Brain Network Analysis with HTC

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Outline

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- Introduction
  - Brain connectivity
  - Measurement of electrical activity

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  - Spina bifida
  - Perception vs imagination
  - Working memory

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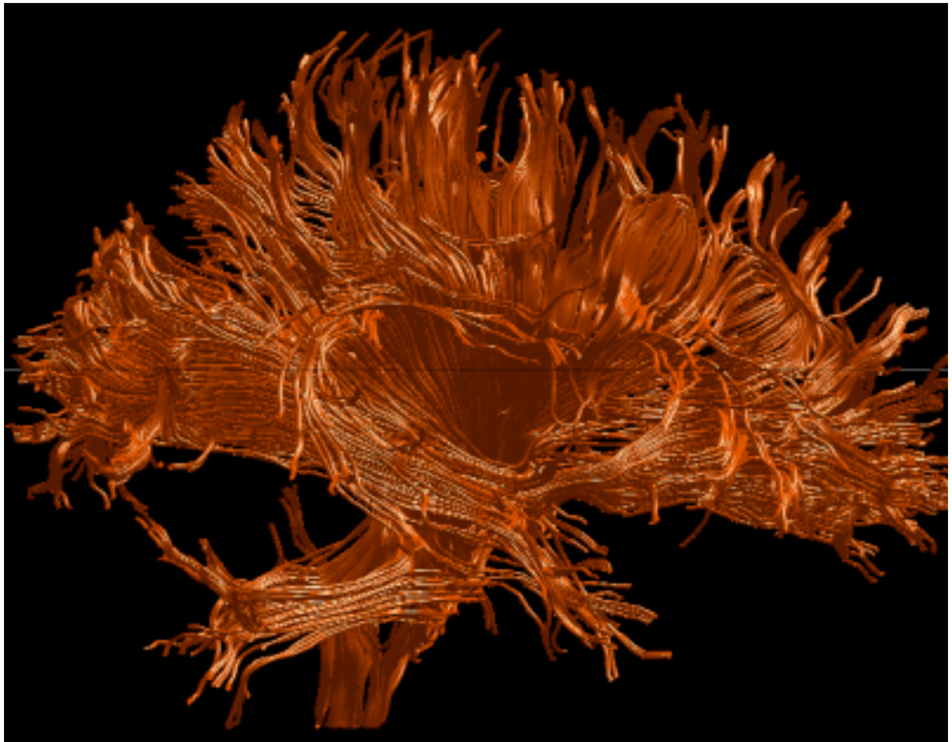
- Summary

Measures of Connectivity

- Anatomical - physical connections
- Functional - correlated activity
- Effective – cause and effect



http://pnl.bwh.harvard.edu/dti.html

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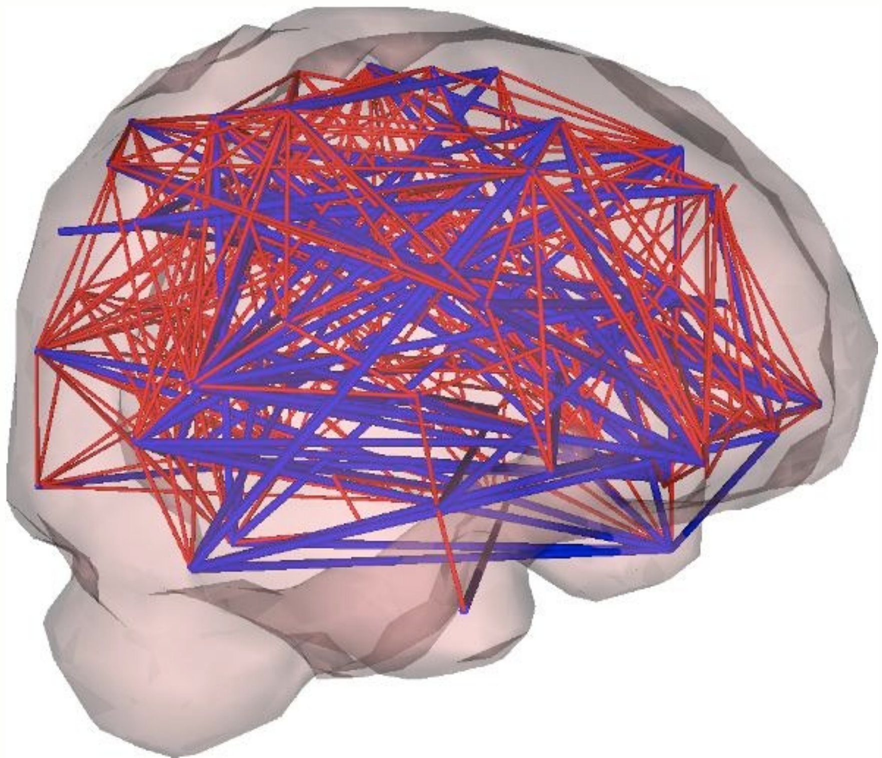

http://www.wbic.cam.ac.uk/~sa428/

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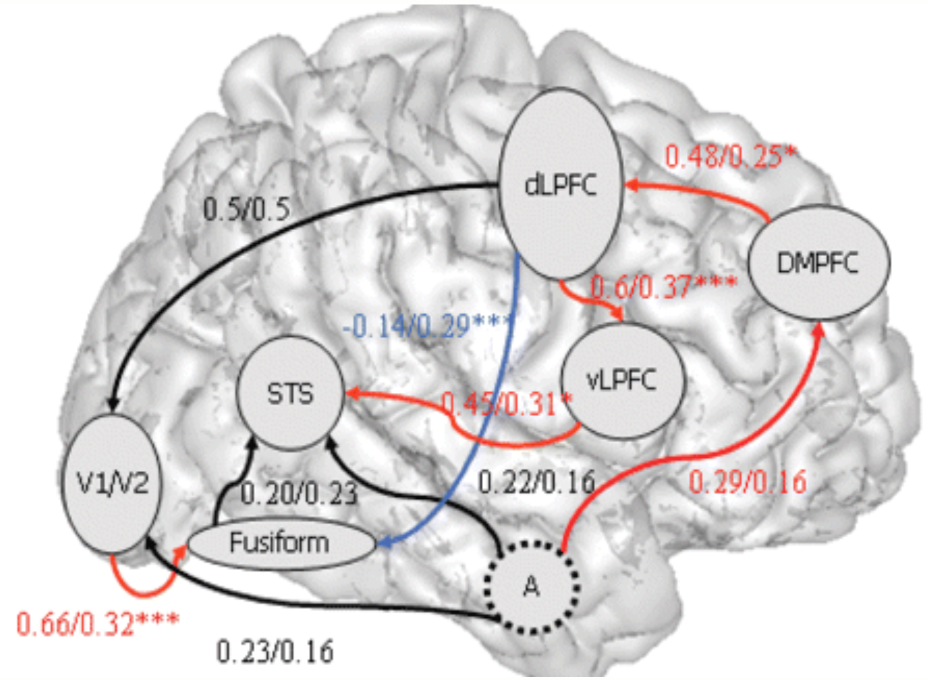

http://www.medscape.com/viewarticle/581686_3

Brain Function-Chess Analogy

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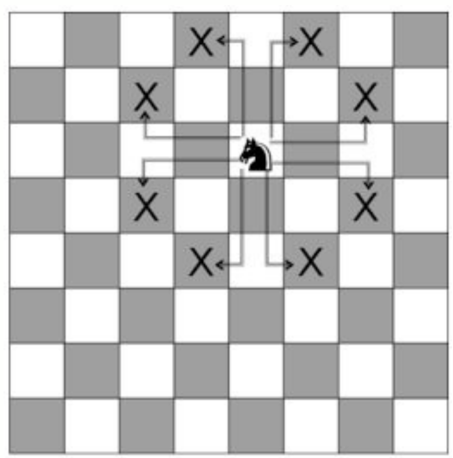

activityvillage.co.uk

Brain Function-Chess Analogy

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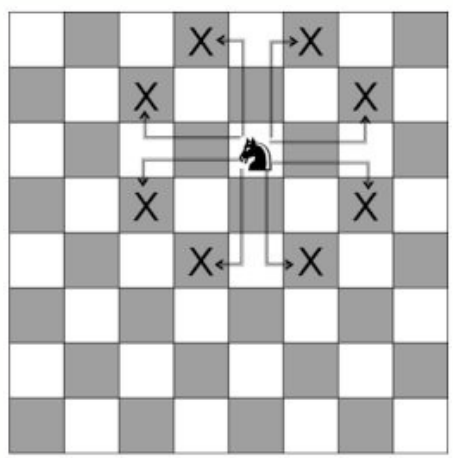
  - How can pieces move? <–> anatomical connectivity
  - What is good strategy? <–> effective connectivity



