

3D extinction mapping of molecular clouds & better photometry matching

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3D extinction mapping of molecular clouds & better photometry matching

Galactic Structure:

Introduction

Distance Determination

3D Extinction – Naïve &
IPHAS

3D Extinction - Bayesian

Symmetric Catalogue Matching:

Introduction

Asymmetry & Symmetrisation

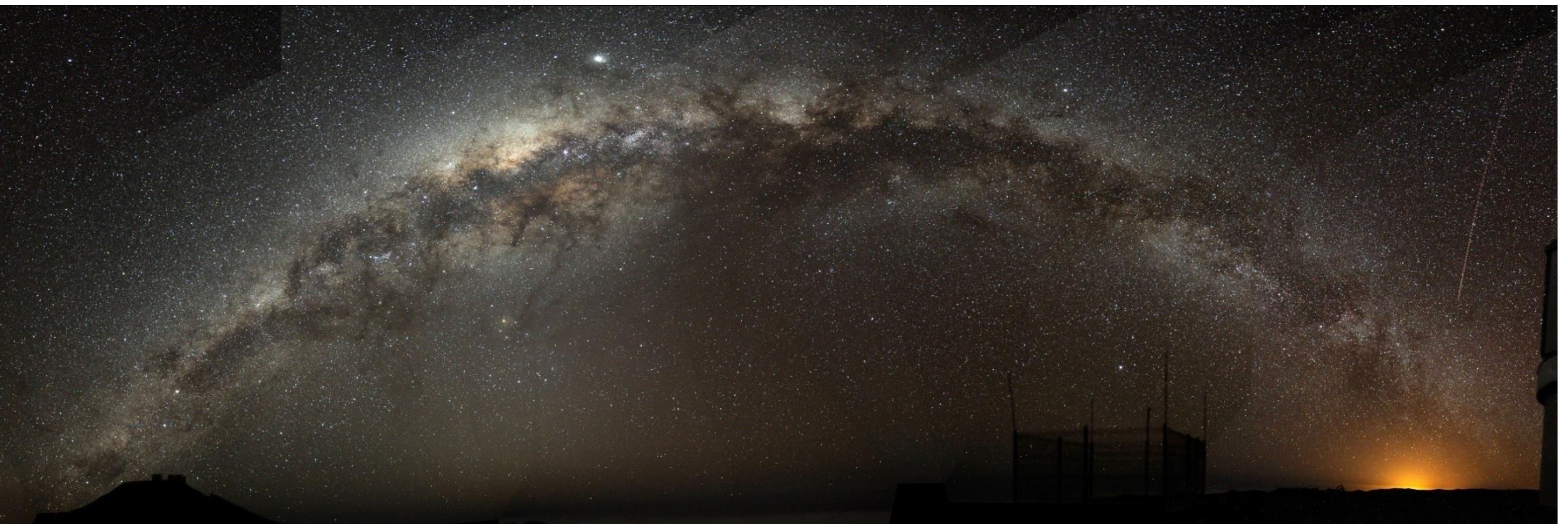
Photometric & Astrometric Distributions
First Results

