An Implementation of Dynamic Causal Modeling

Christian Himpe

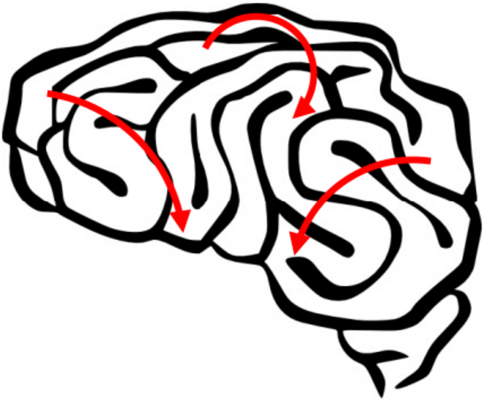
08.12.2011

Overview

- About
- Models
- Inversion
- Implementation
- Example

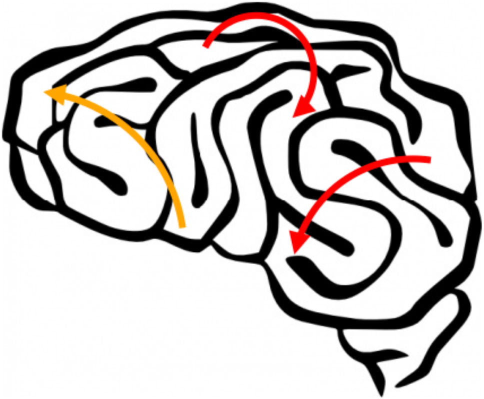
Motivation

- How are brain regions coupled?
- How does this coupling change in an experimental context?
- How are stimuli propagated between brain regions?



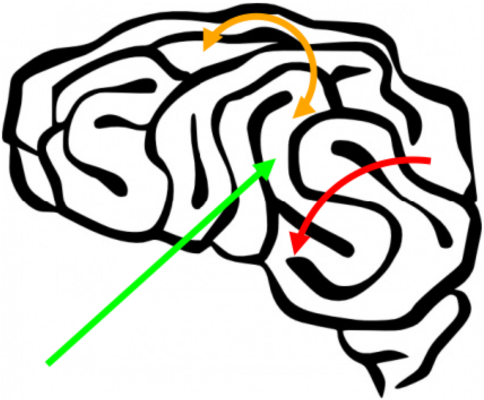
Motivation

- How are brain regions coupled?
- How does this coupling change in an experimental context?
- How are stimuli propagated between brain regions?



Motivation

- How are brain regions coupled?
- How does this coupling change in an experimental context?
- How are stimuli propagated between brain regions?



Dynamic Causal Modeling Process

1. Form Hypothesis
2. Conduct Experiment
3. Preprocess Data (Filtering, Reduction)
4. Select Model
5. Estimate Parameters
6. Compute Solution

Dynamic Causal Modeling Process

1. Form Hypothesis
2. Conduct Experiment
3. Preprocess Data (Filtering, Reduction)
4. Select Model
5. Estimate Parameters
6. Compute Solution

Dynamic Causal Modeling Process

1. Form Hypothesis
2. Conduct Experiment
3. Preprocess Data (Filtering, Reduction)
4. Select Model
5. Estimate Parameters
6. Compute Solution

Dynamic Causal Modeling Process

1. Form Hypothesis
2. Conduct Experiment
3. Preprocess Data (Filtering, Reduction)
4. Select Model
5. Estimate Parameters
6. Compute Solution

Dynamic Causal Modeling Process

1. Form Hypothesis
2. Conduct Experiment
3. Preprocess Data (Filtering, Reduction)
4. Select Model
5. Estimate Parameters
6. Compute Solution

Dynamic Causal Modeling Process

1. Form Hypothesis
2. Conduct Experiment
3. Preprocess Data (Filtering, Reduction)
4. Select Model
5. Estimate Parameters
6. Compute Solution

Model Principles

- Dynamic
- Deterministic
- Multiple Inputs and Outputs
- Two Component Model
    - Dynamic Submodel
    - Forward Submodel
- Differ by Data Acquisition Method
    - fMRI
    - EEG/MEG

DCM for fMRI

- Dynamic Submodel: Bilinear Dynamic System
- Forward Submodel: Balloon-Windkessel Model

DCM for fMRI (Dynamic)

Example:

- 3 brain regions ($z \in \mathbb{R}^3$)
- 2 input sources ($i \in \mathbb{R}^2$)
  - 1 direct input source (i_1)
  - 1 lateral input source (i_2)

$$\dot{z} = Az + B_2 z i_2 + Ci$$

$$A = \begin{pmatrix} -1 & 0 & 0 \\ 0.2 & -1 & 0.4 \\ 0.3 & 0 & -1 \end{pmatrix} \; B_1 = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} \; B_2 = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0.7 & 0 & 0 \end{pmatrix} \; C = \begin{pmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 0 \end{pmatrix}$$

Example:

- 3 brain regions ($z \in \mathbb{R}^3$)
- 2 input sources ($i \in \mathbb{R}^2$)
  - 1 direct input source (i_1)
  - 1 lateral input source (i_2)

$$\dot{z} = Az + B_1 z i_1 + B_2 z i_2 + Ci$$

$$A = \begin{pmatrix} -1 & 0 & 0 \\ 0.2 & -1 & 0.4 \\ 0.3 & 0 & -1 \end{pmatrix} \; B_1 = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} \; B_2 = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0.7 & 0 & 0 \end{pmatrix} \; C = \begin{pmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 0 \end{pmatrix}$$

DCM for fMRI (Dynamic)

Example:

- 3 brain regions ($z \in \mathbb{R}^3$)
- 2 input sources ($i \in \mathbb{R}^2$)
  - 1 direct input source (i_1)
  - 1 lateral input source (i_2)

$$\dot{z} = Az + B_2 z i_2 + Ci$$

$$A = \begin{pmatrix} -1 & 0 & 0 \\ 0.2 & -1 & 0.4 \\ 0.3 & 0 & -1 \end{pmatrix} \; B_1 = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} \; B_2 = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0.7 & 0 & 0 \end{pmatrix} \; C = \begin{pmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 0 \end{pmatrix}$$

DCM for fMRI (Dynamic)

