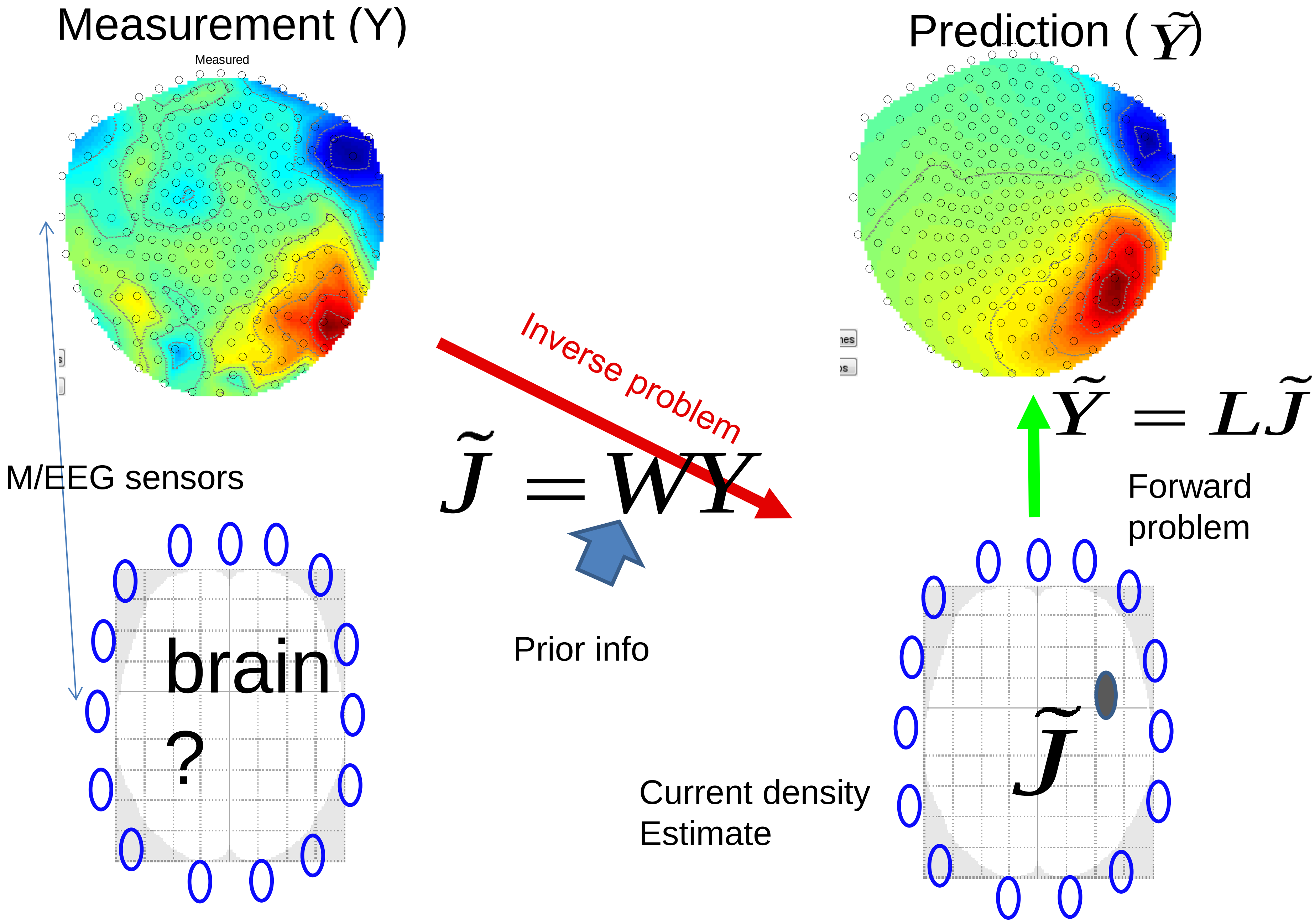
The M/EEG inverse problem

Gareth R. Barnes



Measurement (Y)
Measured
Prediction ($\tilde{Y}$)
M/EEG sensors
brain
?
Inverse problem
$\tilde{J} = WY$
Prior info
$\tilde{Y} = L\tilde{J}$
Forward problem
Current density Estimate
$\tilde{J}$

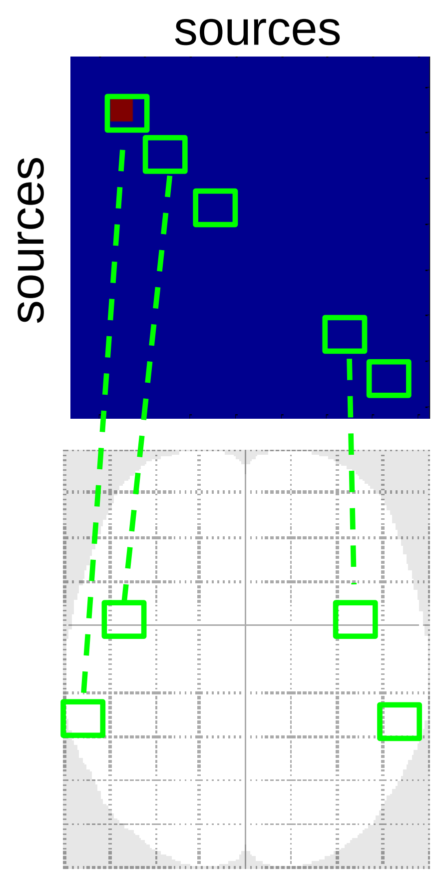
Inversion depends on choice of source covariance matrix (prior information)

$$W = C L' (R + L C L')^{-1}$$

Sensor Noise (known)

