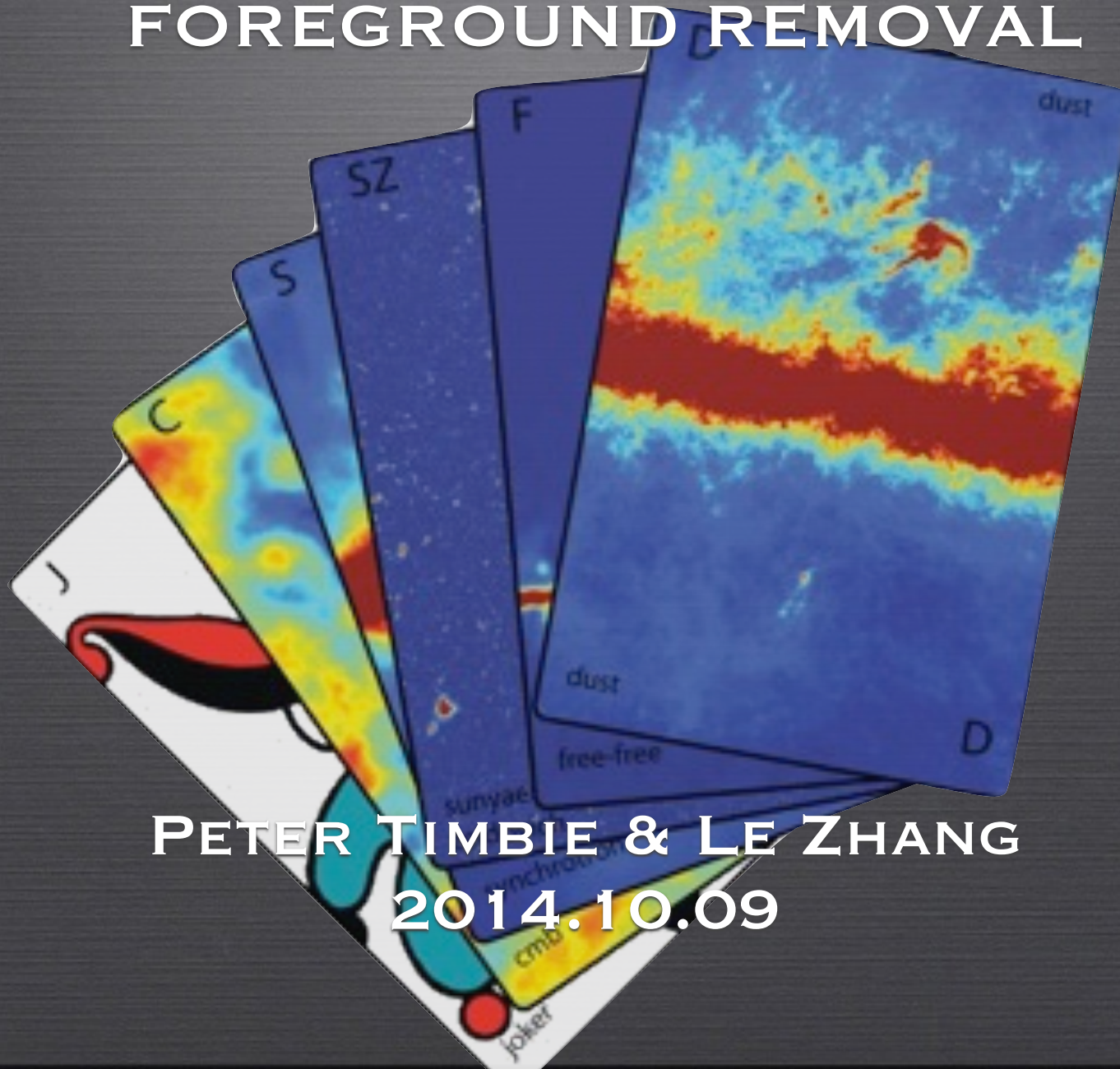


# BAYESIAN SEMI-BLIND COMPONENT SEPARATION FOR FOREGROUND REMOVAL



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# CMB RECONSTRUCTION: ICA APPROACH

- ★ **POLARized Expectation-Maximization Independent Component Analysis**
- ★ adaptation to polarization of the Spectral Matching ICA (SMICA) algorithm [Delabrouille *et al.* 2003]

$$R_Y = AR_S A^T + R_N$$

- ★ sets of parameters to extract, several levels of a priori

**BLIND**

$$\theta_{\text{blind}}(b) = \{A, R_s(b), \text{diag}(R_n(b))\}$$

**CMB-FIXED**

$$\theta_{\text{CMB-fixed}}(b) = \{A_{i,j \neq \text{CMB}}, R_s(b), \text{diag}(R_n(b))\}$$