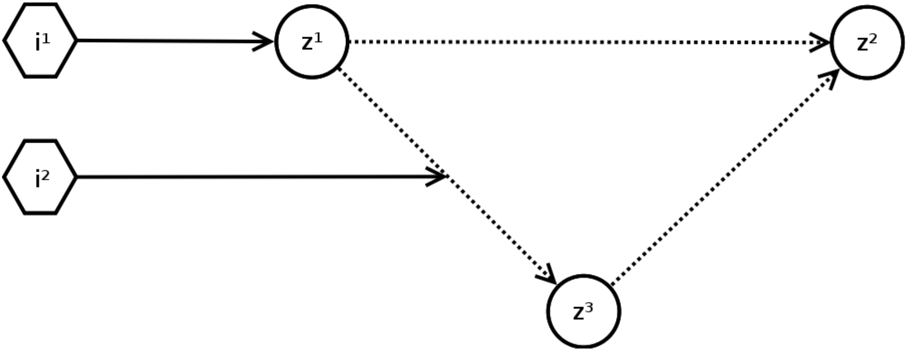
Example:

- 3 brain regions ($z \in \mathbb{R}^3$)
- 2 input sources ($i \in \mathbb{R}^2$)
  - 1 direct input source (i_1)
  - 1 lateral input source (i_2)

$$\dot{z} = Az + B_2 z i_2 + Ci$$

$$A = \begin{pmatrix} -1 & 0 & 0 \\ 0.2 & -1 & 0.4 \\ 0.3 & 0 & -1 \end{pmatrix} \; B_1 = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} \; B_2 = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0.7 & 0 & 0 \end{pmatrix} \; C = \begin{pmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 0 \end{pmatrix}$$

DCM for fMRI (Dynamic)



$$A = \begin{pmatrix} -1 & 0 & 0 \\ 0.2 & -1 & 0.4 \\ 0.3 & 0 & -1 \end{pmatrix} \; B_1 = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} \; B_2 = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0.7 & 0 & 0 \end{pmatrix} \; C = \begin{pmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 0 \end{pmatrix}$$

DCM for MRI (Forward)

- vasolidatory signal (s):
  - receives input (output of the dynamic system)
  - dampens with itself
  - and with normalized inflow
- normalized inflow (f):
  - is caused by the vasoladitory signal
- normalized venomous volume (v):
  - difference between normalized inflow and outflow
- normalized deoxyhemoglobin content (q):
  - difference between inflow and outflow
- output (y):
  - weighted sum of venomous volume and deoxyhemoglobin content

DCM for MRI (Forward)

- vasolidatory signal (s):
  - receives input (output of the dynamic system)
  - dampens with itself
  - and with normalized inflow
- normalized inflow (f):
  - is caused by the vasoladitory signal
- normalized venomous volume (v):
  - difference between normalized inflow and outflow
- normalized deoxyhemoglobin content (q):
  - difference between inflow and outflow
- output (y):
  - weighted sum of venomous volume and deoxyhemoglobin content

DCM for MRI (Forward)

- vasolidatory signal (s):
  - receives input (output of the dynamic system)
  - dampens with itself
  - and with normalized inflow
- normalized inflow (f):
  - is caused by the vasoladitory signal
- normalized venomous volume (v):
  - difference between normalized inflow and outflow
- normalized deoxyhemoglobin content (q):
  - difference between inflow and outflow
- output (y):
  - weighted sum of venomous volume and deoxyhemoglobin content

DCM for MRI (Forward)

- vasolidatory signal (s):
  - receives input (output of the dynamic system)
  - dampens with itself
  - and with normalized inflow
- normalized inflow (f):
  - is caused by the vasoladitory signal
- normalized venomous volume (v):
  - difference between normalized inflow and outflow
- normalized deoxyhemoglobin content (q):
  - difference between inflow and outflow
- output (y):
  - weighted sum of venomous volume and deoxyhemoglobin content

DCM for MRI (Forward)

- vasolidatory signal (s):
  - receives input (output of the dynamic system)
  - dampens with itself
  - and with normalized inflow
- normalized inflow (f):
  - is caused by the vasoladitory signal
- normalized venomous volume (v):
  - difference between normalized inflow and outflow
- normalized deoxyhemoglobin content (q):
  - difference between inflow and outflow
- output (y):
  - weighted sum of venomous volume and deoxyhemoglobin content

DCM for MRI (Forward)

- vasolidatory signal (s):
  - receives input (output of the dynamic system)
  - dampens with itself
  - and with normalized inflow
- normalized inflow (f):
  - is caused by the vasoladitory signal
- normalized venomous volume (v):
  - difference between normalized inflow and outflow
- normalized deoxyhemoglobin content (q):
  - difference between inflow and outflow
- output (y):
  - weighted sum of venomous volume and deoxyhemoglobin content

DCM for MRI (Forward)

$$
\begin{tikzcd}
 & z & \\
 & \boxed{\dot{s}} \arrow[u] \arrow[d, shift left] & \\
 & \boxed{\dot{f}} \arrow[u, shift left] & \\
\boxed{\dot{v}} \arrow[ur] \arrow[rr] & & \boxed{\dot{q}} \arrow[ul] \\
 & \boxed{y} \arrow[ul] \arrow[ur] &
\end{tikzcd}
$$

DCM for EEG

- Dynamic Submodel: Jansen Model
- Forward Submodel: Linear Transformation

DCM for EEG (Dynamic)

Tripartioning:

E	Excitatory Subpopulation
$\uparrow\downarrow$	(Intrinsic Coupling)
O	(Excitatory) Output Subpopulation
$\uparrow\downarrow$	(Intrinsic Coupling)
I	Inhibitory Subpopulation

$$C_F = \begin{pmatrix} 0 & . & . \\ . & 0 & . \\ . & . & 0 \end{pmatrix} \quad C_B = \begin{pmatrix} 0 & . & . \\ . & 0 & . \\ . & . & 0 \end{pmatrix} \quad C_L = \begin{pmatrix} 0 & . & . \\ . & 0 & . \\ . & . & 0 \end{pmatrix}$$

DCM for EEG (Dynamic)

Forward, Backward, Lateral Connections:

$$
\begin{array}{|c|}\hline E_1\\\hline \uparrow\downarrow\\\hline O_1\\\hline \uparrow\downarrow\\\hline I_1\\\hline\end{array}
\begin{array}{c} \\ \nearrow \\ \\ \\ \\ \end{array}
\begin{array}{|c|}\hline E_2\\\hline \uparrow\downarrow\\\hline O_2\\\hline \uparrow\downarrow\\\hline I_2\\\hline\end{array}
\qquad
\begin{array}{|c|}\hline E_1\\\hline \uparrow\downarrow\\\hline O_1\\\hline \uparrow\downarrow\\\hline I_1\\\hline\end{array}
\begin{array}{c} \\ \\ \rightarrow \\ \searrow \\ \\ \end{array}
\begin{array}{|c|}\hline E_2\\\hline \uparrow\downarrow\\\hline O_2\\\hline \uparrow\downarrow\\\hline I_2\\\hline\end{array}
\qquad
\begin{array}{|c|}\hline E_1\\\hline \uparrow\downarrow\\\hline O_1\\\hline \uparrow\downarrow\\\hline I_1\\\hline\end{array}
\begin{array}{c} \\ \nearrow \\ \rightarrow \\ \searrow \\ \\ \end{array}
\begin{array}{|c|}\hline E_2\\\hline \uparrow\downarrow\\\hline O_2\\\hline \uparrow\downarrow\\\hline I_2\\\hline\end{array}
$$

$$
C_F = \begin{pmatrix} 0 & . & . \\ . & 0 & . \\ . & . & 0 \end{pmatrix} \quad
C_B = \begin{pmatrix} 0 & . & . \\ . & 0 & . \\ . & . & 0 \end{pmatrix} \quad
C_L = \begin{pmatrix} 0 & . & . \\ . & 0 & . \\ . & . & 0 \end{pmatrix}
$$