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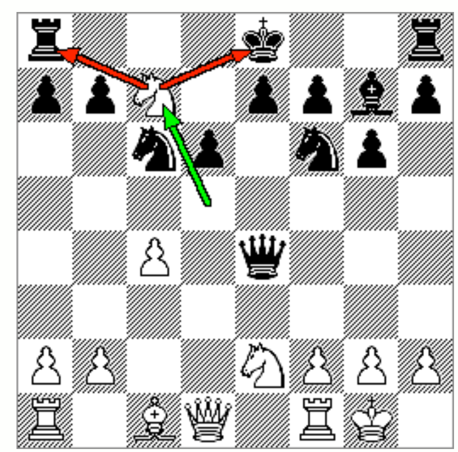

knowledgerush.com

Electric/Magnetic Imaging

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- Electro/magneto-encephalography (EEG/MEG)
  - Excellent temporal resolution
  - Limited spatial resolution

EEG Sensor Net

MEG System

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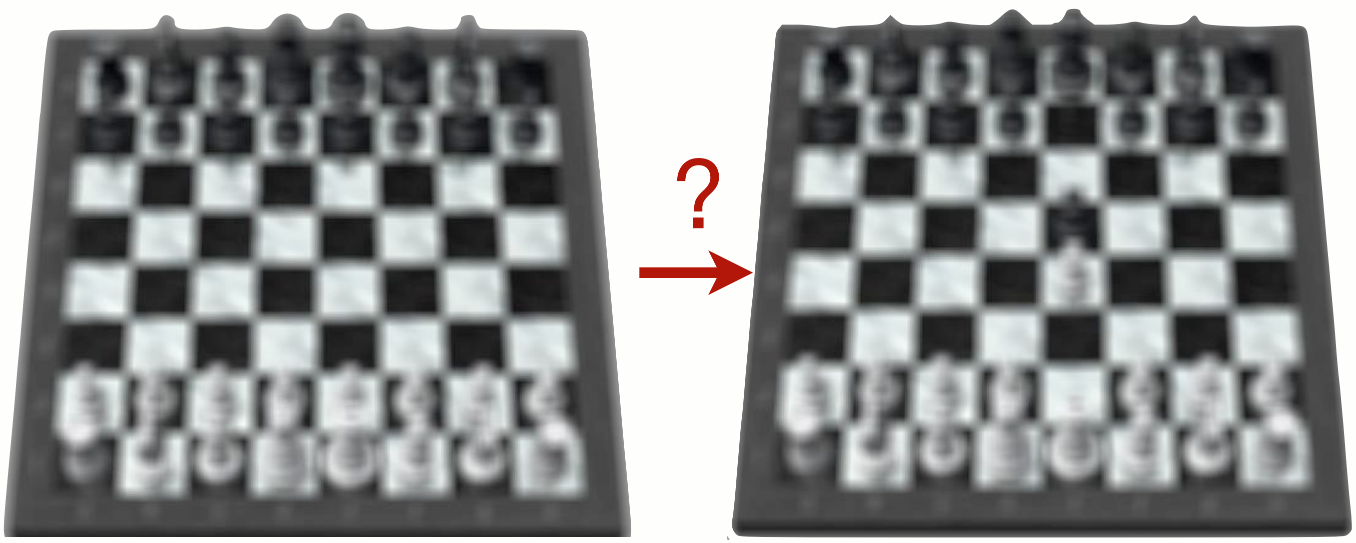
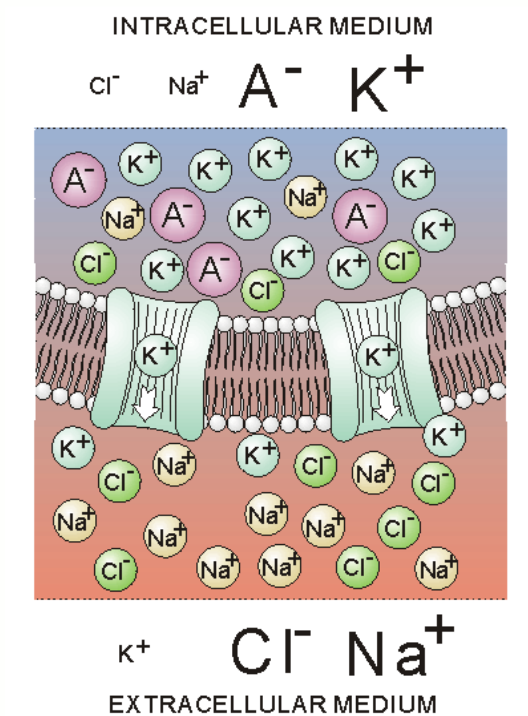
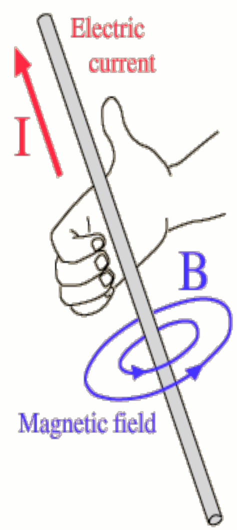


MEG System

Signal Origin: Biology - Physics





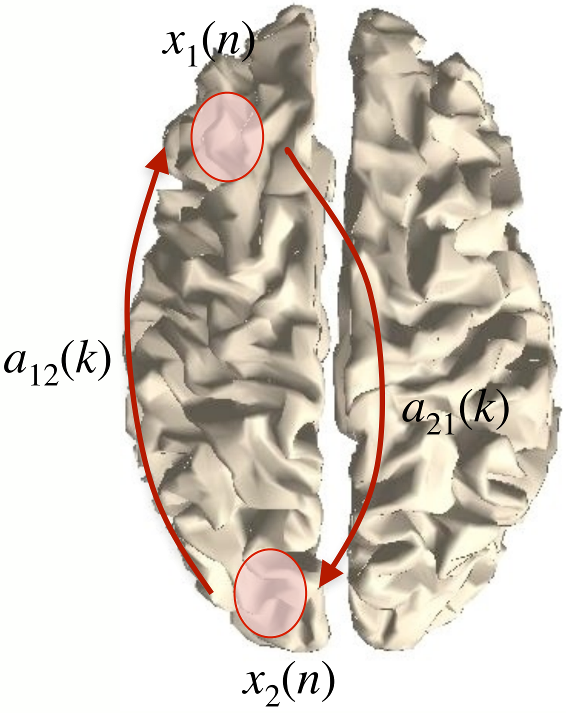
- Trans-membrane ionic currents of neurons (many) generate electric and magnetic fields that can be detected at the scalp
- Generation of the electromagnetic field (EEG or MEG) governed by basic laws of physics

