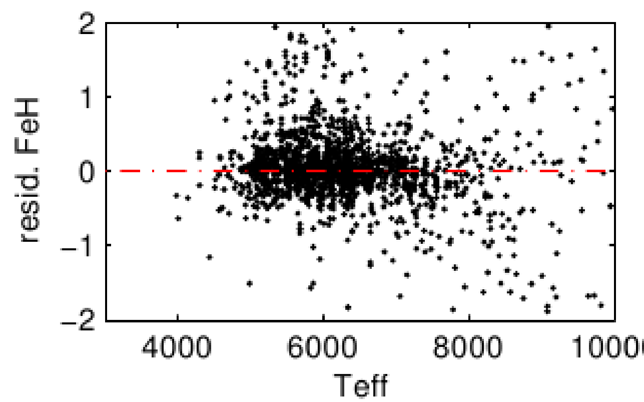
G<16.5mag

AP residual	All stars	A stars	F stars	G stars	K stars
$<\|Teff(true)-Teff(est)\|>$	363	483	419	279	291
$<\|A0(true)-A0(est)\|>$	0.25	0.18	0.29	0.21	0.24
$<\|FeH(true)-FeH(est)\|>$	0.35	0.78	0.29	0.32	0.29
$<\|LogG(true)-LogG(est)\|>$	0.61	0.49	0.59	0.62	0.77

G<16.5mag

AP residual	All stars	A stars	F stars	G stars	K stars
$<\|Teff(true)-Teff(est)\|>$	753	971	803	640	706
$<\|A0(true)-A0(est)\|>$	0.47	0.41	0.48	0.45	0.55
$<\|FeH(true)-FeH(est)\|>$	0.75	1.24	0.68	0.70	0.74
$<\|LogG(true)-LogG(est)\|>$	1.45	0.99	1.40	1.65	1.51





Analysis

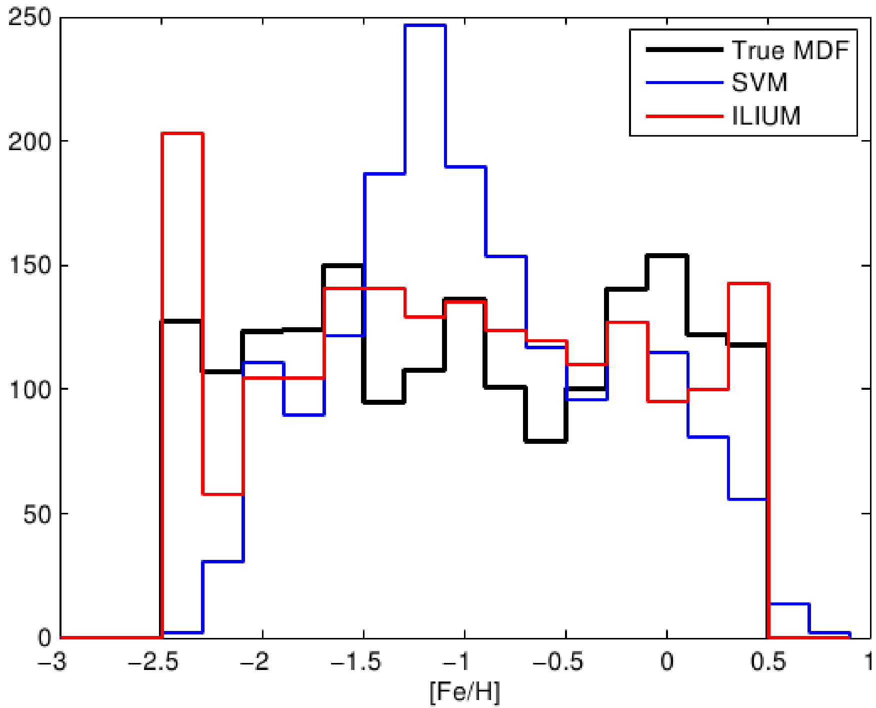
- Suppose that we select certain spectral. type, e.g. F stars, from Gaia catalog using estimated Teff
- Q1: How many true F stars are contained in the sample (completeness)?
- Q2: How many stars in the sample are contaminations?

Algorithm	G mag		A stars	F stars	G stars	K stars
SVM	< 16.5	completeness	0.992	0.983	0.962	0.922
SVM	< 16.5	contamination	0.030	0.030	0.032	0.037
SVM	> 16.5	completeness	0.848	0.899	0.753	0.475
SVM	> 16.5	contamination	0.043	0.215	0.241	0.256
ILIUM	< 16.5	completeness	0.939	0.931	0.829	0.915
ILIUM	< 16.5	contamination	0.031	0.082	0.106	0.287
ILIUM	> 16.5	completeness	0.826	0.681	0.448	0.638
ILIUM	> 16.5	contamination	0.238	0.313	0.390	0.637

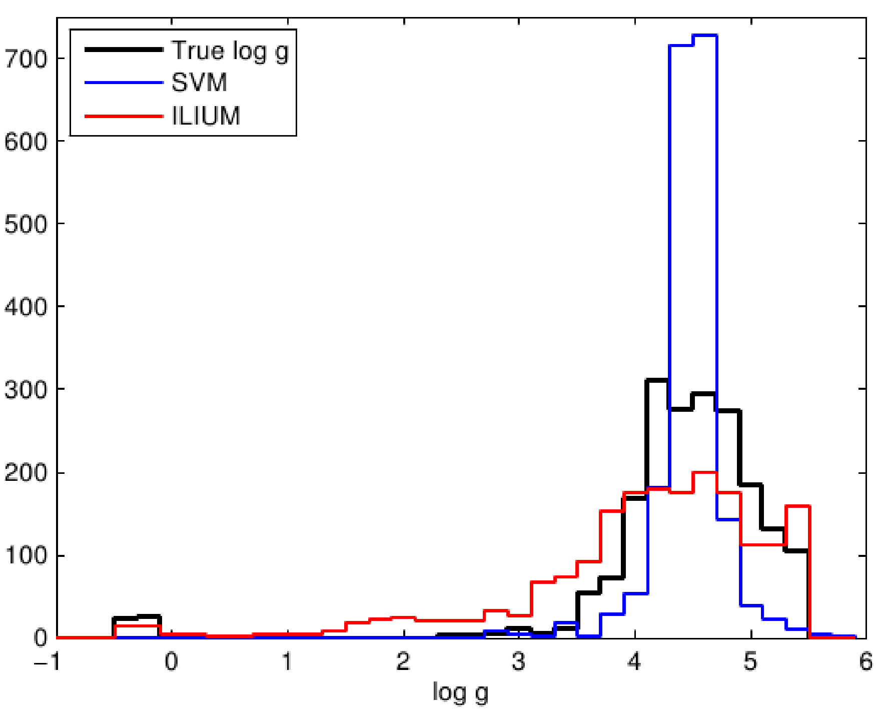
(A0<3mag)

Analysis

- For [Fe/H], we concern about its distribution
- For logg, we concern about if we can separate giant, subgiant from dwarfs



G stars with A0<3mag



K stars with A0<3mag

Summary

- GSP-Phot is implemented for parametrizing stars with Gaia photometric data
- Three algorithms are applied: SVM, ILIUM and q-method
- SVM performs much better for strong APs (Teff and A0)
- ILIUM gives more unbiased estimates for weak APs ([Fe/H] and logg)
- q-method works well on breaking the degeneracy between Teff and A0, though it still needs to be fine tuned
- Based on simulated data the performance of SVM and ILIUM for bright sources is almost ready for science
- The real data is a different story, calibration should be taken cared of and the algorithms need to be tuned