DCM for EEG (Dynamic)

Forward, Backward, Lateral Connections:

$$
\begin{array}{|c|}\hline E_1 \\ \hline \uparrow\downarrow \\ \hline O_1 \\ \hline \uparrow\downarrow \\ \hline I_1 \\ \hline \end{array}
\begin{array}{c} \\ \nearrow \\ \\ \\ \\ \end{array}
\begin{array}{|c|}\hline E_2 \\ \hline \uparrow\downarrow \\ \hline O_2 \\ \hline \uparrow\downarrow \\ \hline I_2 \\ \hline \end{array}
\qquad
\begin{array}{|c|}\hline E_1 \\ \hline \uparrow\downarrow \\ \hline O_1 \\ \hline \uparrow\downarrow \\ \hline I_1 \\ \hline \end{array}
\begin{array}{c} \\ \\ \rightarrow \\ \searrow \\ \\ \end{array}
\begin{array}{|c|}\hline E_2 \\ \hline \uparrow\downarrow \\ \hline O_2 \\ \hline \uparrow\downarrow \\ \hline I_2 \\ \hline \end{array}
\qquad
\begin{array}{|c|}\hline E_1 \\ \hline \uparrow\downarrow \\ \hline O_1 \\ \hline \uparrow\downarrow \\ \hline I_1 \\ \hline \end{array}
\begin{array}{c} \\ \nearrow \\ \rightarrow \\ \searrow \\ \\ \end{array}
\begin{array}{|c|}\hline E_2 \\ \hline \uparrow\downarrow \\ \hline O_2 \\ \hline \uparrow\downarrow \\ \hline I_2 \\ \hline \end{array}
$$

$$
C_F = \begin{pmatrix} 0 & . & . \\ . & 0 & . \\ . & . & 0 \end{pmatrix} \quad C_B = \begin{pmatrix} 0 & . & . \\ . & 0 & . \\ . & . & 0 \end{pmatrix} \quad C_L = \begin{pmatrix} 0 & . & . \\ . & 0 & . \\ . & . & 0 \end{pmatrix}
$$

Model Overview and Drift

$$h = y + X\beta + \epsilon$$

Drift:

- Frequency Filtering (ie equipment-related drift) $\rightarrow$ Discrete Cosine Set
- Y-shift of data $\rightarrow$ 0th-Order is Constant Term

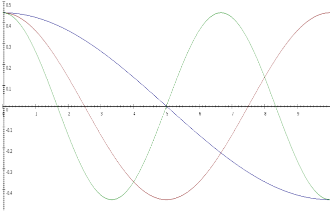
Model is now complete!

Model Overview and Drift

$$h = y + X\beta + \epsilon$$

Drift:

- Frequency Filtering (ie equipment-related drift) →Discrete Cosine Set
- Y-shift of data → 0th-Order is Constant Term



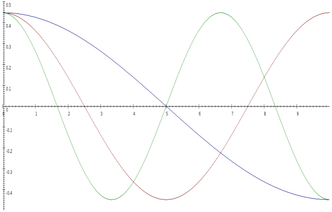
Model is now complete!

Model Overview and Drift

$$h = y + X\beta + \epsilon$$

Drift:

- Frequency Filtering (ie equipment-related drift) $\rightarrow$Discrete Cosine Set
- Y-shift of data $\rightarrow$ 0th-Order is Constant Term



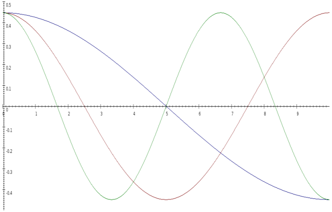
Model is now complete!

Model Overview and Drift

$$h = y + X\beta + \epsilon$$

Drift:

- Frequency Filtering (ie equipment-related drift) $\rightarrow$Discrete Cosine Set
- Y-shift of data $\rightarrow$ 0th-Order is Constant Term



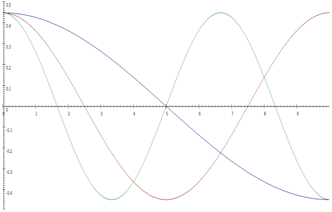
Model is now complete!

Model Overview and Drift

$$h = y + X\beta + \epsilon$$

Drift:

- Frequency Filtering (ie equipment-related drift) $\rightarrow$Discrete Cosine Set
- Y-shift of data $\rightarrow$ 0th-Order is Constant Term



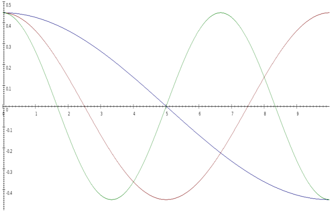
Model is now complete!

Model Overview and Drift

$$h = y + X\beta + \epsilon$$

Drift:

- Frequency Filtering (ie equipment-related drift) $\rightarrow$Discrete Cosine Set
- Y-shift of data $\rightarrow$ 0th-Order is Constant Term



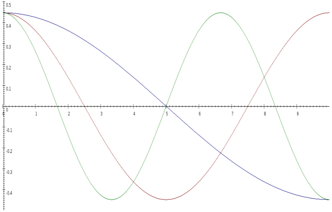
Model is now complete!

Model Overview and Drift

$$h = y + X\beta + \epsilon$$

Drift:

- Frequency Filtering (ie equipment-related drift) $\rightarrow$Discrete Cosine Set
- Y-shift of data $\rightarrow$ 0th-Order is Constant Term



Model is now complete!

