

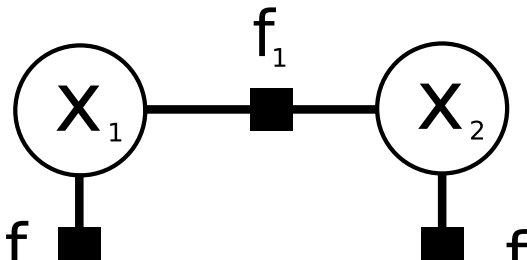
Bayesian Phase Unwrapping with Factor Graphs

6.556 Final Project

Eric Jonas

MIT Brain & Cognitive Sciences

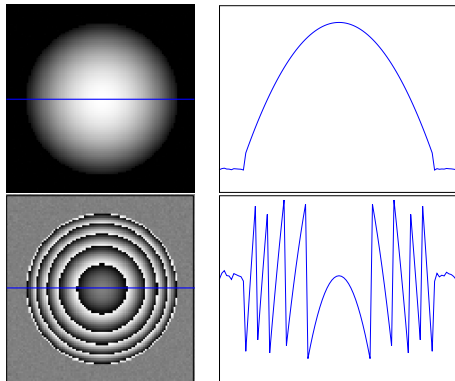
May 12, 2009



- ① Phase Unwrapping for MR
- ② MRFs and Factor Graphs
 - MRFs for Phase Unwrapping
- ③ Inference in MRFs
- ④ Results
 - Synthetic Data
 - Actual Data
- ⑤ Conclusion and Future Directions

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Phase Unwrapping for MR

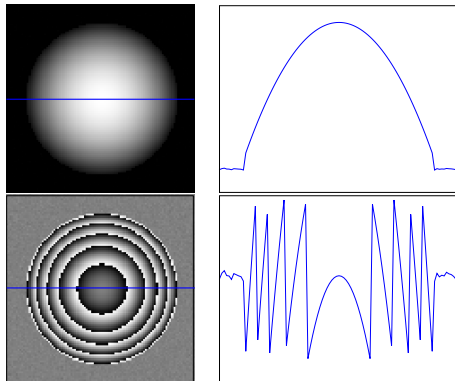


We think phase information varies smoothly except at boundaries

Right now most clinical applications only focus on magnitude

Phase provides additional information, such as field inhomogeneity and fluid velocity

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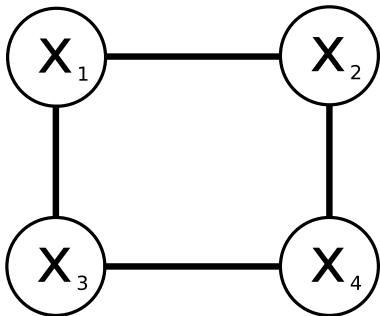
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Phase Wrapping

Our phase observations map $(-\infty, \infty)$ to $(0, 2\pi)$

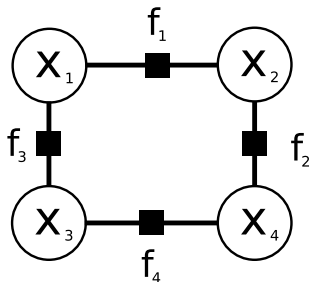
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Markov Random Fields



- You may know as “Undirected graphical model”
- Each X_i is a variable, we’ll call it “state”
- Implicitly we know a series of joint distributions on the x_i represented by edges

Factor Graphs



Factor Graphs [4] express the same concepts as MRFs but make the **factors** explicit.