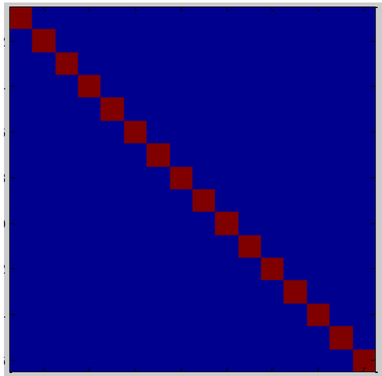
Lead field (known)

Source covariance matrix,
One diagonal element per source

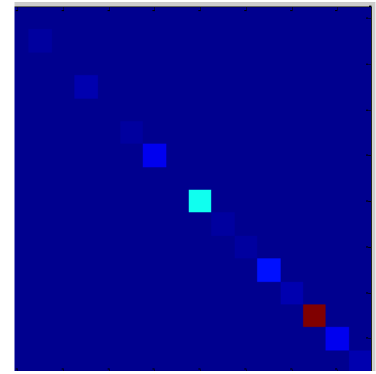


Prior information

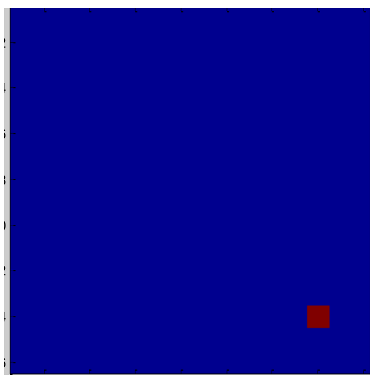
Some popular priors



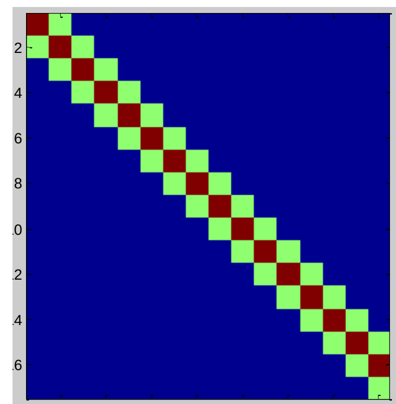
Minimum norm