Introduction



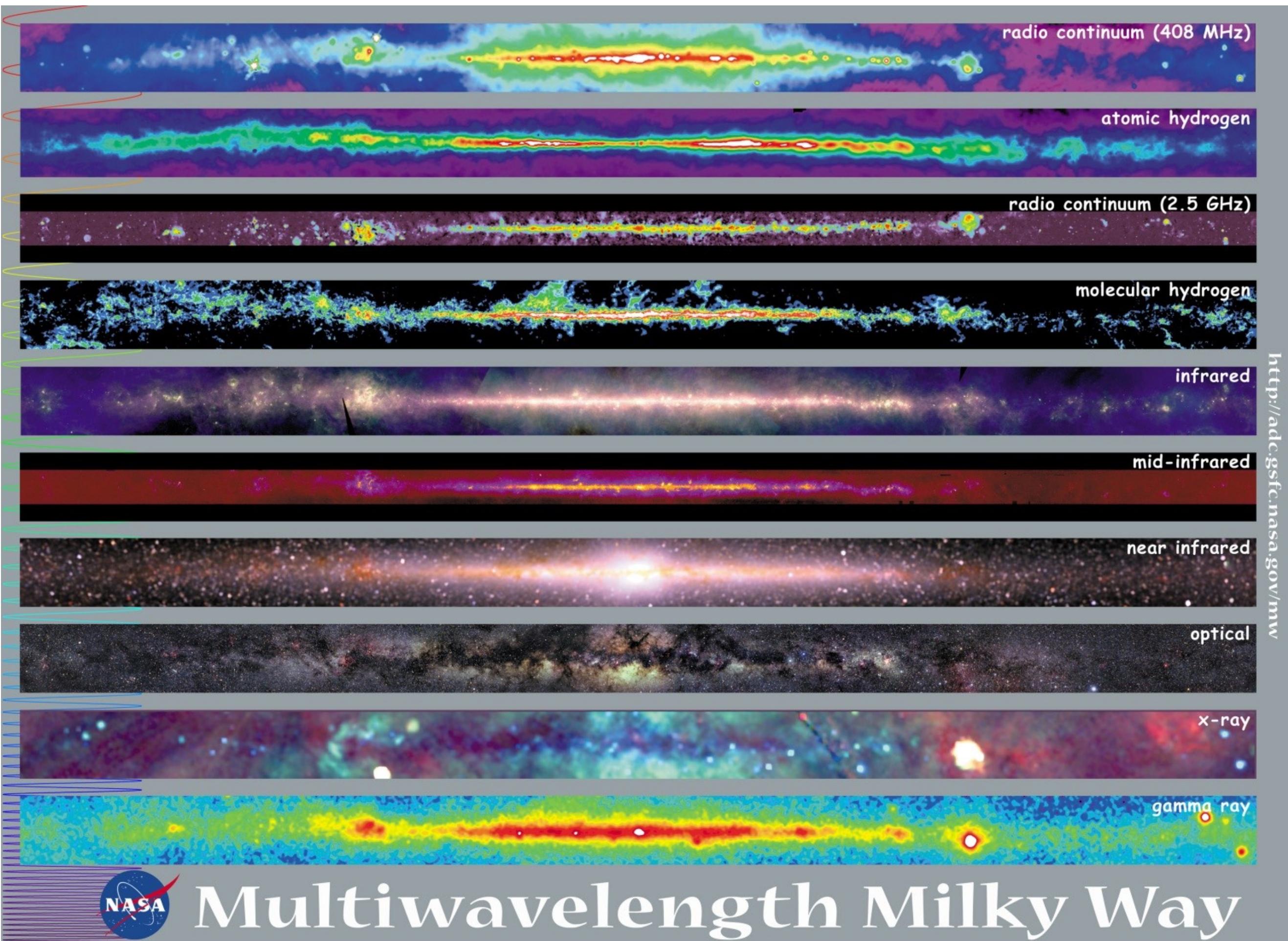
ESA/NASA

Introduction

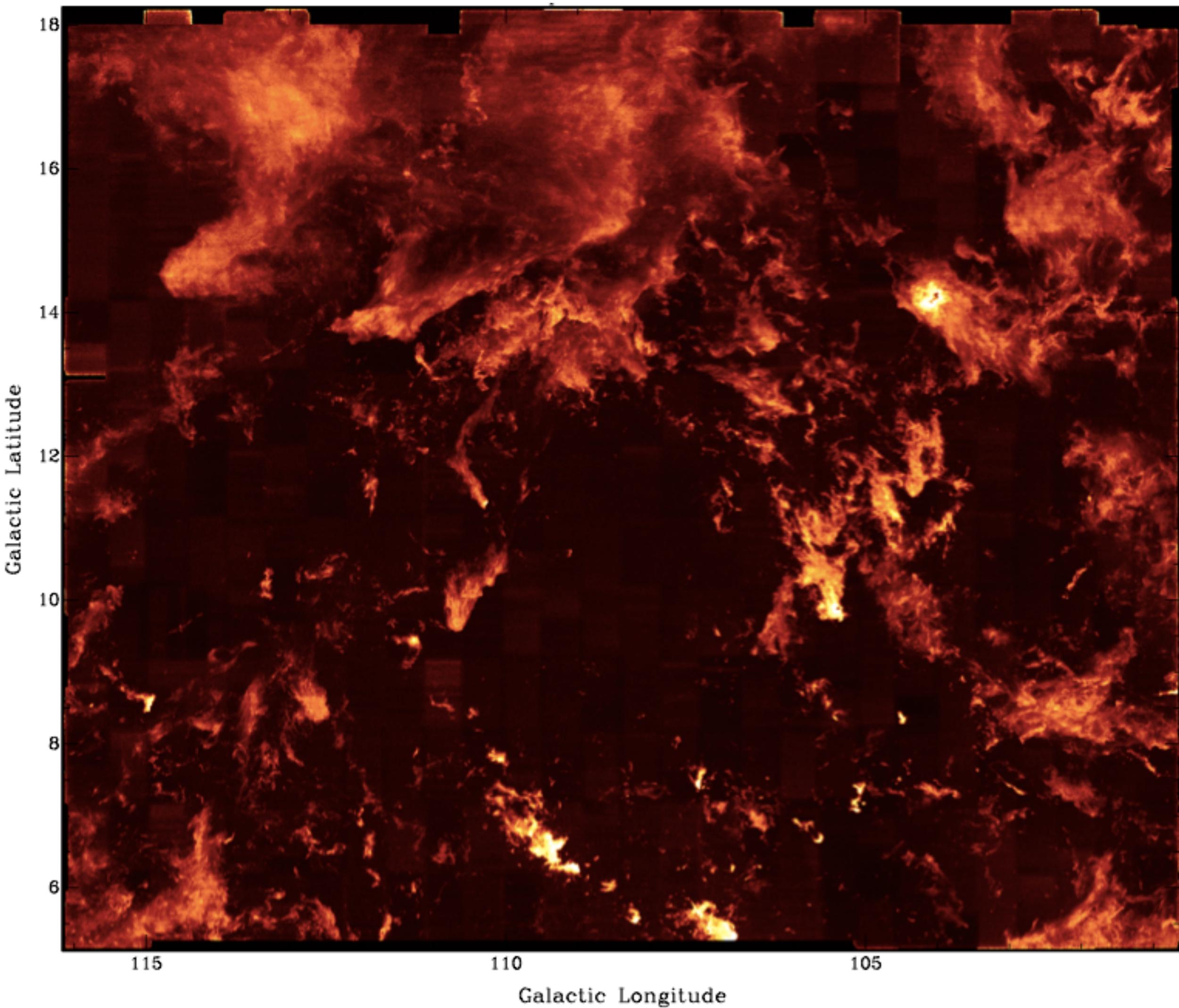


Bruno Gilli/ESO

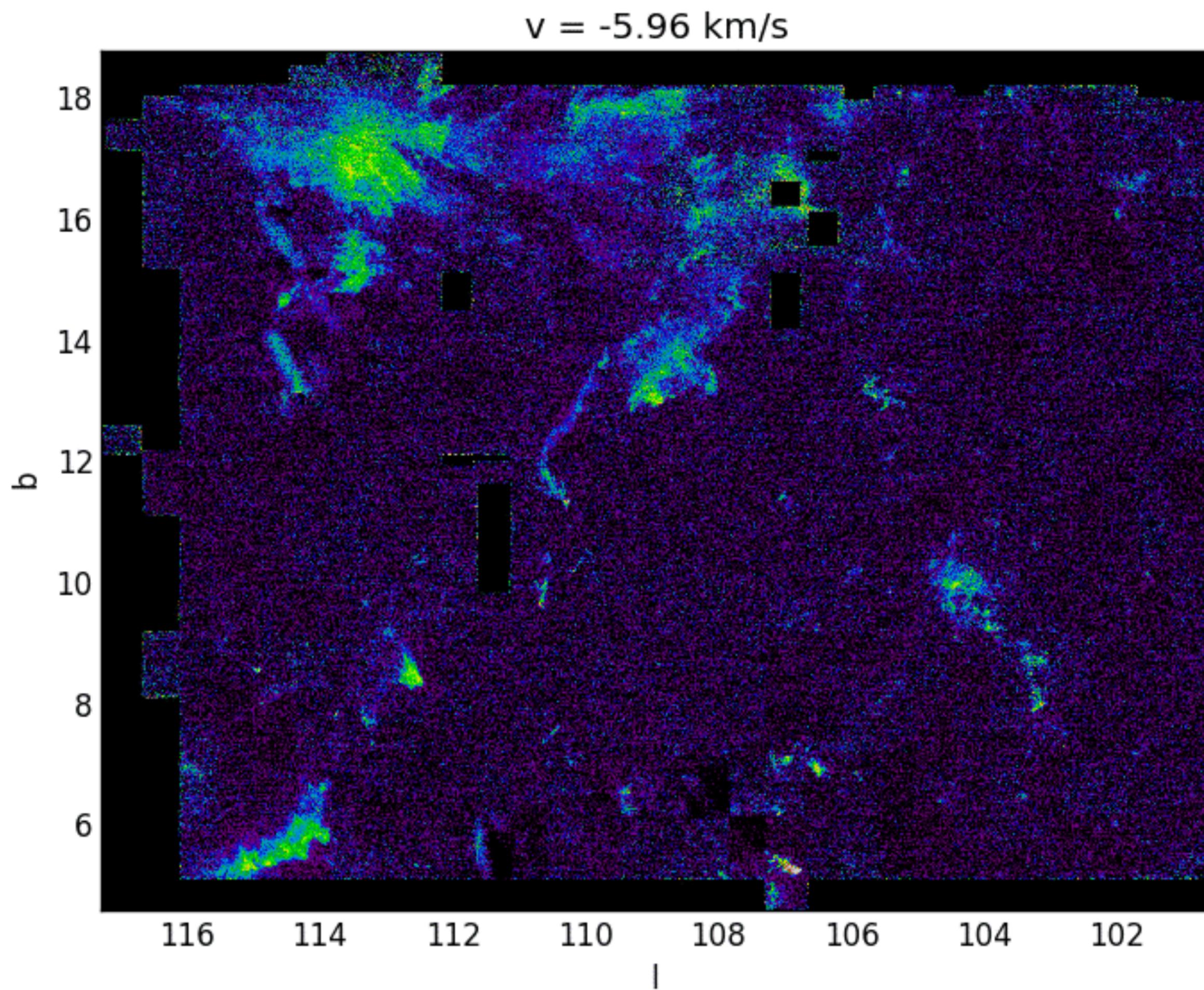
Introduction



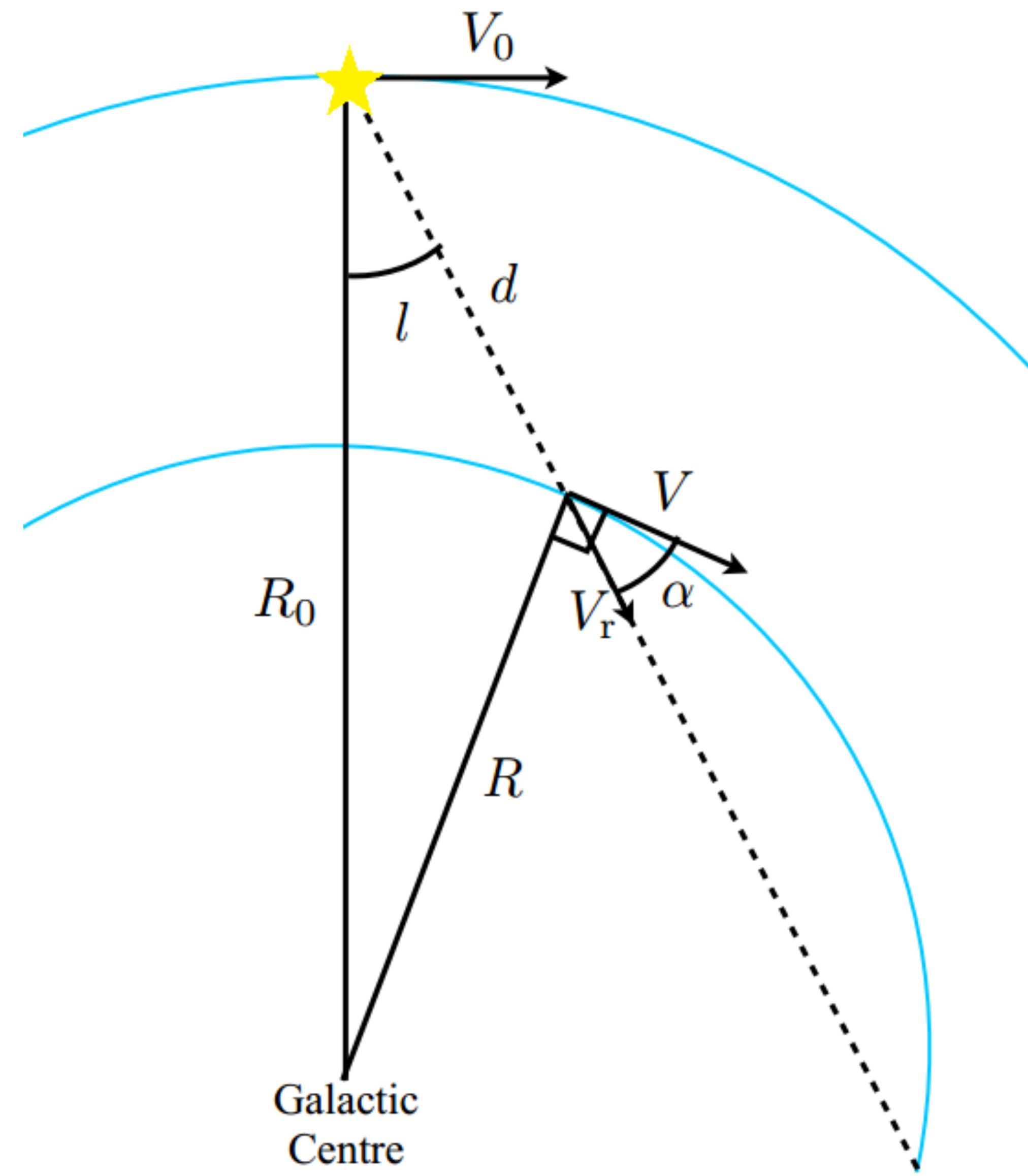
Mapping the Milky Way



Mapping the Milky Way



Distance Determination



Distance Determination



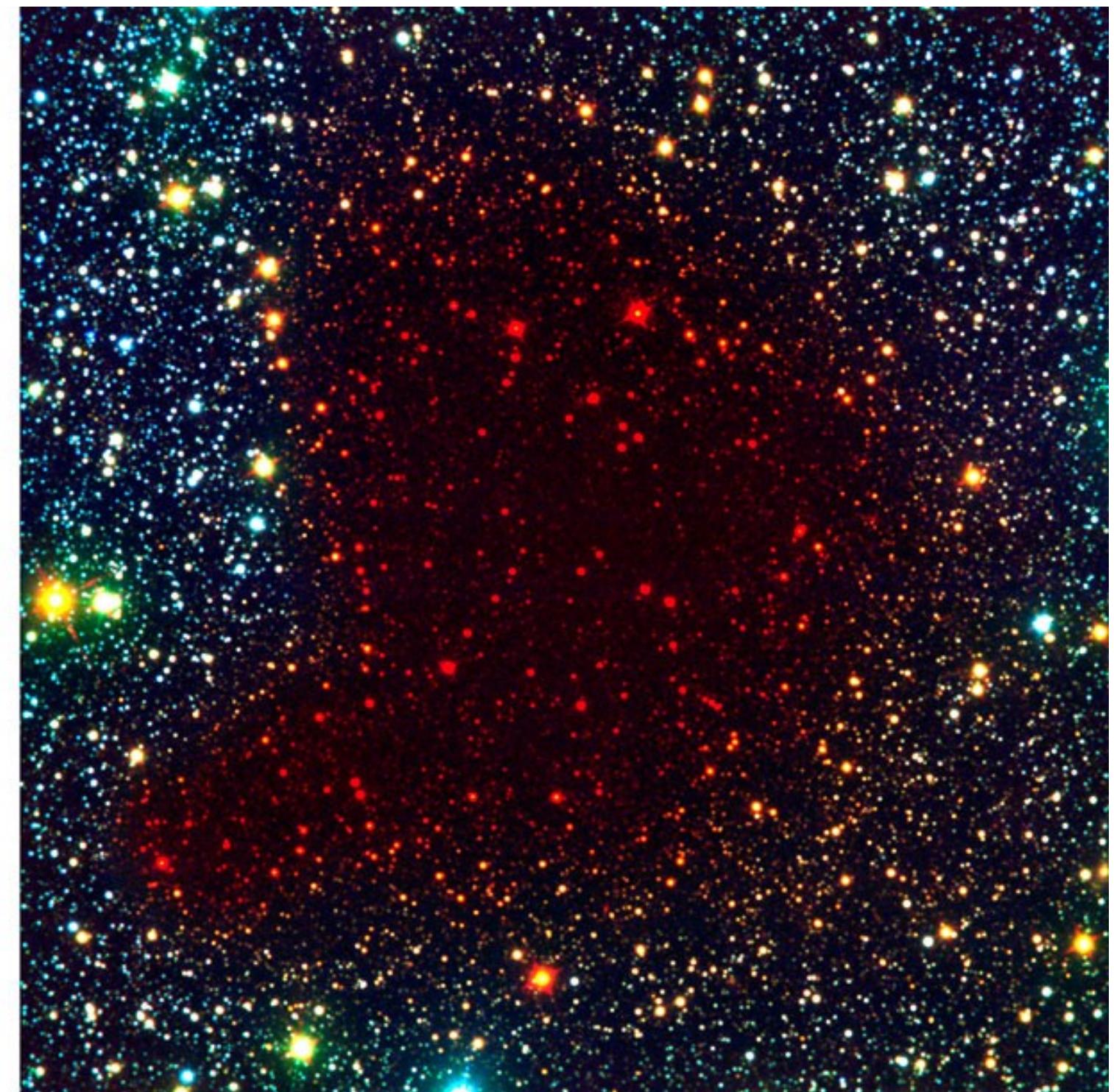
APOD/NASA

Distance Determination



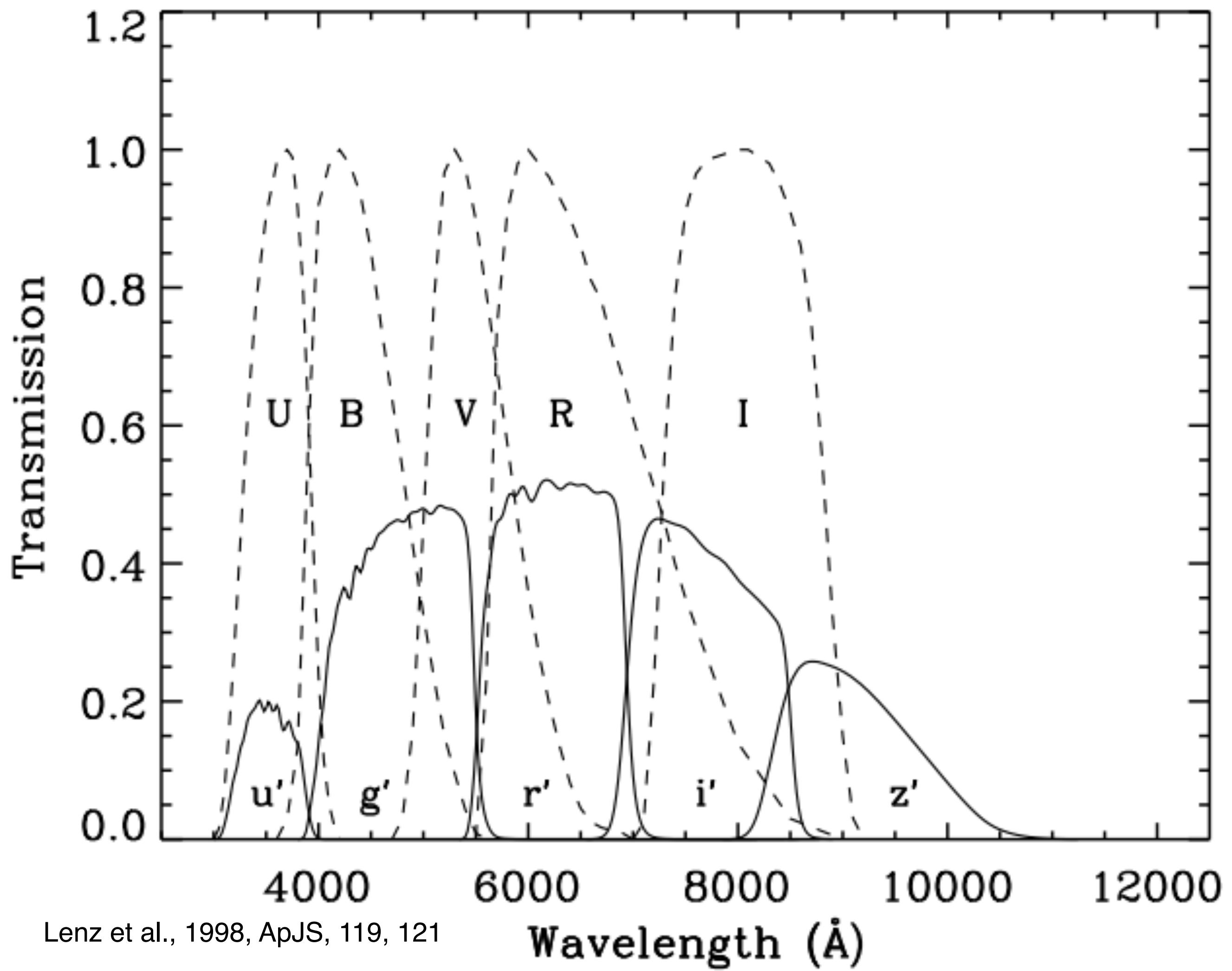
B, V, I

ESO



B, I, K

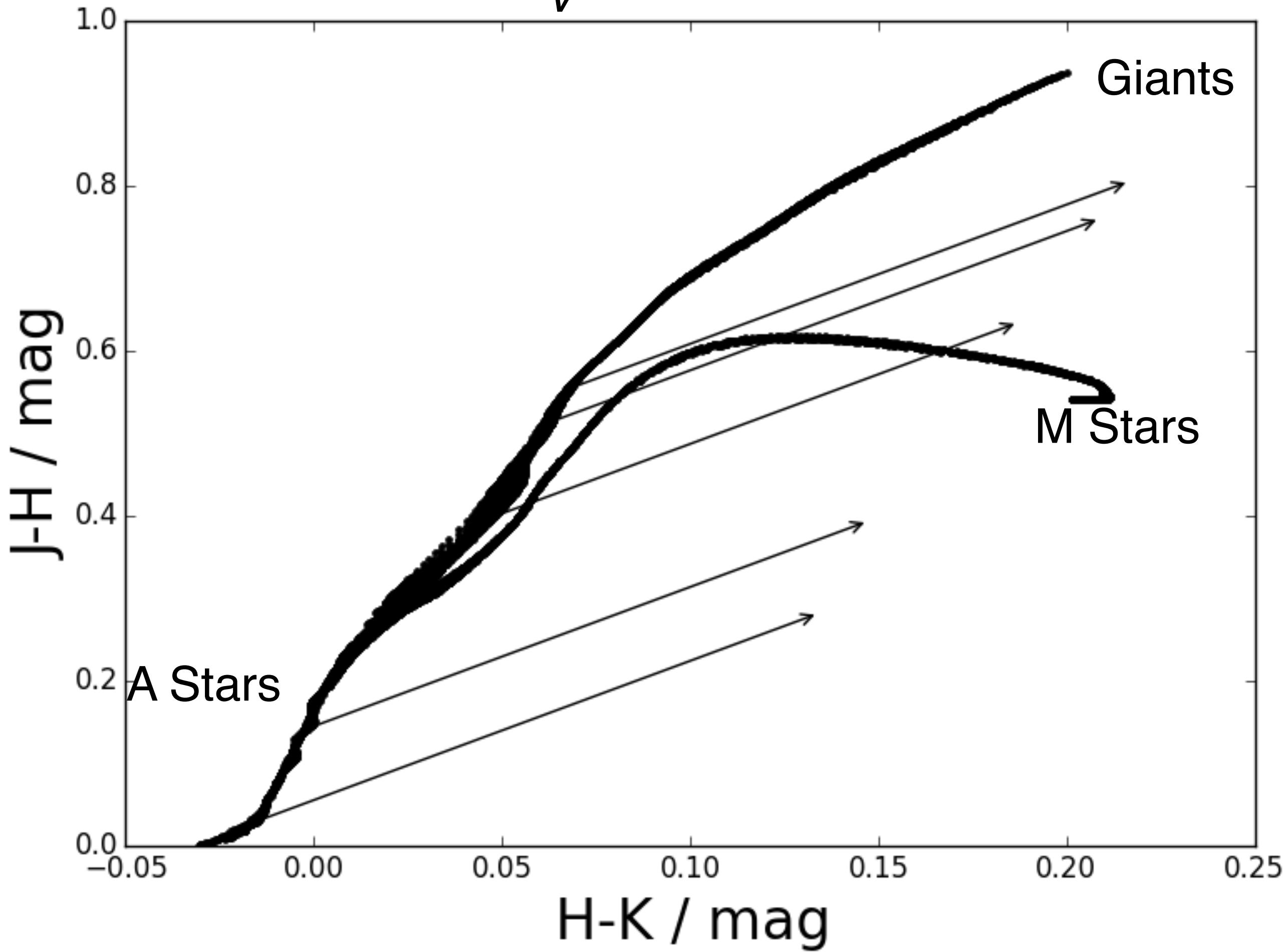
3D Extinction



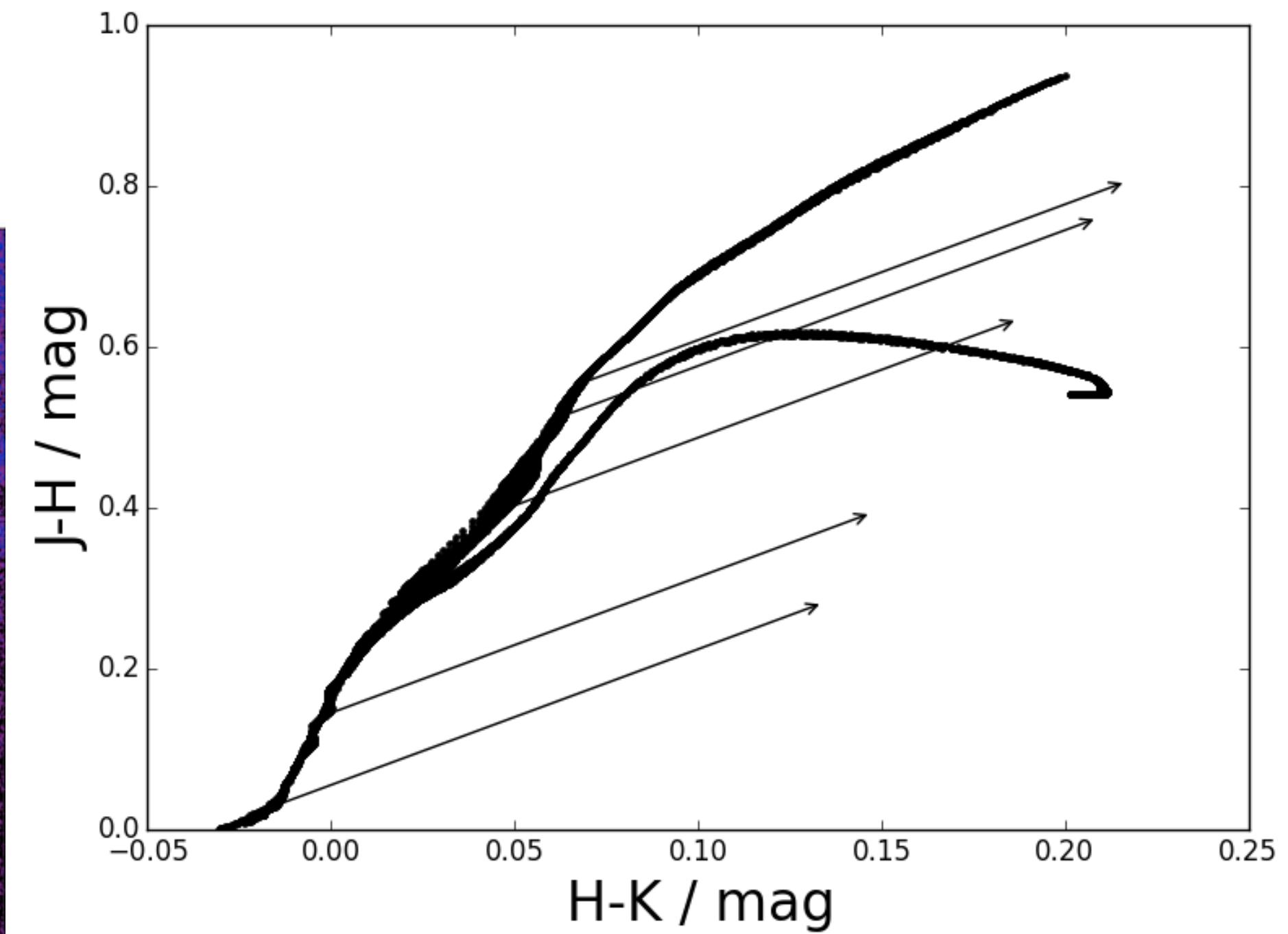
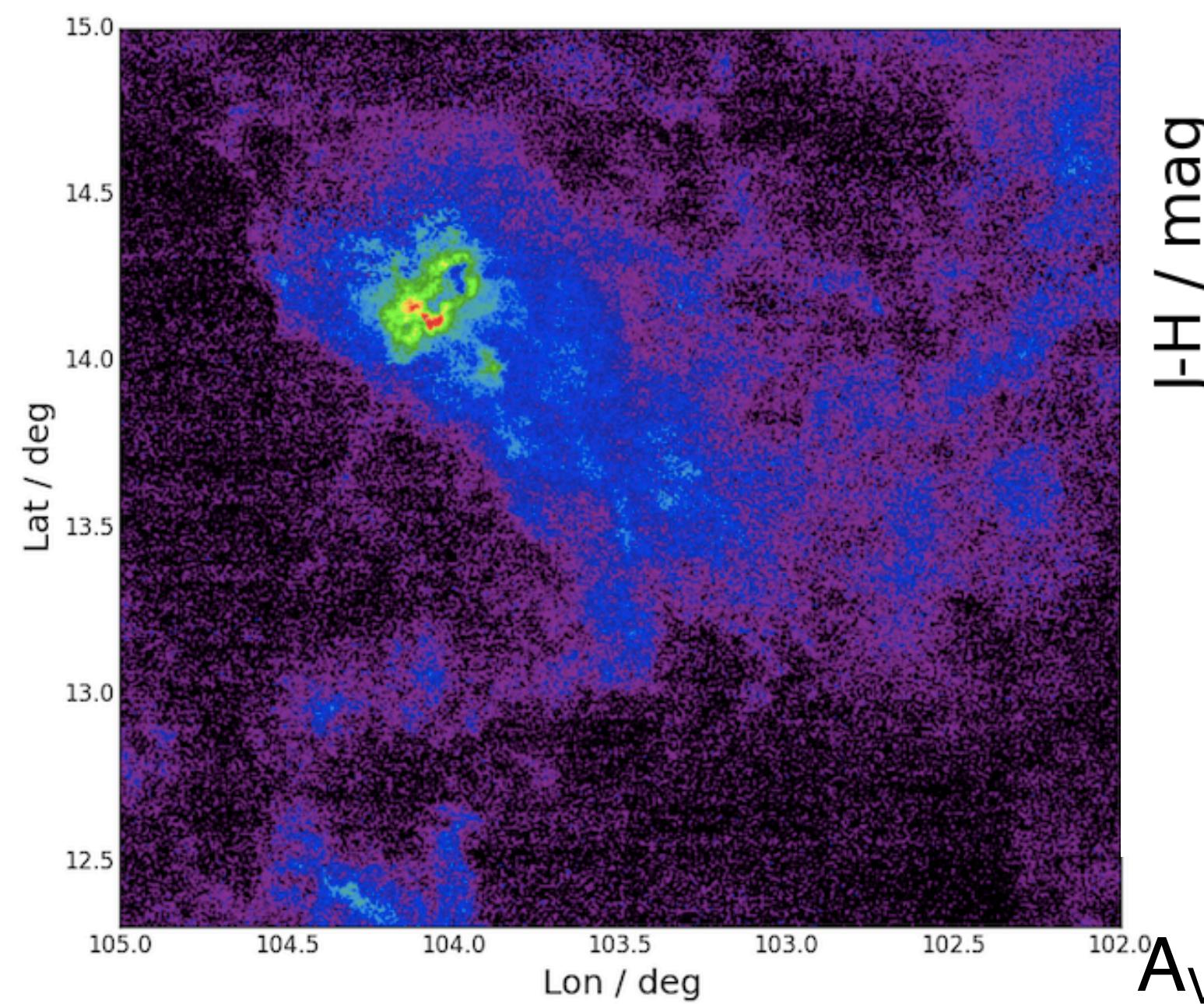
Lenz et al., 1998, ApJS, 119, 121

3D Extinction

$$m_{\lambda} = M_{\lambda} + \frac{A_{\lambda}}{A_V} A_V + 5 \log_{10}(d) - 5$$



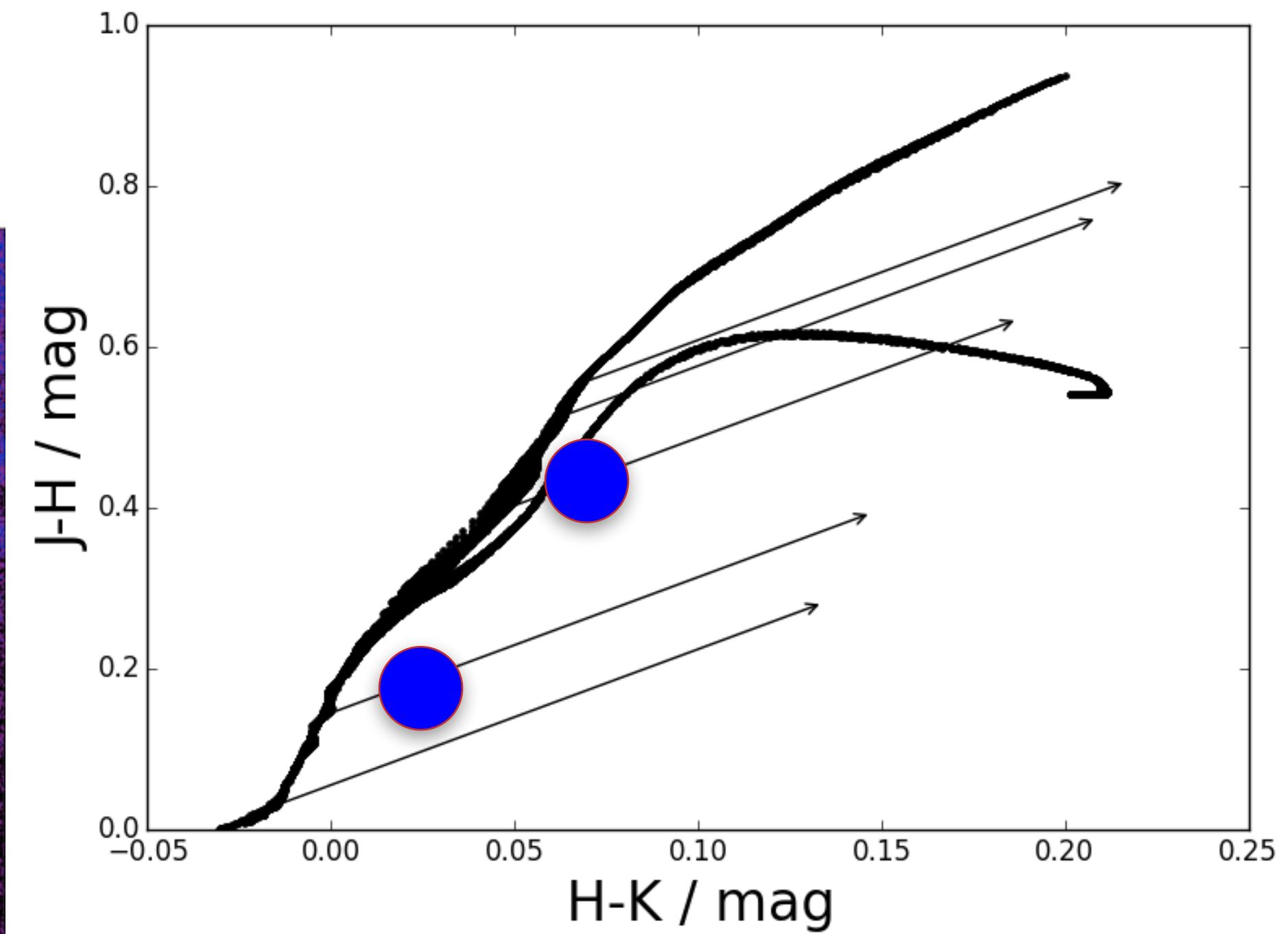
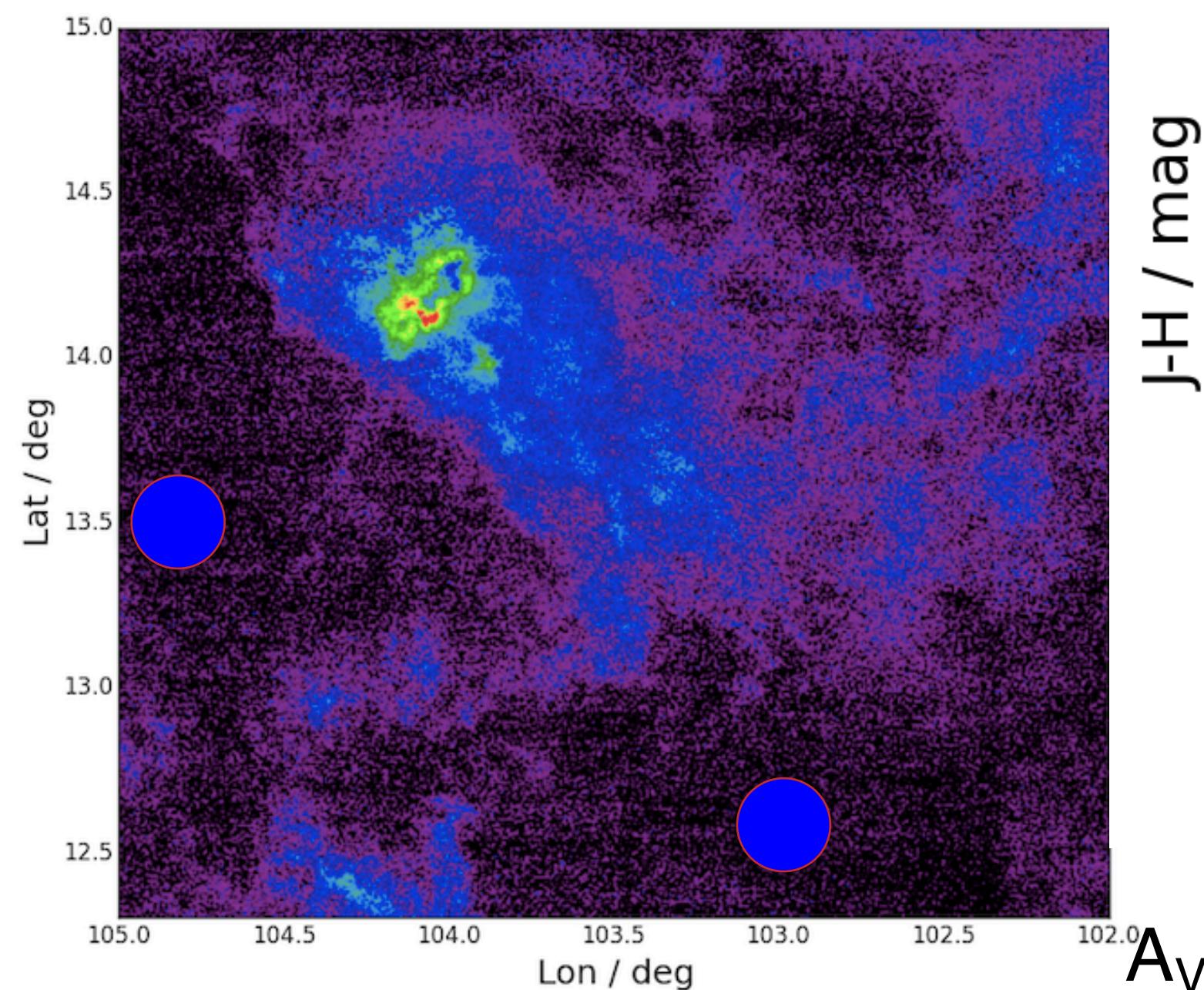
3D Extinction – Naive Approach



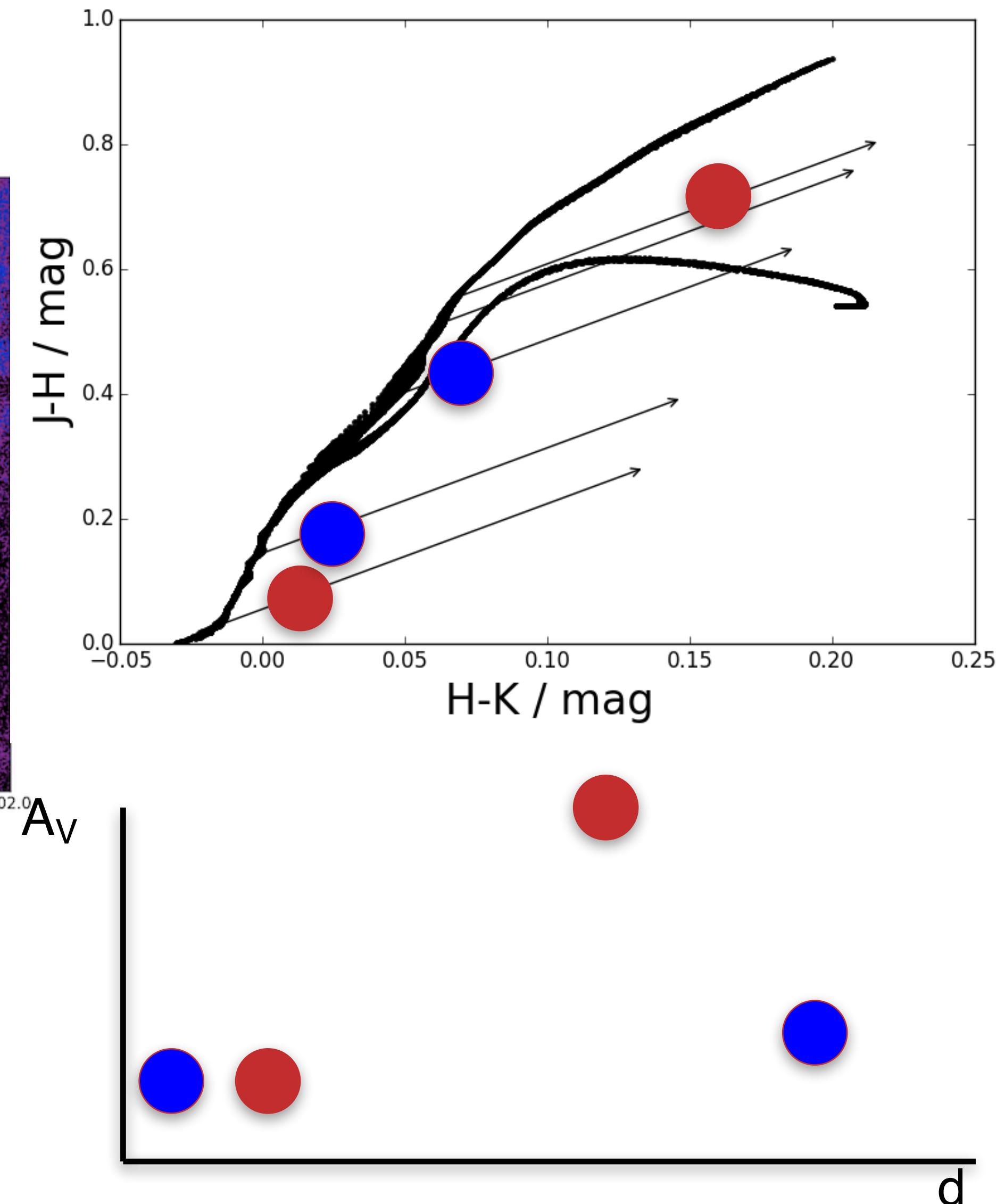
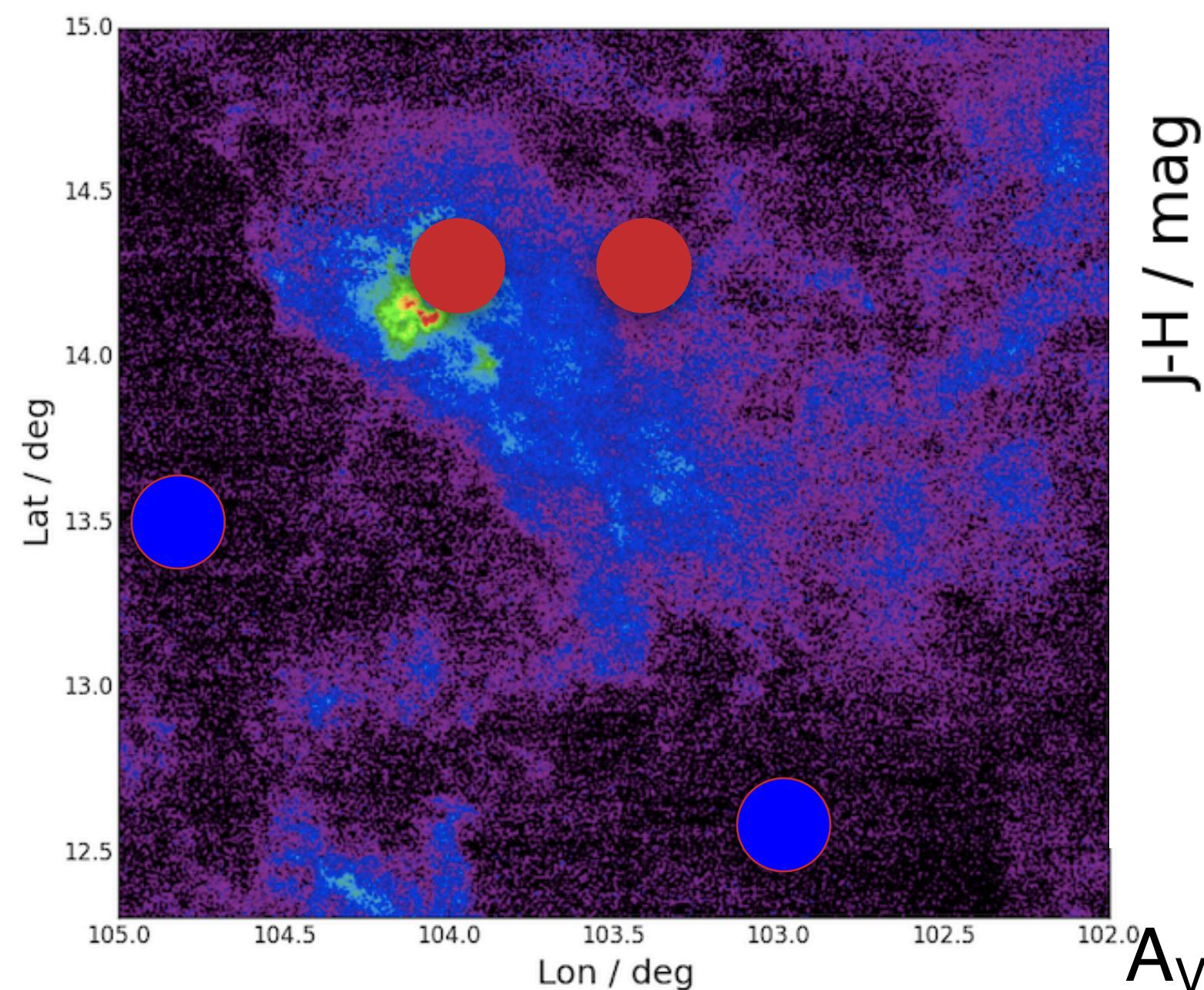
A_V