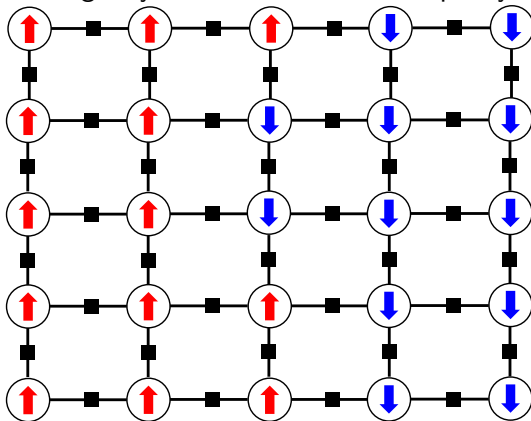
- bipartite graph
- represents functional decomposition
- lots of ways to solve them (BP, loopy BP, monte carlo, etc.)

Factor Graph Probability

$$P(x_1, x_2, x_3, x_4) = f_1(x_1, x_2) \cdot f_2(x_2, x_3) \cdot f_3(x_3, x_4) \cdot f_4(x_4, x_1)$$

Example : Ising Model

Imagine you want to simulate a spin system, like in a magnet

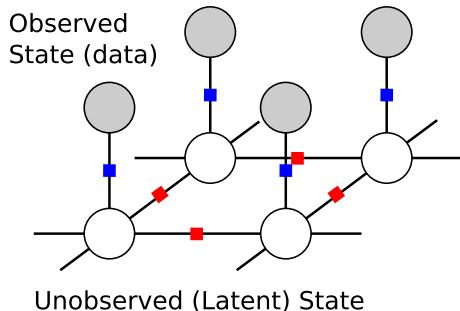


Adjacent spins are in a lower energy (more probable) state if they are parallel (sound familiar?).

Factor value

$$f_{mn} = \frac{1}{2} \exp(-\beta J_{mn} X_m X_N)$$

Factor Graphs for Low-Level Vision



Properties of Image Factor Graphs [2]:

- Use observed state (data) to infer hidden state
- Have lattice structure like the ising
- Large number of vertices ($O(n)$ in number of pixels)
- $O(1)$ per-vertex connectivity
- Typically have homogeneous factors

Bayesian Factor Graphs

Bayes Rule

$$P(X|Y) = \frac{P(Y|X)P(X)}{\sum_X P(Y|X)P(X)}$$

- $Y = y_{(i,j)}$: Observed Nodes
- $X = x_{(bi,j)}$: Hidden state we wish to estimate
- $P(Y|X)$: measurement model (“likelihood”)
- $P(X)$: prior

Bayesian Factor Graphs For Low-Level vision

Our factor graph gives us $P(X, Y)$, we want $P(X|Y)$.

Bayes Rule

$$P(X|Y) = \frac{P(Y|X)P(X)}{\sum_X P(Y|X)P(X)} \propto P(Y|X) \cdot P(X)$$

For a low-level vision factor graph,

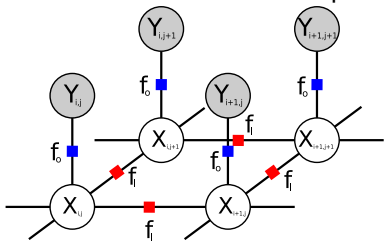
$$P(Y|X) = \prod f_o(Y_i, X_i)$$

$$P(X) = \prod_{(i,j) \in G} f_l(X_i, X_j)$$

That sum, $\sum_X P(Y|X)P(X)$, looks hard! This is a big part of why Bayesian inference is tricky.

MRFs for Phase: Frey's approach

In Ying and Frey's model [9] they formulate 2-D phase unwrapping as a low-level vision MRF problem.



- $Y_{(i,j)} \in \mathbb{R}$ (continuous!)
- $x_{(i,j)} \in [0, 2\pi)$ (continuous!)