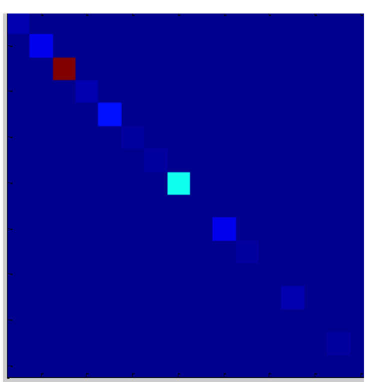
SAM,DICs
Beamformer



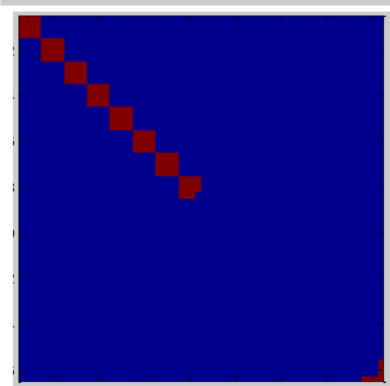
Dipole fit



LORETA

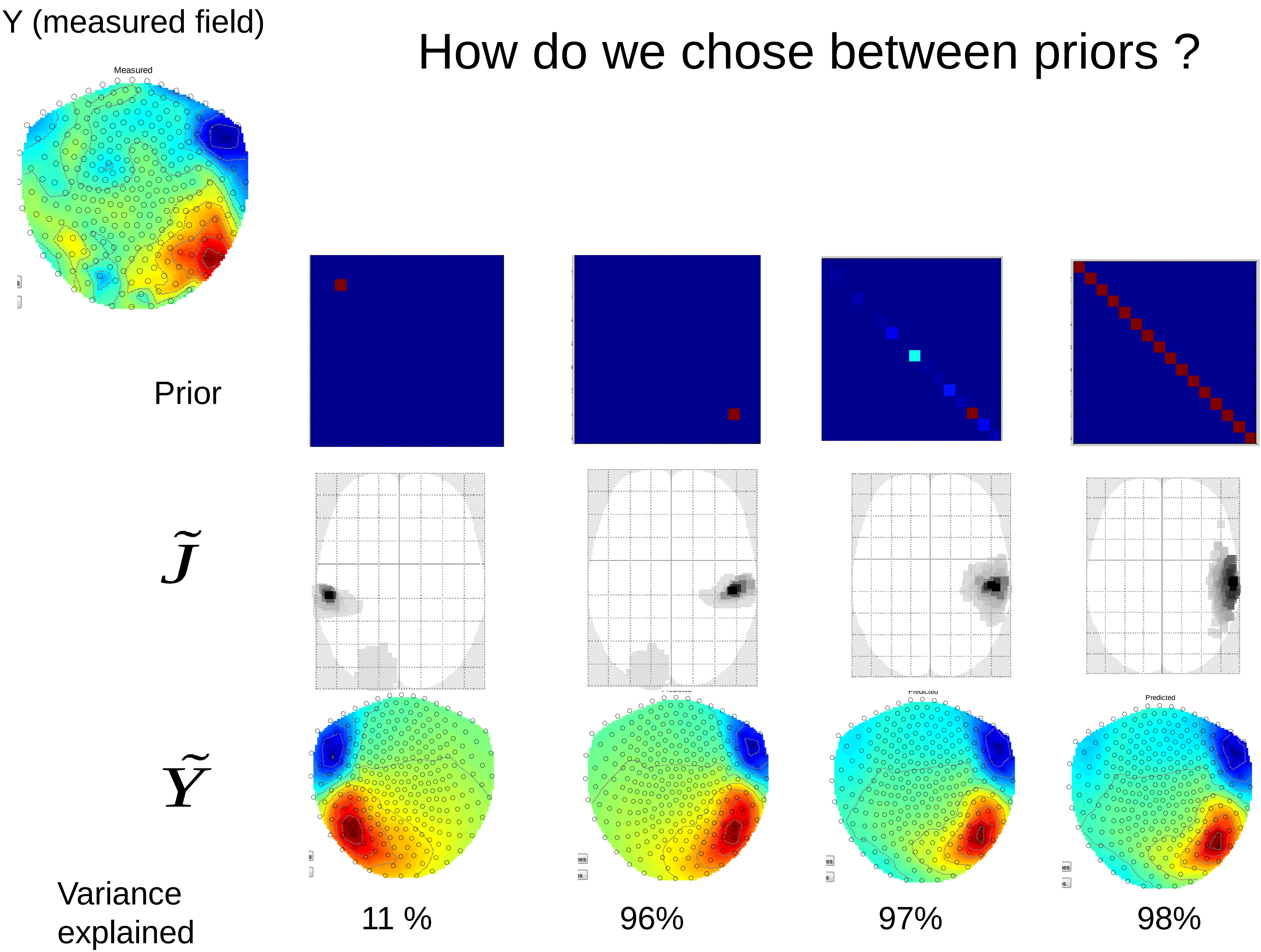


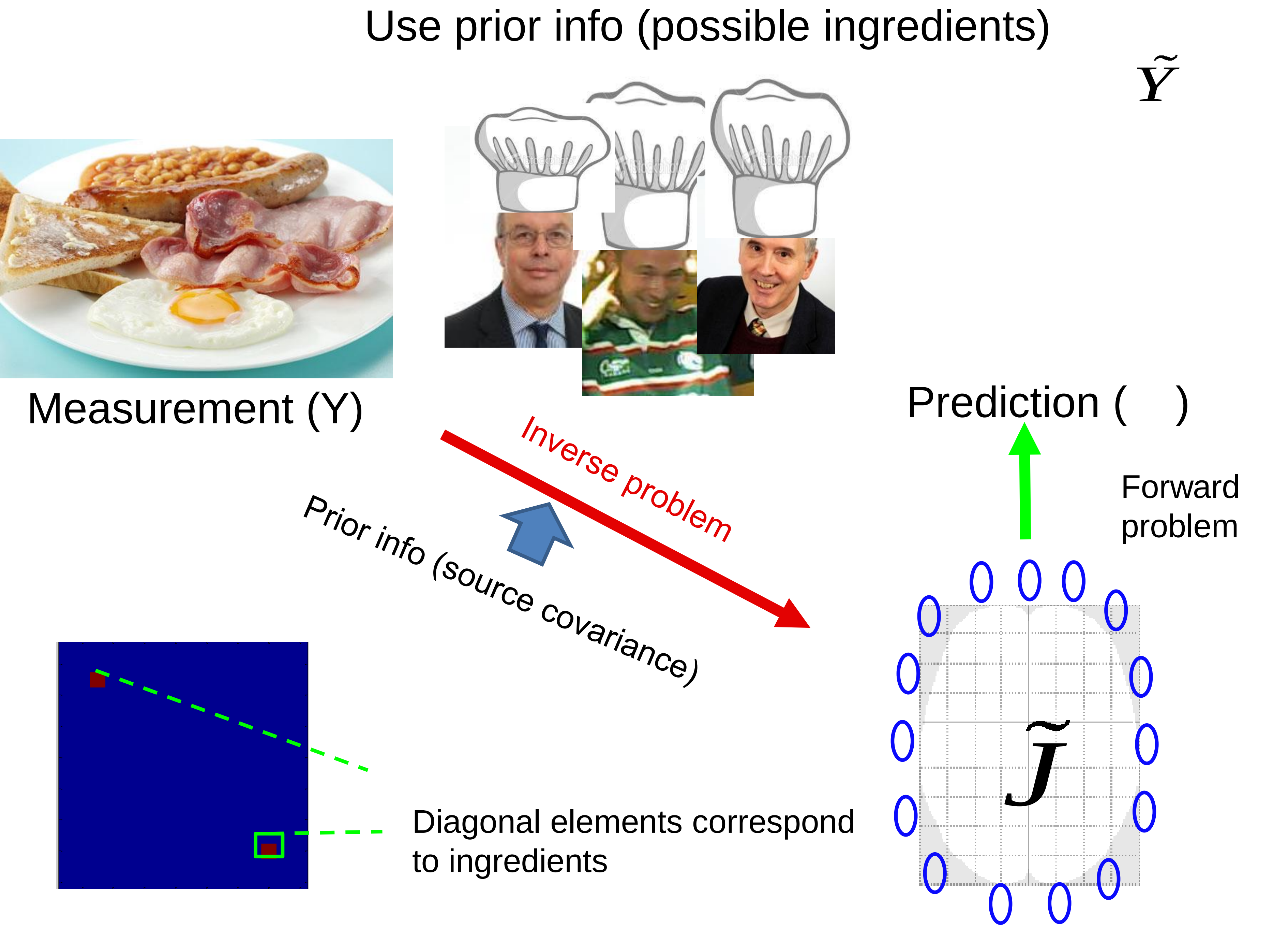
fMRI biased
dSPM



?

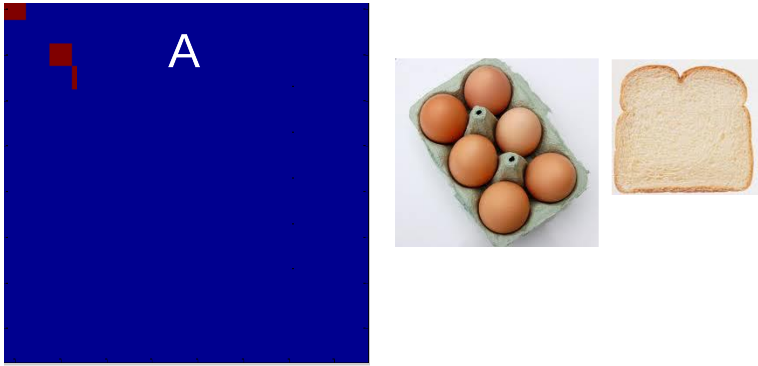
How do we chose between priors ?