Parameter Estimation

- Bayesian Inversion
  - All parameters are assumed to independently and identically distributed
  - Bayes Rule is assumed to apply $P(A|B) = \frac{P(B|A)P(B)}{P(A)}$
  - Prior Information on Parameters
- EM-algorithm (Two Step Procedure)
  1. E-Step (Expectation)
     - Estimate Mean
     - Least-Squares-Method
  2. M-Step (Maximization)
     - Estimate Hyperparameters
     -

Parameter Distribution Estimation

- Bayesian Inversion
  - All parameters are assumed to independently and identically distributed
  - Bayes Rule is assumed to apply $P(A|B) = \frac{P(B|A)P(B)}{P(A)}$
  - Prior Information on Parameters
- EM-algorithm (Two Step Procedure)
  1. E-Step (Expectation)
     - Estimate Mean
     - Least-Squares-Method
  2. M-Step (Maximization)
     - Estimate Hyperparameters
     -

Parameter Distribution Estimation

- Bayesian Inversion
  - All parameters are assumed to independently and identically distributed
  - Bayes Rule is assumed to apply $P(A|B) = \frac{P(B|A)P(B)}{P(A)}$
  - Prior Information on Parameters
- EM-algorithm (Two Step Procedure)
  1. E-Step (Expectation)
     - Estimate Mean
     - Least-Squares-Method
  2. M-Step (Maximization)
     - Estimate Hyperparameters
     -

Parameter Distribution Estimation

- Bayesian Inversion
  - All parameters are assumed to independently and identically distributed
  - Bayes Rule is assumed to apply
  - Prior Information on Parameters
- EM-algorithm (Two Step Procedure)
  1. E-Step (Expectation)
     - Estimate Mean
     - Least-Squares-Method
  2. M-Step (Maximization)
     - Estimate Hyperparameters
     -

Parameter Distribution Estimation

- Bayesian Inversion
  - All parameters are assumed to independently and identically distributed
  - Bayes Rule is assumed to apply
  - Prior Information on Parameters
- EM-algorithm (Two Step Procedure)
  1. E-Step (Expectation)
     - Estimate Mean
     - Least-Squares-Method
  2. M-Step (Maximization)
     - Estimate Hyperparameters
     -

Parameter Distribution Estimation

- Bayesian Inversion
  - All parameters are assumed to independently and identically distributed
  - Bayes Rule is assumed to apply
  - Prior Information on Parameters
- EM-algorithm (Two Step Procedure)
  1. E-Step (Expectation)
     - Estimate Mean
     - Weighted-Least-Squares-Method
  2. M-Step (Maximization)
     - Estimate Hyperparameters
     -

Parameter Distribution Estimation

- Bayesian Inversion
  - All parameters are assumed to independently and identically distributed
  - Bayes Rule is assumed to apply
  - Prior Information on Parameters
- EM-algorithm (Two Step Procedure)
  1. E-Step (Expectation)
     - Estimate Mean
     - Augmented-Weighted-Least-Squares-Method
  2. M-Step (Maximization)
     - Estimate Hyperparameters
     -

Parameter Distribution Estimation

- Bayesian Inversion
  - All parameters are assumed to independently and identically distributed
  - Bayes Rule is assumed to apply
  - Prior Information on Parameters
- EM-algorithm (Two Step Procedure)
  1. E-Step (Expectation)
     - Estimate Mean
     - Augmented-Weighted-Least-Squares-Method
  2. M-Step (Maximization)
     - Estimate Hyperparameters
     - Newton-method

Parameter Distribution Estimation

- Bayesian Inversion
  - All parameters are assumed to independently and identically distributed
  - Bayes Rule is assumed to apply
  - Prior Information on Parameters
- EM-algorithm (Two Step Procedure)
  1. E-Step (Expectation)
     - Estimate Mean
     - Augmented-Weighted-Least-Squares-Method
  2. M-Step (Maximization)
     - Estimate Hyperparameters
     - Newton-method for Maximum Likelihood Problems

Parameter Distribution Estimation

- Bayesian Inversion
  - All parameters are assumed to independently and identically distributed
  - Bayes Rule is assumed to apply
  - Prior Information on Parameters
- EM-algorithm (Two Step Procedure)
  1. E-Step (Expectation)
     - Estimate Mean
     - Augmented-Weighted-Least-Squares-Method
  2. M-Step (Maximization)
     - Estimate Hyperparameters
     - Scoring-Algorithm

Parameter Distribution Estimation

- Bayesian Inversion
  - All parameters are assumed to independently and identically distributed
  - Bayes Rule is assumed to apply
  - Prior Information on Parameters
- EM-algorithm (Two Step Procedure)
  1. E-Step (Expectation)
     - Estimate Mean
     - Augmented-Weighted-Least-Squares-Method
  2. M-Step (Maximization)
     - Estimate Hyperparameters
     - Scoring-Algorithm utilizing Fisher-Information

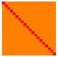
Parameter Distribution Estimation

- Bayesian Inversion
  - All parameters are assumed to independently and identically distributed
  - Bayes Rule is assumed to apply
  - Prior Information on Parameters
- EM-algorithm (Two Step Procedure)
  1. E-Step (Expectation)
     - Estimate Mean
     - Augmented-Weighted-Least-Squares-Method
  2. M-Step (Maximization)
     - Estimate Hyperparameters
     - Fisher-Scoring-Algorithm

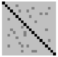
EM-Algorithm Improvements

1. Residual Forming Matrix (Residuals in M-Step)
   →Rearrange computation sequence

2. Traces of Products (Derivatives in M-Step)
   →Compute traces directly



3. Solving Linear Systems (in E- and M-Step)
   →Cholesky direct solver



4. Preventing Double Calculations (M-Step and E-Step)
   →Rearrange E-Step and recycle in M-Step

Implementation Details

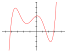
6500 LoC in C++

- no parsing and interpreting overhead
- machine specific optimizations possible

Parallelization with OpenMP

- Parallelization of 1st Derivative of E-Step (Jacobian)
- Parallelization of 1st and “2nd” Derivative of M-Step

Runge-Kutta-Fehlberg Solver



- 5th Order Single Step Solver
- allows extension to adaptive stepping

Modular Dynamic and Forward Submodels

- Extendable to further submodels
- Easy Switching between submodels

Benchmarks

Dataset	Classic |	Classic ||	Improved |	Improved ||
syn2f	74.68*s*	33.43*s*	8.38*s*	2.73*s*
syn2b	74.61*s*	32.92*s*	8.44*s*	2.66*s*
syn2l	74.40*s*	33.12*s*	9.97*s*	2.41*s*
syn3a	498.78*s*	169.14*s*	21.57*s*	5.39*s*
syn3b	495.31*s*	167.75*s*	21.66*s*	5.35*s*
syn3c	499.30*s*	166.36*s*	21.50*s*	5.52*s*
syn3d	500.64*s*	168.26*s*	21.68*s*	5.44*s*
syn3e	496.84*s*	168.27*s*	21.56*s*	5.33*s*