d

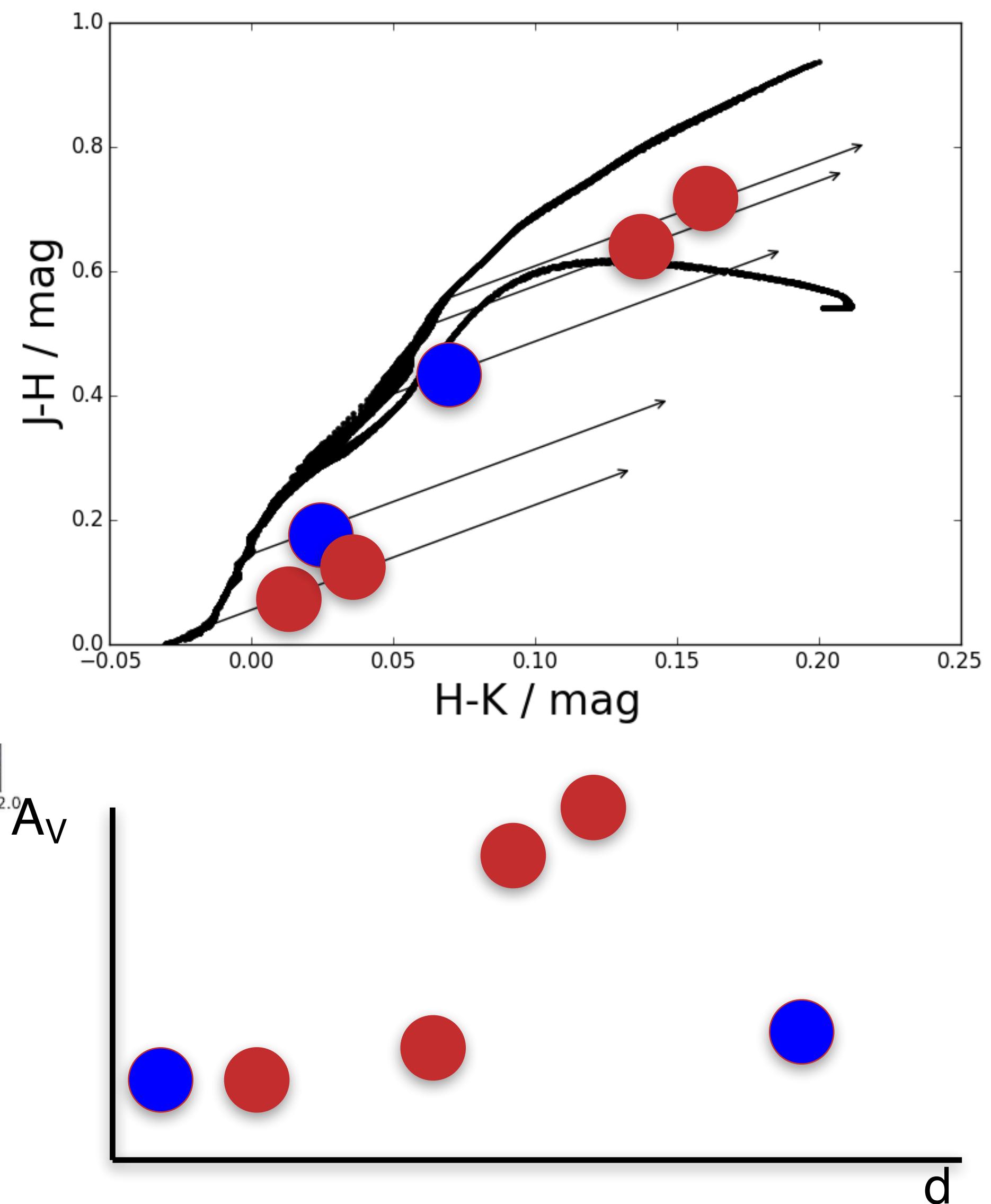
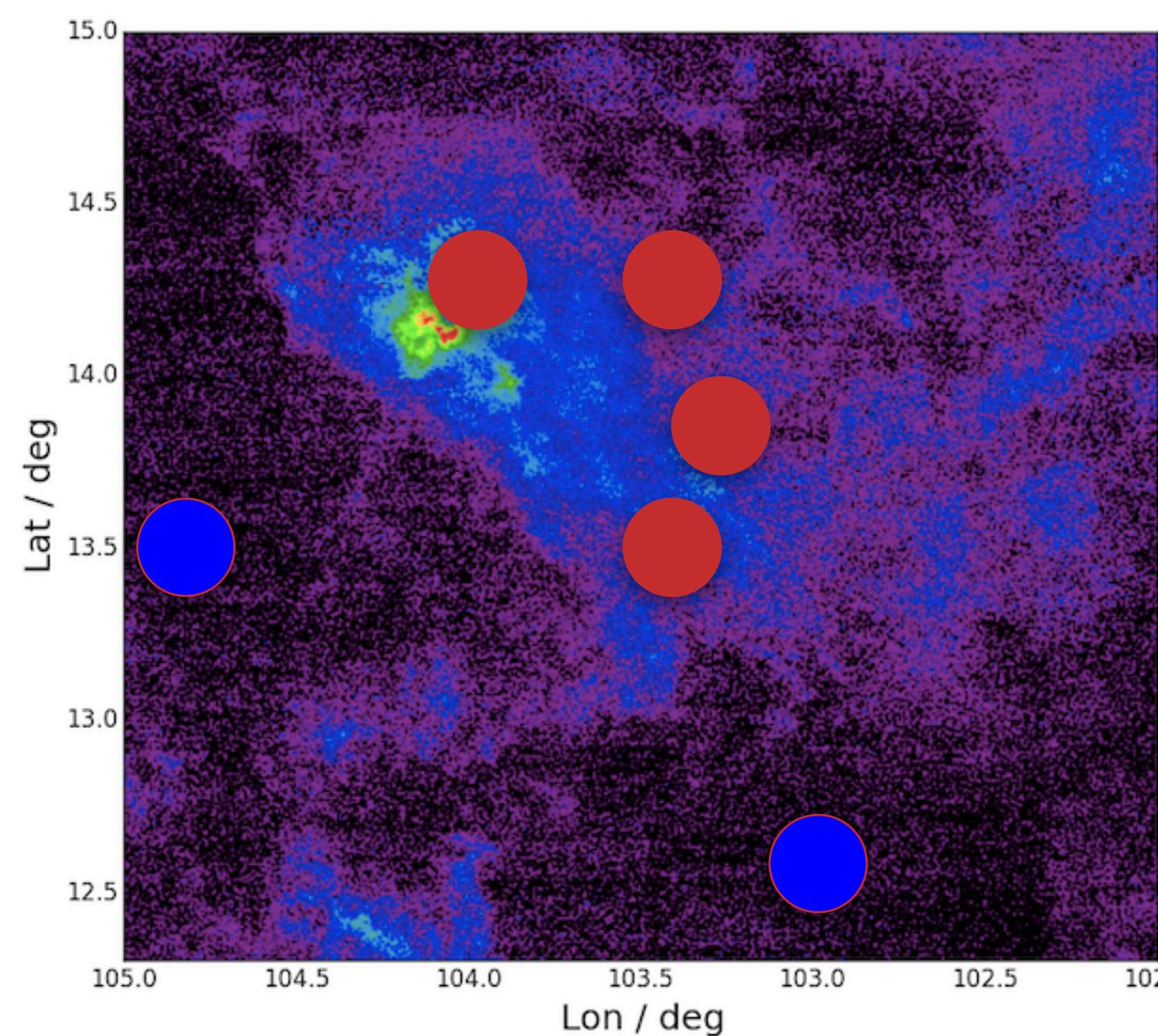
3D Extinction – Naive Approach



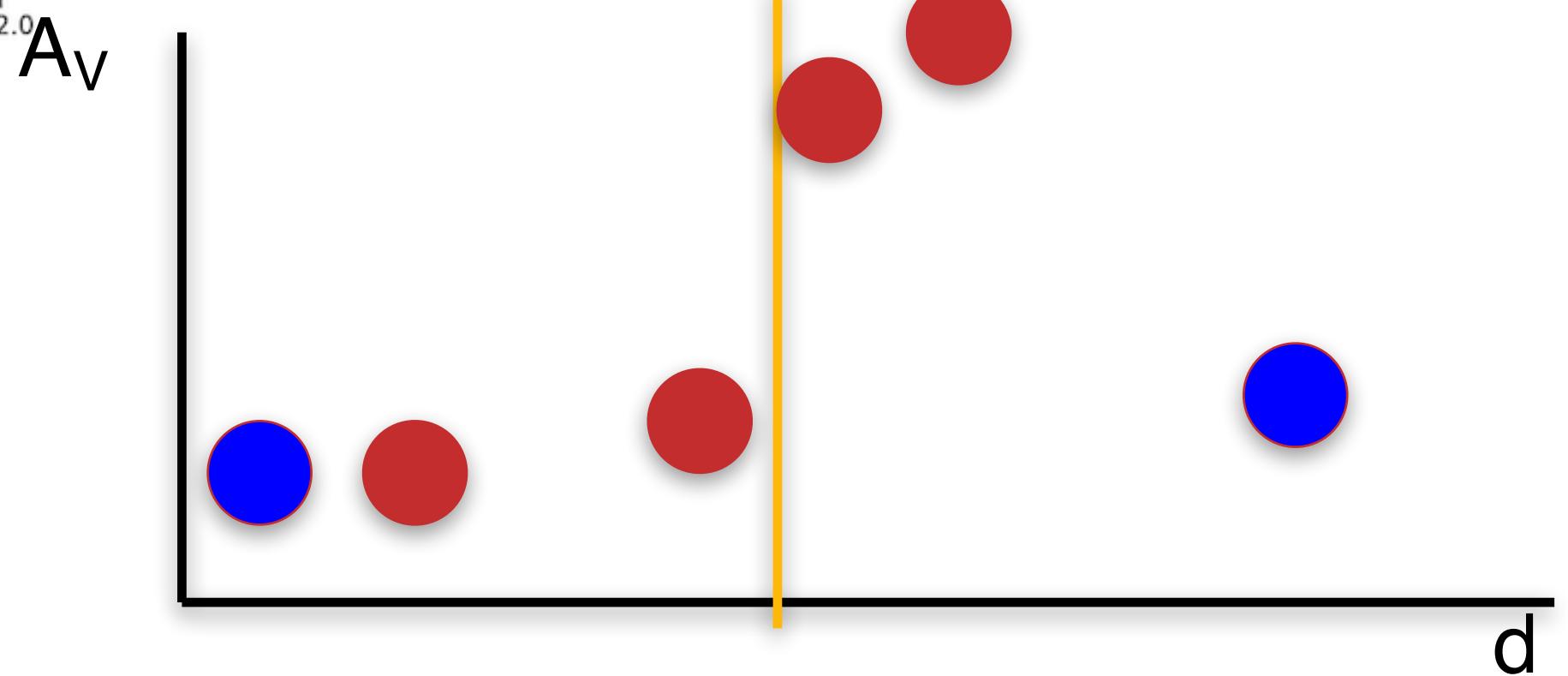
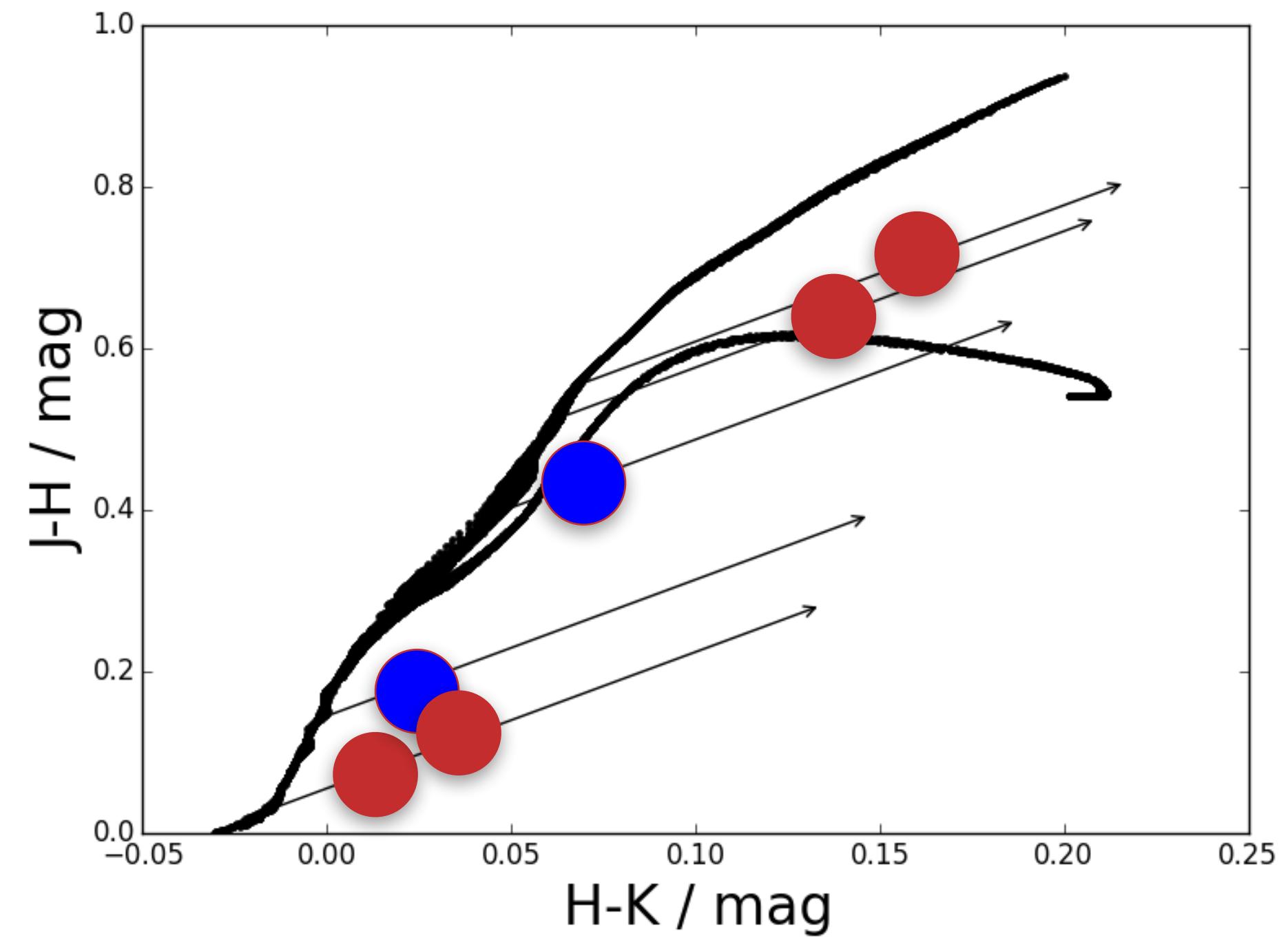
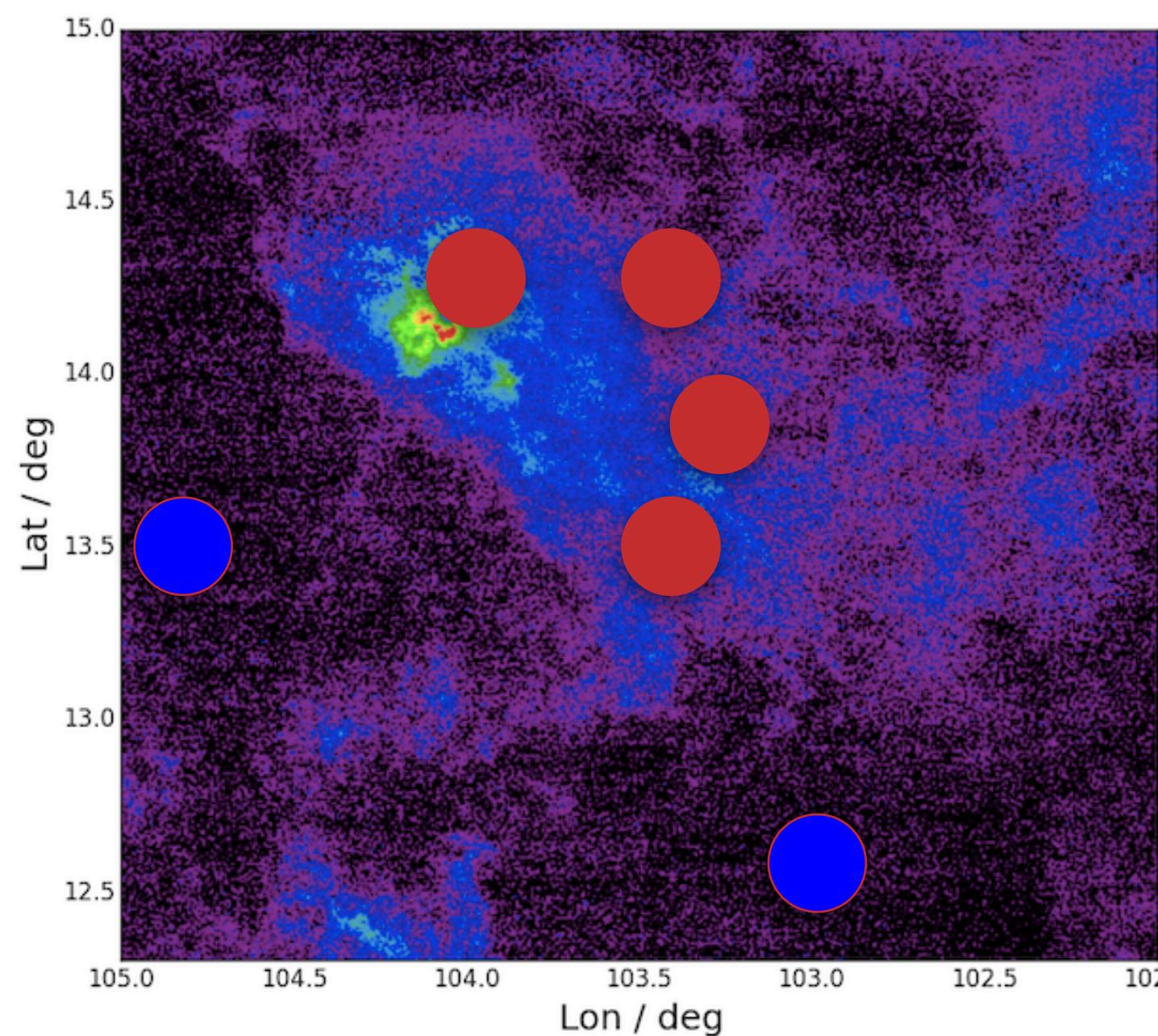
3D Extinction – Naive Approach