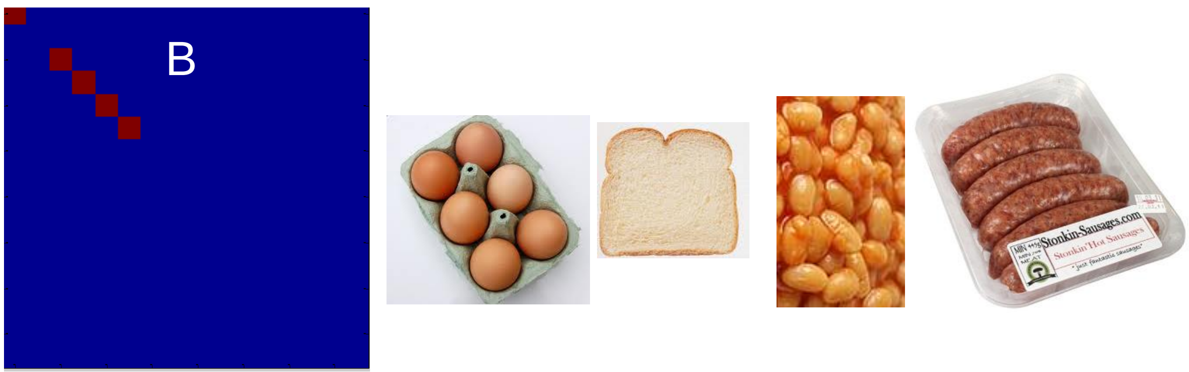




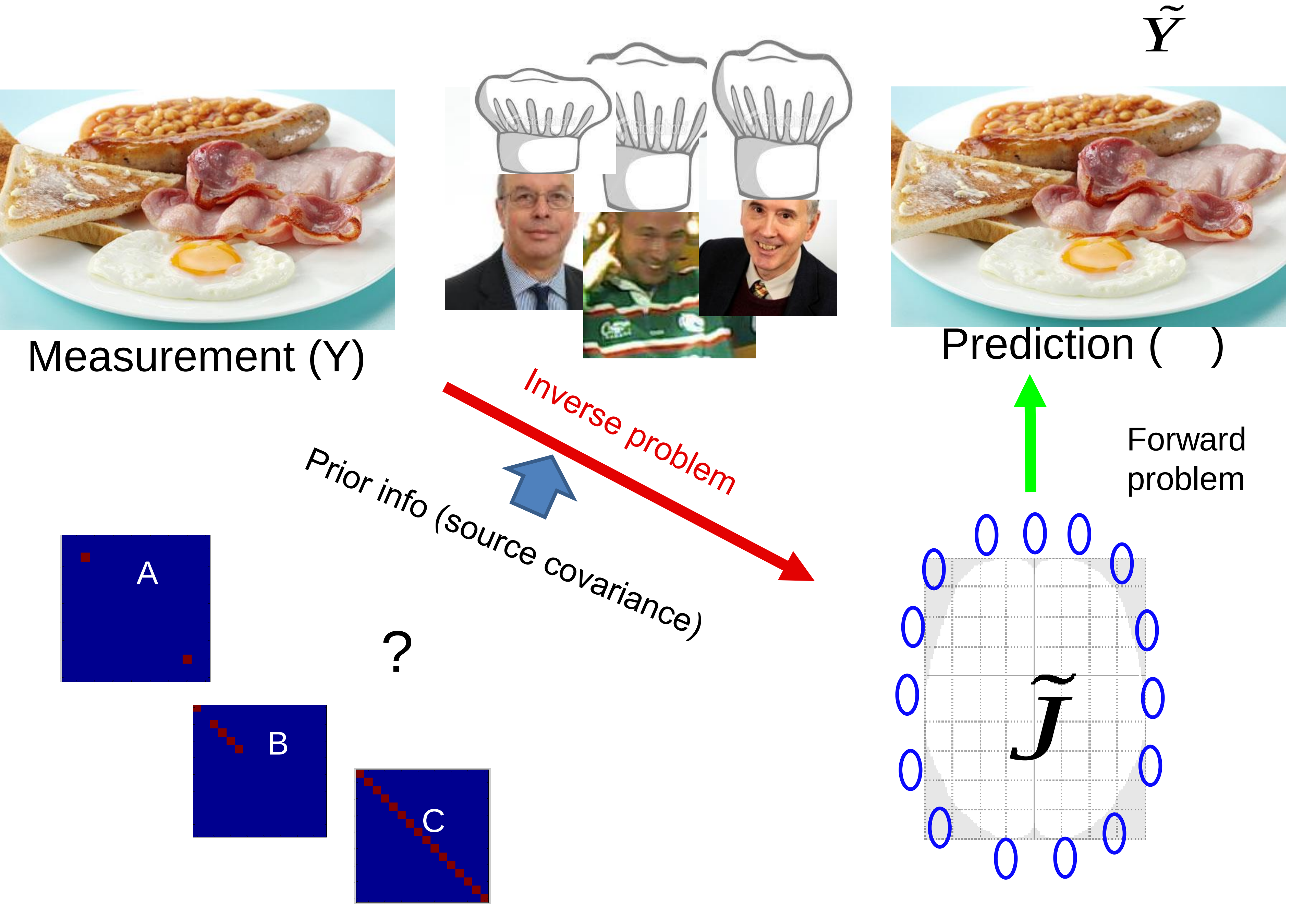
Use prior info (possible ingredients)
$\tilde{Y}$
Measurement (Y)
Prediction ( )
Inverse problem
Forward problem
Prior info (source covariance)
$\tilde{J}$
Diagonal elements correspond to ingredients