Benchmarks

Dataset	Classic |	Classic ||	Improved |	Improved ||
$syn2f$	$74.68s$	$33.43s$	$8.38s$	$2.73s$
$syn2b$	$74.61s$	$32.92s$	$8.44s$	$2.66s$
$syn2l$	$74.40s$	$33.12s$	$9.97s$	$2.41s$
$syn3a$	$498.78s$	$169.14s$	$21.57s$	$5.39s$
$syn3b$	$495.31s$	$167.75s$	$21.66s$	$5.35s$
$syn3c$	$499.30s$	$166.36s$	$21.50s$	$5.52s$
$syn3d$	$500.64s$	$168.26s$	$21.68s$	$5.44s$
$syn3e$	$496.84s$	$168.27s$	$21.56s$	$5.33s$

Benchmarks

Dataset	Classic |	Classic ||	Improved |	Improved ||
syn2f	74.68*s*	33.43*s*	8.38*s*	2.73*s*
syn2b	74.61*s*	32.92*s*	8.44*s*	2.66*s*
syn2l	74.40*s*	33.12*s*	9.97*s*	2.41*s*
syn3a	498.78*s*	169.14*s*	21.57*s*	5.39*s*
syn3b	495.31*s*	167.75*s*	21.66*s*	5.35*s*
syn3c	499.30*s*	166.36*s*	21.50*s*	5.52*s*
syn3d	500.64*s*	168.26*s*	21.68*s*	5.44*s*
syn3e	496.84*s*	168.27*s*	21.56*s*	5.33*s*

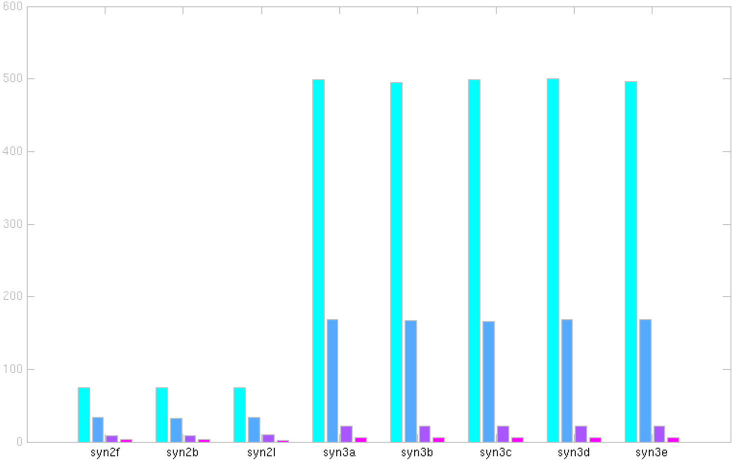
Benchmarks

Dataset	Classic |	Classic ||	Improved |	Improved ||
syn2f	74.68*s*	33.43*s*	8.38*s*	2.73*s*
syn2b	74.61*s*	32.92*s*	8.44*s*	2.66*s*
syn2l	74.40*s*	33.12*s*	9.97*s*	2.41*s*
syn3a	498.78*s*	169.14*s*	21.57*s*	5.39*s*
syn3b	495.31*s*	167.75*s*	21.66*s*	5.35*s*
syn3c	499.30*s*	166.36*s*	21.50*s*	5.52*s*
syn3d	500.64*s*	168.26*s*	21.68*s*	5.44*s*
syn3e	496.84*s*	168.27*s*	21.56*s*	5.33*s*

Benchmarks

Dataset	Classic |	Classic ||	Improved |	Improved ||
syn2f	74.68s	33.43s	8.38s	2.73s
syn2b	74.61s	32.92s	8.44s	2.66s
syn2l	74.40s	33.12s	9.97s	2.41s
syn3a	498.78s	169.14s	21.57s	5.39s
syn3b	495.31s	167.75s	21.66s	5.35s
syn3c	499.30s	166.36s	21.50s	5.52s
syn3d	500.64s	168.26s	21.68s	5.44s
syn3e	496.84s	168.27s	21.56s	5.33s

Benchmarks



600
500
400
300
200
100
0
syn2f
syn2b
syn2l
syn3a
syn3b
syn3c
syn3d
syn3e

Estimation Process (Real Data)

Experimental context:

- Fear Extinction

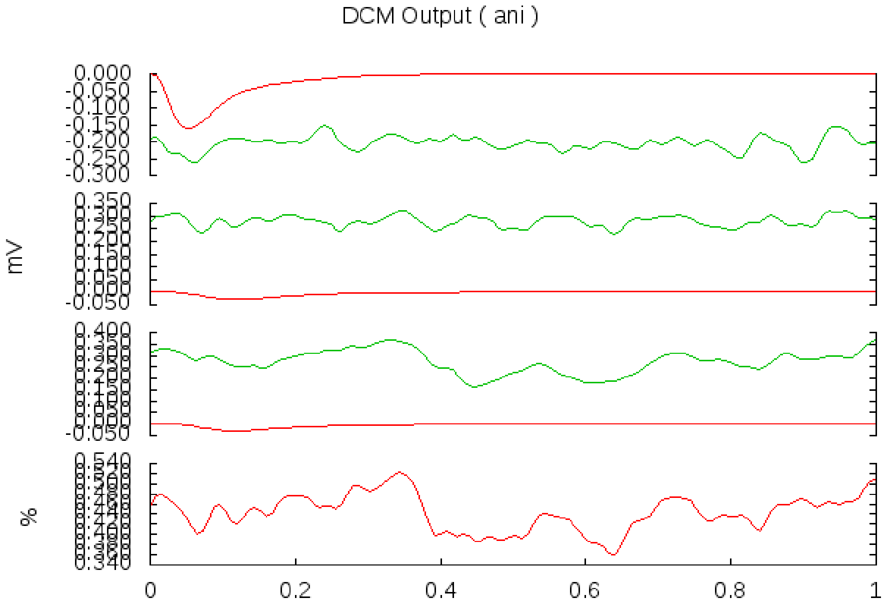
Situation:

- 3 Regions (AMY, CA1, PFC)
- 1 (direct) Input (sound)