**A-FIXED**

$$\theta_{\text{A-fixed}}(b) = \{R_s(b), \text{diag}(R_n(b))\}$$

- ★ Expectation-Maximization (EM) algorithm [Dempster *et al.* 1977]

**E-STEP:** computation of the conditional statistics from  $\theta_i$   
(gaussian a priori)

**M-STEP:** maximization of the likelihood and update of  
the parameters to compute  $\theta_{i+1}$

**MAXIMIZATION OF  
THE LIKELIHOOD  
ANALYTICALLY  
GUARANTEED**



# APPLICATION TO 21CM DATA CUBE

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- Data model:  $V(u,v,\nu) = s(u,v,\nu) + \sum M_{\nu c} \cdot f_c(u,v) + n(u,v,\nu)$
- Power spectrum:  $\langle ss^* \rangle = \mathbf{F}_{\parallel}^{\dagger} \mathbf{P}_{3D}(\mathbf{k}) \mathbf{F}_{\parallel}$ ;  $\langle f_c f_c^* \rangle = C_c(l)$
- Semi-Blind search: find the best-fitted  $\mathbf{P}_{3D}(\mathbf{k})$ ,  $C(l)$  and  $M$  to data without any assumption about foregrounds and signal and only fix  $N = \langle nn^* \rangle$
- Instrument effects: beam pattern, bandpass and frequency-dependent uv-coverage could mix the angular Fourier modes and radial Fourier modes. We will consider these effects in future

# THE EM ALGORITHM

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## Basic steps in the EM algorithm

The implementation of the EM algorithm starts by choosing an initial guess for the unknown parameters,  $\boldsymbol{\theta}^0$ , which is used in the first iteration of the algorithm. Then, at each iteration  $j + 1$  the following basic steps are performed

- **i)**  $\boldsymbol{\theta} = \hat{\boldsymbol{\theta}}^j$ .
- **ii)** E-step: Compute  $Q(\boldsymbol{\theta}', \boldsymbol{\theta})$ .
- **iii)** M-step: Find  $\boldsymbol{\theta}^{j+1}$  such that  $Q(\boldsymbol{\theta}^{j+1}, \boldsymbol{\theta}) \geq Q(\boldsymbol{\theta}', \boldsymbol{\theta})$  for all  $\boldsymbol{\theta}' \in \Theta$ .

The iterative procedure is stopped when a fixed point is reached so that  $\boldsymbol{\theta}^{j+1} = \boldsymbol{\theta}^j$ .

The functional  $Q(\boldsymbol{\theta}, \boldsymbol{\theta}^k)$  is given by

$$\begin{aligned} Q(\boldsymbol{\theta} | \boldsymbol{\theta}^j) &= E_{\mathbf{s} | \boldsymbol{\theta}^j} [\log p(\mathbf{y}_{1..K}, \mathbf{s}_{1..K} | \boldsymbol{\theta}) | \mathbf{y}_{1..K}, \boldsymbol{\theta}^j] \\ &= \int_{\mathbf{s}_{1..K}} \log p(\mathbf{y}_{1..K}, \mathbf{s}_{1..K} | \boldsymbol{\theta}) p(\mathbf{s}_{1..K} | \mathbf{y}_{1..K}, \boldsymbol{\theta}^j) d\mathbf{s}_{1..K} \end{aligned}$$

$\mathbf{y}=\mathbf{A}\mathbf{s}+\mathbf{n}$  Consider a probability model  $p(y, s|\theta)$  for a pair  $(y, s)$  of random variables with  $\theta$  a parameter set. The maximization of the log-likelihood  $l(\theta)$  can be made easier by considering the EM functional:

$$l(\theta, \theta') = \int \log(p(y, s|\theta)) p(s|y, \theta') ds.$$

Both the E step and the M step turn out to be straight-forward; EM step amounts to solving

$$0 = \int \frac{\partial \log(p(y, s|\theta^{(n+1)}))}{\partial \theta} p(s|y, \theta^{(n)}) ds.$$

update scheme:

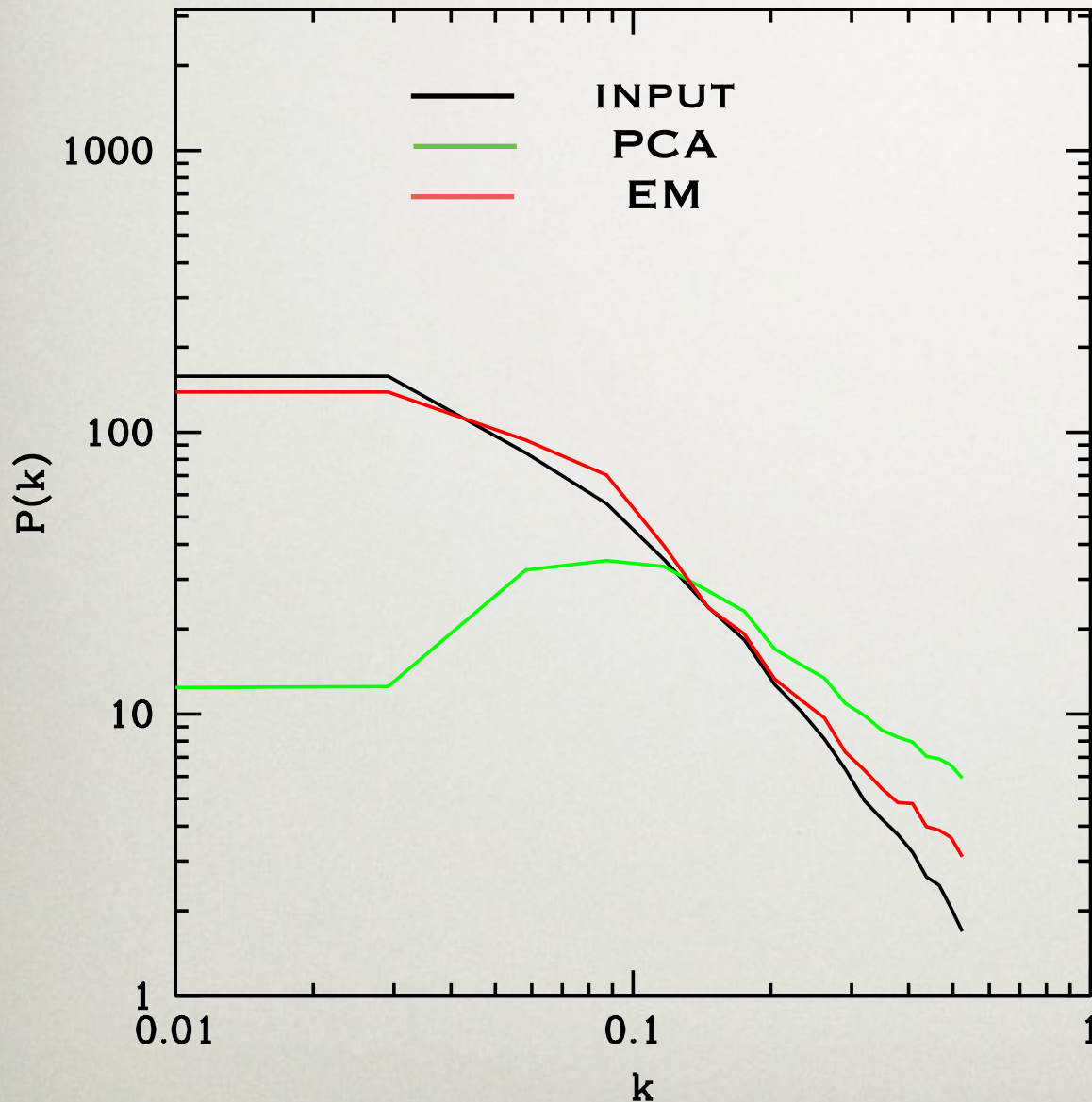
$$\begin{aligned} A &= \tilde{R}_{ys}(\theta') \tilde{R}_{ss}(\theta')^{-1} \\ \sigma_i^2 &= \left[ \tilde{R}_{yy}(\theta') - \tilde{R}_{ys}(\theta') \tilde{R}_{ss}(\theta')^{-1} \tilde{R}_{sy}(\theta') \right]_{ii} \\ P_i(q) &= [\tilde{R}_{ss}(\theta', q)]_{ii} \end{aligned}$$

where

$$\begin{aligned} C(q) &= (A^\dagger R_n^{-1} A + R_s(q)^{-1})^{-1} \\ W(q) &= (A^\dagger R_n^{-1} A + R_s(q)^{-1})^{-1} A^\dagger R_n^{-1} \\ \tilde{R}_{ss}(q) &= W(q) \hat{R}_y(q) W(q)^\dagger + C(q) \\ \tilde{R}_{sy}(q) &= W(q) \hat{R}_y(q) \end{aligned}$$



# HI POWER SPECTRUM RECOVERY



- **Data cube**( $32^3$  grids):  $20^\circ \times 20^\circ$  sky patch 800-830 MHz( $z \sim 0.8$ )
- **Foregrounds**: synchrotron, free-free, points source
- **PCA**: remove the first 2 eigen-foregrounds with largest eigenvalues
- **EM**: assume 3 independent foreground components
- Consider noise ( $S/N \sim 3$ ) in uv-plane, but not include beam pattern and incomplete uv-coverage