Scaling up Cognitive Neuroscience with HTC

Chris Cox July 25, 2018

Cognitive Neuroscience in 2018

- Huge online (OpenNeuro, Human Connectome Project, etc.) and offline (lab/department/collaborator archives) data repositories.
- Non-linear optimization routines to align anatomical structures.
- Probabilistic routines for image segmentation.
- High-dimensional signal reconstruction/feature extraction.
- Whole-brain function and connectivity analyses w/ machine learning.
- Modeling and simulating spatiotemporal signal.
- Real-time neurofeedback.





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- More responsive and personalized experimental tools.
- More computational demand, meaning ...
- More time between having an idea and obtaining a result.

High Throughput Computing

- Highly effective if a task can be split into independent pieces.
- Scaling up the science can be accommodated by recruiting more machines.
- HTC is widely available through the Open Science Grid.

HTC is widely applicable to cognitive neuroscience

• Many conventional and state of the art procedures can be naturally divided into pieces that can be run in parallel.



Image coregistration, normalization, and segmentation

- Each subject can be allocated to a different machine.
- Accommodate more complex image processing, and keep processing time under control.
- Scale up to datasets with hundreds or thousands of participants.

Univariate Analyses and Searchlight Analyses

- Voxels and searchlights are independent.
- Sophisticated modeling can be done at each voxel/searchlight by distributing load over multiple machines.
- Scale up to datasets with hundreds or thousands of participants.

Relating brain and behavior with Machine Learning

- Cross validation.
- Hyper-parameter selection.
- Permutation testing.
- A full analysis can involve hundreds of thousands of models, but each is independent.

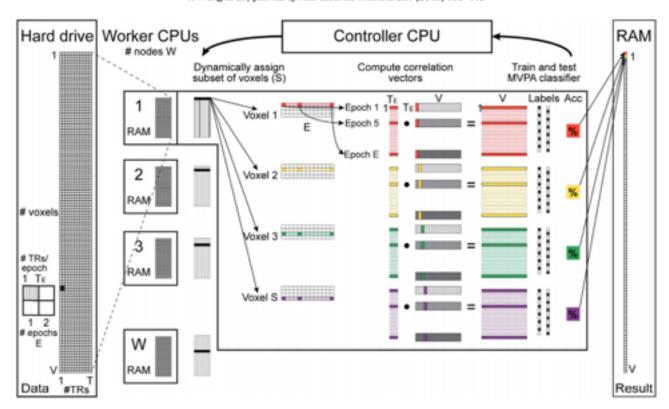
Network Discovery through Whole-brain modeling

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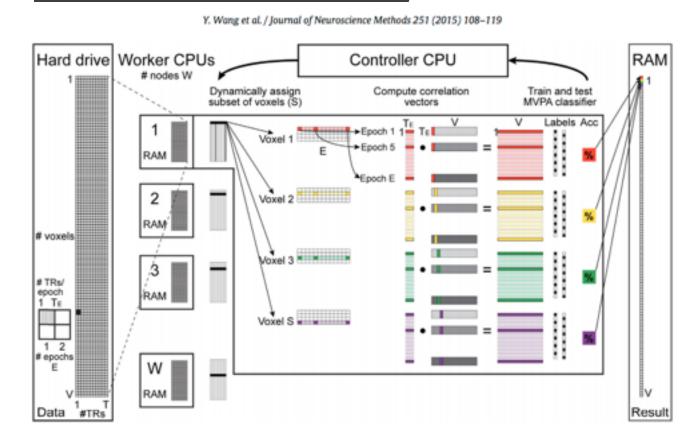
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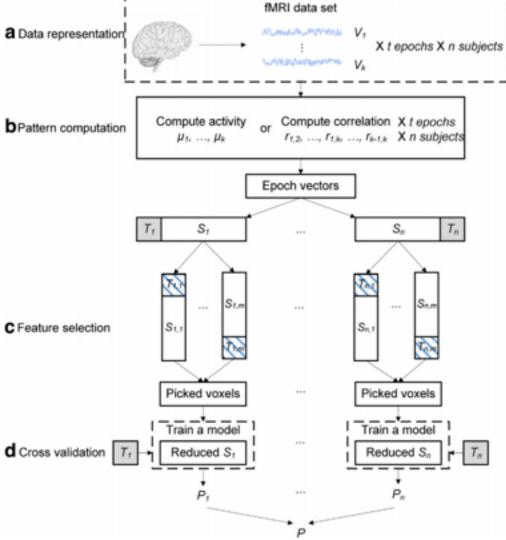