MVAR Network Model

- Linear model (time index - *n*)
  - Example: two signals, $x_1(n)$ and $x_2(n)$

$$x_1(n) = \sum_{k=1}^{p} a_{11}(k)x_1(n-k) + a_{12}(k)x_2(n-k) + w_1(n)$$

$$x_2(n) = \sum_{k=1}^{p} a_{21}(k)x_1(n-k) + a_{22}(k)x_2(n-k) + w_2(n)$$



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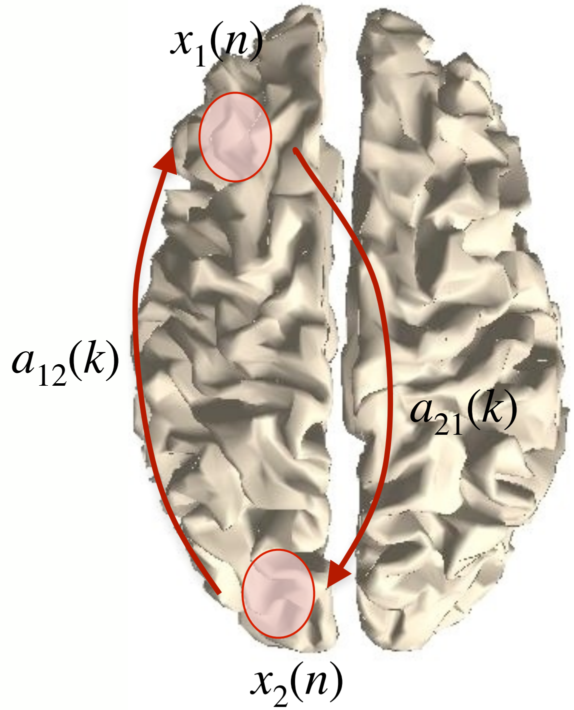

- In general, for *M* signals

$$\boxed{\mathbf{x}(n) = \sum_{k=1}^{p} \mathbf{A}_k \mathbf{x}(n-k) + \mathbf{w}(n)}$$

State-Space Model

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- MVAR model for cortical activity - Biology

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- Scalp measurement of cortical signals - Physics

$$\mathbf{y}(n) = \begin{bmatrix} \mathbf{C}_1\mathbf{d}_1 & \mathbf{C}_2\mathbf{d}_2 & \dots & \mathbf{C}_M\mathbf{d}_M \end{bmatrix} \begin{bmatrix} x_1(n) \\ x_2(n) \\ \vdots \\ x_M(n) \end{bmatrix} + \mathbf{v}(n)$$

- Solve for $\mathbf{A}_k$ directly from $\mathbf{y}(n)$ and $\mathbf{C}_k$

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- Solve for $\mathbf{A}_k$ directly from $\mathbf{y}(n)$ and $\mathbf{C}_k$
- Measured data: 256 channels by ~ 15,000 time samples

Maximum Likelihood Estimation

- Unknown parameters $\Theta = \{\mathbf{A}_1, \ldots, \mathbf{A}_p, \mathbf{Q}, \mathbf{d}_1, \ldots, \mathbf{d}_M, \mathbf{R}\}$

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- No closed form solution: iterate
  - E-step: Given Θ, we can estimate $\mathbf{X}$ – fixed interval smoother
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Workflow

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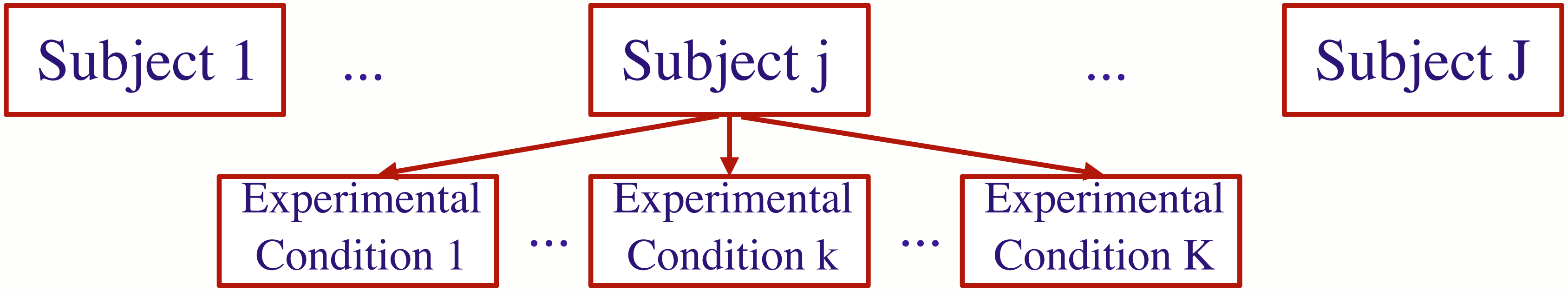
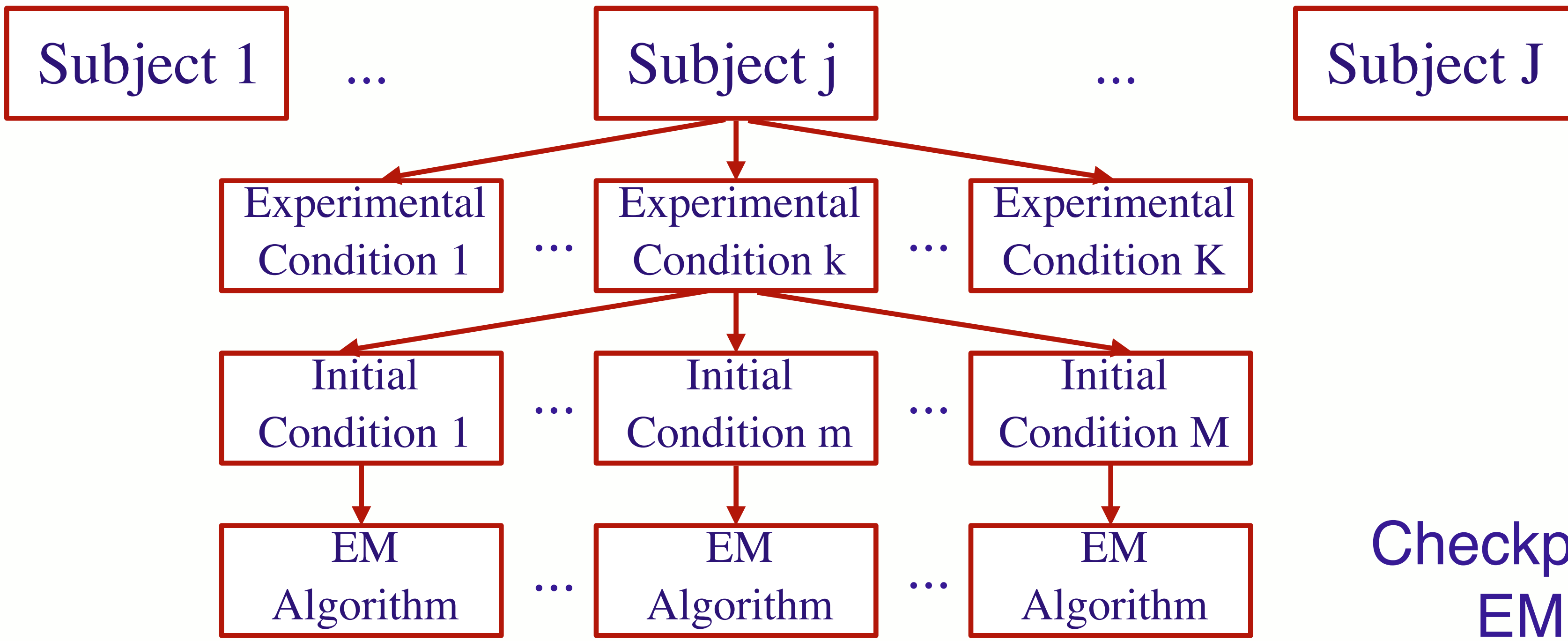
Subject 1 … Subject j … Subject J