Possible priors

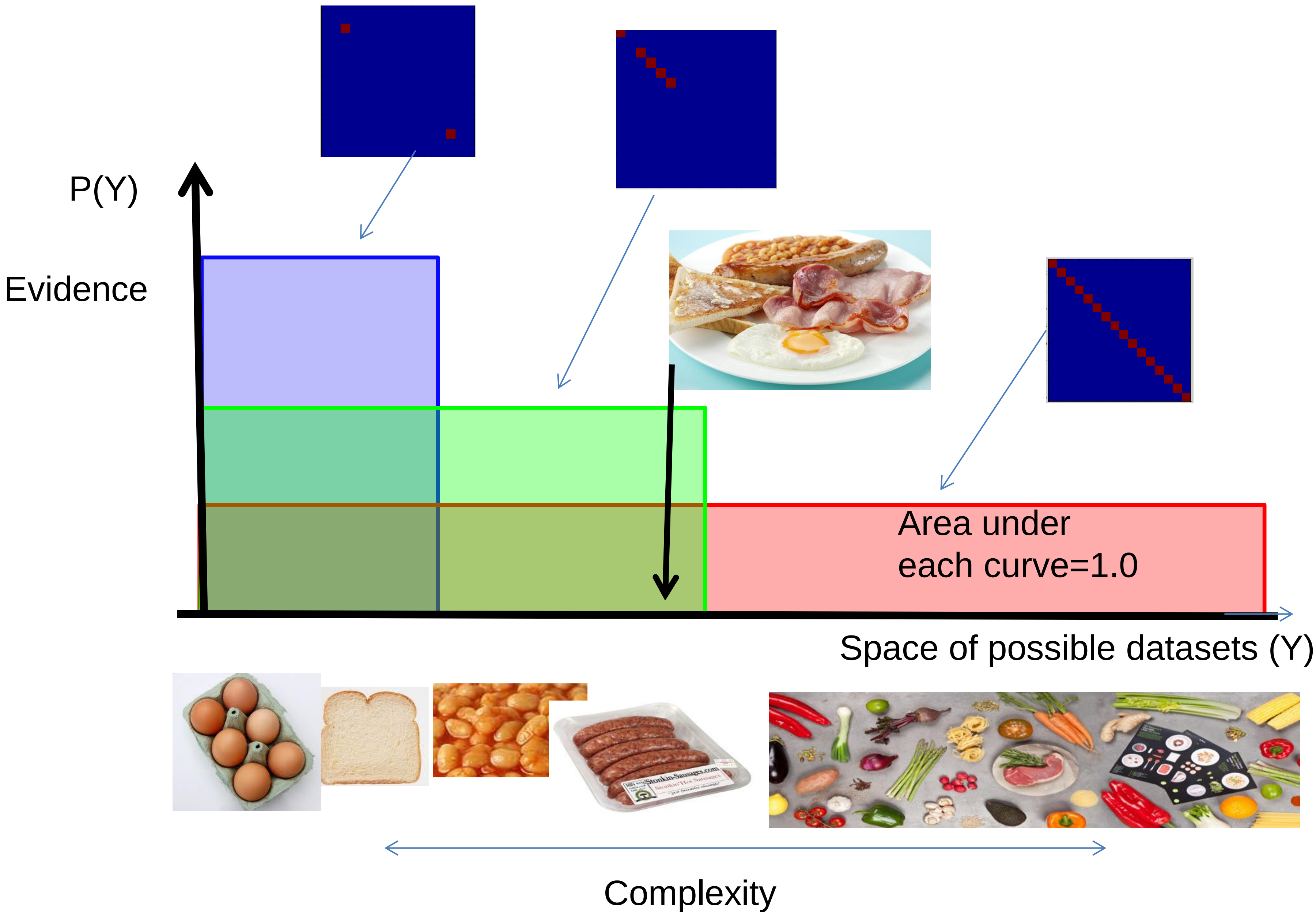




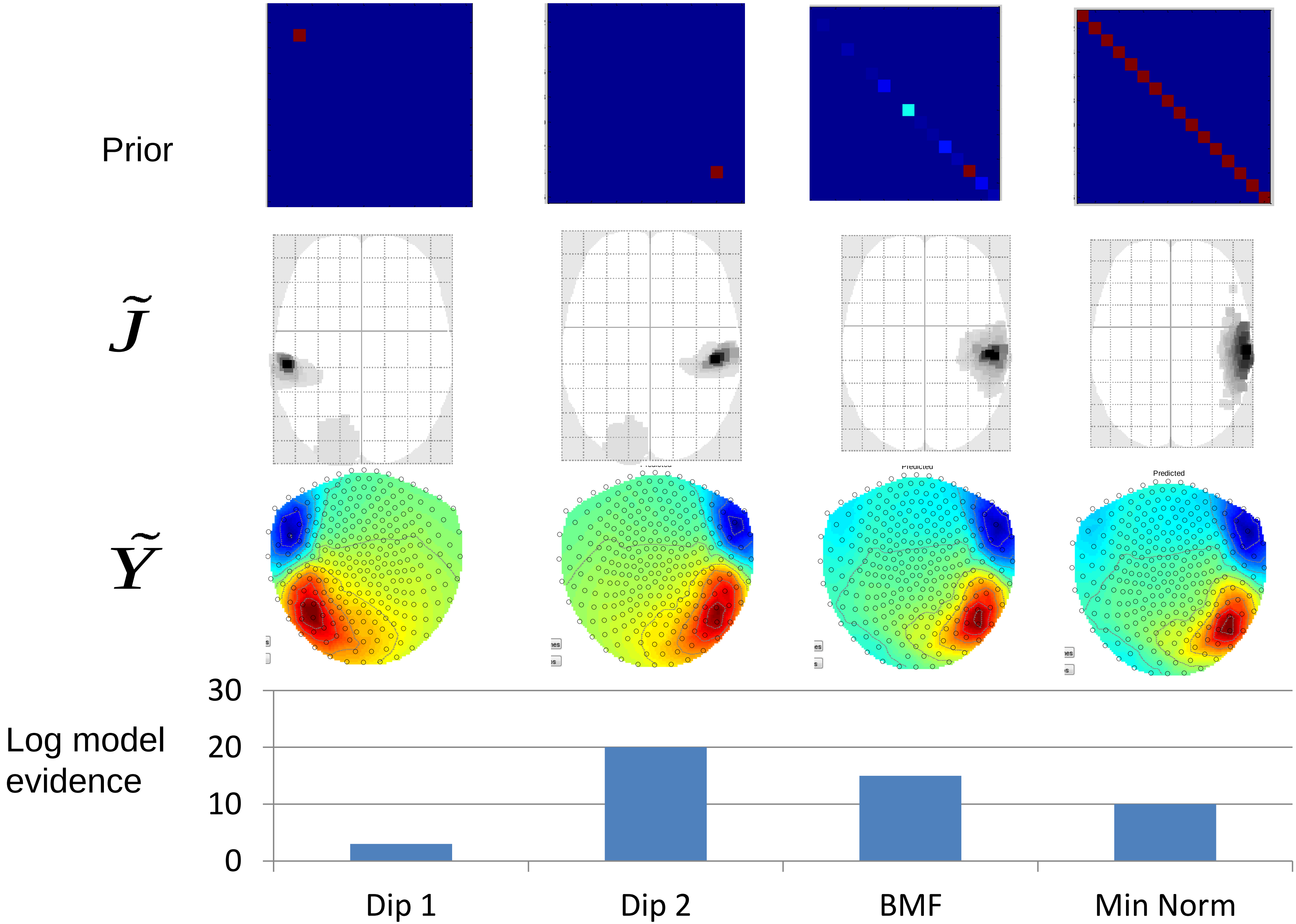
Which is most likely prior (which prior has highest evidence) ?