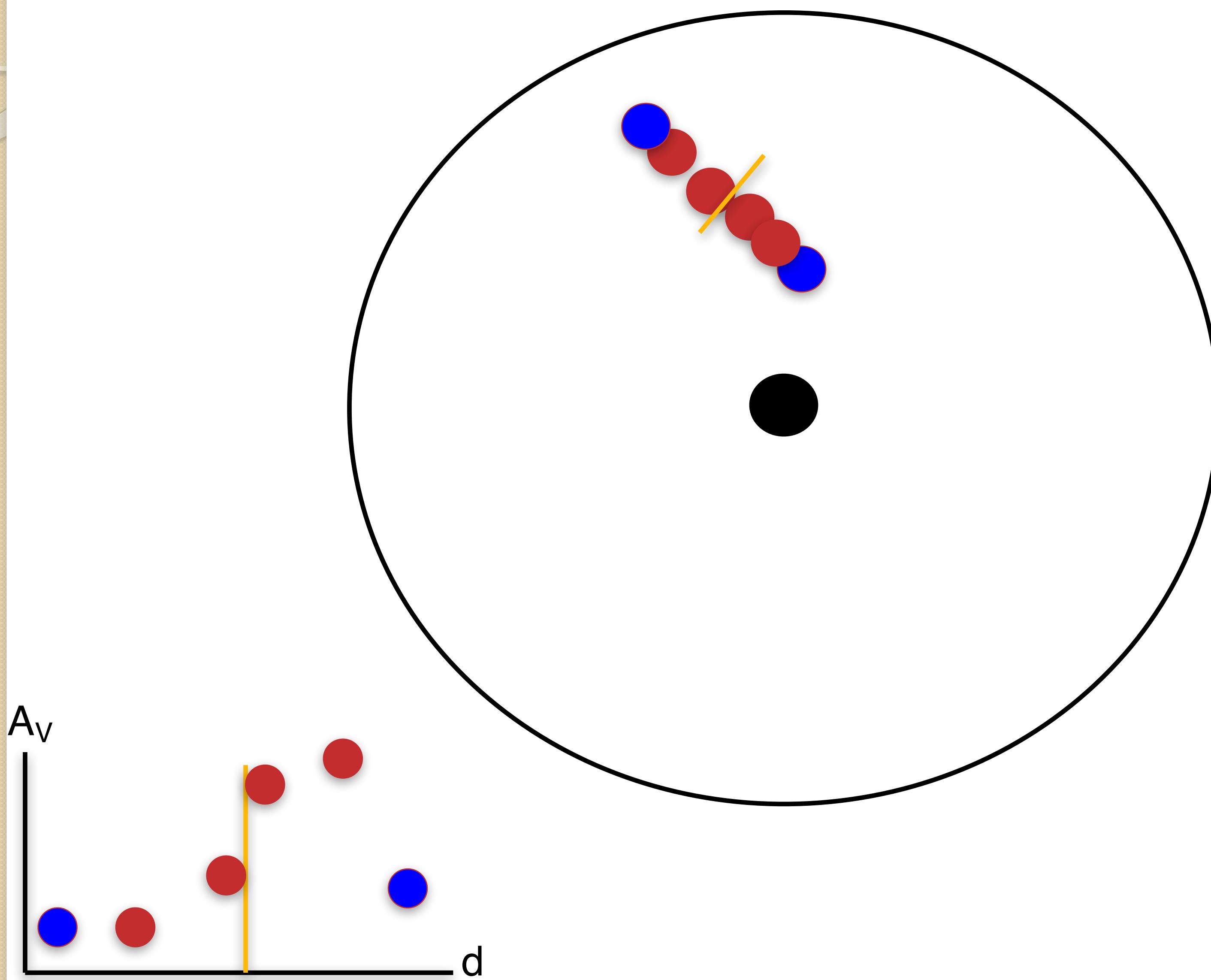
3D Extinction – Naive Approach



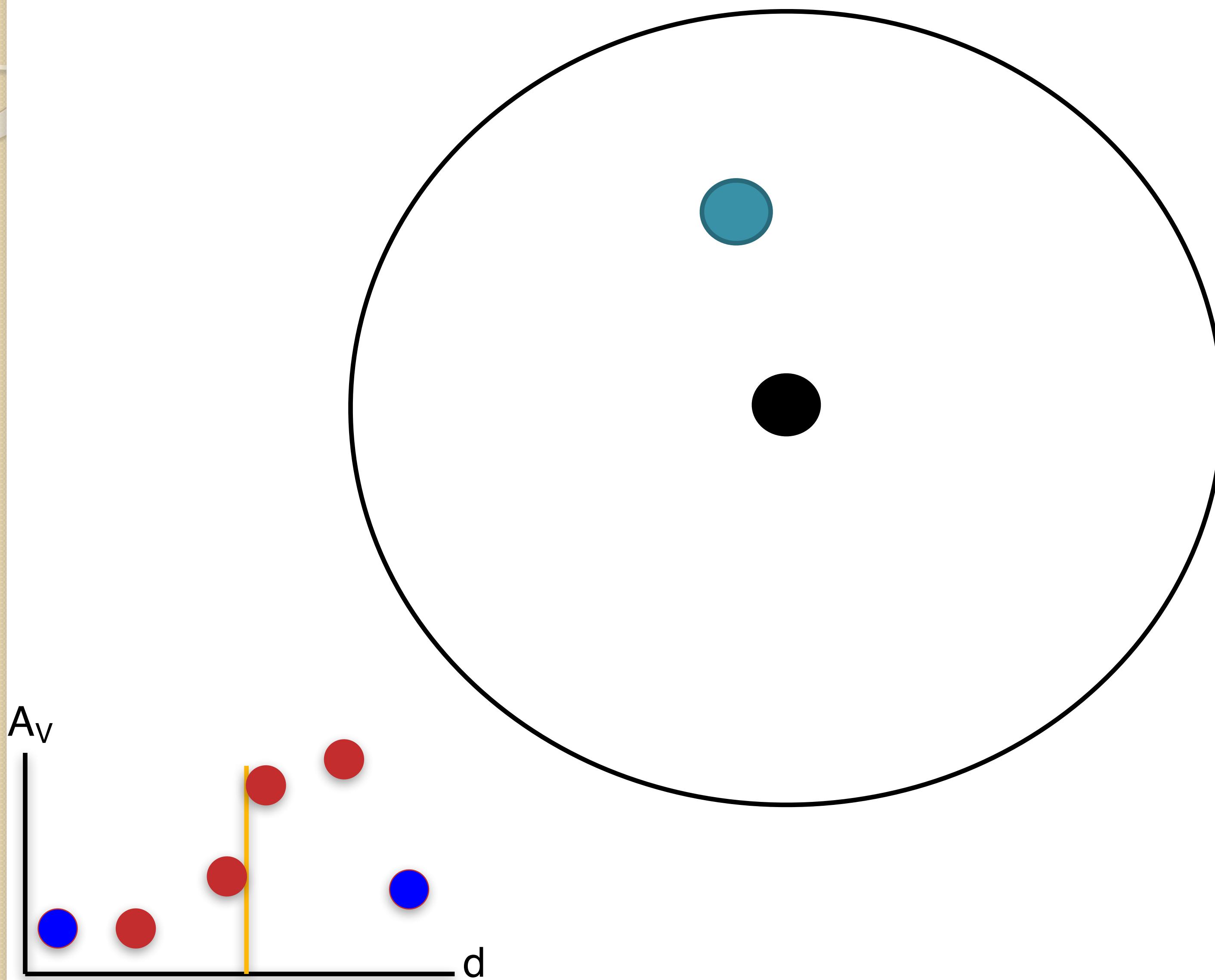
3D Extinction – Naive Approach



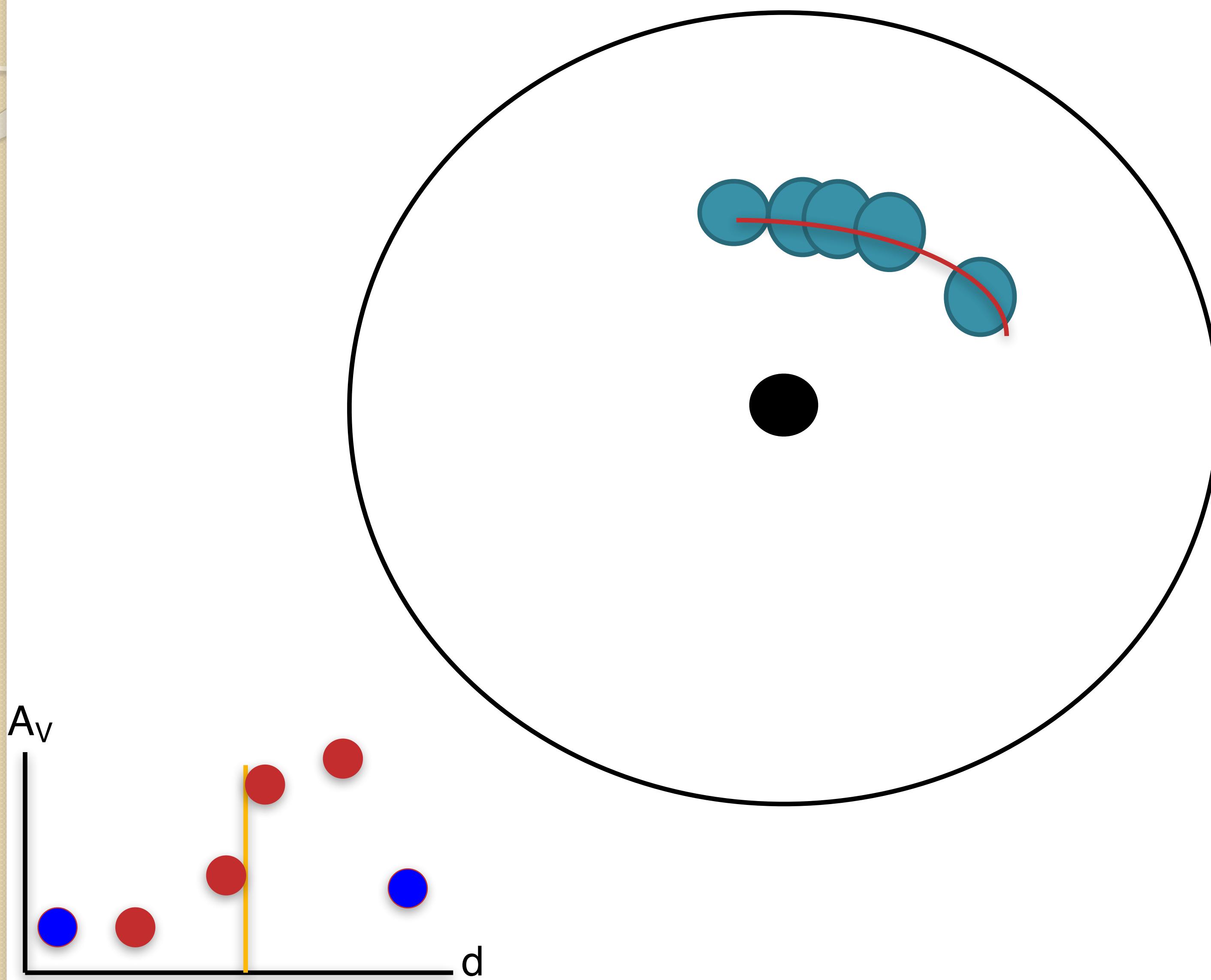
3D Extinction – Naive Approach



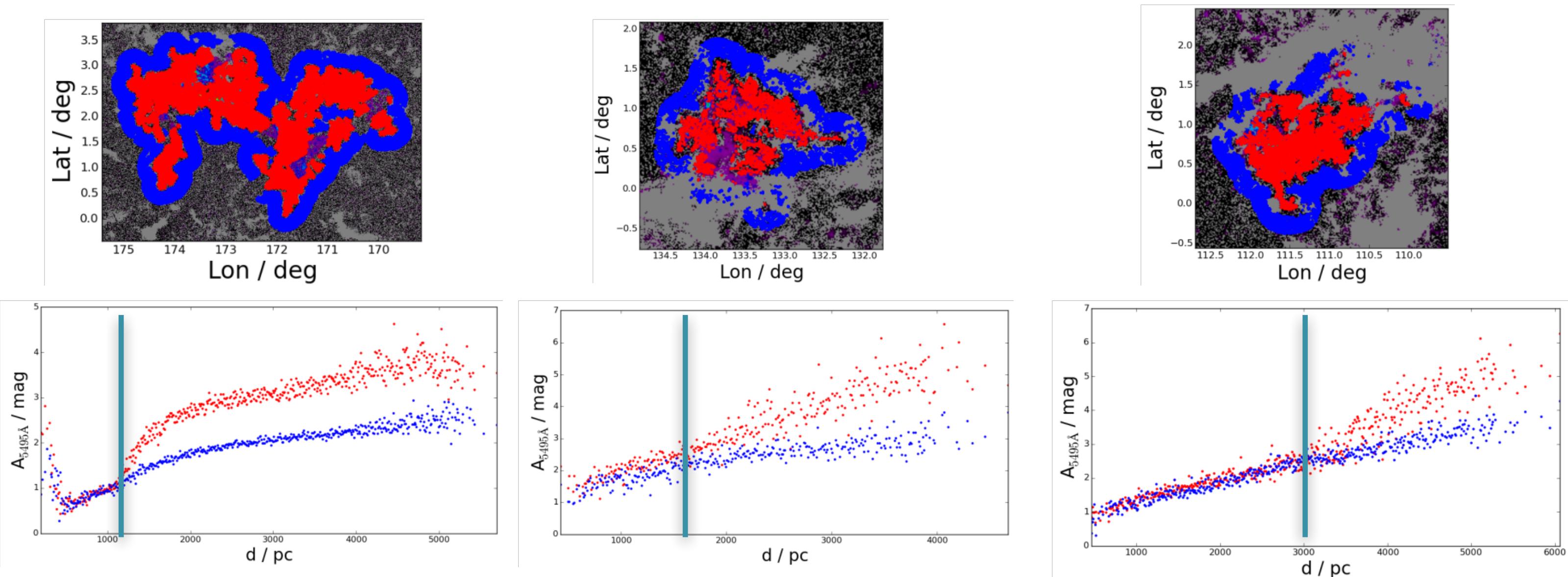
3D Extinction – Naive Approach



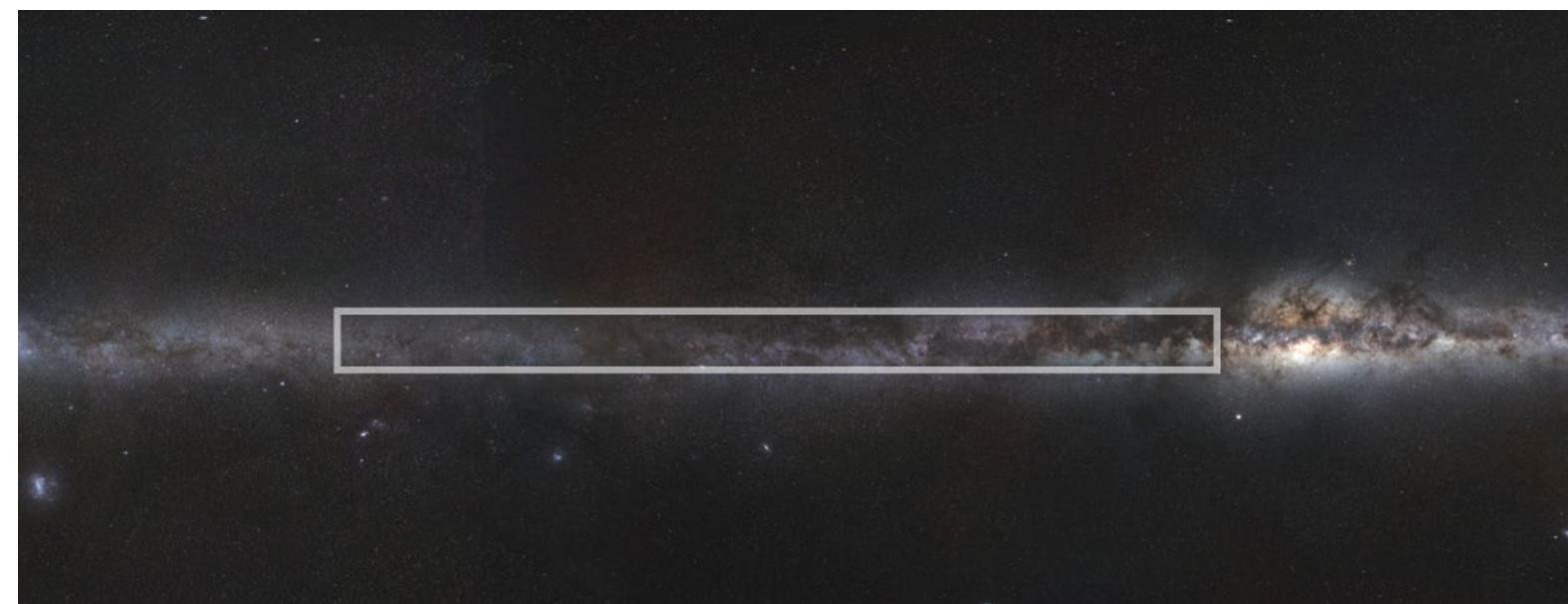
3D Extinction – Naive Approach



3D Extinction – IPHAS



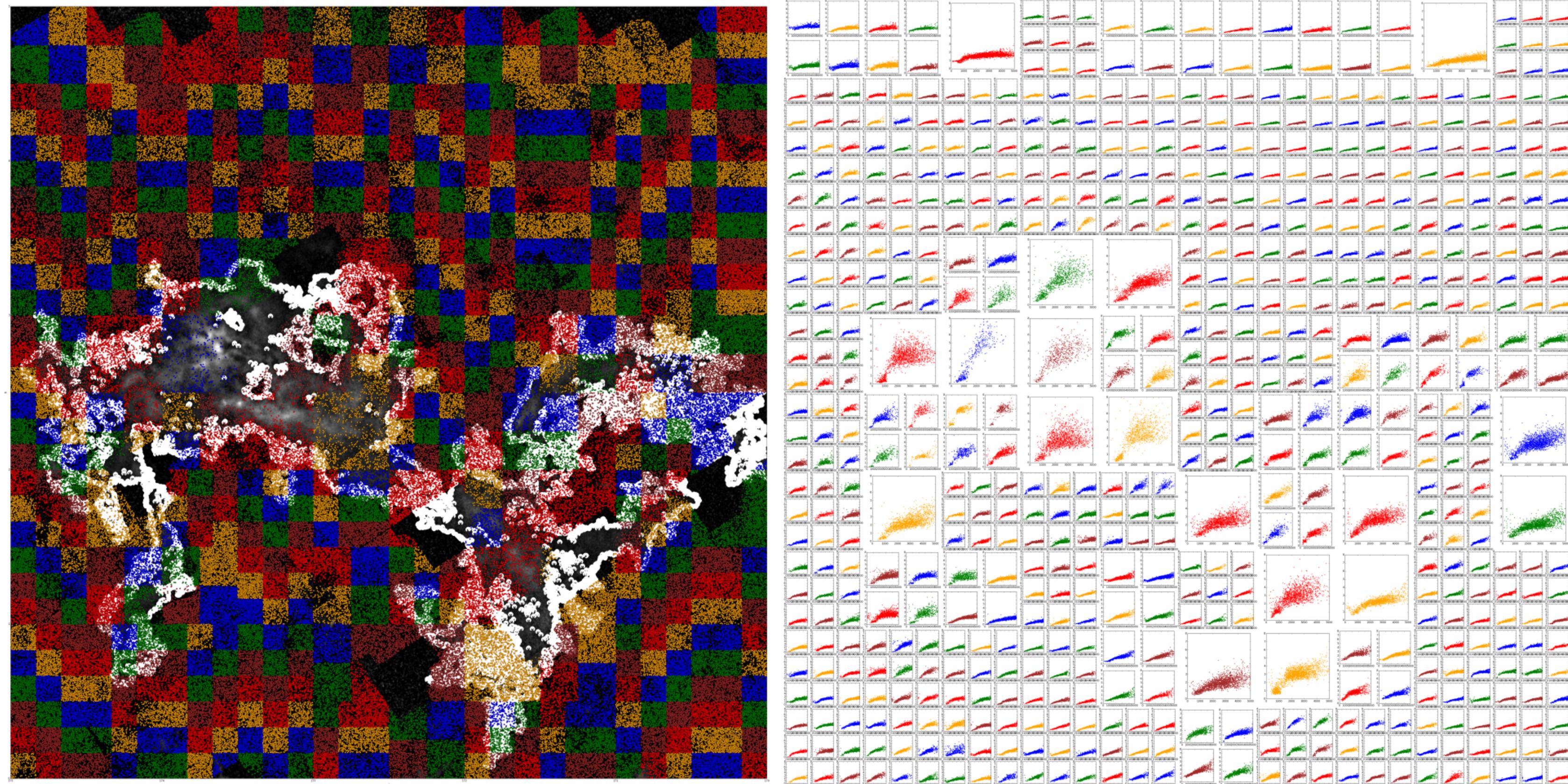
Cloud	Literature Distance	Sale et al. 2014 ^[1] Distance
Sh 2-235	1.8kpc ^[2]	1.2kpc
W3	1.95kpc ^[3]	1.7kpc
NGC7538	2.7kpc ^[4]	3kpc



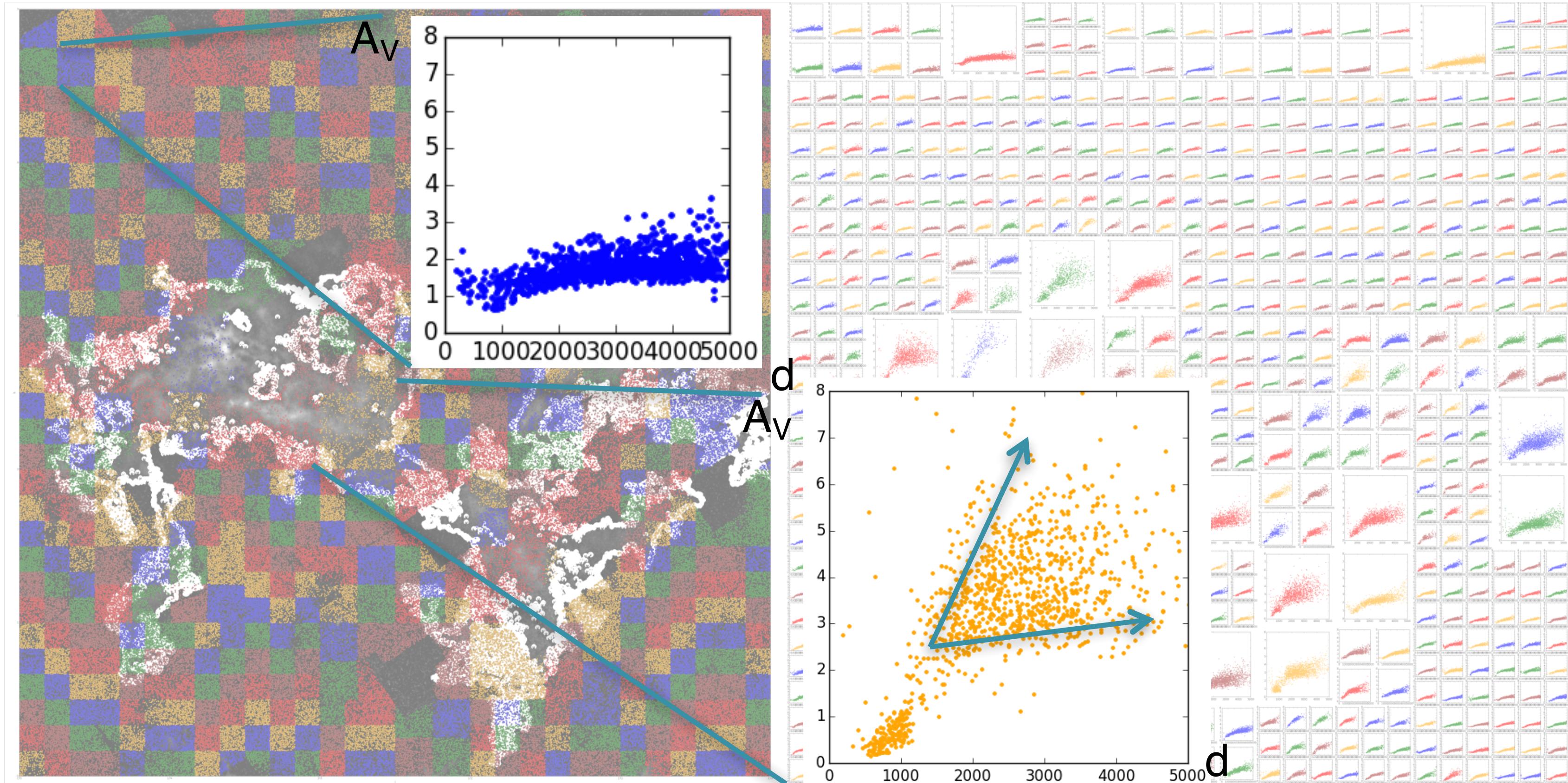
Brunier, ESO

1. Sale, S. et al., 2014, MNRAS, 443, 2907
2. Evans N. II, Blair G., 1981, ApJ, 246, 394
3. Xu Y. et al., 2006, Science, 311, 54
4. Moscadelli L. et al., 2009, ApJ, 693, 406

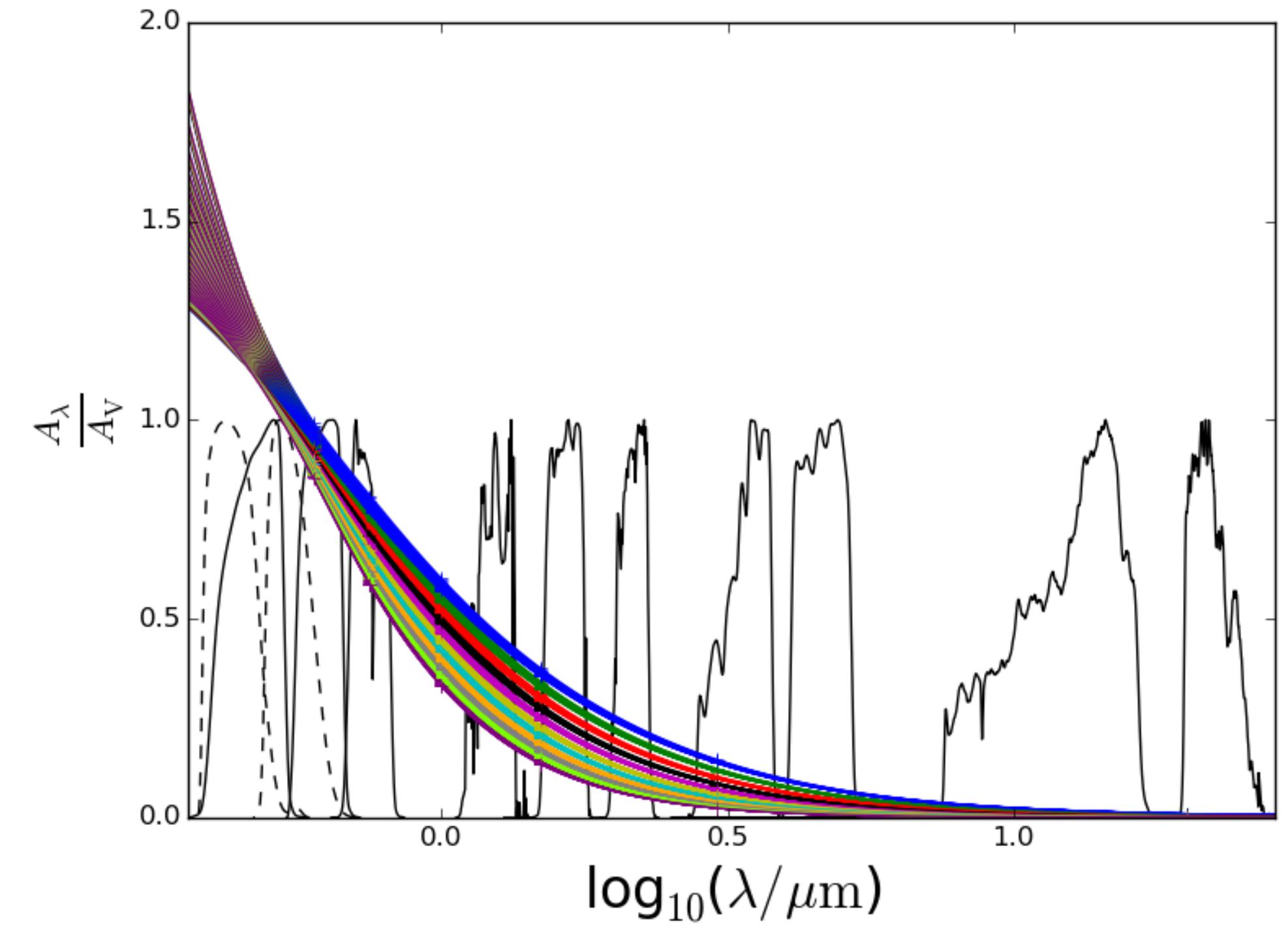
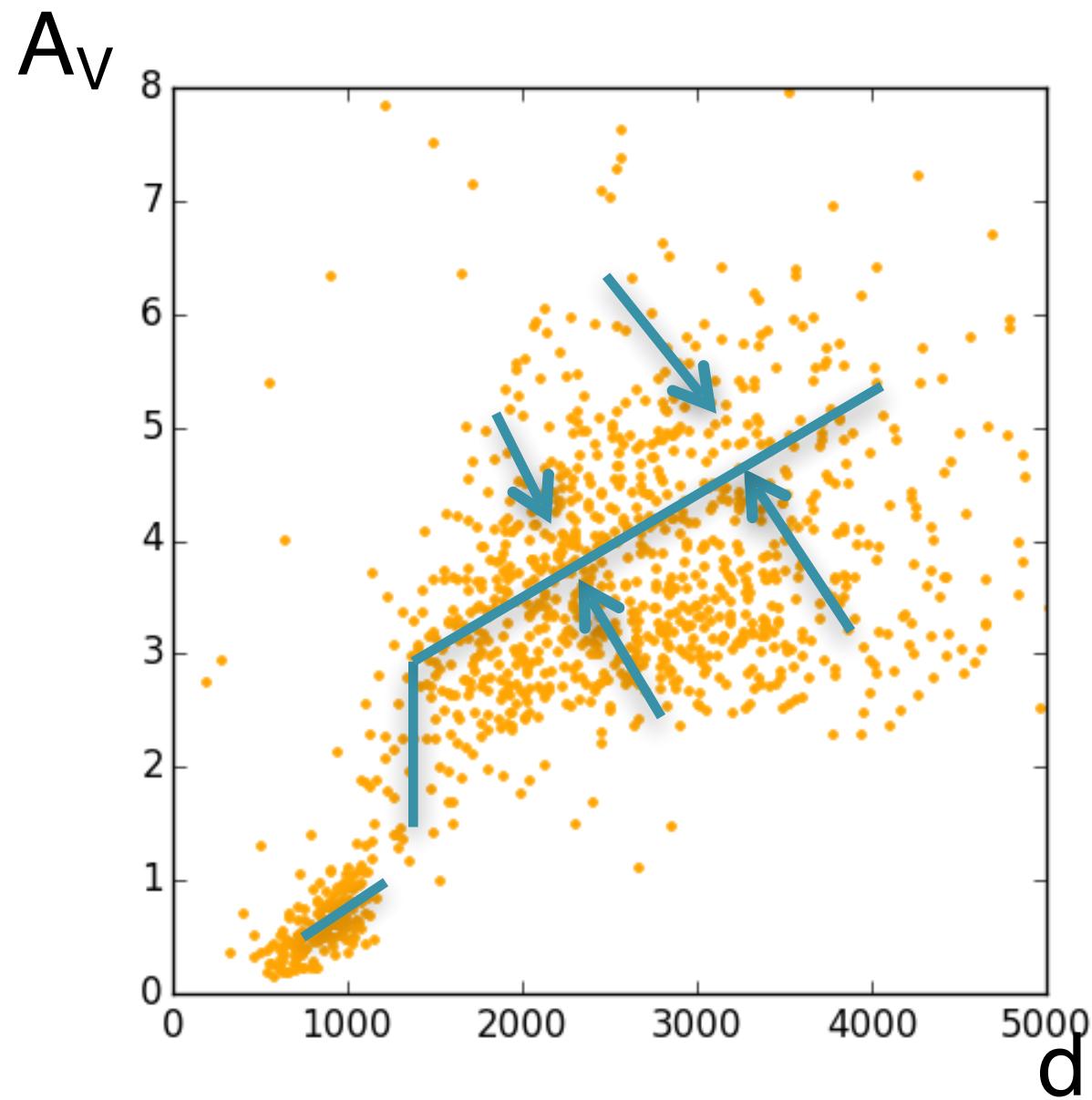
3D Extinction – IPHAS



3D Extinction – IPHAS



3D Extinction – IPHAS



$$A_\lambda = \frac{A_\lambda}{A_V} A_V = \left(\frac{k(\lambda - V)}{E(B-V)} R_V^{-1} + 1 \right) A_V$$

$$k(\lambda - V) = \frac{E(\lambda - V)}{E(B - V)} = \frac{0.349 + 2.087 \cdot R_V}{1 + (\frac{\lambda}{0.507})^\alpha},$$

$$k(\lambda - V) = c_1 + c_2 \lambda^{-1} + c_3 \frac{\lambda^{-2}}{(\lambda^{-2} - \lambda_0^2)^2 + \lambda^{-2} \gamma^2} + c_4 F$$

Fitzpatrick E., Massa D., 2009, ApJ, 699, 1209
 Fitzpatrick E., Massa D., 1990, ApJS, 72, 163