Workflow

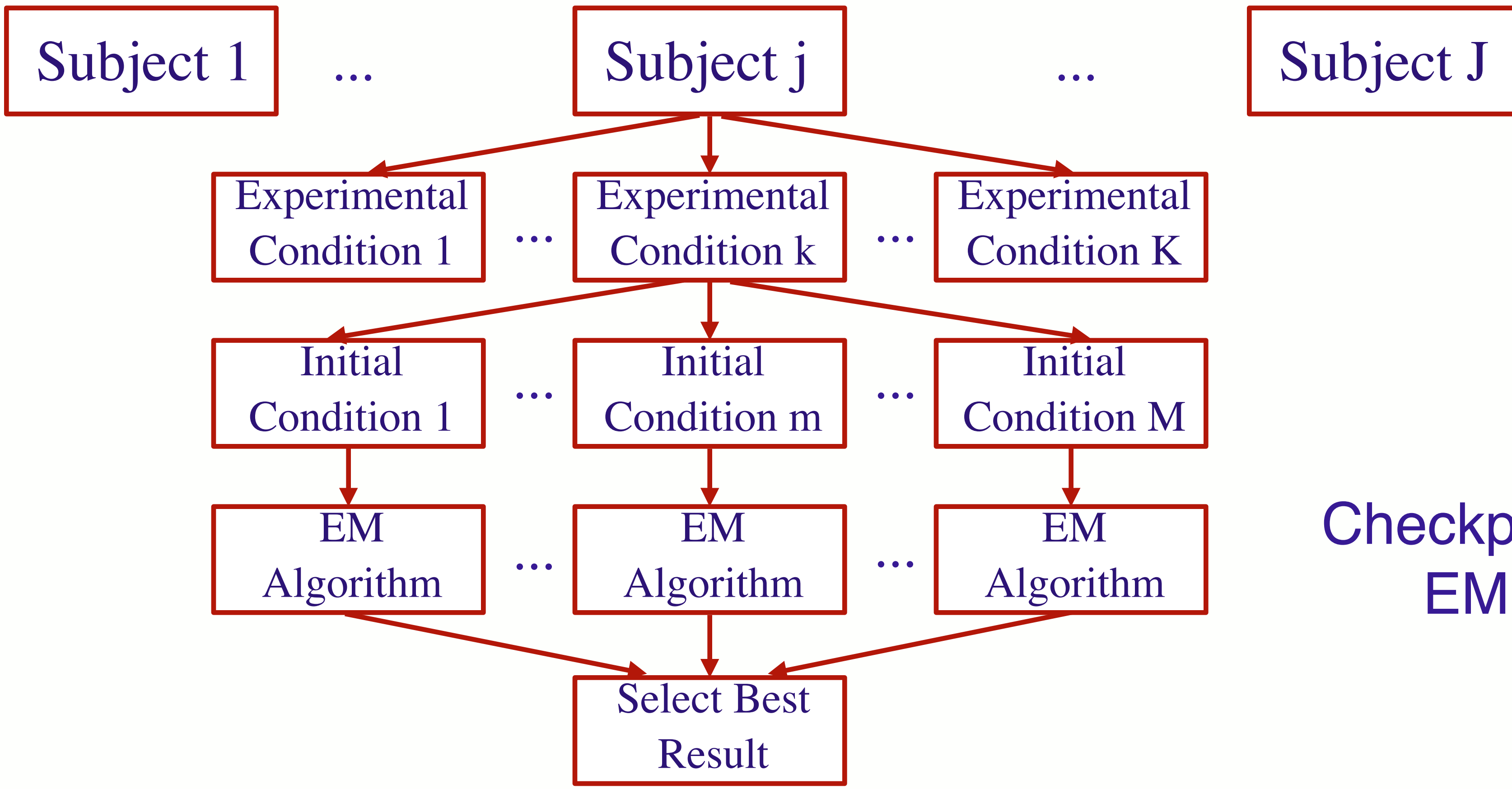

Subject 1
…
Subject j
…
Subject J
Experimental Condition 1
…
Experimental Condition k
…
Experimental Condition K

Workflow



Checkpoint EM

Workflow



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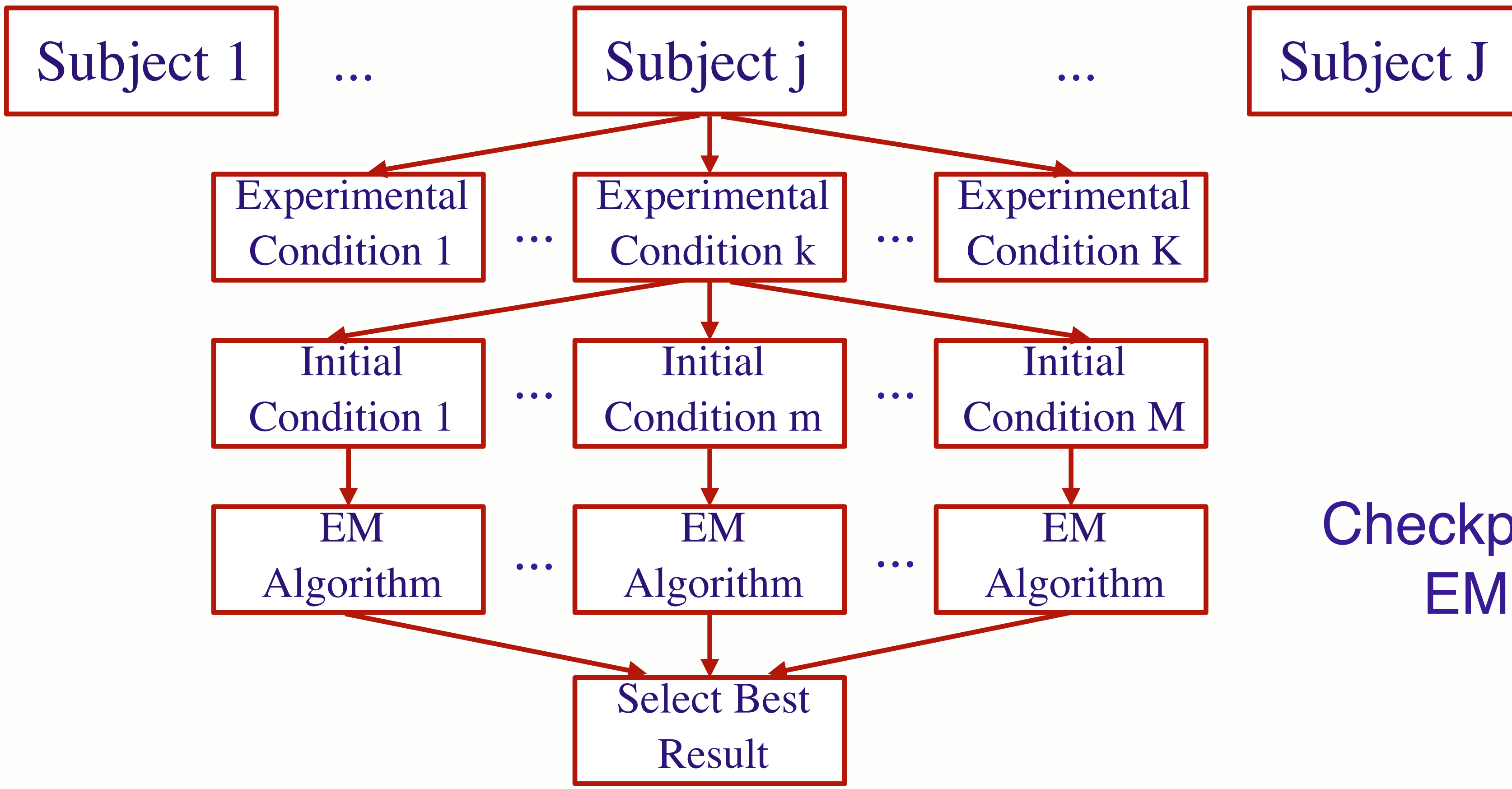