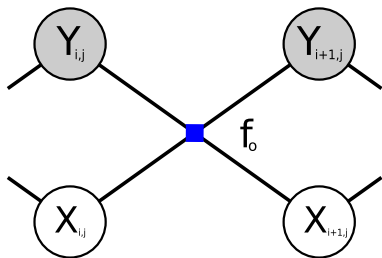
Observation Potential

$$f_o = \delta((Y_{(i,j)} \bmod 2\pi) - X_{(i,j)})$$

Latent potential

$$f_l(X_1, X_2) = (X_1 - X_2)^2$$

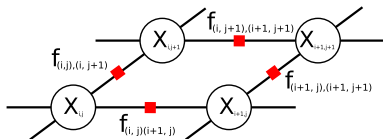
Discrete latent state, homogeneous factors



- $Y_{i,j} \in \mathbb{R}$
- $x_{i,j} \in [1 \dots K]$

Discrete latent state, unique factors

I reformulated the problem to make inference easier.



- $x_{(i,j)} \in [1 \dots K]$

Unique (non-homogeneous) factors

Every two adjacent X_i, X_j on the lattice have a unique factor between them that incorporates the information from the data.

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Inference in MRFs

- The MRF tells us how to compute $P(X, Y)$.
- Bayes rule tells us how to compute $P(X|Y)$.

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$$P(X|Y) = \frac{P(Y|X)P(X)}{\sum_x P(Y|X)P(X)} \propto P(Y|X) \cdot P(X) = P(X, Y)$$

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There are some generic approaches to get around this:

- Traditional numerical integration

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There are some generic approaches to get around this:

- Traditional numerical integration
- optimize to find MAP solution
- Solve a similar, easier problem and perturb (variational methods)
- draw samples from $p(X|Y)$ to empirically estimate posterior

Markov-Chain Monte Carlo

Markov Property: next state only depends on current state

$$p(x_{t+1}|x_{1:t}) = p(x_{t+1}|x_t)$$

Main idea

Construct a Markov chain with the equilibrium distribution equal to your target distribution

Used in situations where you want to sample from $\pi(x)$ but only can compute $\pi^*(x) = Z\pi(x)$, Z unknown.

But how do we construct a chain with equilibrium distribution $\pi(x)$?

Metropolis-Hastings (1953)

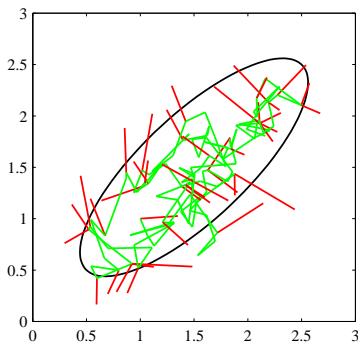
Simple idea: randomly propose new location in state space, sometimes go there! (From statistical physics [6])

We use a proposal distribution, $q(x \rightarrow x^*)$ Draw x^* as a *new target state* from this distribution.

$$x^* \sim q(x^*|x)$$

We compute the “Acceptance” ratio :

$$a = \min\left(1, \frac{p(x^*)}{p(x)} \cdot \frac{q(x \rightarrow x^*)}{q(x^* \rightarrow x)}\right)$$



Gibbs Sampling (1990)

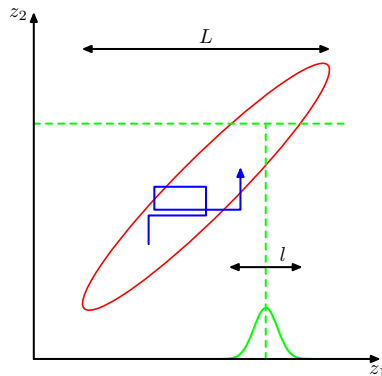
If we can sample from conditional distributions, we can use a more intelligent form of MH known as Gibbs Sampling [3]

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Requirements

To use Gibbs sampling on state variable x_i we must be able to draw samples from $x_i \sim p(x_i | \{x_{j \neq i}\})$

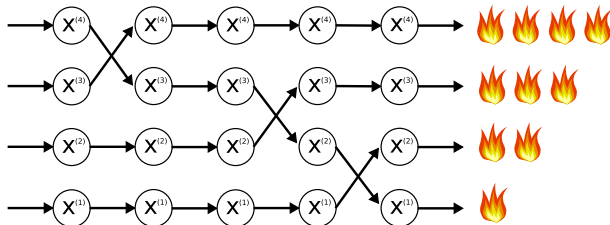


From Christopher Bishop.