3D Extinction – Bayesian

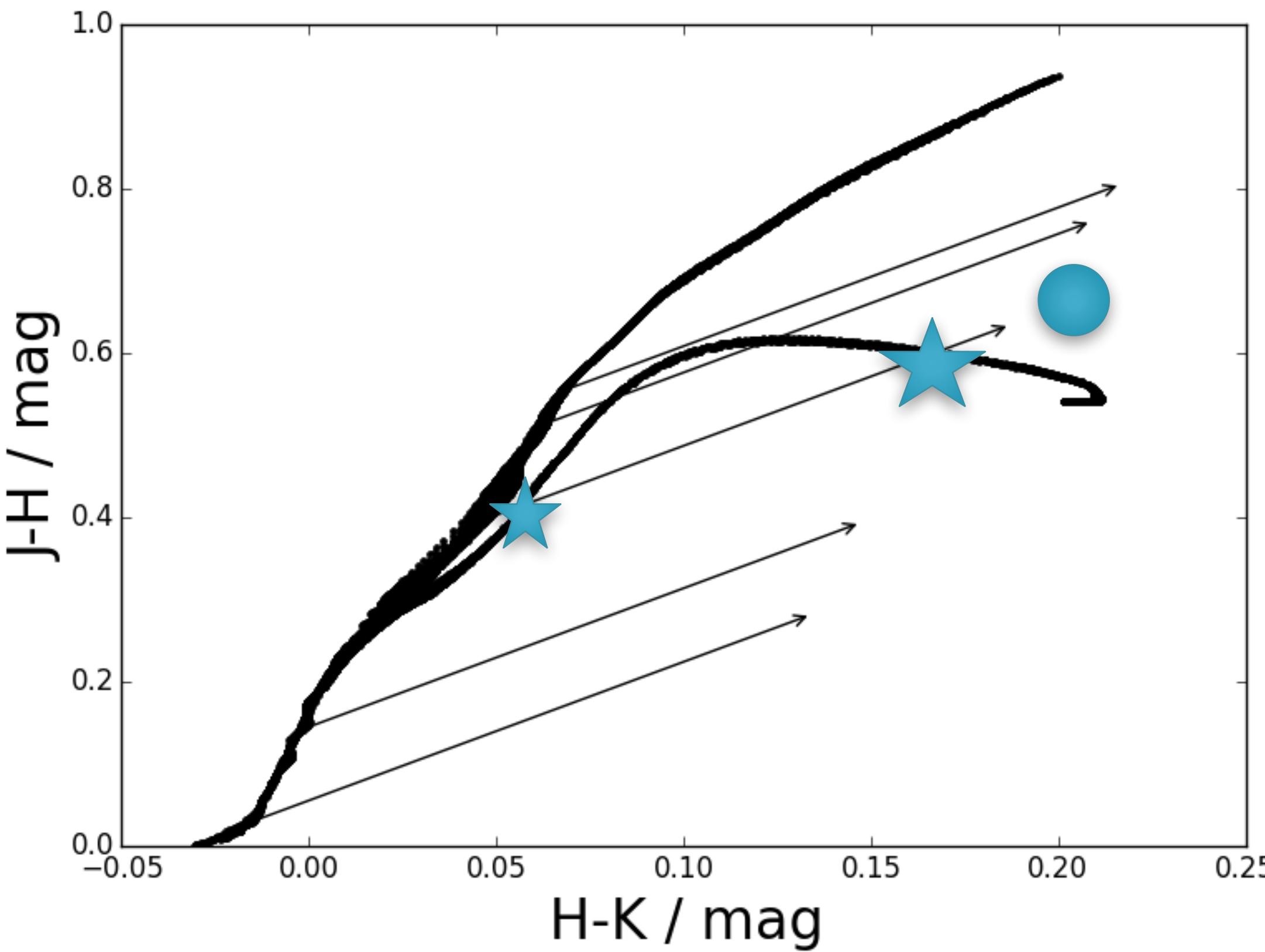
- $p(M)$ – the prior
- $p(M | D)$ – the posterior
- $p(D | M)$ – the likelihood
- $p(D)$ – normalisation

$$p(M | D) = \frac{p(D | M)p(M)}{p(D)}$$

3D Extinction – Bayesian

- $p(M)$ – the prior
- $p(M | D)$ – the posterior
- $p(D | M)$ – the likelihood
- $p(D)$ – normalisation

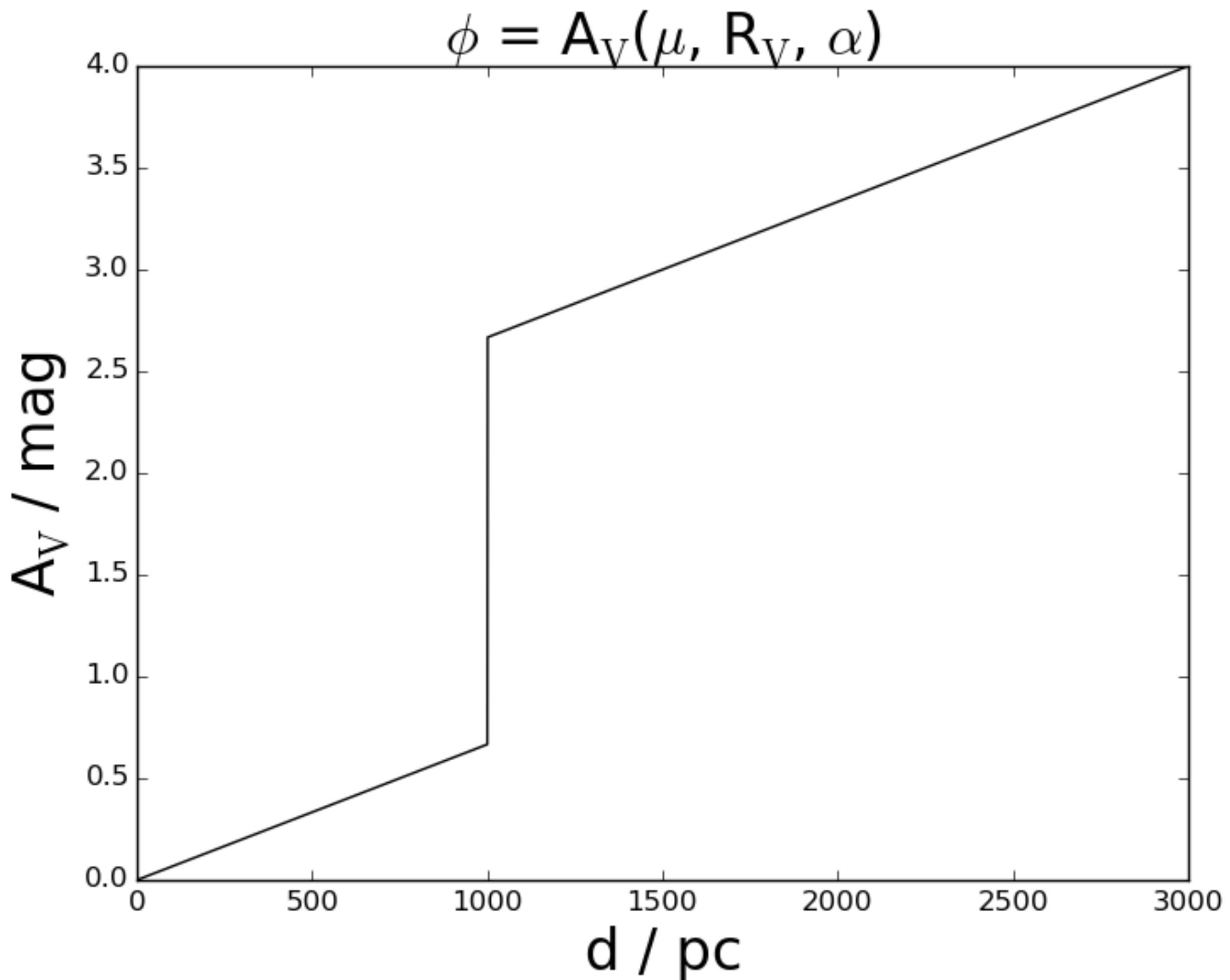
$$p(M | D) = \frac{p(D | M)p(M)}{p(D)}$$



3D Extinction – Bayesian

$$p(\phi | \{\mathbf{D}\}) = \prod_i \iint \frac{p(\mathbf{D}_i | \phi, \mu, \Theta) p(\phi, \mu, \Theta)}{p(\mathbf{D}_i)} d\Theta d\mu$$

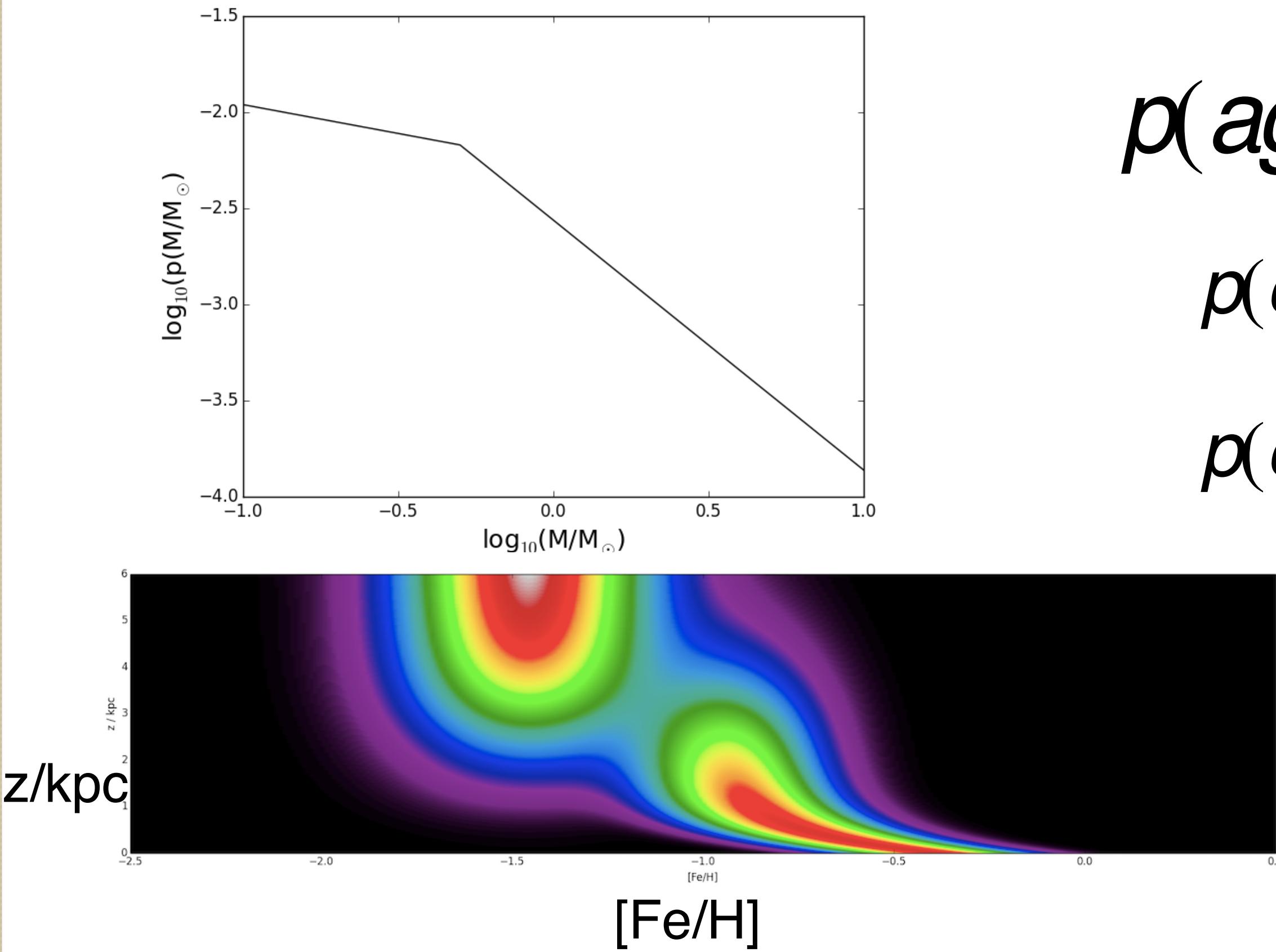
$$p(M | D) = \frac{p(D | M)p(M)}{p(D)}$$



$$\phi = \begin{cases} A_{V,ISM}(\mu, R_{V,ISM}, \alpha_{ISM}) & \mu < \mu_{cloud} \\ A_{V,ISM}(\mu, R_{V,ISM}, \alpha_{ISM}) + A_{V,cloud}(R_{V,cloud}, \alpha_{cloud}) & \mu \geq \mu_{cloud} \end{cases}$$

3D Extinction – Bayesian

$$p(\phi|\{\mathbf{D}\}) = \prod_i \int \int \frac{p(\mathbf{D}_i|\phi, \mu, \Theta) p(\phi, \mu, \Theta)}{p(\mathbf{D}_i)} d\Theta d\mu$$



$$p(\text{age}) \propto \text{const}$$

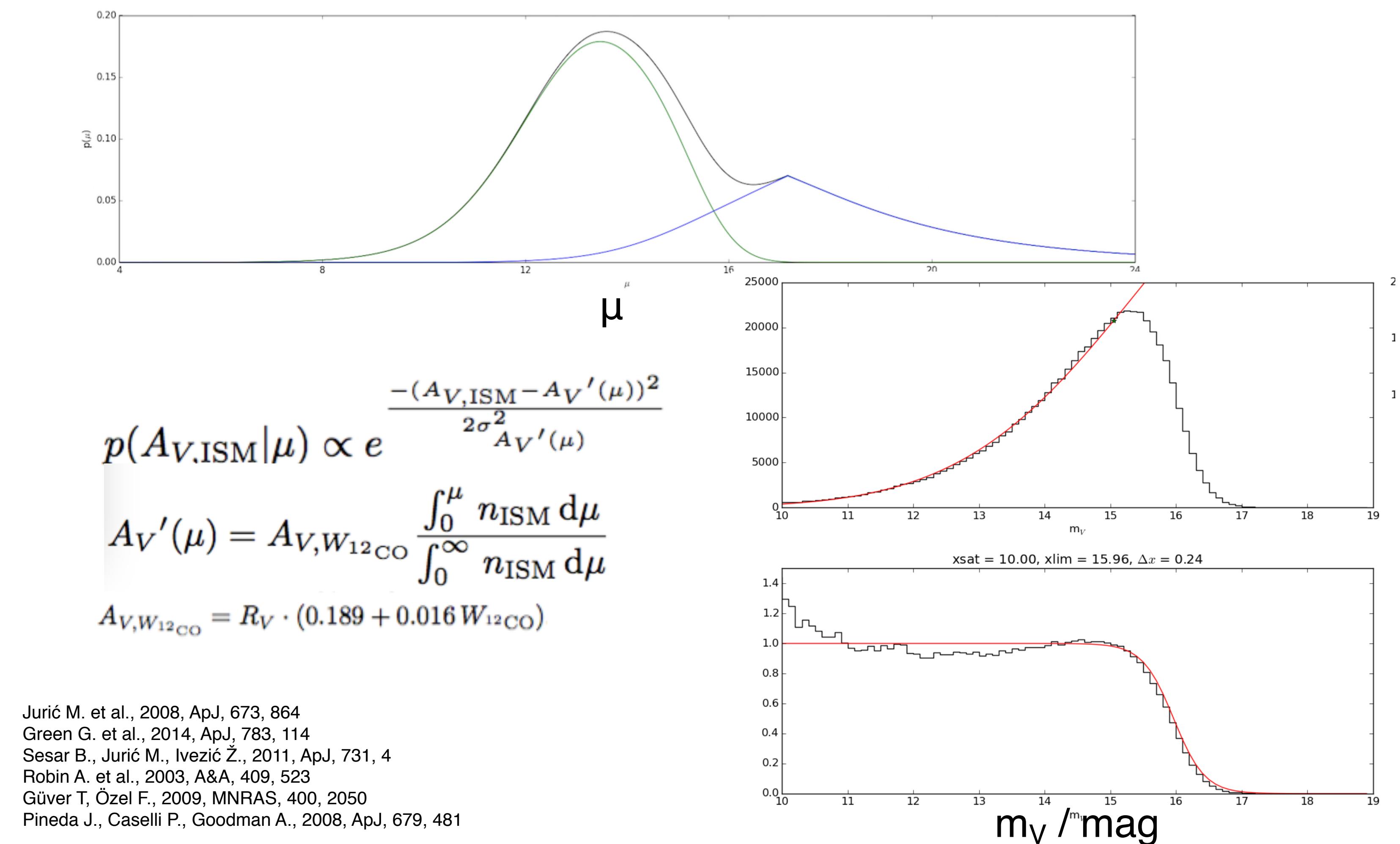
$$p(q=0) = 0.5$$

$$p(q>0) = \frac{0.5}{N}$$

- Kroupa P., 2001, MNRAS, 322, 231
 Green G.. et al., 2014, ApJ, 783, 114
 Bell C. et al., 2014, MNRAS, 445, 3496
 Dotter A. et al., 2008, ApJS, 178, 89
 Allard F., Homeier D., Freytag B., 2011, ASPCS, 448, 91

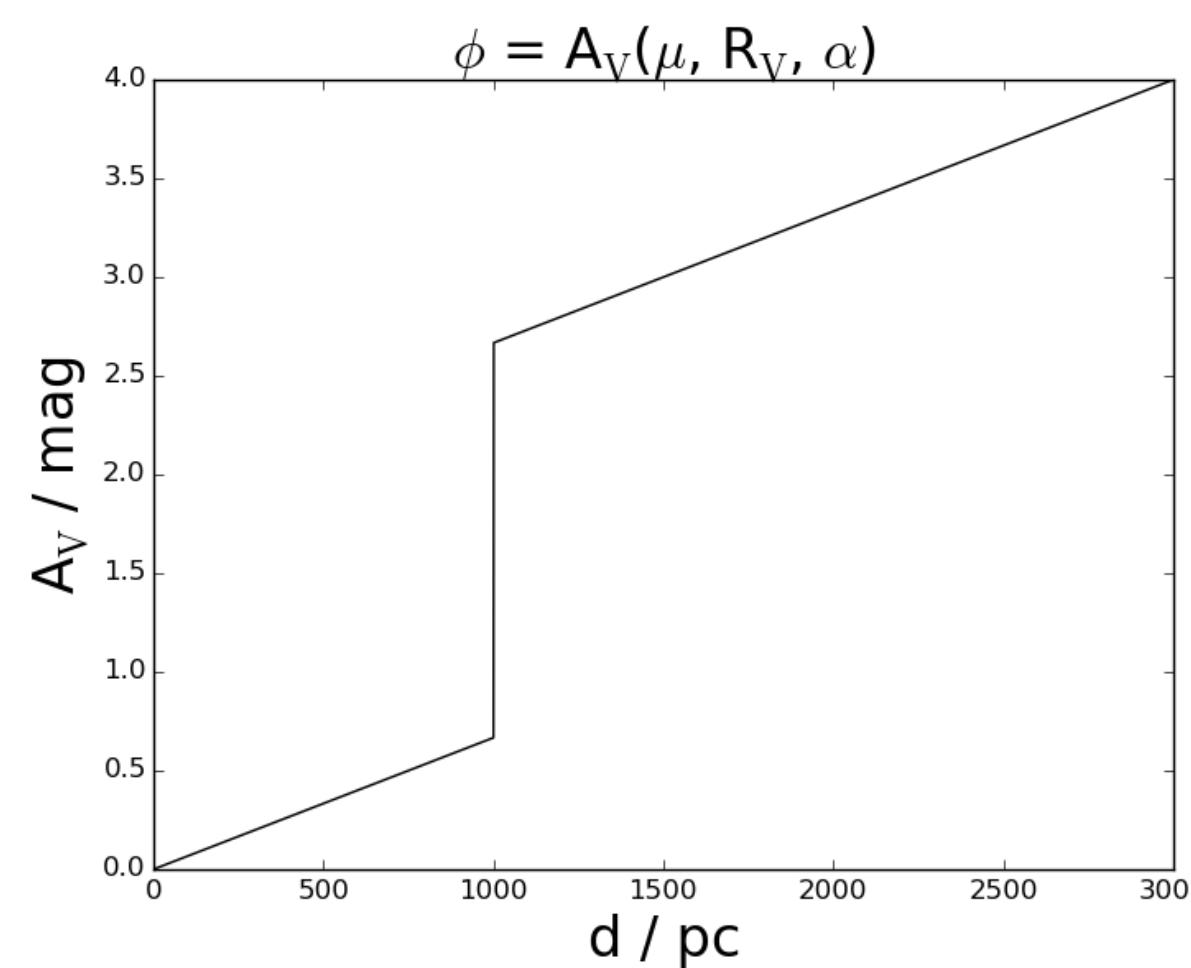
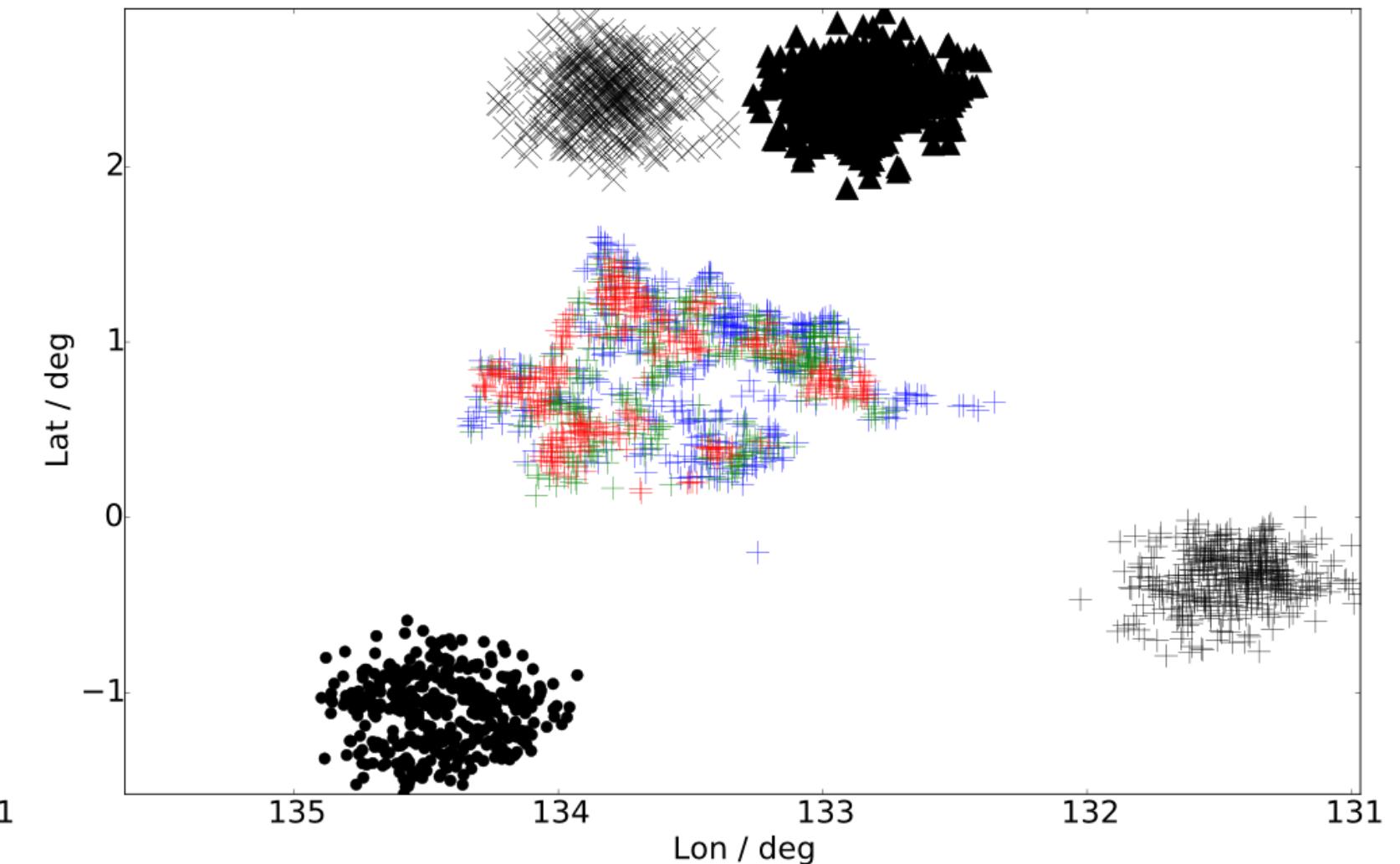
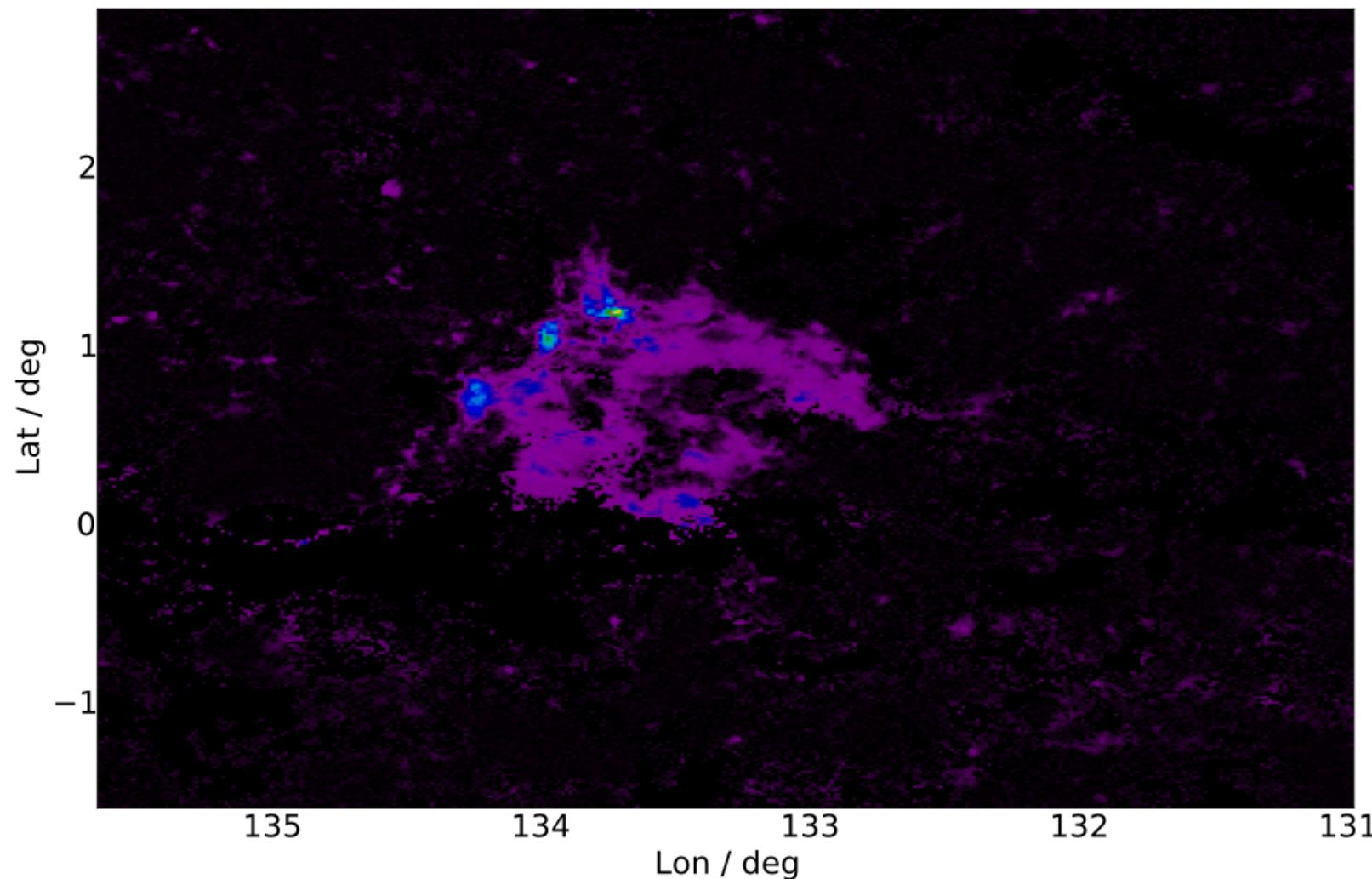
3D Extinction – Bayesian

$$p(\phi|\{\mathbf{D}\}) = \prod_i \int \int \frac{p(\mathbf{D}_i|\phi, \mu, \Theta) p(\phi, \mu, \Theta)}{p(\mathbf{D}_i)} d\Theta d\mu$$