Checkpoint EM

Parallel Jobs: J (subjects) x K (exp cond) x M (init cond)

~ 20 x 3 x 50 = 3000

HTC to the Rescue

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- Each job takes several CPU hours

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- GPU computing?
  - Custom code
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- HTC
  - Port MATLAB code to HTC environment
  - Code efficiency vs large number of CPUs
  - 3 day typical turnaround
  - ~ 2,400,000 hours last year (274 years!!!)

HTC Transforms Science

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- Without HTC
  - Still writing code?
  - Limited attempts to get algorithms right…
  - Would it ever work?

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  - Still writing code?
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  - Would it ever work?
- With HTC
  - Minimal up front investment
  - No need to optimize code (factor of 2?)
  - Many chances to get algorithms right
  - Four major human studies so far
  - Demonstrate value of our algorithms

Anatomical and Effective Connectivity: Spina Bifida

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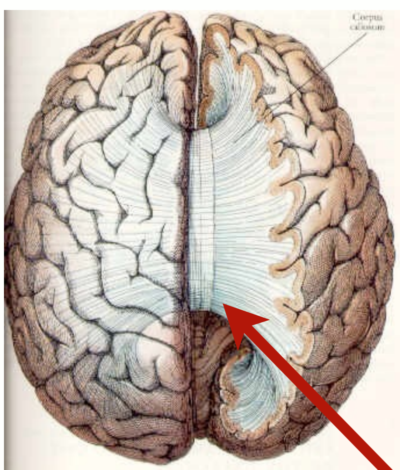

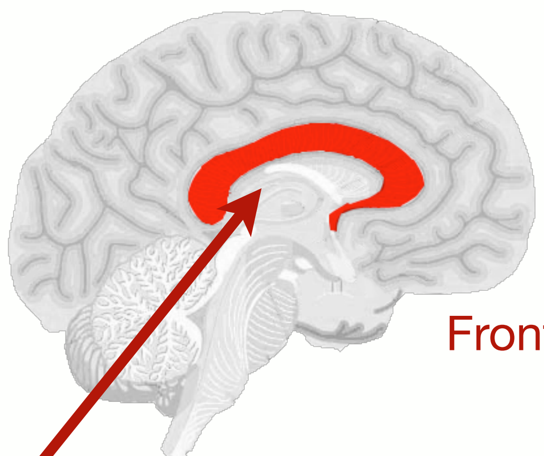

Huble. Eye, brain and vision. (1988)

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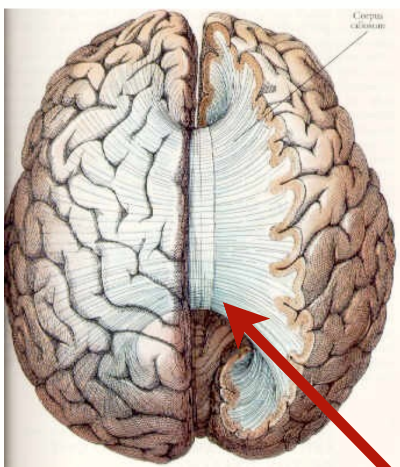

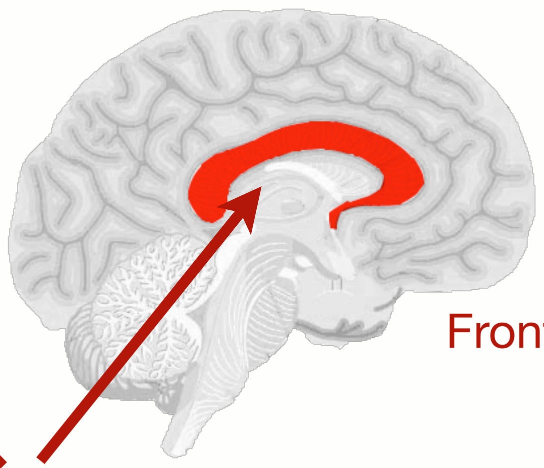

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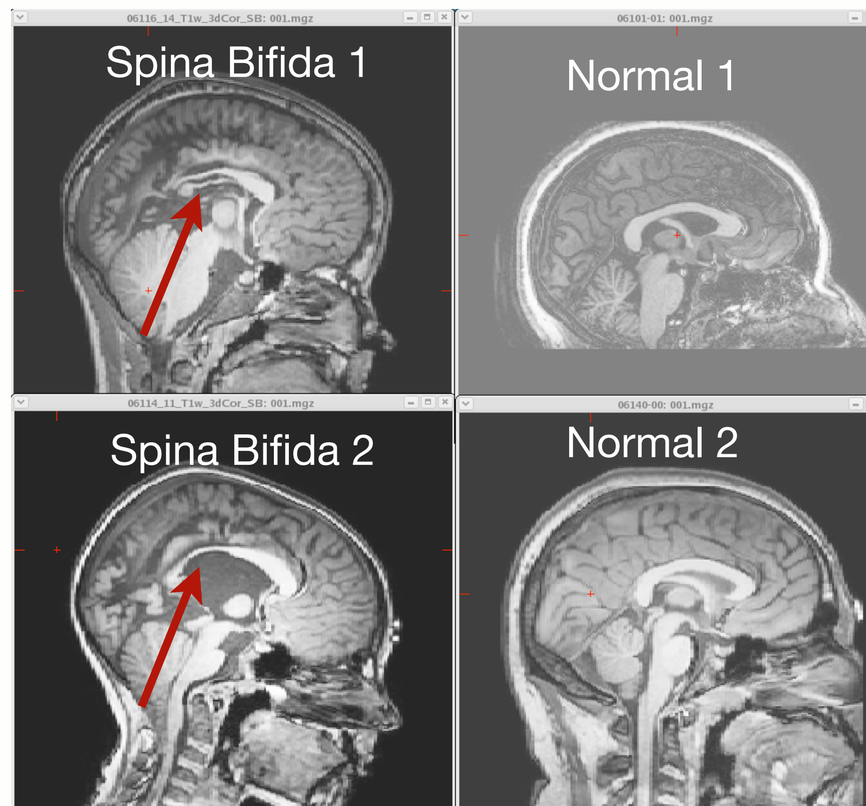
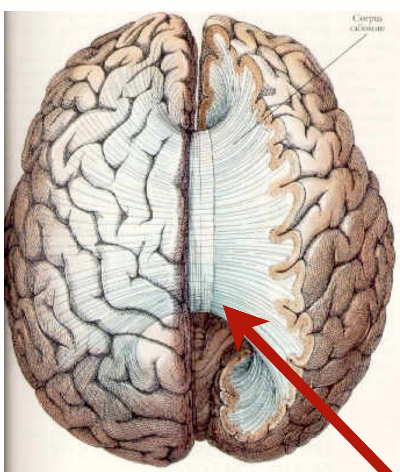
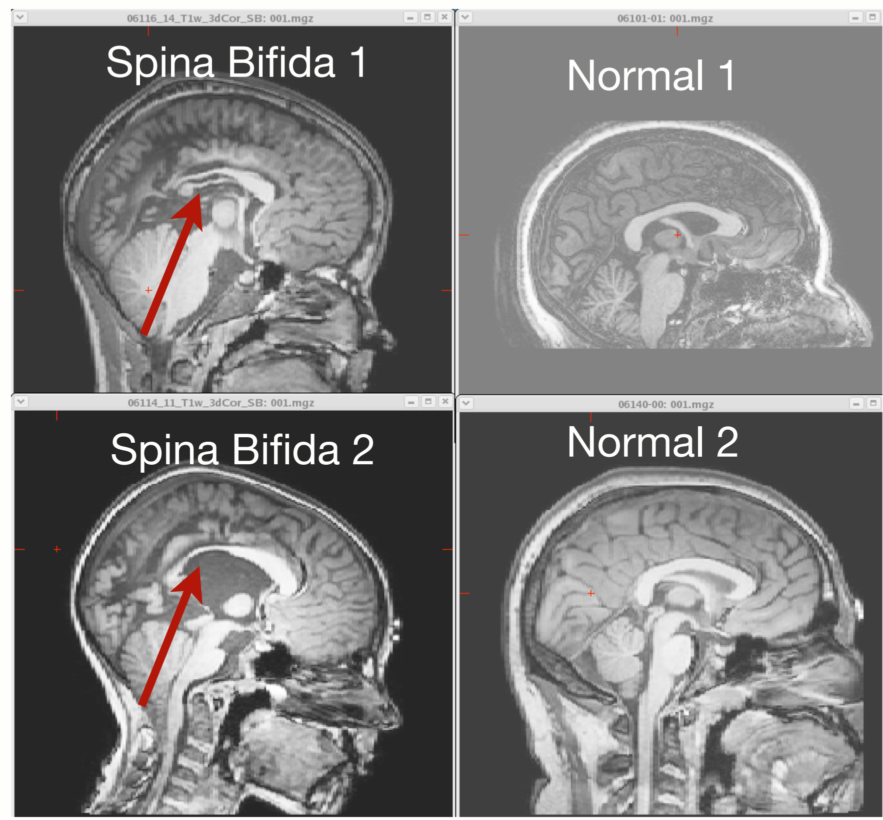