Consider 3 generative models



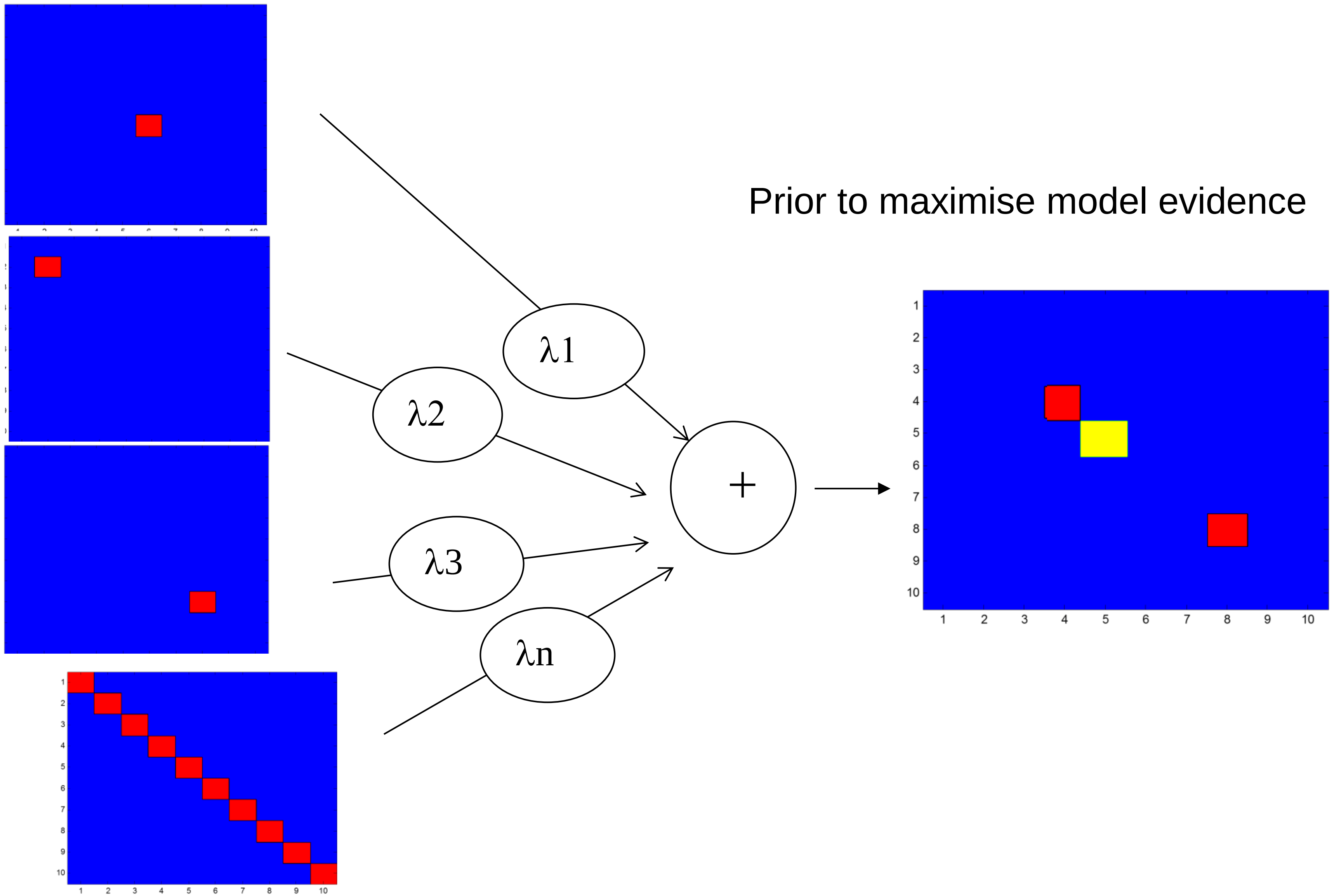
How do we chose between priors ?