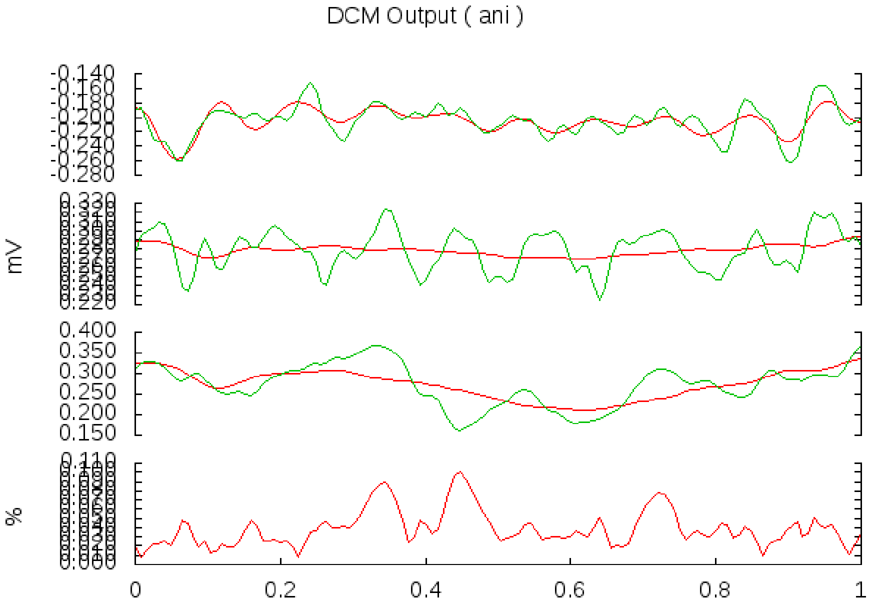
Hypothesis:

- full connectivity possible
- AMY $\rightarrow$ CA1 $\rightarrow$ PFC

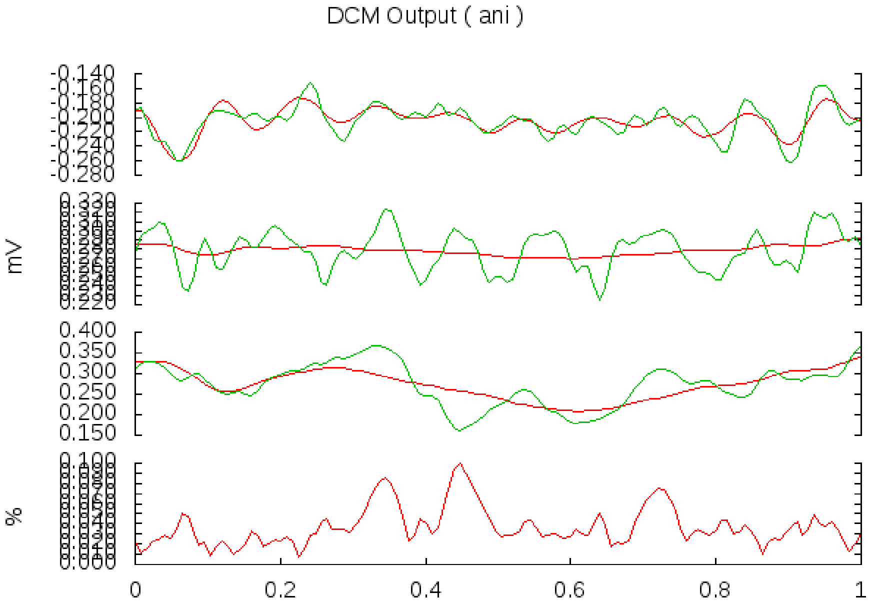
Estimation Process (Real Data)



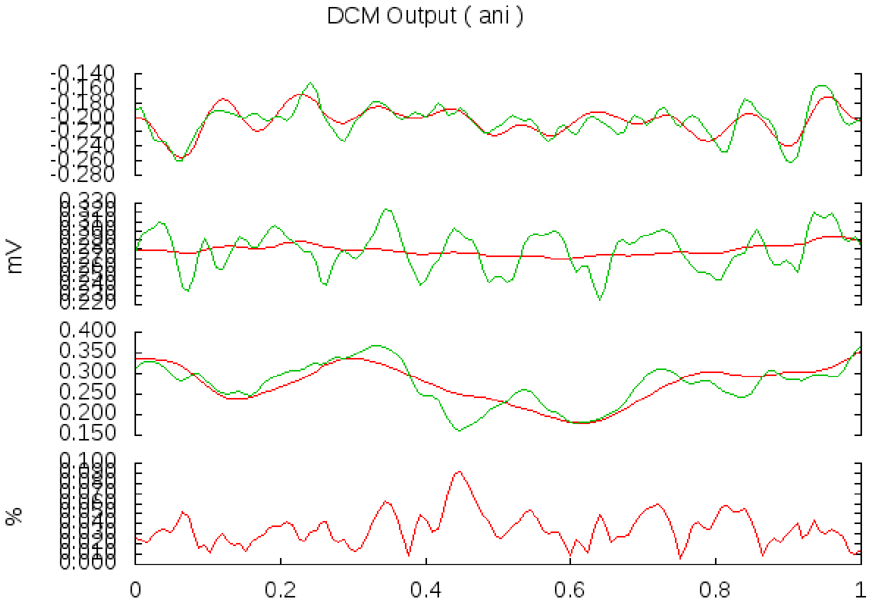
Estimation Process (Real Data)



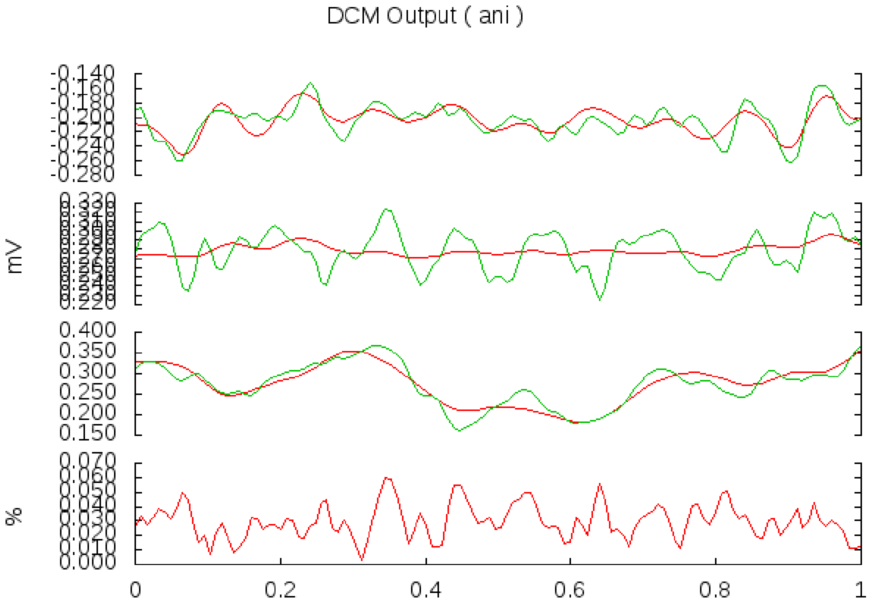
Estimation Process (Real Data)