Anatomical and Effective Connectivity: Spina Bifida

- Corpus callosum connects L and R hemispheres
- Back portion thin/anomolous in children with spina bifida
- Does reduced anatomical connectivity imply reduced effective connectivity?





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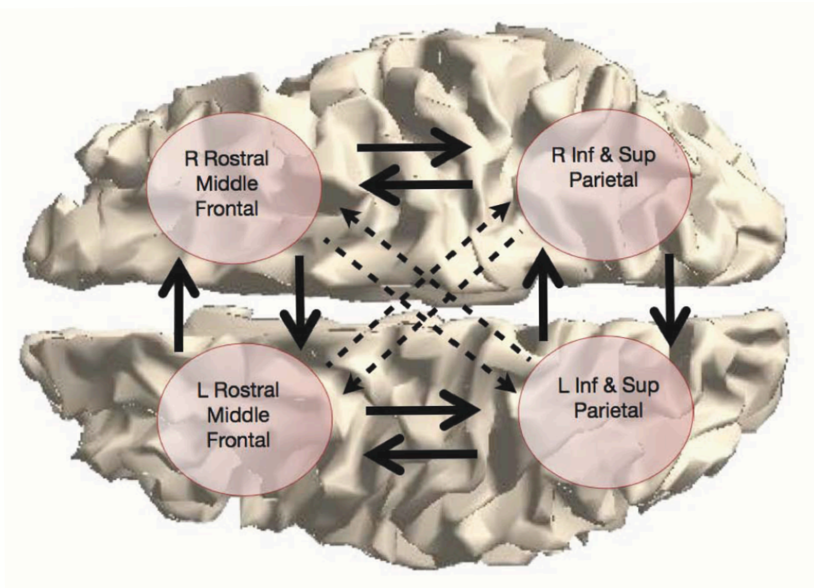
  - Rostral middle frontal and inferior +superior parietal in each hemisphere
  - EM based estimates with $p = 12$



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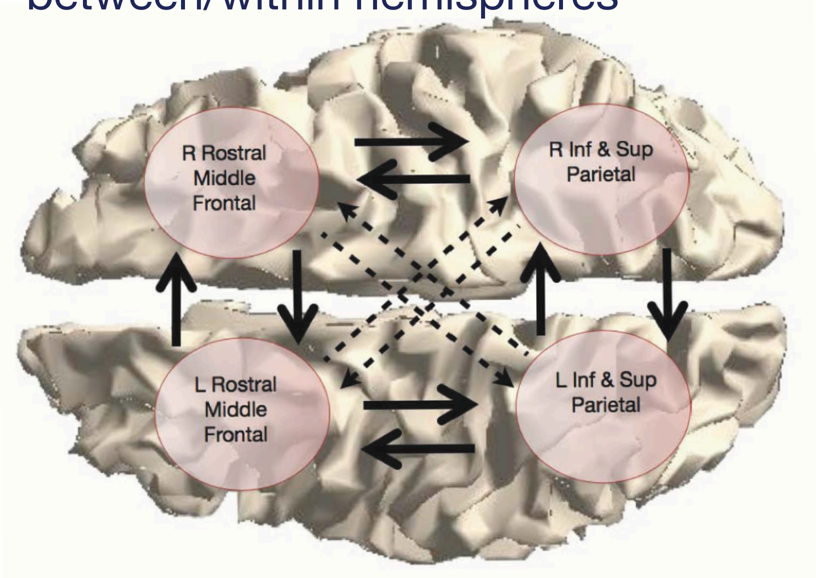
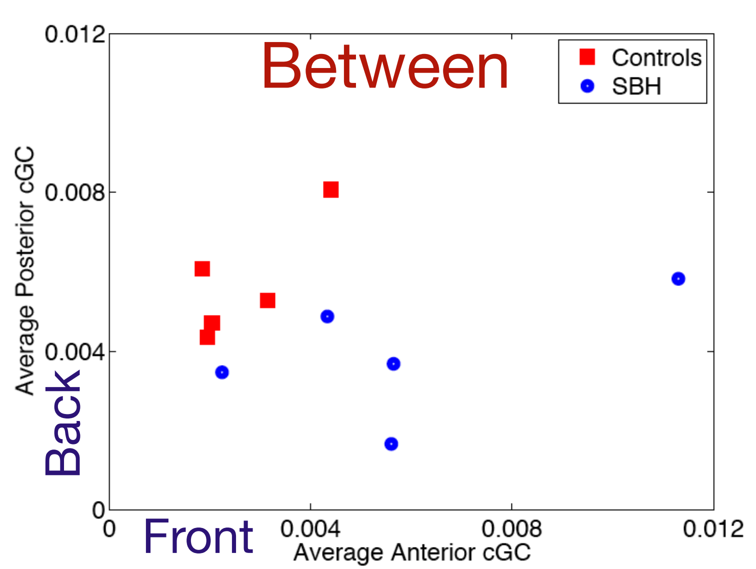
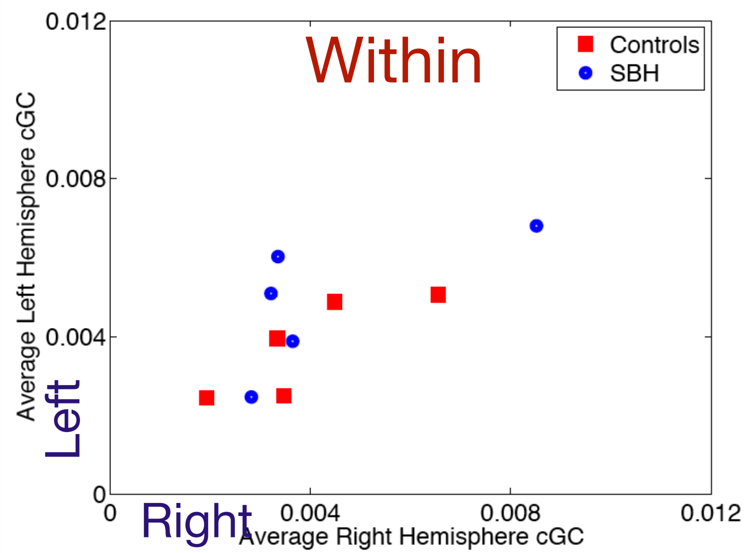
- Conditional Granger causality (cGC) between/within hemispheres