3D Extinction – Bayesian

$$p(\phi|\{\mathbf{D}\}) = \prod_i \iint \frac{p(\mathbf{D}_i|\phi, \mu, \Theta) p(\phi, \mu, \Theta)}{p(\mathbf{D}_i)} d\Theta d\mu$$

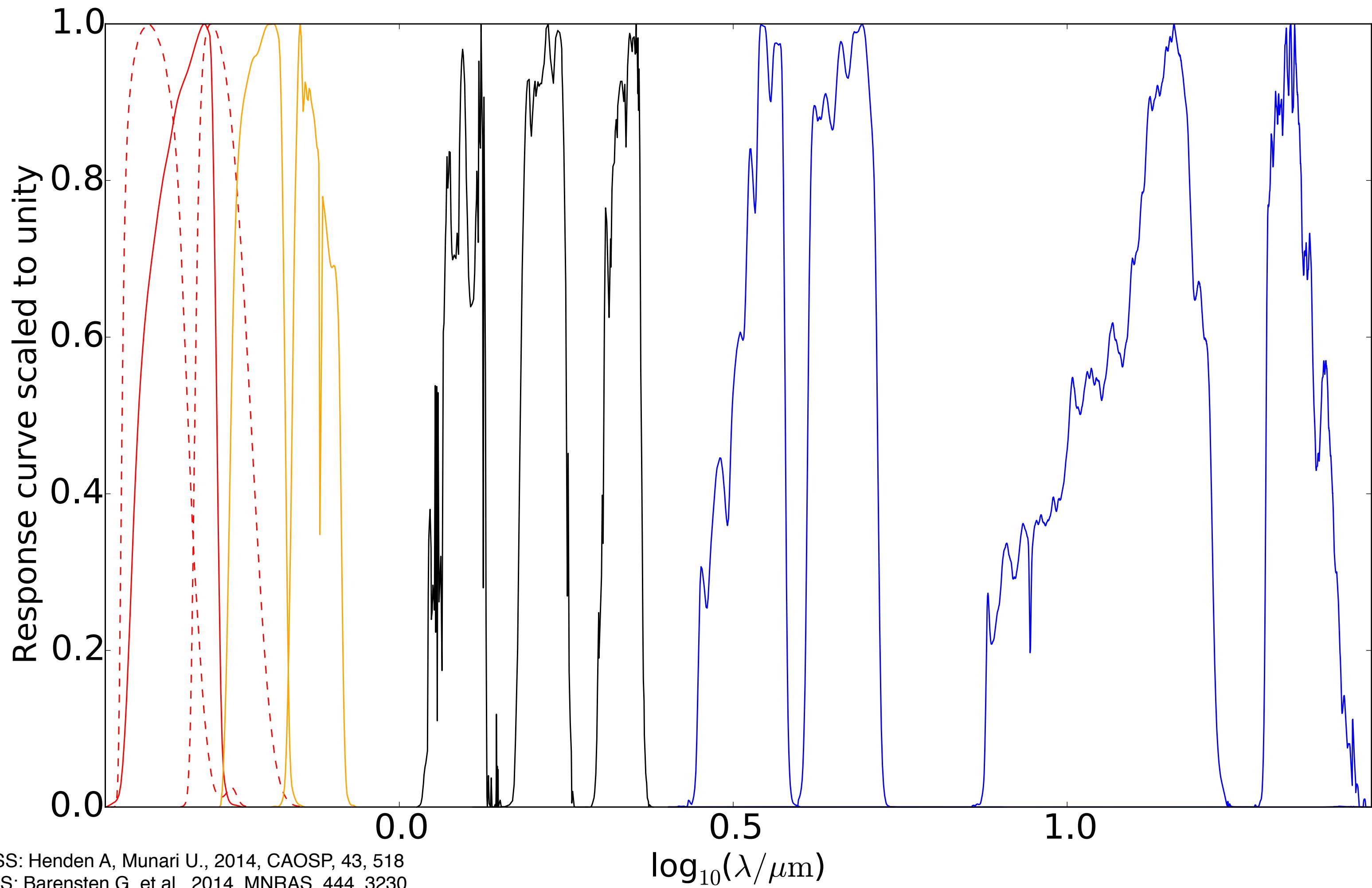


3D Extinction - RESULTS

- Just kidding, no results yet
- The answer is probably 42, or something

Symmetric Probabilistic Catalogue Matching - Intro

APASS; APASS+IPHAS; 2MASS; WISE



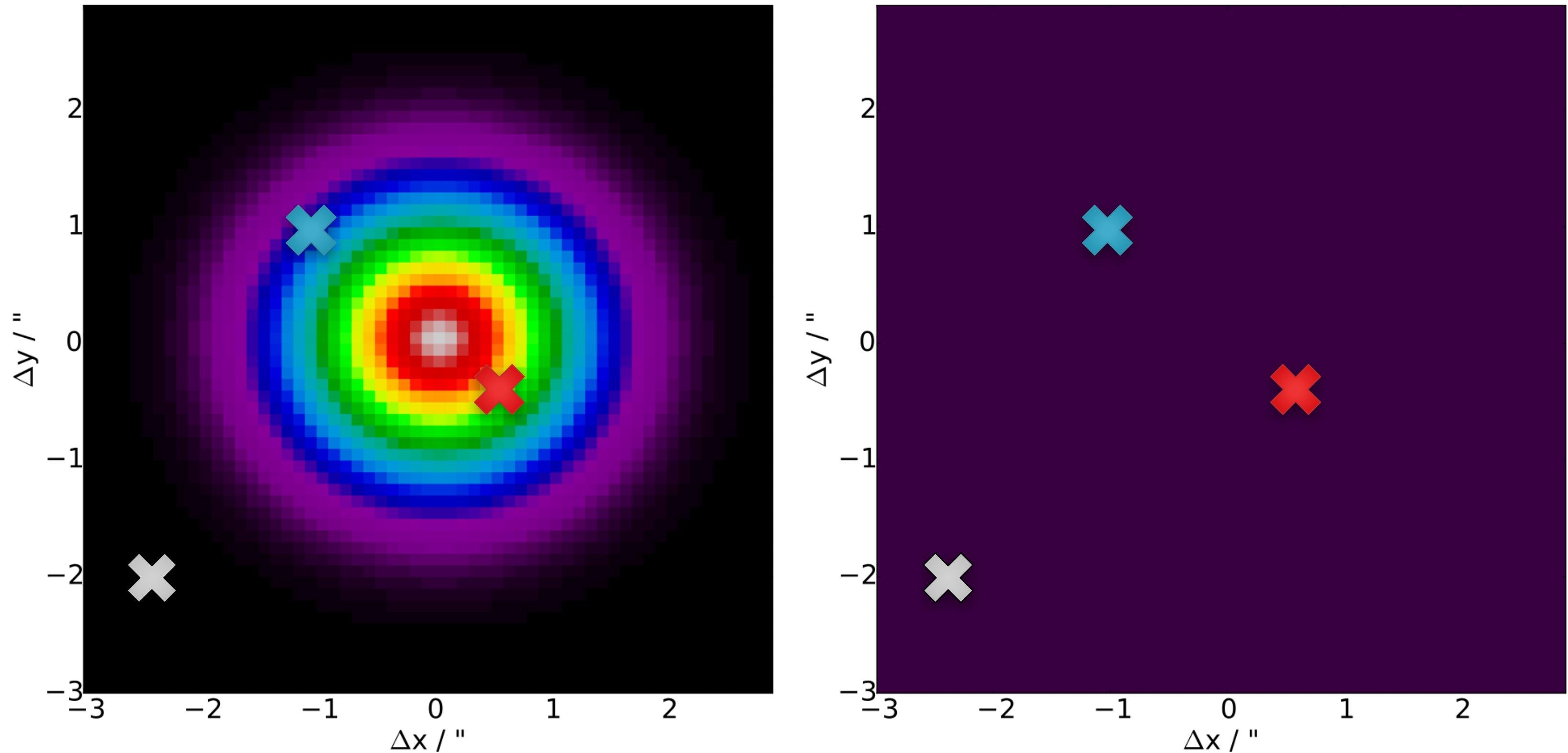
APASS: Henden A, Munari U., 2014, CAOSP, 43, 518

IPHAS: Barensten G. et al., 2014, MNRAS, 444, 3230

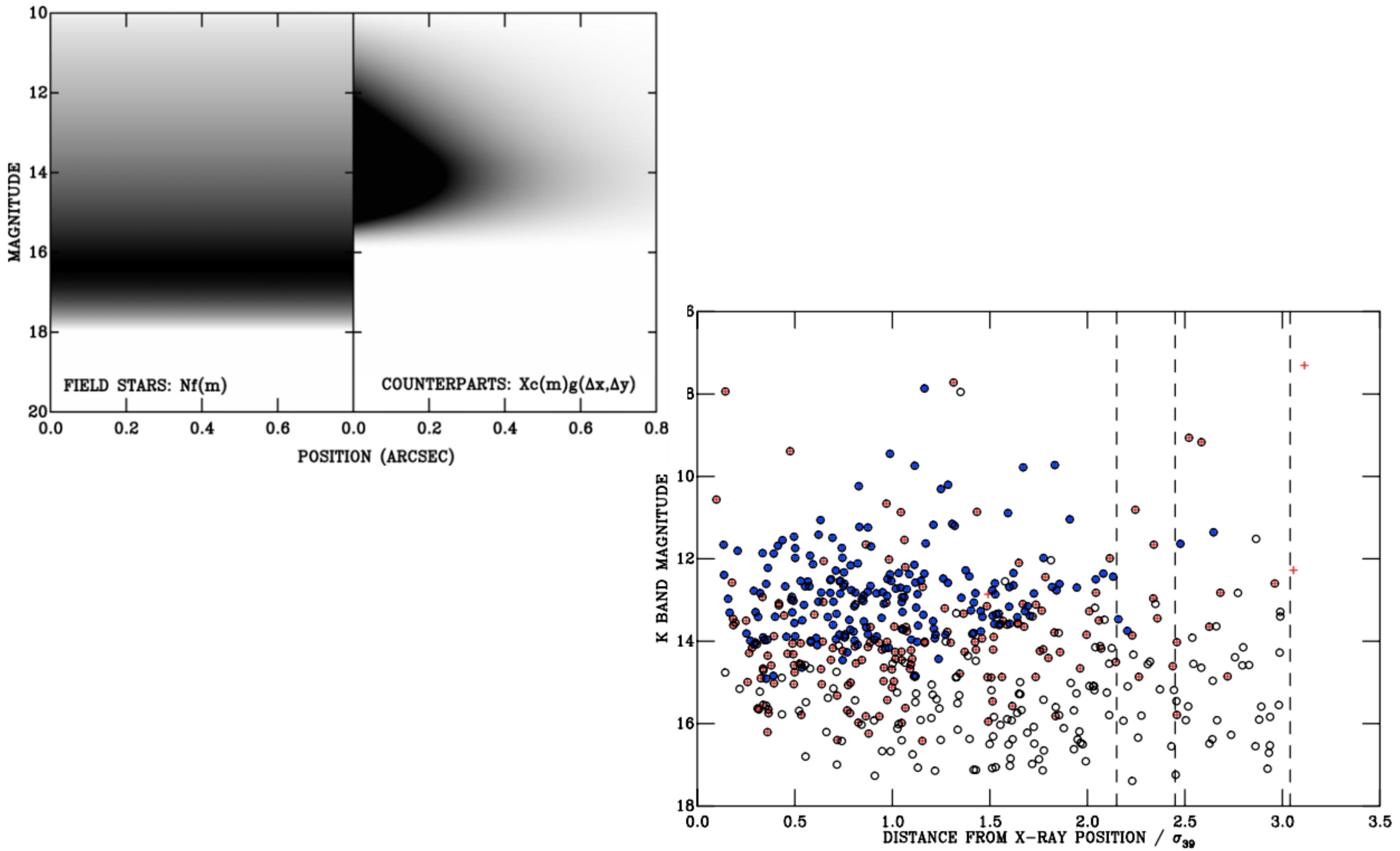
2MASS: Skrutskie M. F. et al., 2006, AJ, 131, 1163

WISE: Wright E. L. et al., 2010, AJ, 140, 1868

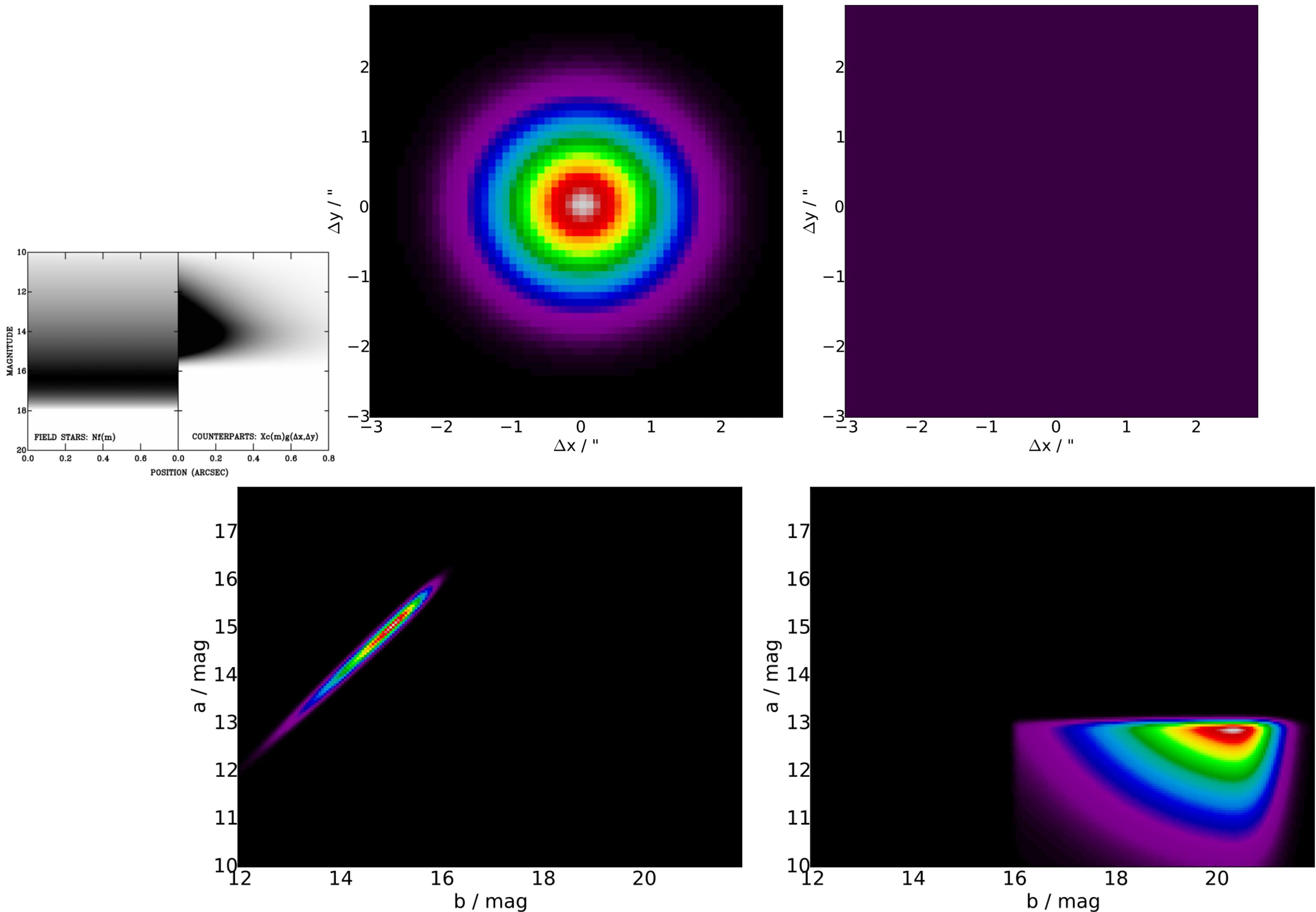
SPCMatching - Intro



SPCMatching – Asymmetry



SPCMatching – Symmetrisation



SPCMatching – functions

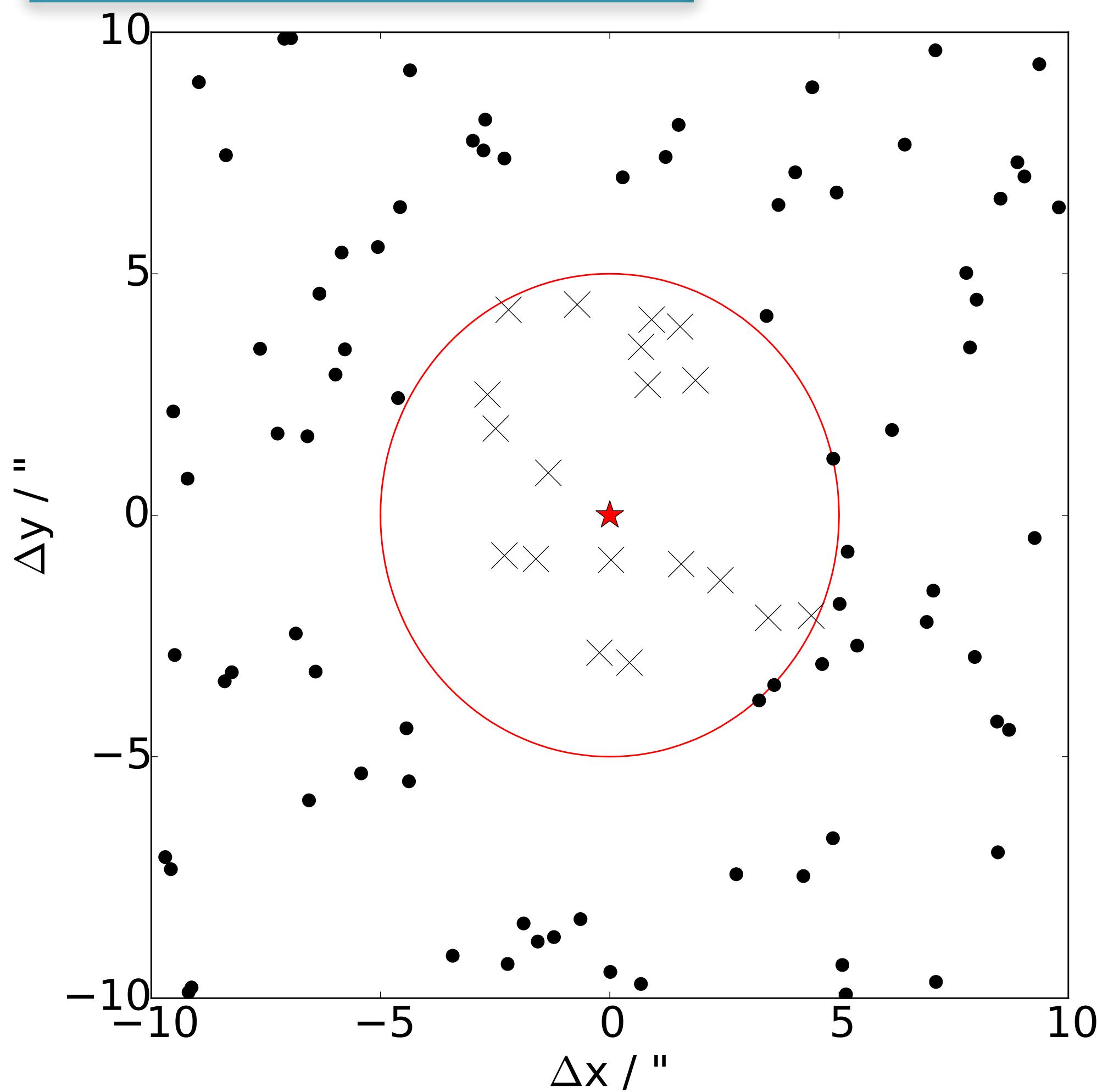
$$p(\sigma, \lambda, M | \gamma, \phi) = K \prod_{\delta \notin \sigma \cap \delta \in \gamma} N_\gamma f_\gamma(m_\delta) \prod_{\omega \notin \lambda \cap \omega \in \phi} N_\phi f_\phi(m_\omega) \prod_{i=1}^M N_C G(\Delta x_{\sigma_i \lambda_i}, \Delta y_{\sigma_i \lambda_i}) p(m_{\sigma_i}, m_{\lambda_i})$$

Normalisation Field star magnitude distribution and number density Counterpart position distribution and number density Counterpart magnitude distribution

The diagram illustrates the components of the probability function. Four blue arrows point from labels below the equation to specific terms: the first arrow points to the normalization factor K ; the second to the product over field stars $\prod_{\delta \notin \sigma \cap \delta \in \gamma} N_\gamma f_\gamma(m_\delta)$; the third to the product over counterparts $\prod_{i=1}^M N_C G(\Delta x_{\sigma_i \lambda_i}, \Delta y_{\sigma_i \lambda_i}) p(m_{\sigma_i}, m_{\lambda_i})$; and the fourth to the counterpart magnitude distribution term $p(m_{\sigma_i}, m_{\lambda_i})$.

SPCMatching – functions: f

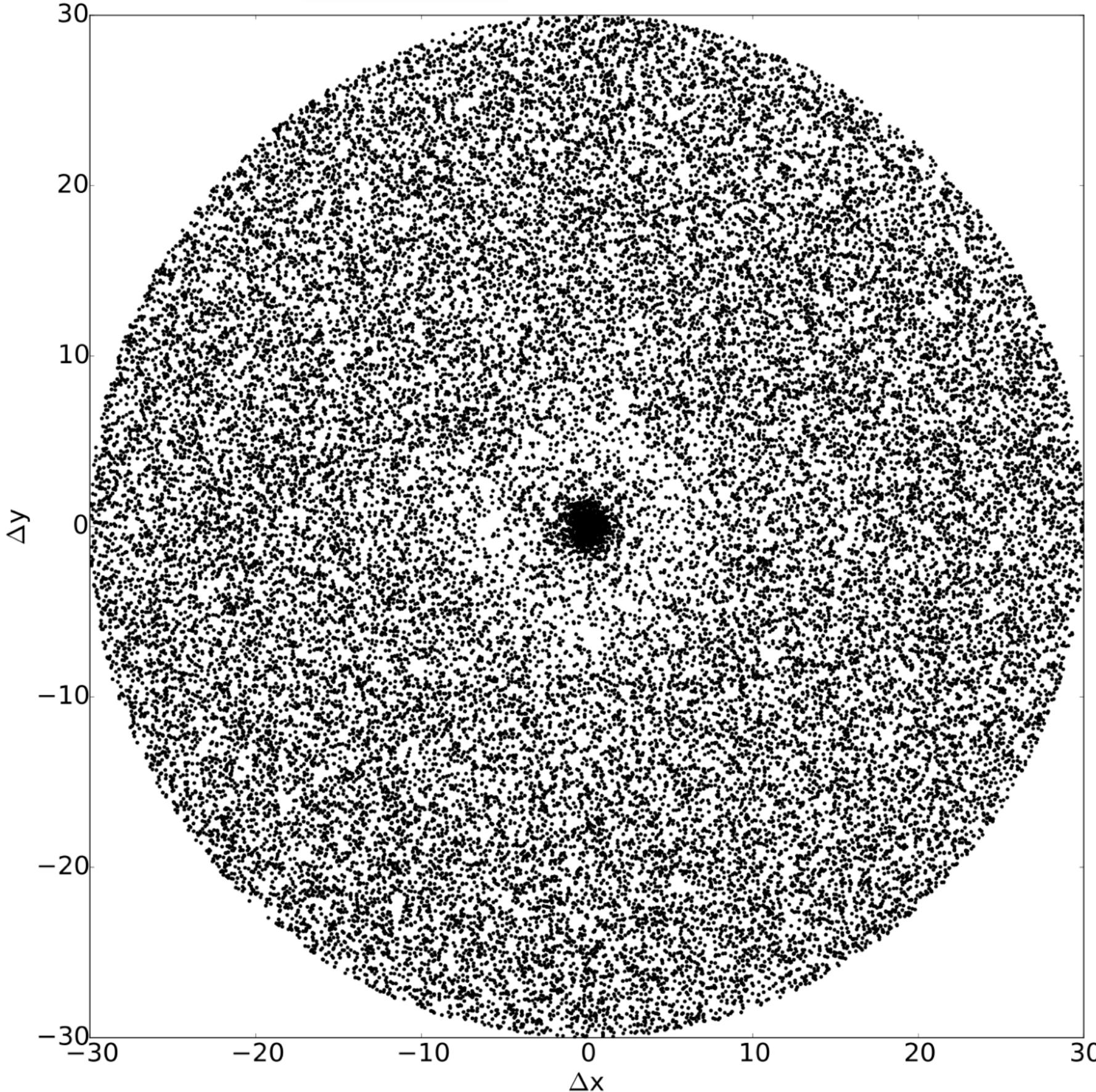
$$p(\sigma, \lambda, M | \gamma, \phi) = K \left[\prod_{\delta \notin \sigma \cap \delta \in \gamma} N_\gamma f_\gamma(m_\delta) \prod_{\omega \notin \lambda \cap \omega \in \phi} N_\phi f_\phi(m_\omega) \right] \prod_{i=1}^M N_C G(\Delta x_{\sigma_i \lambda_i}, \Delta y_{\sigma_i \lambda_i}) p(m_{\sigma_i}, m_{\lambda_i})$$



SPCMatching – functions: c

$$p(\sigma, \lambda, M | \gamma, \phi) = K \prod_{\delta \notin \sigma \cap \delta \in \gamma} N_\gamma f_\gamma(m_\delta) \prod_{\omega \notin \lambda \cap \omega \in \phi} N_\phi f_\phi(m_\omega) \prod_{i=1}^M N_C G(\Delta x_{\sigma_i \lambda_i}, \Delta y_{\sigma_i \lambda_i}) p(m_{\sigma_i}, m_{\lambda_i})$$