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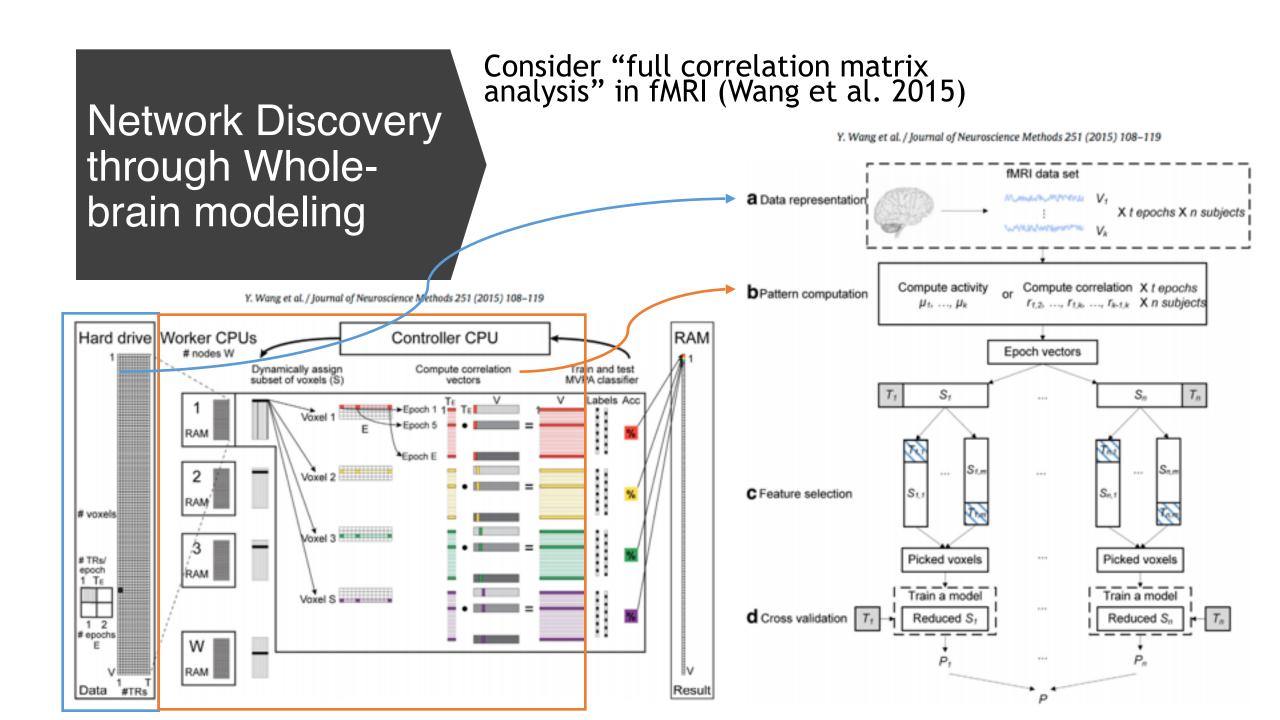
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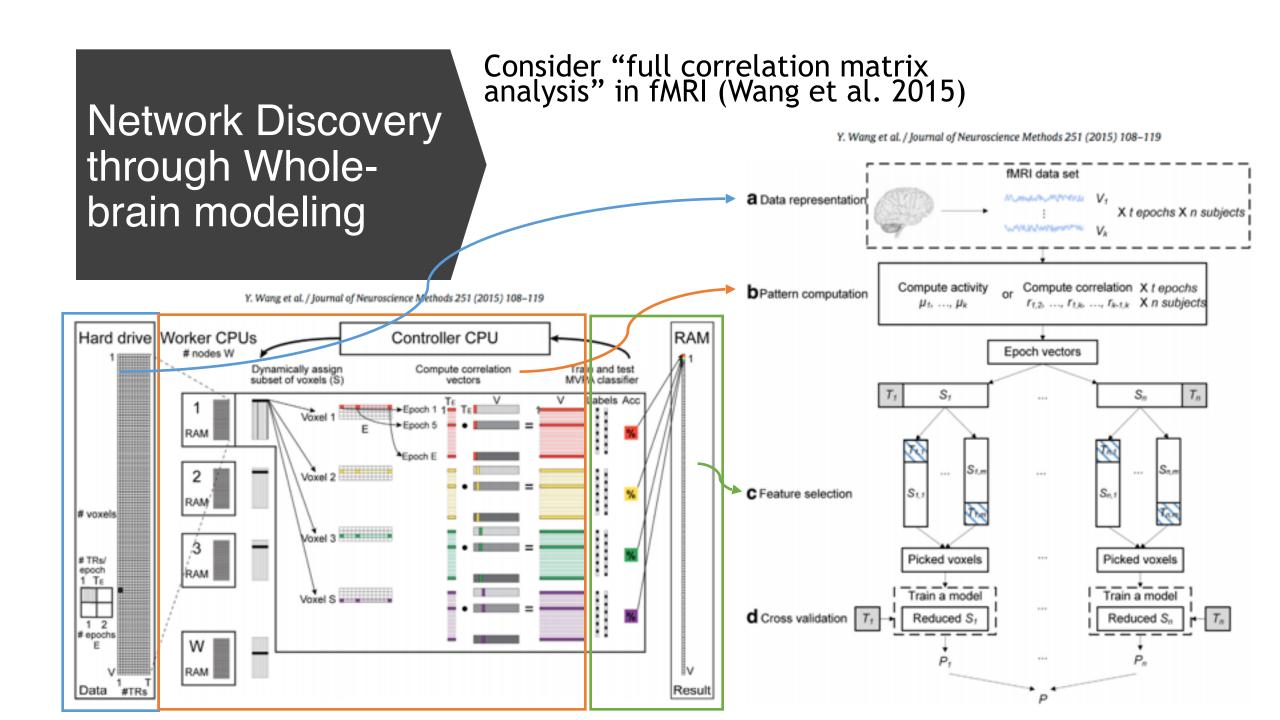
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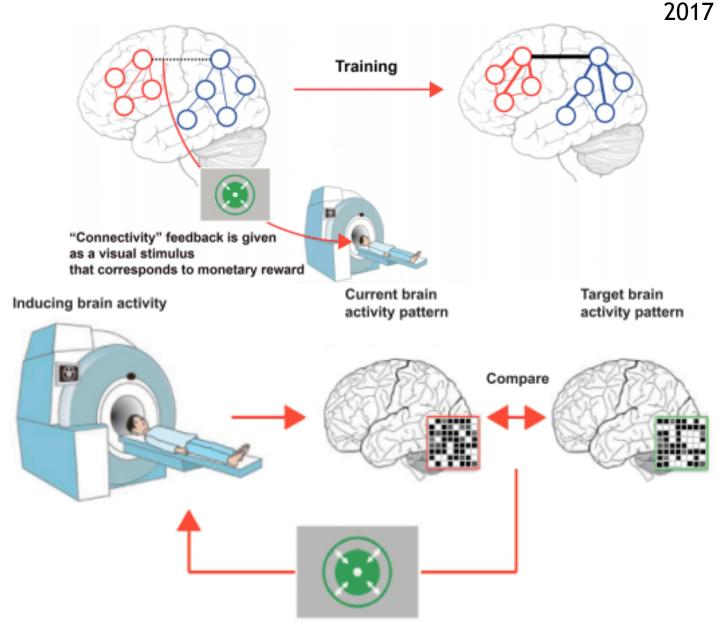
Consider "full correlation matrix analysis" in fMRI (Wang et al. 2015) **Network Discovery** Y. Wang et al. / Journal of Neuroscience Methods 251 (2015) 108-119 through WholefMRI data set brain modeling a Data representatio X t epochs X n subjects Compute correlation X t epochs DPattern computation Y. Wang et al. / Journal of Neuroscience Methods 251 (2015) 108-119 r_{1,2}, ..., r_{1,k}, ..., r_{k-1,k} X n subjects Hard drive Worker CPUs Controller CPU RAM Epoch vectors # nodes W Dynamically assign Compute correlation Train and test subset of voxels (S) MVPA classifier Labels Acc →Epoch 1 1 TE Epoch E Voxel 2 C Feature selection # voxels Voxel 3 Picked voxels Picked voxels # TRs/ epoch Train a model Train a model d Cross validation T₁ Reduced S-# epochs Data #TRs





Real-time Neurofeedbac k

- Brain may be segmented and processed in parallel.
- Cross validation can be performed in parallel if necessary.



"Similarity" feedback is given as a visual stimulus that corresponds to monetary reward

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- 4. Patterns need not be localized.

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- Need a whole-brain model that is flexibly sensitive to localization, while still being sensitive to complex patterns that vary across people.

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- Rao, Cox, Rogers, and Nowak (2013; 2015) introduced SOS Lasso, which is a complex optimization with multiple hyperparameters.
- No way to estimate them without searching the parameter space.
- No way to evaluate performance without cross validation.
- No way to understand voxel significance without permutation testing.
- Models are fit to all voxels in cortex for all participants in an experiment simultaneously.
- An exciting method, with intense computational needs.

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