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  - Watch short video clips ~ 5 mins
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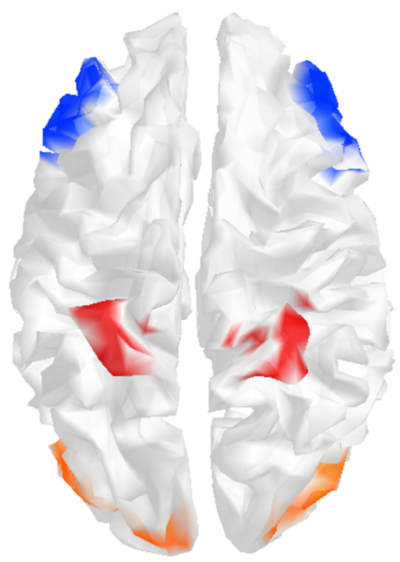

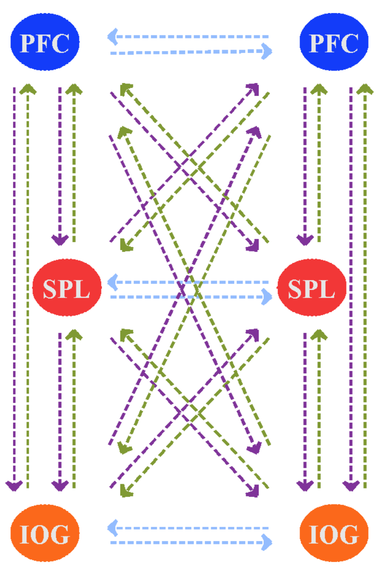

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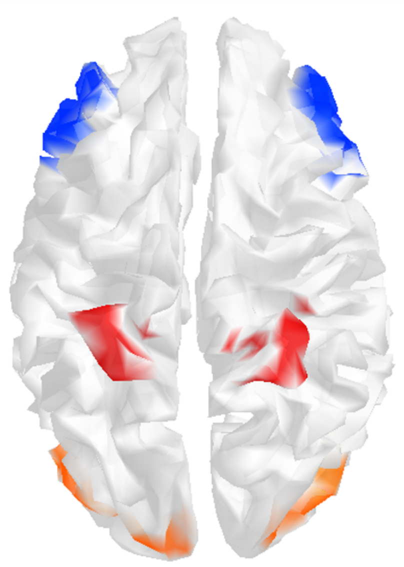

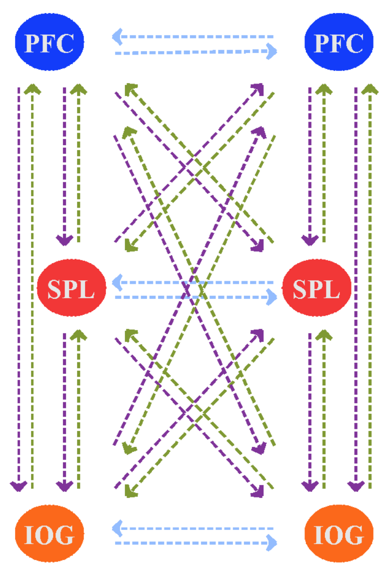

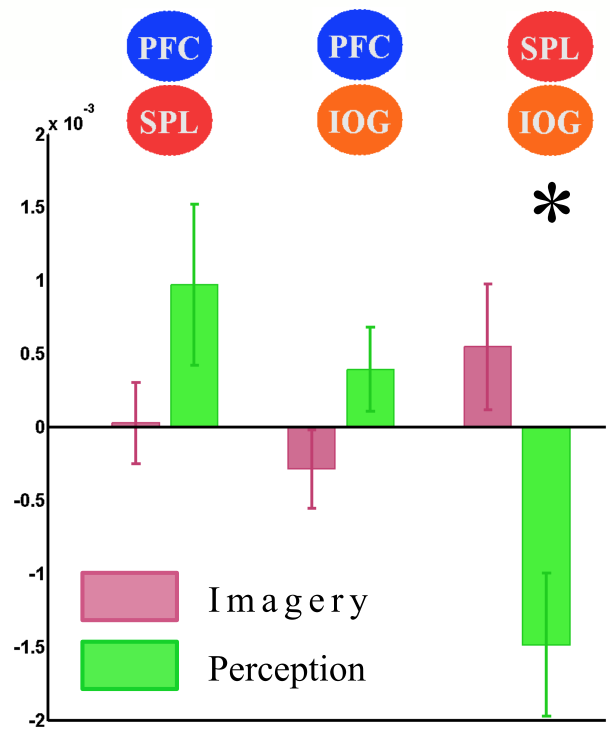

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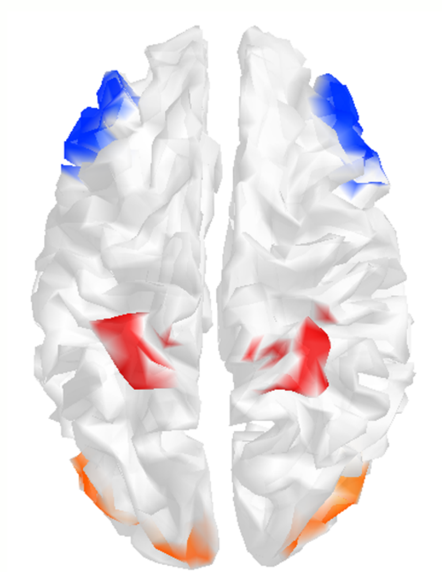