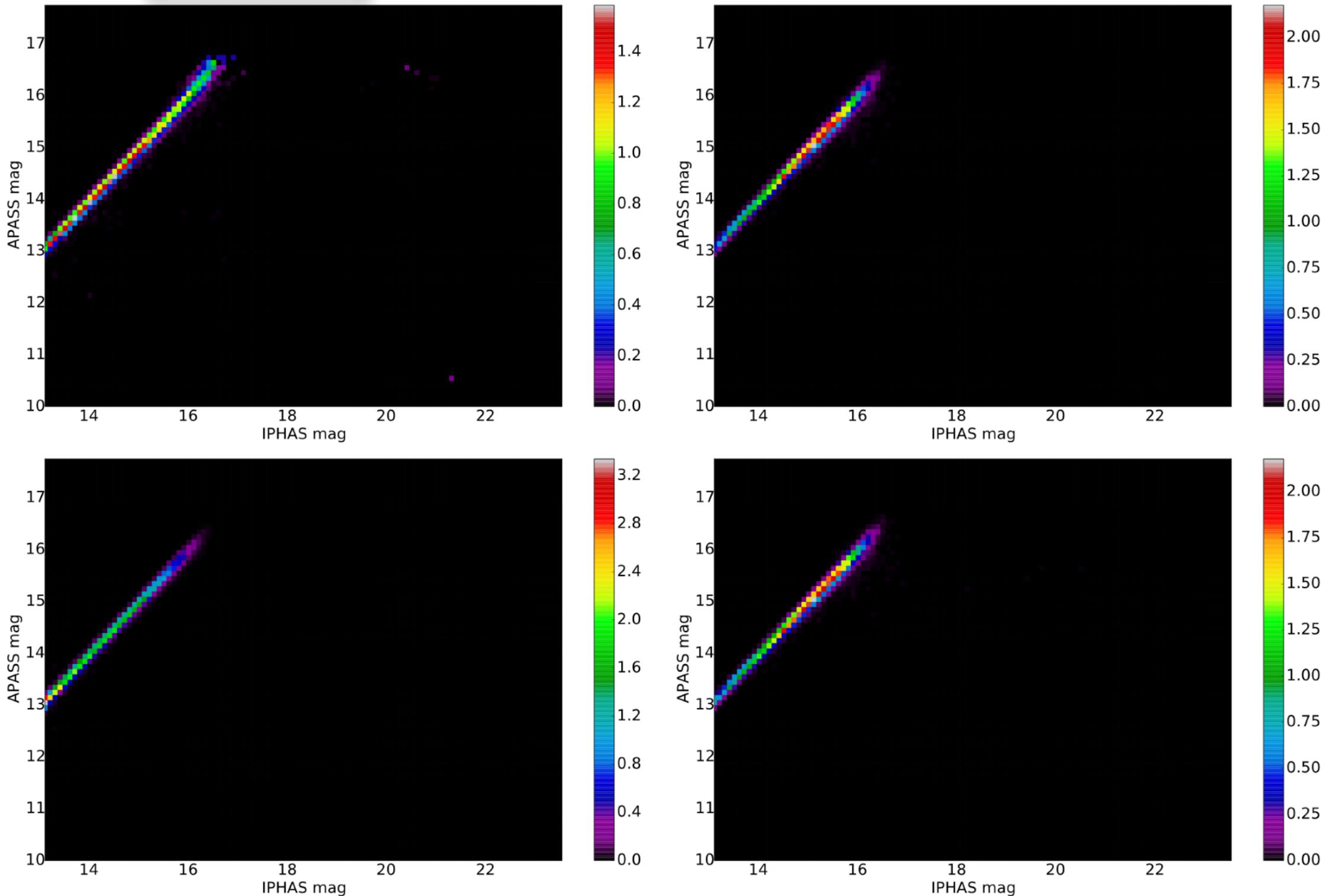
$$p(m_k, m_l) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} p(m_k | m_a) p(m_l | m_b) c(m_a, m_b) dm_a dm_b$$



SPCMatching – functions: c

$$p(\sigma, \lambda, M | \gamma, \phi) = K \prod_{\delta \notin \sigma \cap \delta \in \gamma} N_\gamma f_\gamma(m_\delta) \prod_{\omega \notin \lambda \cap \omega \in \phi} N_\phi f_\phi(m_\omega) \prod_{i=1}^M N_C G(\Delta x_{\sigma_i \lambda_i}, \Delta y_{\sigma_i \lambda_i}) p(m_{\sigma_i}, m_{\lambda_i})$$

$$p(m_k, m_l) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} p(m_k | m_a) p(m_l | m_b) c(m_a, m_b) dm_a dm_b$$



$$Z_{c,\beta} c_\gamma(m|m_\beta) = Z_\beta b_\beta(m) e^{A_\beta N_\phi F_\phi(m)} - (1 - Z_{c,\beta} C(m|m_\beta)) A_\beta N_\phi f_\phi(m)$$

SPCMatching – functions: g

$$p(\sigma, \lambda, M | \gamma, \phi) = K \prod_{\delta \notin \sigma \cap \delta \in \gamma} N_\gamma f_\gamma(m_\delta) \prod_{\omega \notin \lambda \cap \omega \in \phi} N_\phi f_\phi(m_\omega)$$

$$\prod_{i=1}^M N_C G(\Delta x_{\sigma_i \lambda_i}, \Delta y_{\sigma_i \lambda_i}) p(m_{\sigma_i}, m_{\lambda_i})$$

$$G(\Delta x_{kl}) = \int_{-\infty}^{+\infty} f(x_0 - x_k) g(x_l - x_0) dx_0$$

↓

$$G(\Delta x_{kl}) = \int_{-\infty}^{+\infty} f(\Delta x - x) g(x) dx$$

×

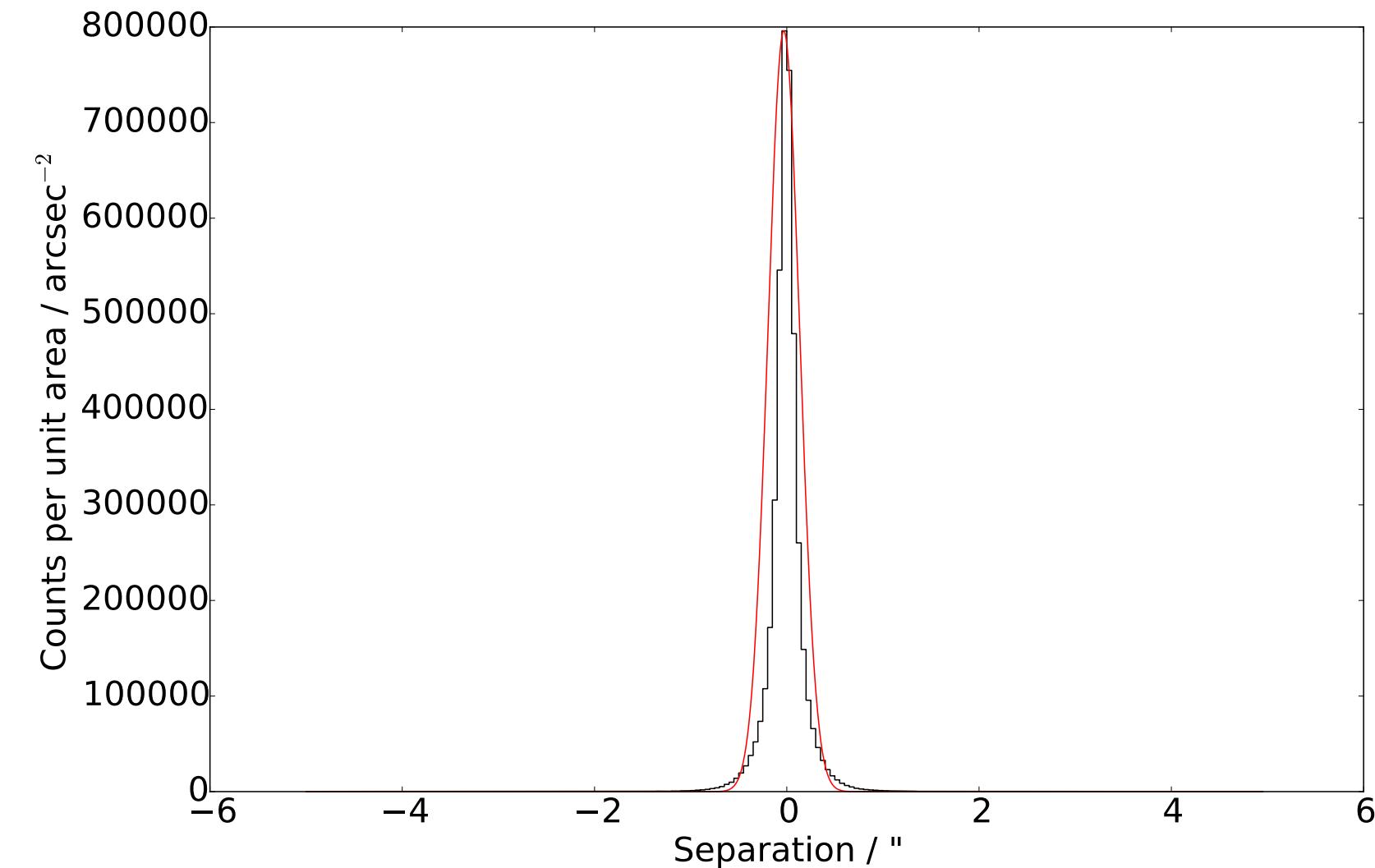
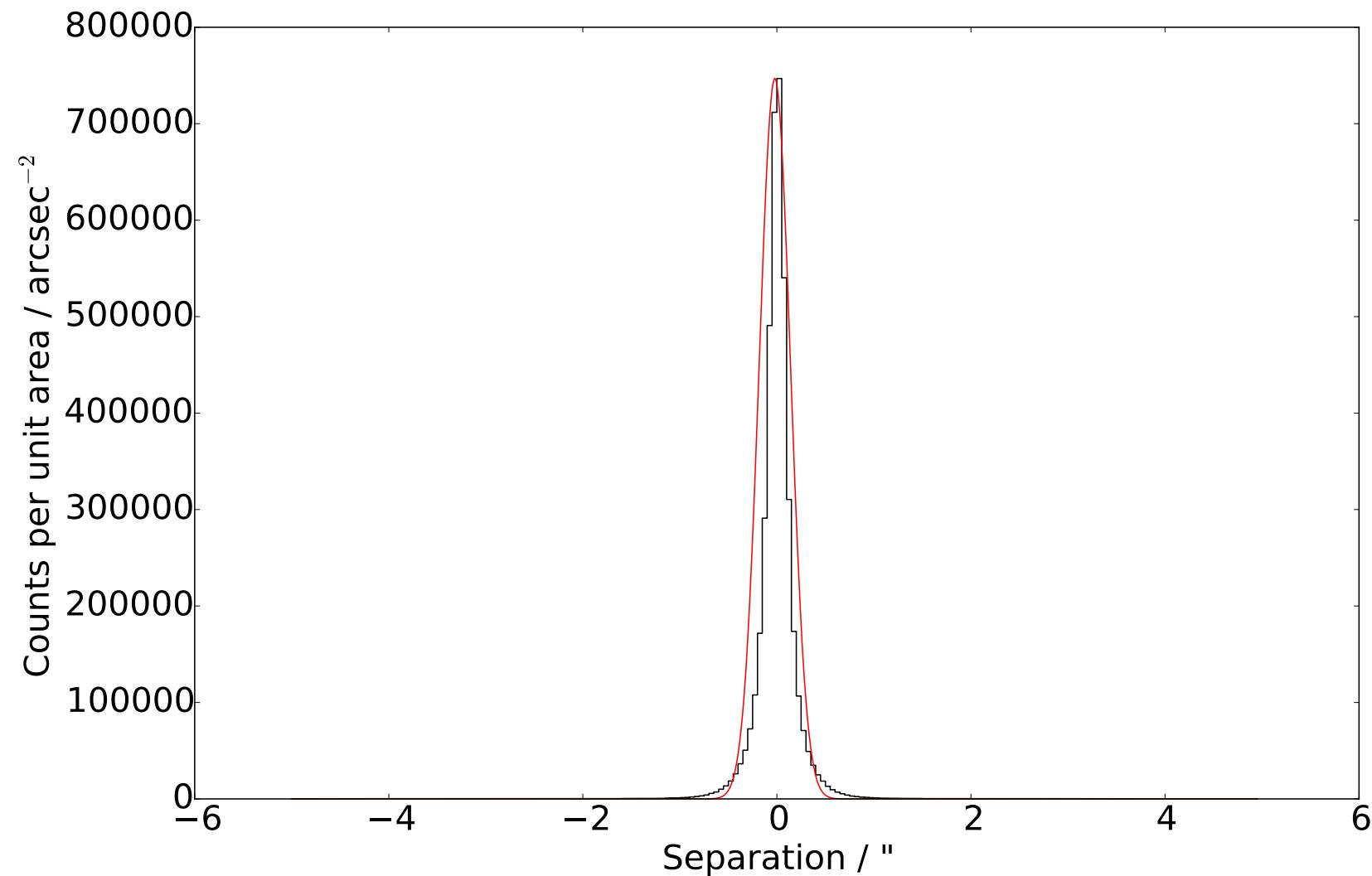
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SPCMatching – functions: g

$$p(\sigma, \lambda, M | \gamma, \phi) = K \prod_{\delta \notin \sigma \cap \delta \in \gamma} N_\gamma f_\gamma(m_\delta) \prod_{\omega \notin \lambda \cap \omega \in \phi} N_\phi f_\phi(m_\omega)$$

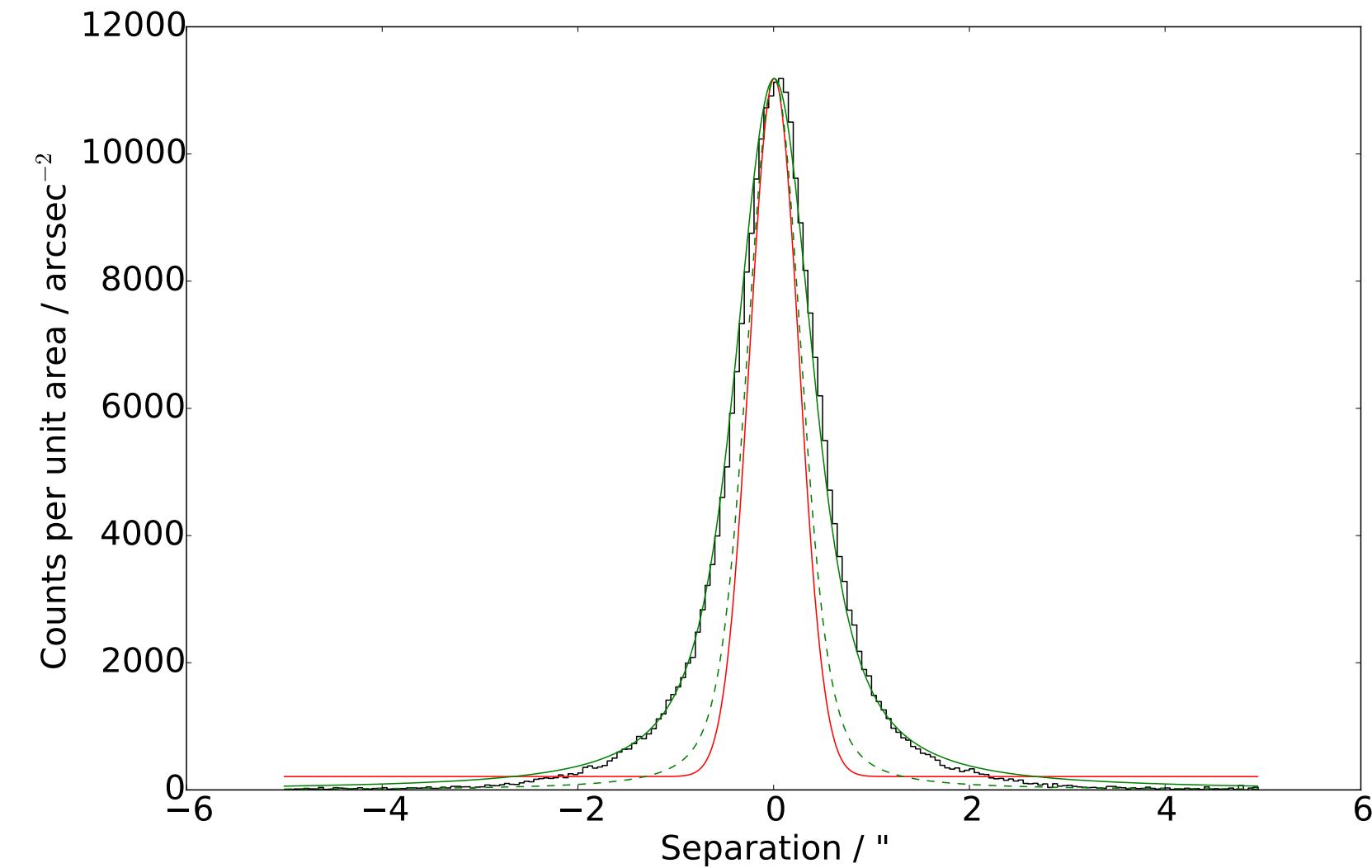
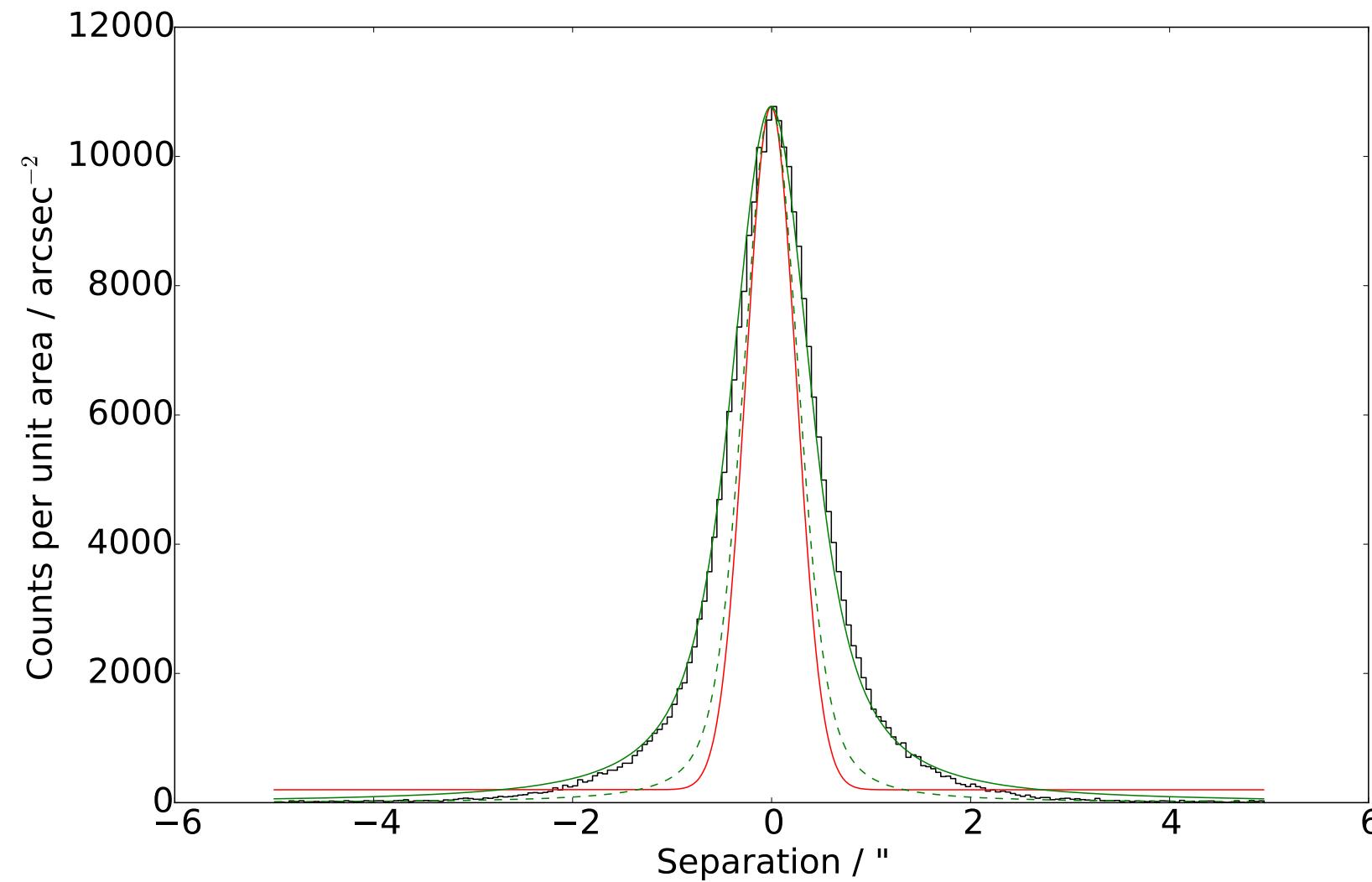
$$\prod_{i=1}^M N_C G(\Delta x_{\sigma_i \lambda_i}, \Delta y_{\sigma_i \lambda_i}) p(m_{\sigma_i}, m_{\lambda_i})$$



SPCMatching – functions: g

$$p(\sigma, \lambda, M | \gamma, \phi) = K \prod_{\delta \notin \sigma \cap \delta \in \gamma} N_\gamma f_\gamma(m_\delta) \prod_{\omega \notin \lambda \cap \omega \in \phi} N_\phi f_\phi(m_\omega)$$

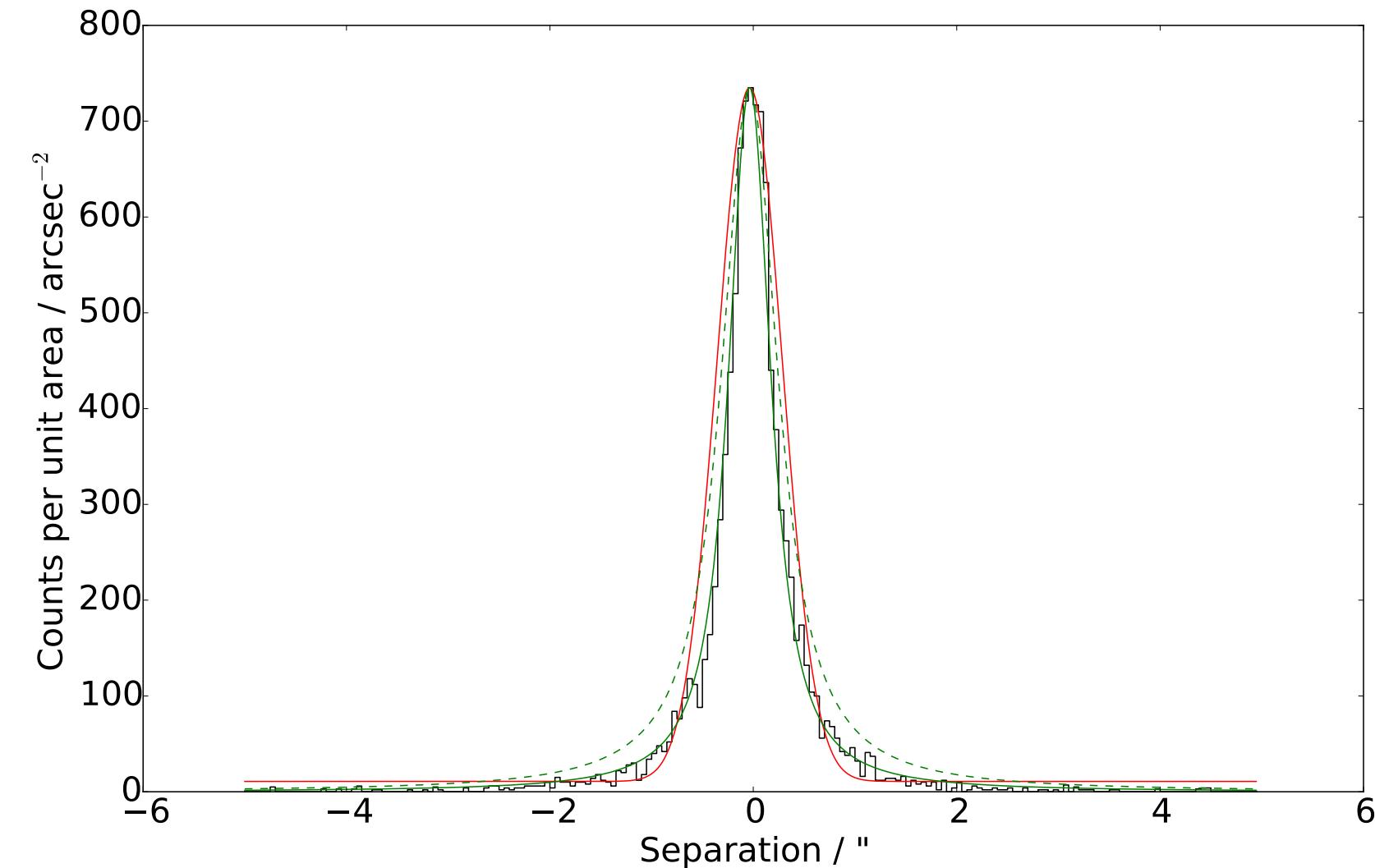
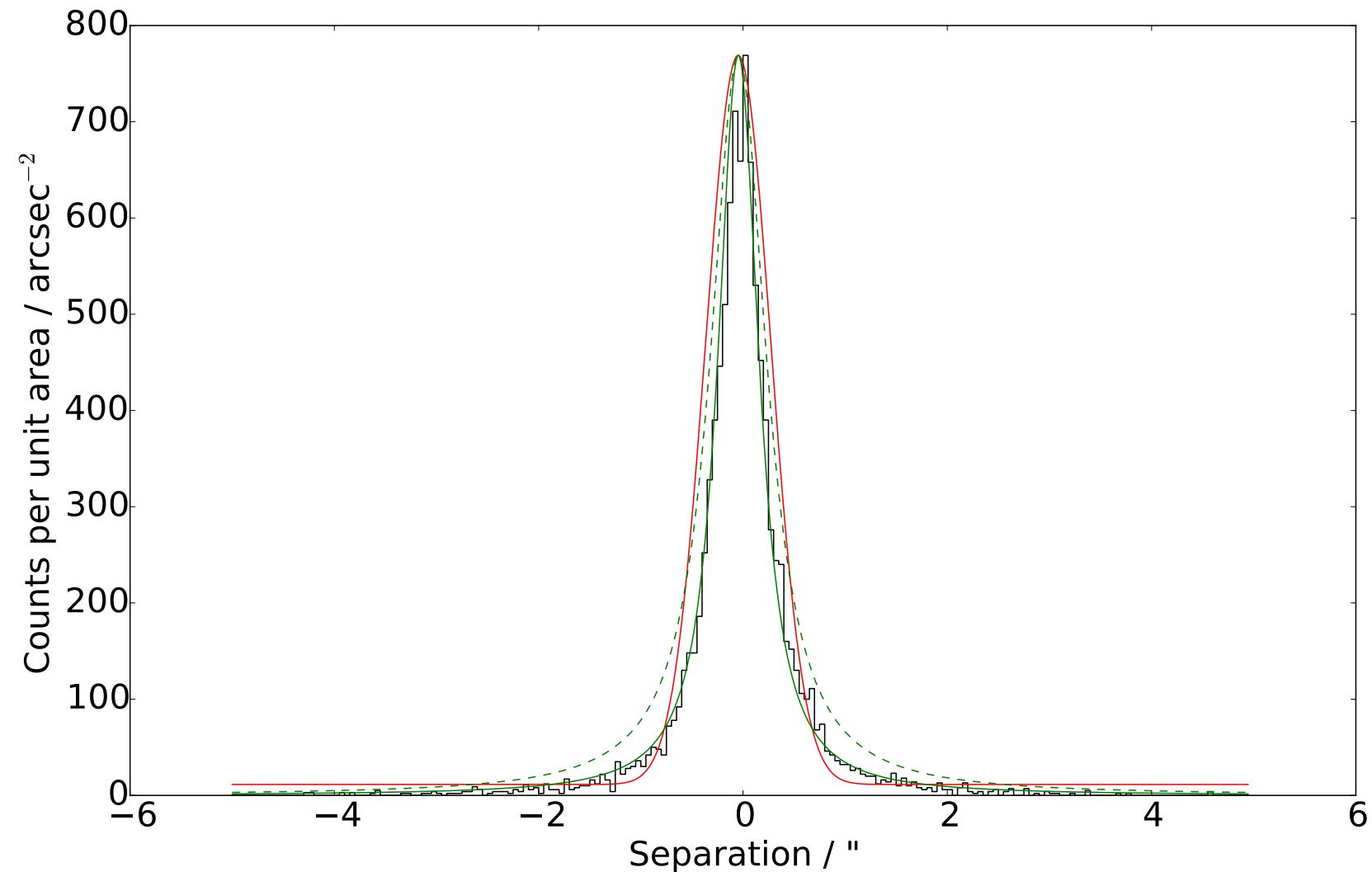
$$\prod_{i=1}^M N_C G(\Delta x_{\sigma_i \lambda_i}, \Delta y_{\sigma_i \lambda_i}) p(m_{\sigma_i}, m_{\lambda_i})$$