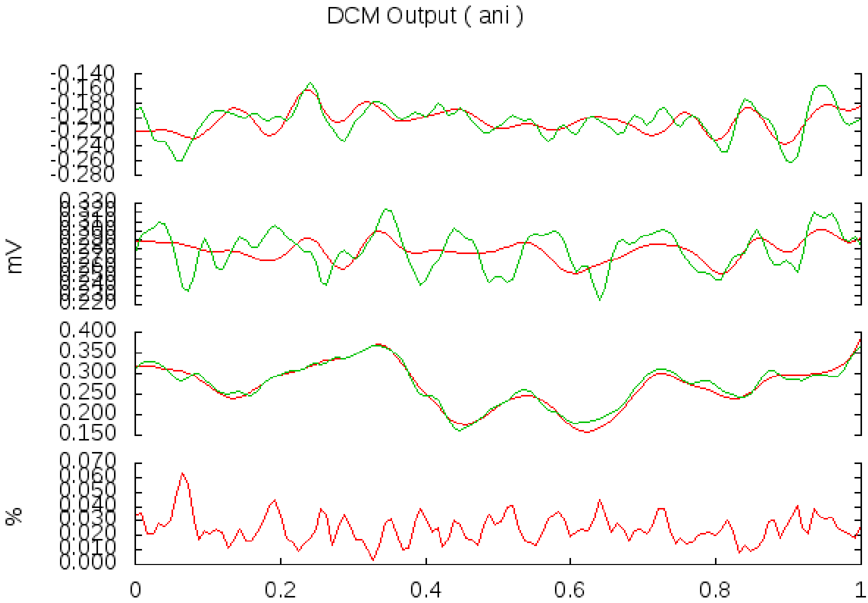
Estimation Process (Real Data)



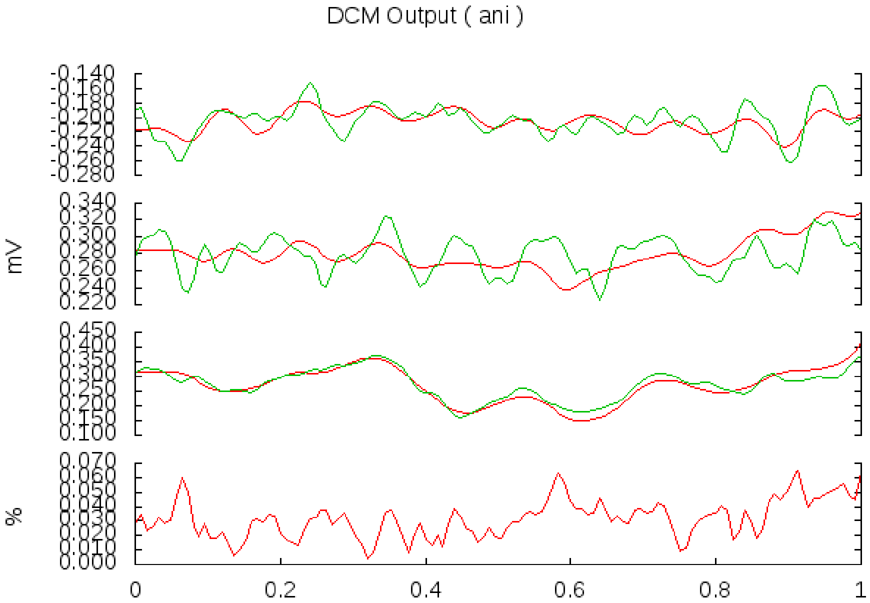
Estimation Process (Real Data)



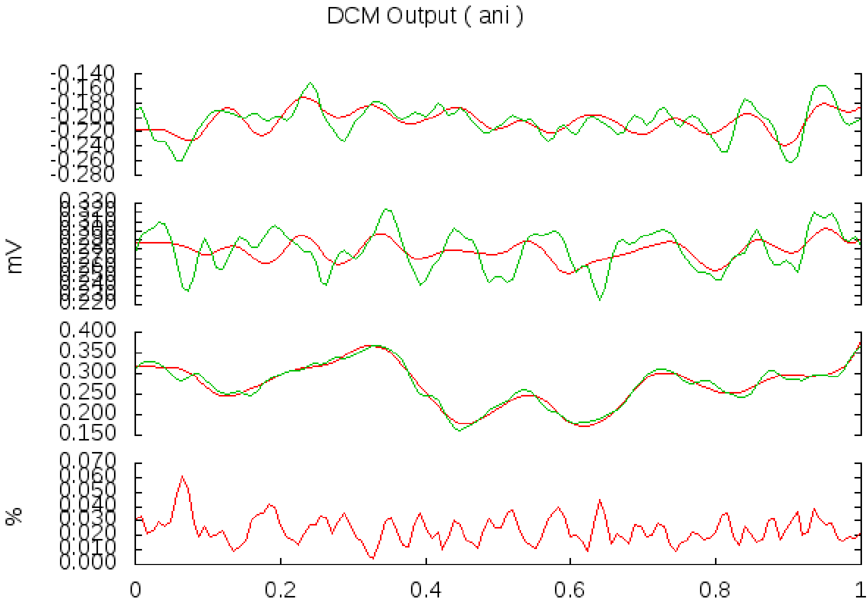
Estimation Process (Real Data)

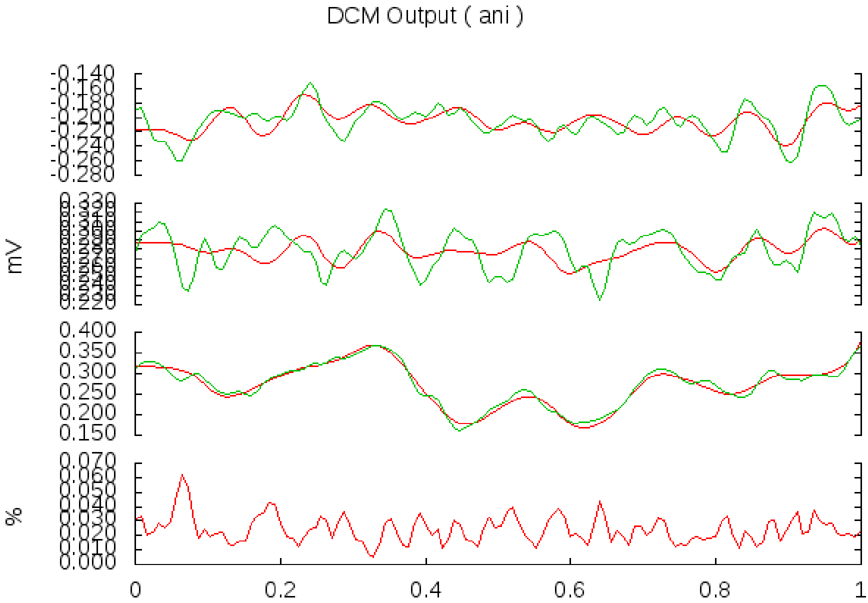


Estimation Process (Real Data)