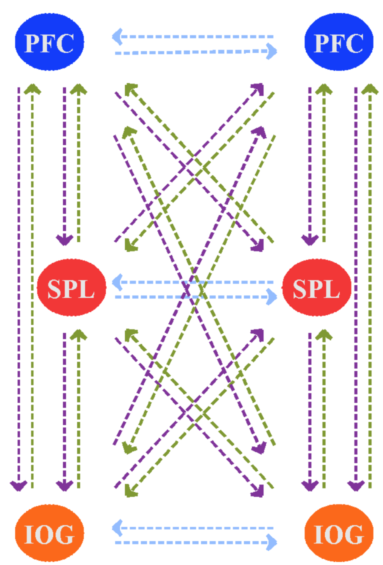

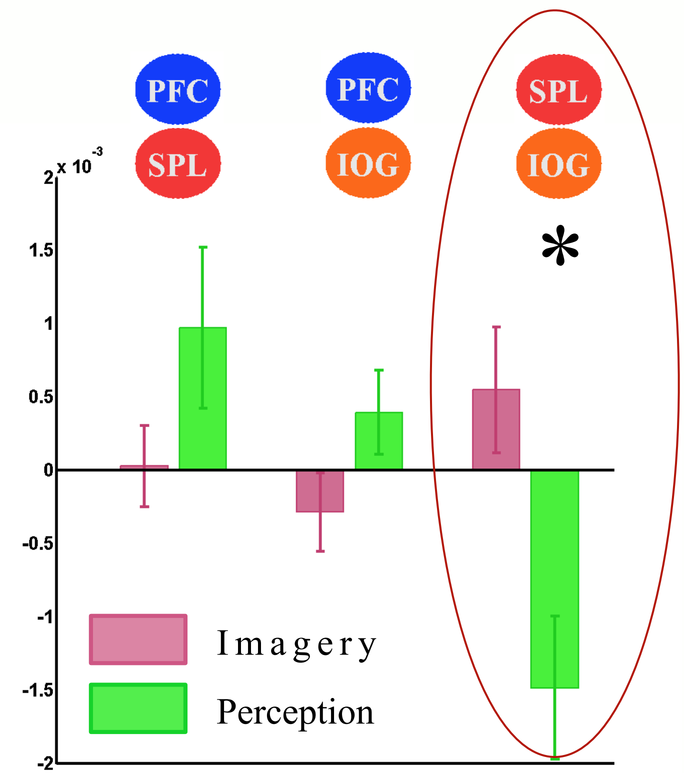

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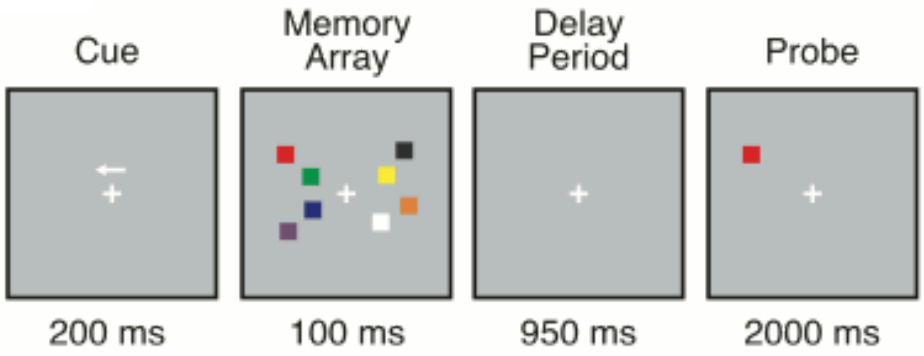

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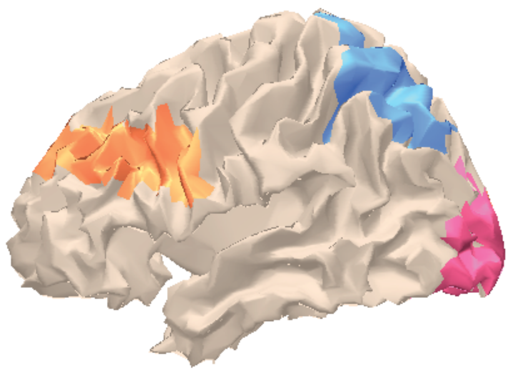

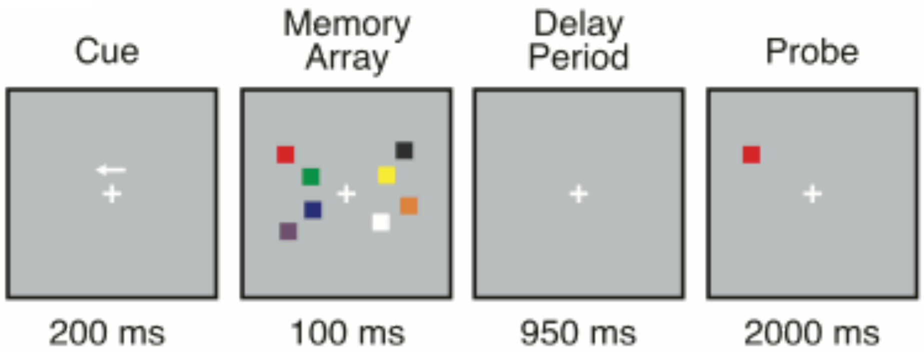

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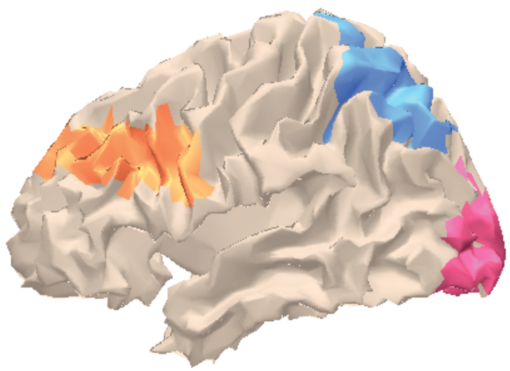

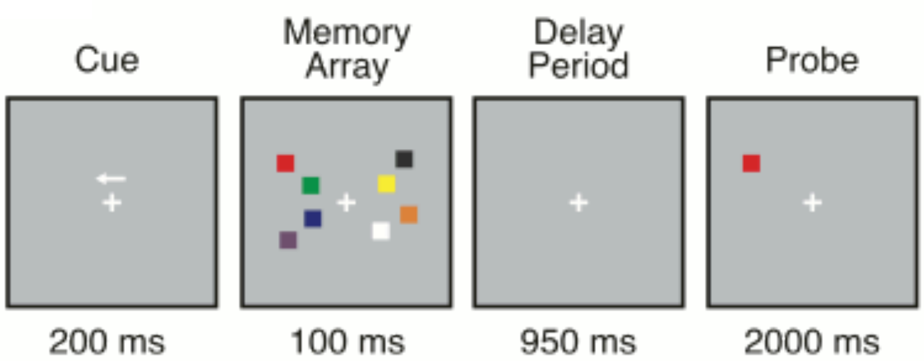

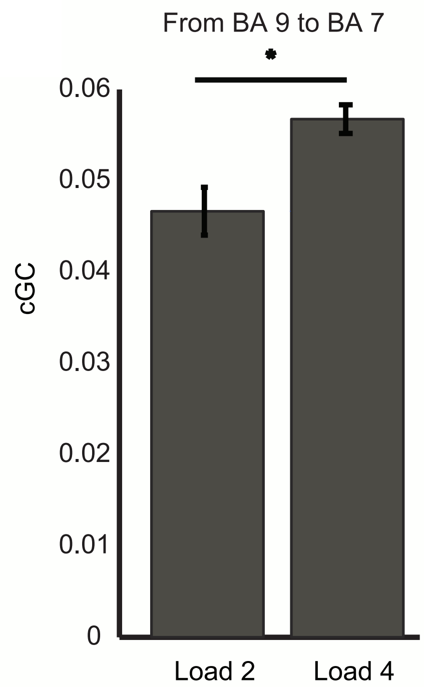

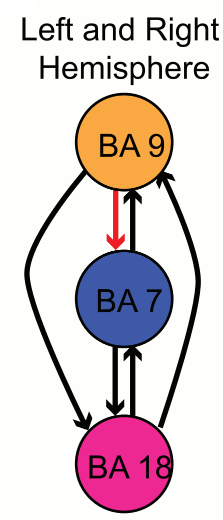

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- Interesting scientific conclusions from several studies
- Impossible without high throughput computing

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- State-space approach involves iterative algorithms
- High level of parallelism - subjects, conditions, initial conditions
- Interesting scientific conclusions from several studies
- Impossible without high throughput computing
- Support of Bill Taylor and the CHTC team