Muliple Sparse Priors (MSP), Champagne

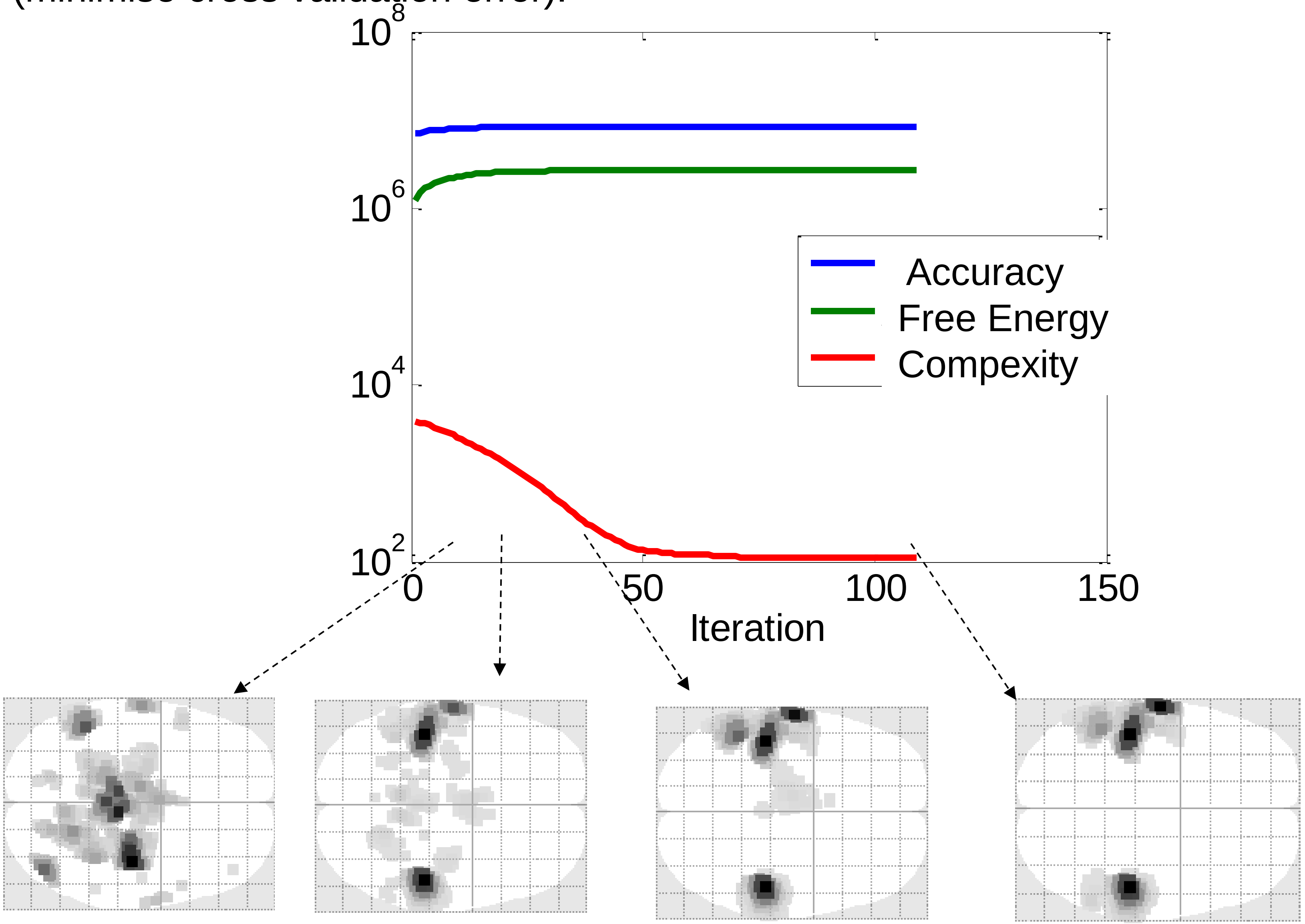
Candidate Priors

Prior to maximise model evidence



Multiple Sparse priors

So now construct the priors to maximise model evidence
(minimise cross validation error).



Conclusion

- MEG inverse problem can be solved easily with some prior knowledge.
- All prior knowledge encapsulated in a source covariance matrix.
- Can test between priors (or develop new priors) using Bayesian framework.

Thank you

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- Chris Mathys
- Saskia Helbling

And all SPM developers

References

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- Wipf and Nagarajan, 2009
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- **A unified Bayesian framework for MEG/EEG source imaging**
- NeuroImage, 44 (2009), pp. 947–966

LONGER VERSION OF THIS TALK:

- http://www.nottingham.ac.uk/conference/fac-sci/physics/meg-uk-conference/workshop.aspx

Analytical approximation to model evidence

- Free energy= accuracy- complexity

$$F = -\frac{N_n}{2}\mathrm{tr}\left(\Sigma_\gamma \Sigma^{-1}\right) - \frac{N_n}{2}\log|\Sigma| - \frac{N_n N_c}{2} log 2\pi$$
$$-\frac{1}{2}\left(\hat{\lambda}-\nu\right)^T \Pi \left(\hat{\lambda}-\nu\right) + \frac{1}{2}\log|\Sigma_\lambda \Pi|$$

$$F = -\begin{bmatrix}\text{Model}\\ \text{error}\end{bmatrix} - \begin{bmatrix}\text{Size of model}\\ \text{covariance}\end{bmatrix} - \begin{bmatrix}\text{Num of data}\\ \text{samples}\end{bmatrix}$$
$$-\begin{bmatrix}\text{Error in}\\ \text{hyperparameters}\end{bmatrix} + \begin{bmatrix}\text{Error in covariance}\\ \text{of hyperparameters}\end{bmatrix}.$$