Parallel Tempering (1991)

(aka “Replica Exchange Monte Carlo” [7], aka “Something to do with your 8 cores”)

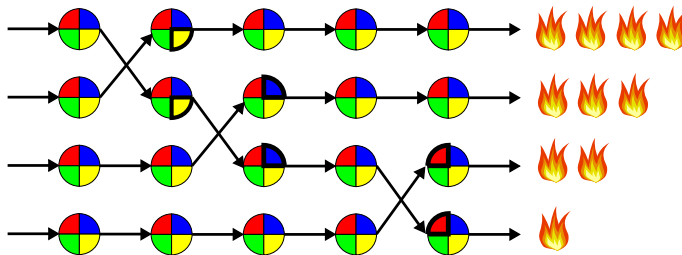
- Run N replicas of your chain, each at a different temperature
- Periodically propose MH-style swaps between adjacent chains
- Let’s hot chains move around in flatter energy landscape



Partial Replica Exchange (2000)

(aka “Evolutionary MCMC” [5] aka “Return of the GA”)

- Run N replicas of your chain, each at a different temperature
- Periodically propose MH-style swaps between **substates** in adjacent chains
- Let’s hot chains move around in flatter energy landscape, but **lets better partial solutions move to cold chain**

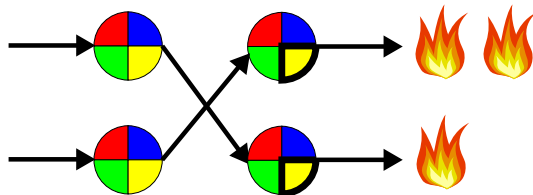


Data-driven MCMC (2002)

- Any “move” is valid as long as it is reversible.
- We can cheat a little bit and construct moves based on the data to help the chains mix, without changing the target distribution

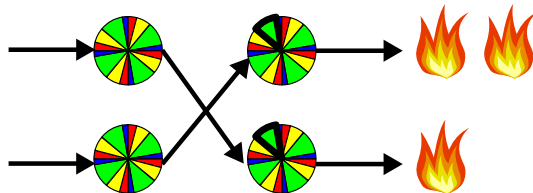
Zhuowen and Tu [8] would pre-segment images with a heuristic and then use those segments as an MCMC proposal distribution.

Data-driven Partial Replica Exchange (2009)



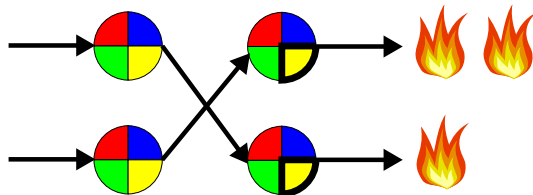
Traditional Partial Replica Exchange

- I just invented it!