SPCMatching – functions: g

$$p(\sigma, \lambda, M | \gamma, \phi) = K \prod_{\delta \notin \sigma \cap \delta \in \gamma} N_\gamma f_\gamma(m_\delta) \prod_{\omega \notin \lambda \cap \omega \in \phi} N_\phi f_\phi(m_\omega)$$

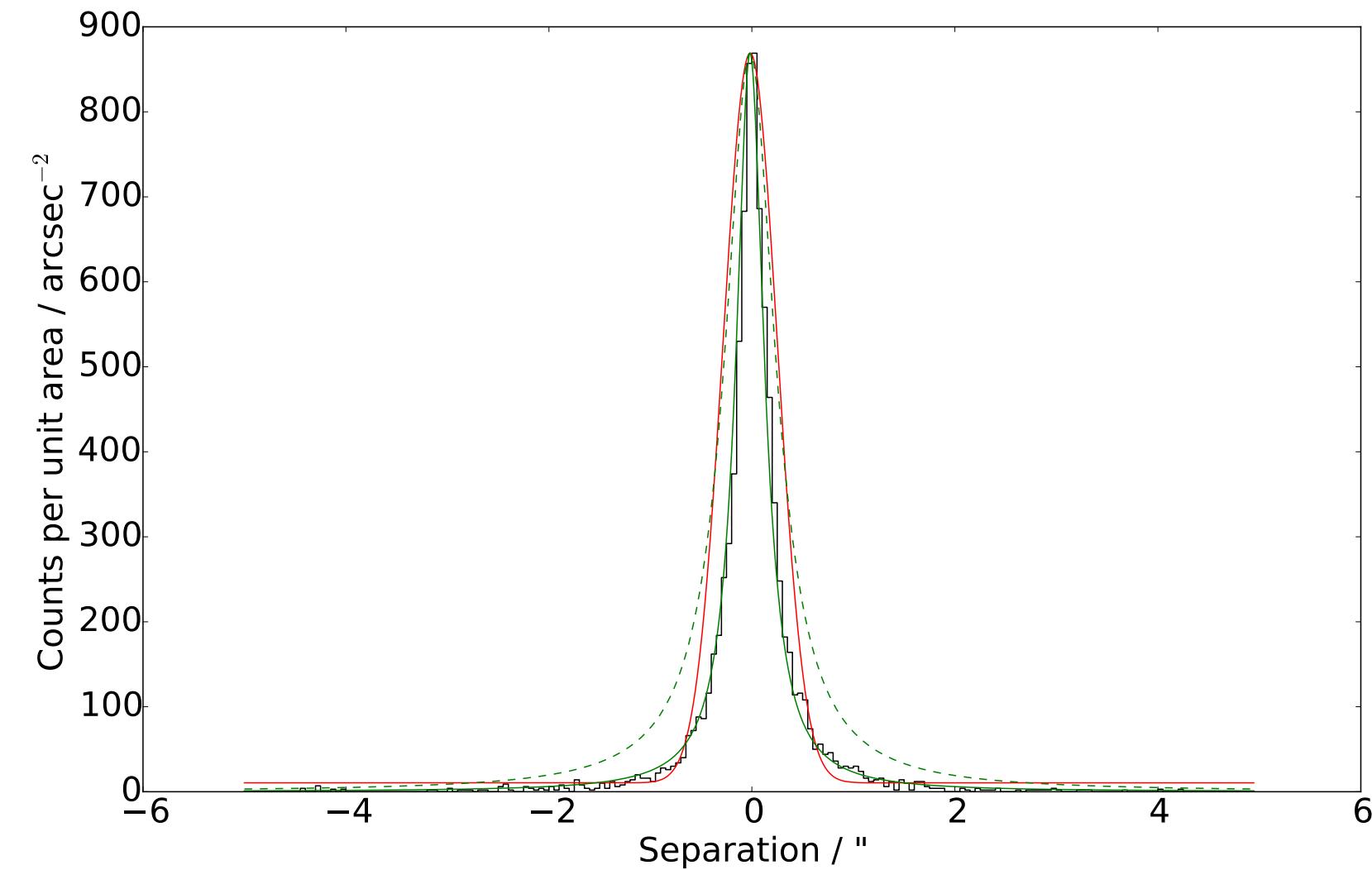
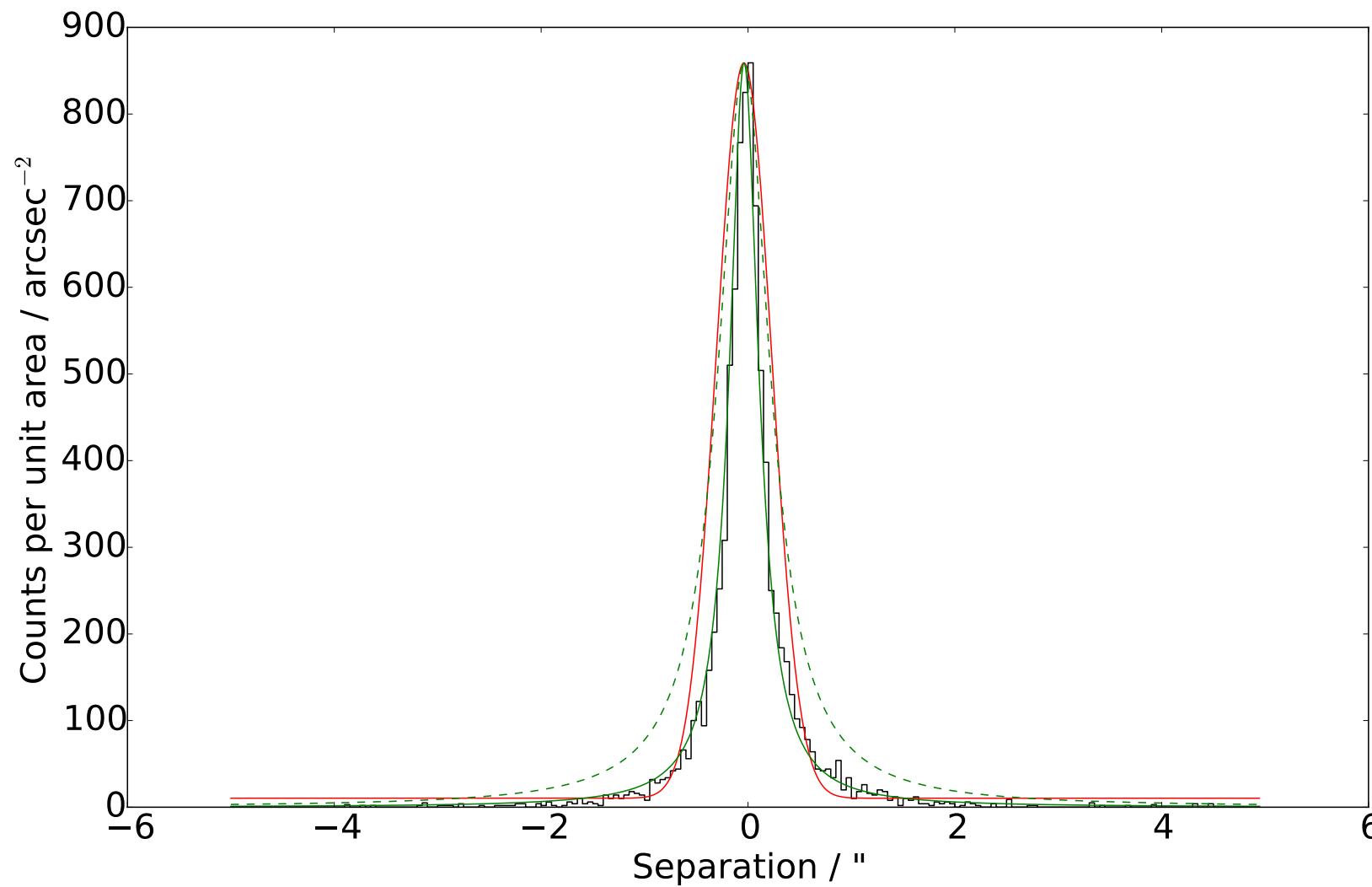
$$\prod_{i=1}^M N_C G(\Delta x_{\sigma_i \lambda_i}, \Delta y_{\sigma_i \lambda_i}) p(m_{\sigma_i}, m_{\lambda_i})$$



SPCMatching – functions: g

$$p(\sigma, \lambda, M | \gamma, \phi) = K \prod_{\delta \notin \sigma \cap \delta \in \gamma} N_\gamma f_\gamma(m_\delta) \prod_{\omega \notin \lambda \cap \omega \in \phi} N_\phi f_\phi(m_\omega)$$

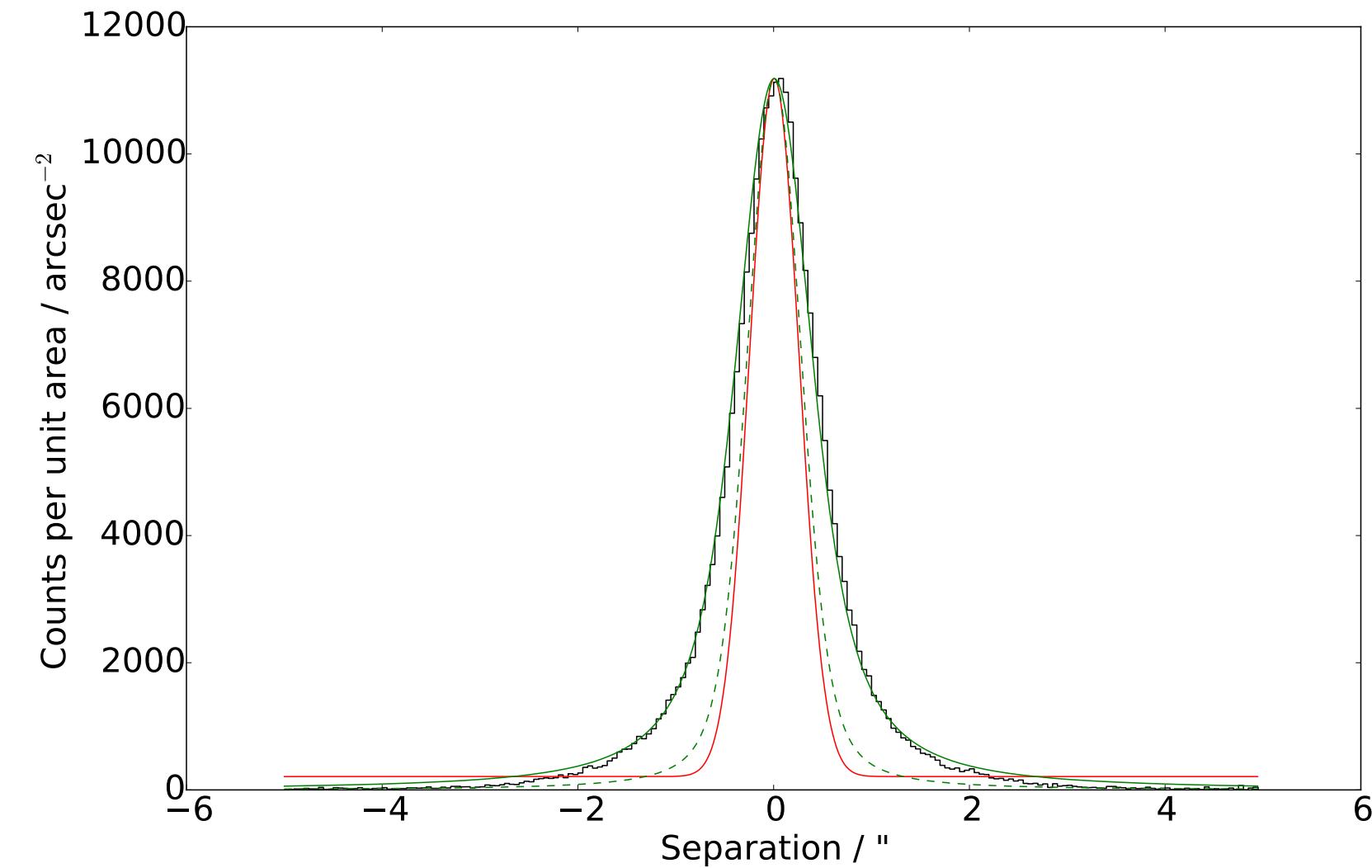
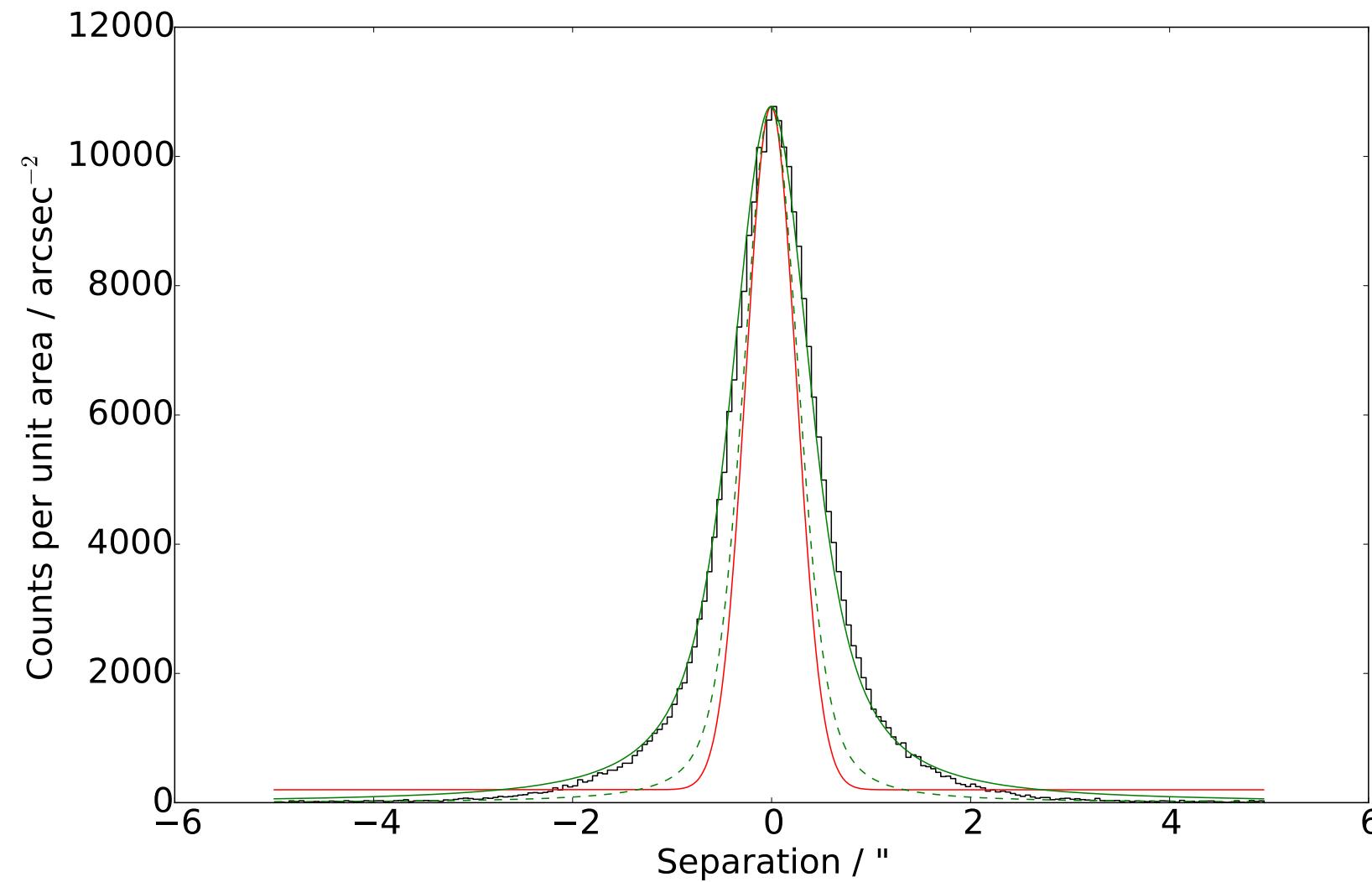
$$\prod_{i=1}^M N_C G(\Delta x_{\sigma_i \lambda_i}, \Delta y_{\sigma_i \lambda_i}) p(m_{\sigma_i}, m_{\lambda_i})$$



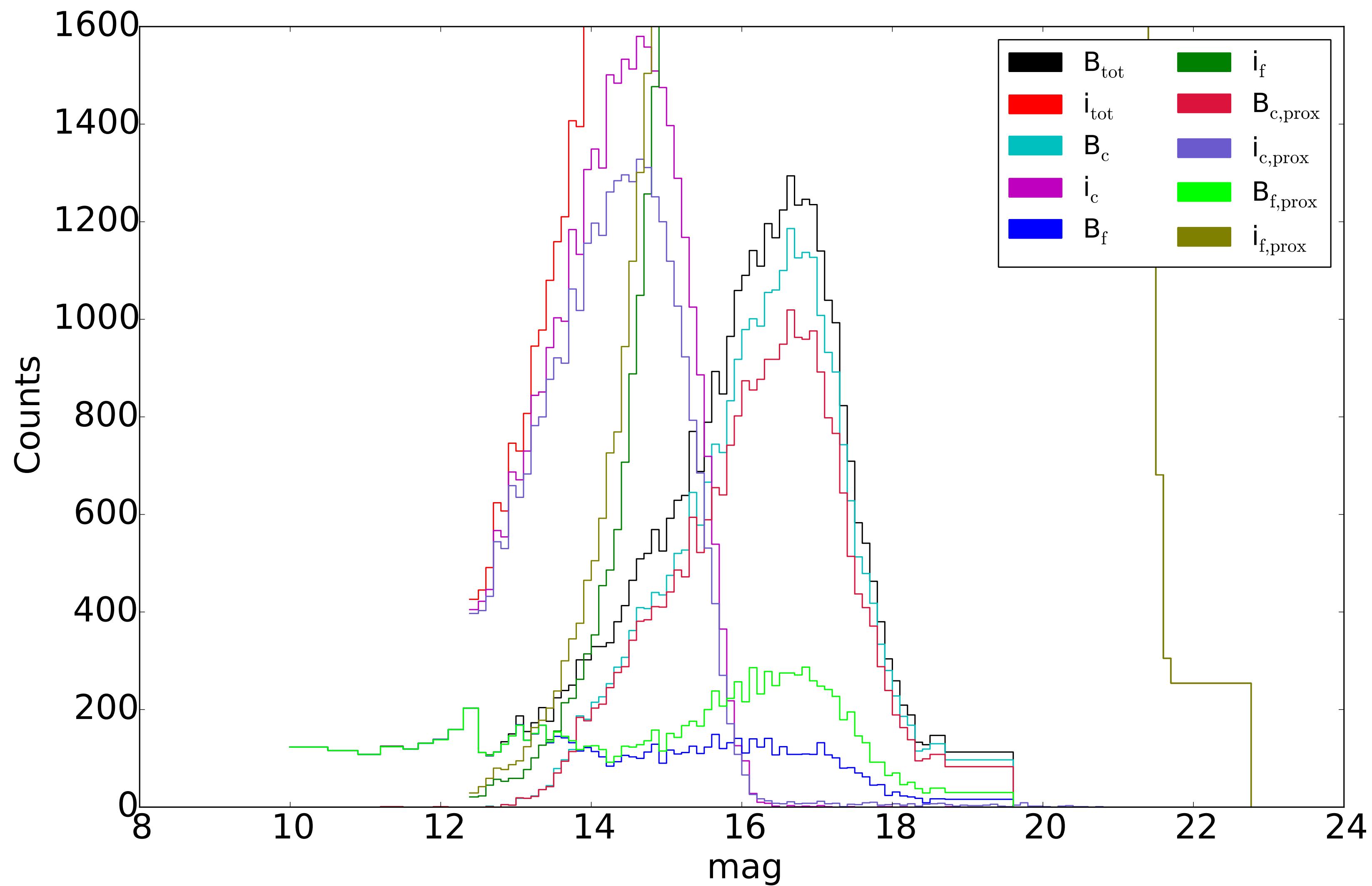
SPCMatching – functions: g

$$p(\sigma, \lambda, M | \gamma, \phi) = K \prod_{\delta \notin \sigma \cap \delta \in \gamma} N_\gamma f_\gamma(m_\delta) \prod_{\omega \notin \lambda \cap \omega \in \phi} N_\phi f_\phi(m_\omega)$$

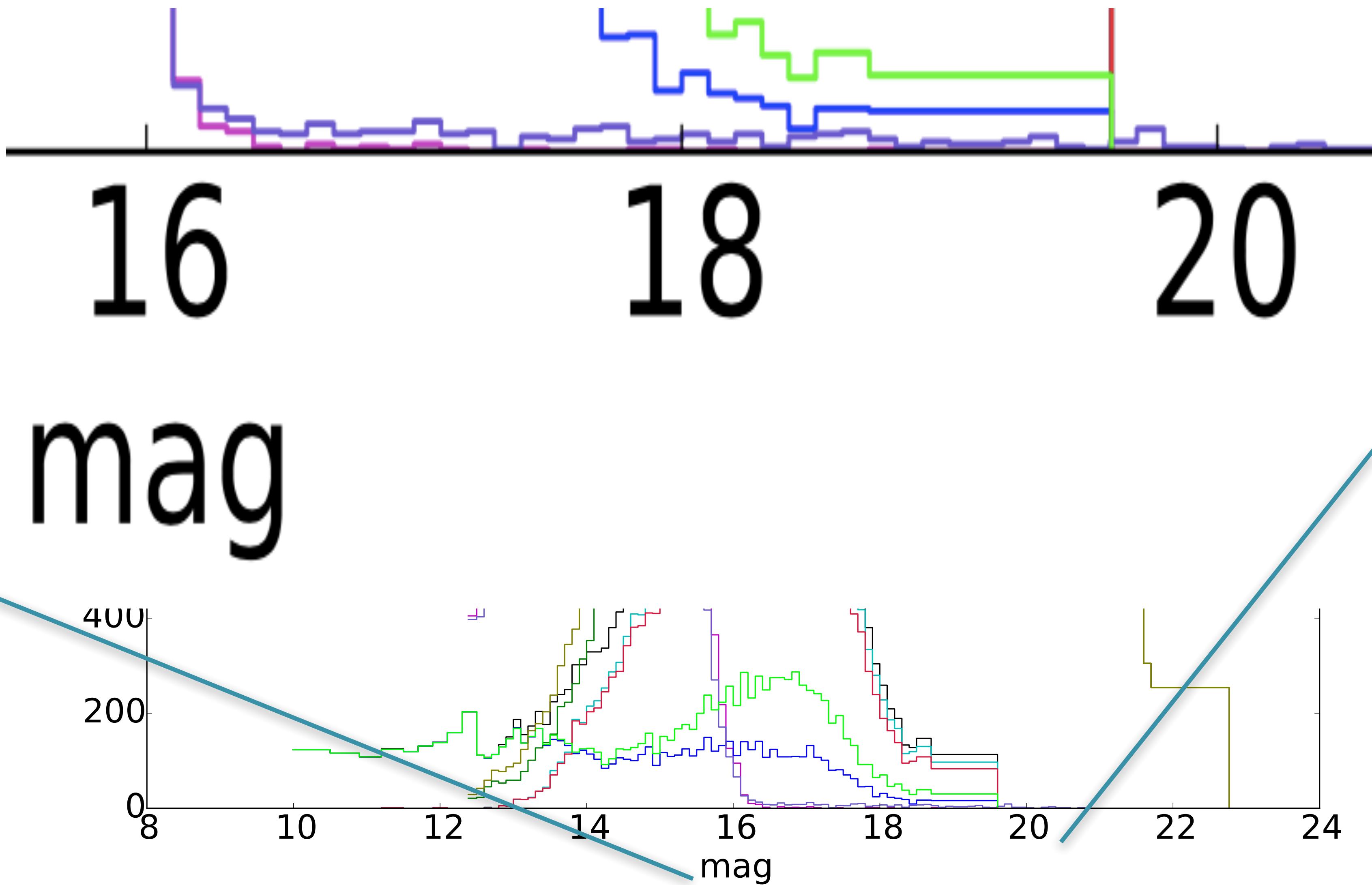
$$\prod_{i=1}^M N_C G(\Delta x_{\sigma_i \lambda_i}, \Delta y_{\sigma_i \lambda_i}) p(m_{\sigma_i}, m_{\lambda_i})$$



SPCMatching – Results



SPCMatching – Results



3D Extinction + Catalogue Matching Conclusions

- Powerful technique to analyse galactic structure
- Allows for kinematics and distances simultaneously
- Applicable to wide range of data sources, e.g., 2MASS+IPHAS
- Allows for probing of fundamental properties of the ISM, e.g., R_V
- Symmetrised method for more accurate catalogue matching
- Avoids faint star mismatches
- Allows for more reliable and distant photometric matches for poor quality data