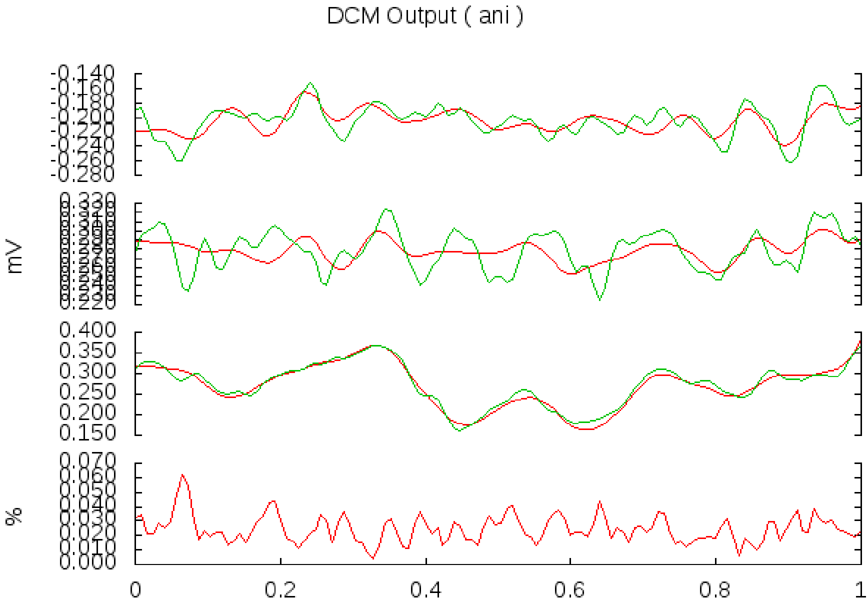


Estimation Process (Real Data)

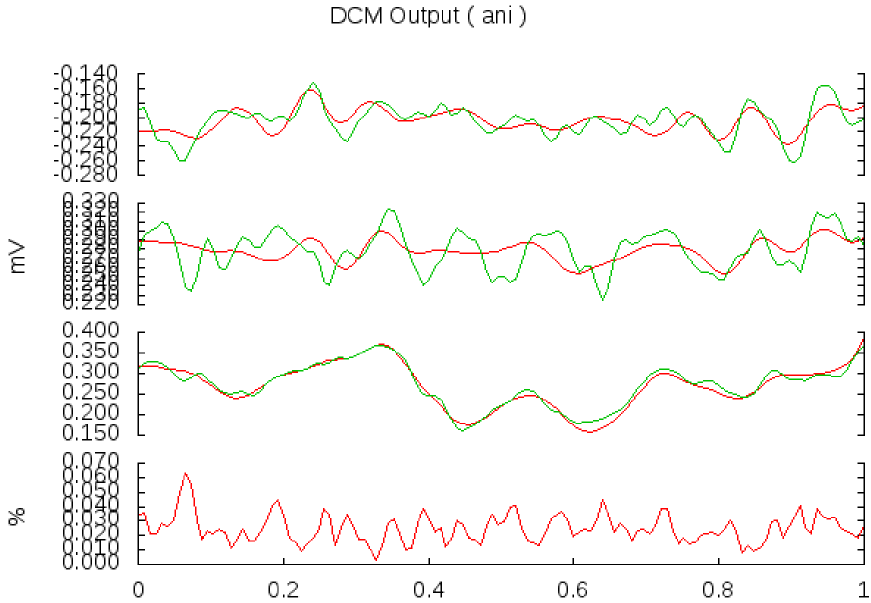



DCM Output (ani)
-0.140
-0.160
-0.180
-0.200
-0.220
-0.240
-0.260
-0.280
mV
0.330
0.220
0.400
0.350
0.300
0.250
0.200
0.150
%
0.070
0.060
0.050
0.040
0.030
0.020
0.010
0.000
0
0.2
0.4
0.6
0.8
1

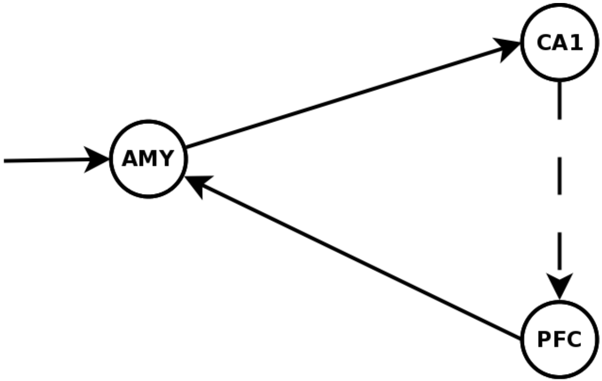
Estimation Process (Real Data)



Estimation Process (Real Data)



Estimation Process (Real Data)



Outlook

- Runtime reduction
- Improvement of EM-algorithm
- More dynamic and forward submodels
- Include preprocessing capabilities
- Lower order and adaptive solvers
- Include further DCM extensions

Outlook

- Runtime reduction
- Improvement of EM-algorithm
- More dynamic and forward submodels
- Include preprocessing capabilities
- Lower order and adaptive solvers
- Include further DCM extensions

Outlook

- Runtime reduction
- Improvement of EM-algorithm
- More dynamic and forward submodels
- Include preprocessing capabilities
- Lower order and adaptive solvers
- Include further DCM extensions

Outlook

- Runtime reduction
- Improvement of EM-algorithm
- More dynamic and forward submodels
- Include preprocessing capabilities
- Lower order and adaptive solvers
- Include further DCM extensions

Outlook

- Runtime reduction
- Improvement of EM-algorithm
- More dynamic and forward submodels
- Include preprocessing capabilities
- Lower order and adaptive solvers
- Include further DCM extensions

Outlook

- Runtime reduction
- Improvement of EM-algorithm
- More dynamic and forward submodels
- Include preprocessing capabilities
- Lower order and adaptive solvers
- Include further DCM extensions

tl;dl

A modular and extendable implementation of dynamic causal modeling with a notable runtime reduction.

(Thesis: http://j.mp/himpe)