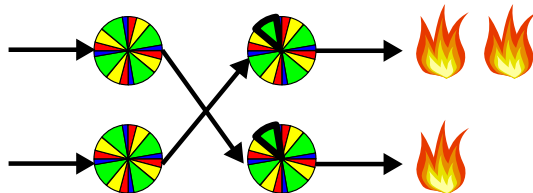
Data-Driven Partial Replica Exchange

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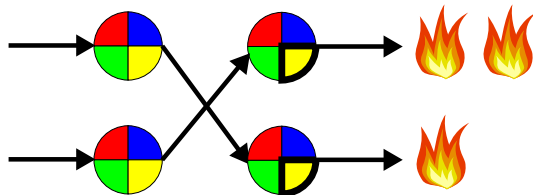
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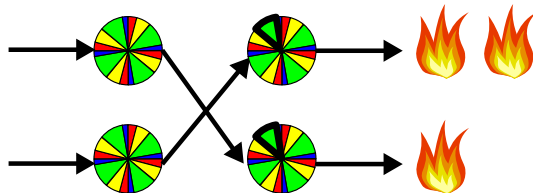
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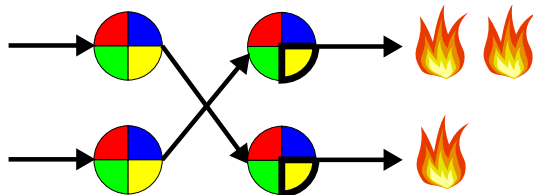
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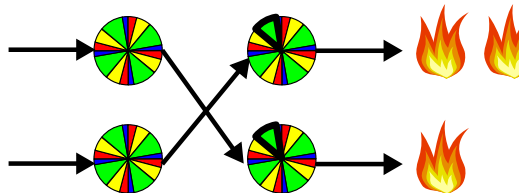
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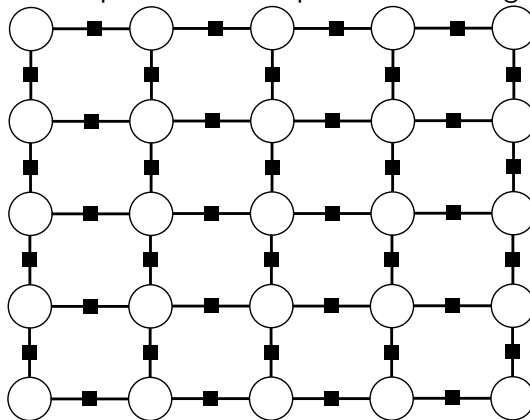
Data-Driven Partial Replica Exchange

This is the power of MCMC

Transition kernels (moves) nicely compose.

MRFs and Parallelism

The conditional independence assumptions allow fine-grained



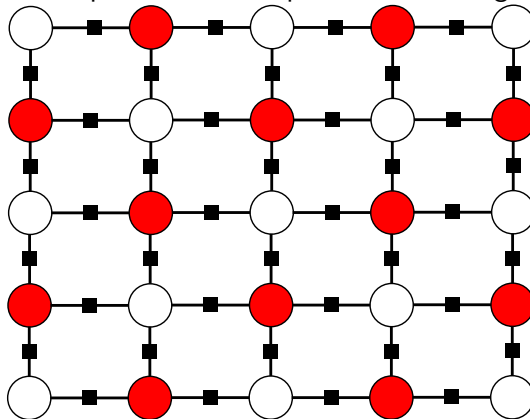
parallelism

Once colored, all nodes of a single color can be Gibbs sampled *simultaneously*.

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- Multi-threaded C++ engine, scales to 8 cores
- Python wrapper for GUI, vis, control, parameter tuning,

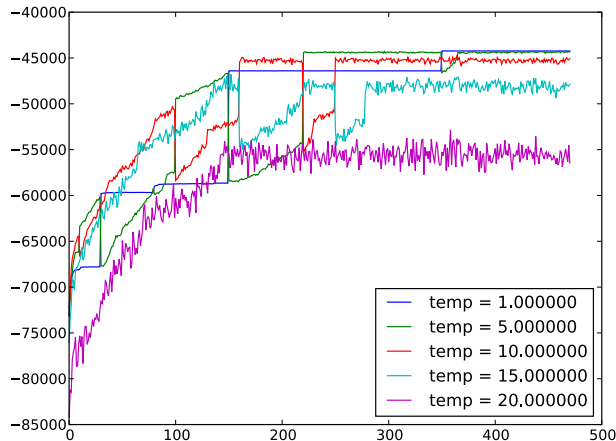
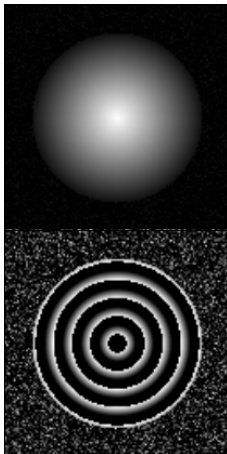
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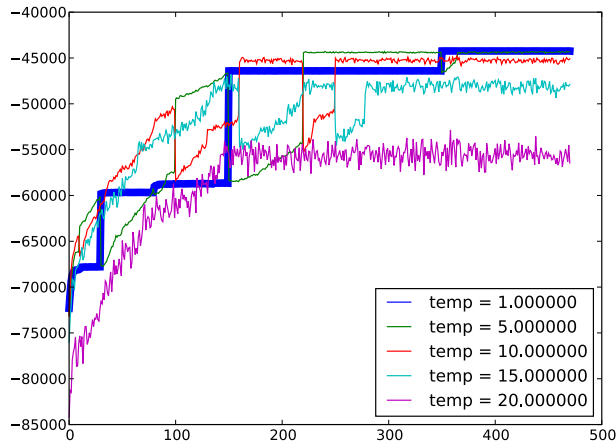
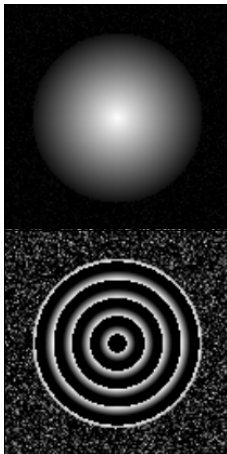
Try it out

Source and presentation available for download on github
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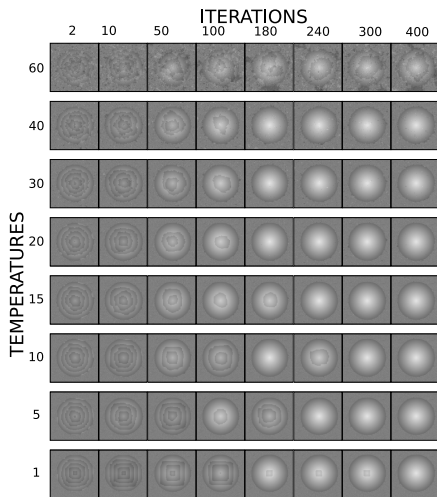
2-D Synthetic Data : The Sphere



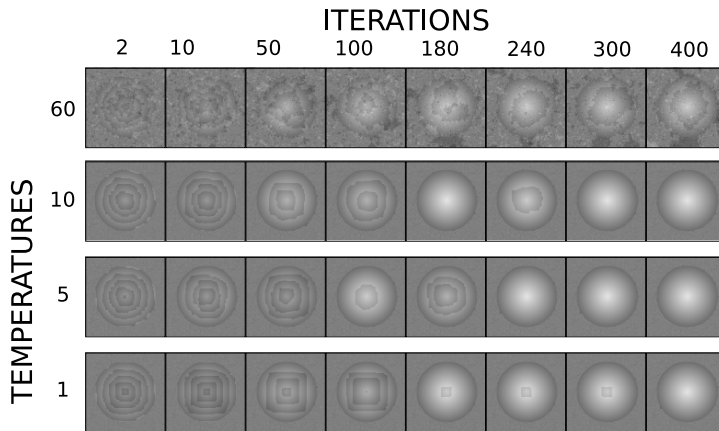
2-D Synthetic Data : The Sphere



2-D Synthetic Data : The Sphere : PT exchange



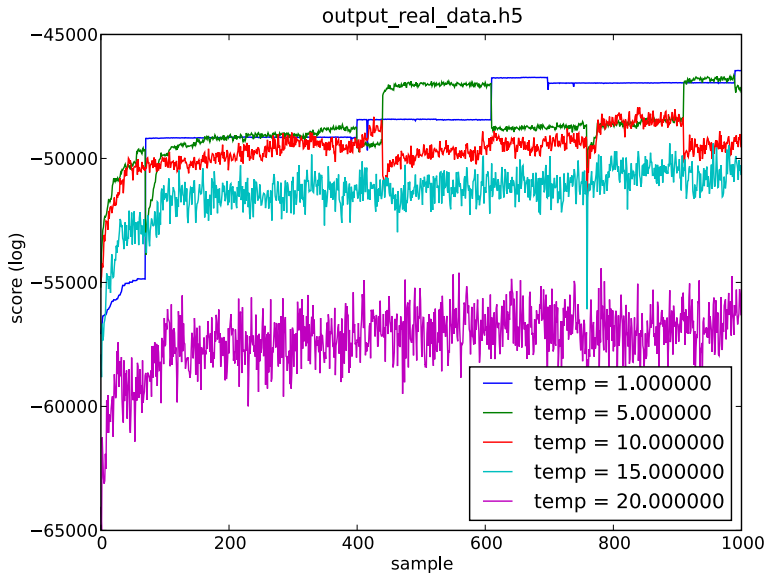
2-D Synthetic Data : The Sphere : PT exchange



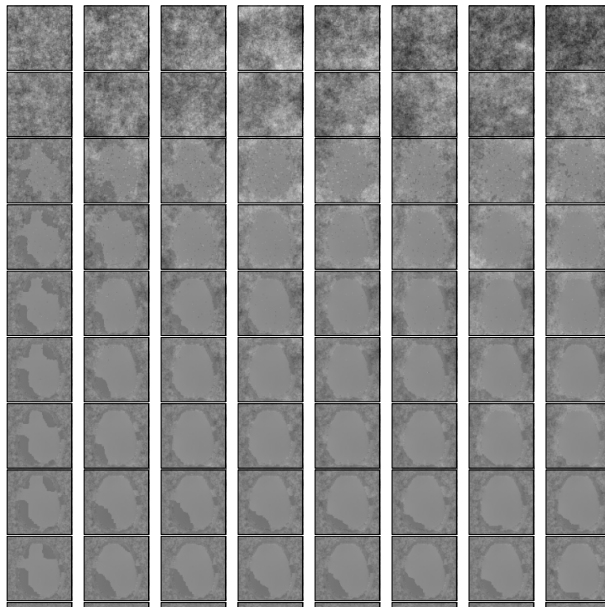
Actual Data Results

- Thanks to Div and Audrey for providing the data
- $0.5\text{mm} \times 0.5\text{mm} \times 3\text{mm}$
- $TE = 15\text{ ms}$; 60 ms is available (more wraps!) but didn't convert
- subsampled by 4x
- still took an hour!

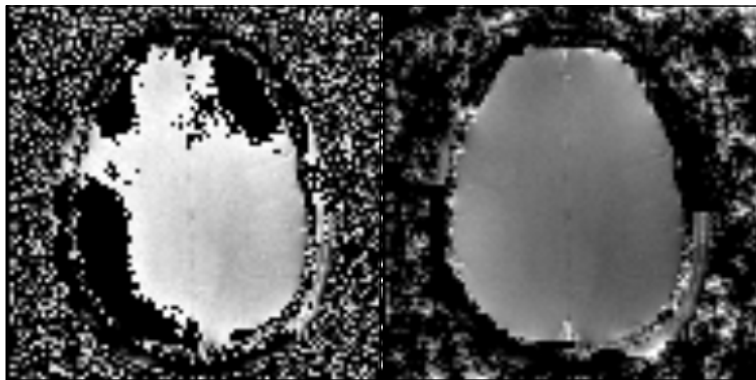
Scores from run



Chains over time



Final Sample from Cold Chain



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Why use MCMC?

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Why use factor graphs?

- reasonable prior expressing local dependence
- factors allow programmatic analysis of conditional independencies, thus can easily identify opportunities for parallelism

Where to now?

Factor graphs have tremendous potential for imaging applications

- Exact sampling using Systematic Stochastic Search [?]

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Questions?

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