Models of Perceptual Uncertainty and Decision Making

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- How do we integrate sensory percepts?
- How do we weigh ambiguous evidence?

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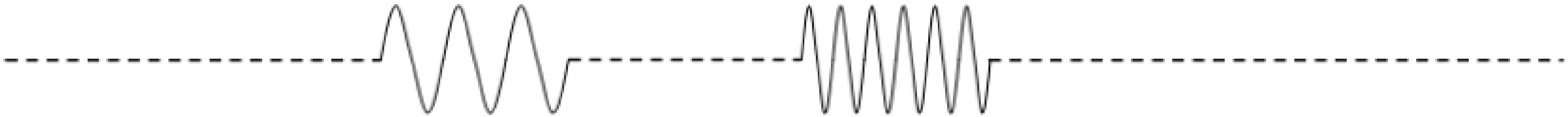
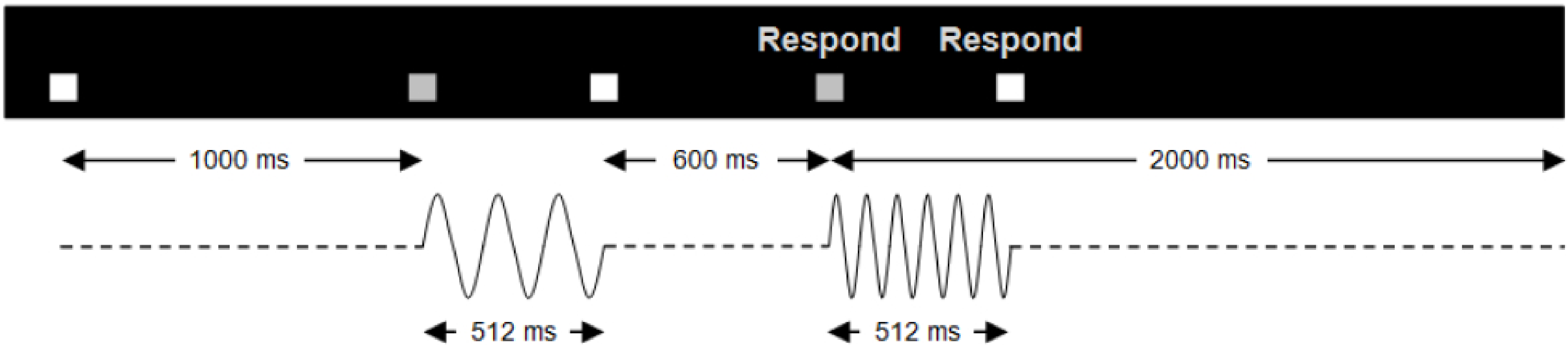
- How do we weigh ambiguous evidence?

Vibrotactile experiment: perceptual decision making



Perceptual decision-making task

Vibrotactile discrimination task



Two-alternative forced choice:

1: Same or Different? S D
2: f2>f1?

Perceptual decision-making task

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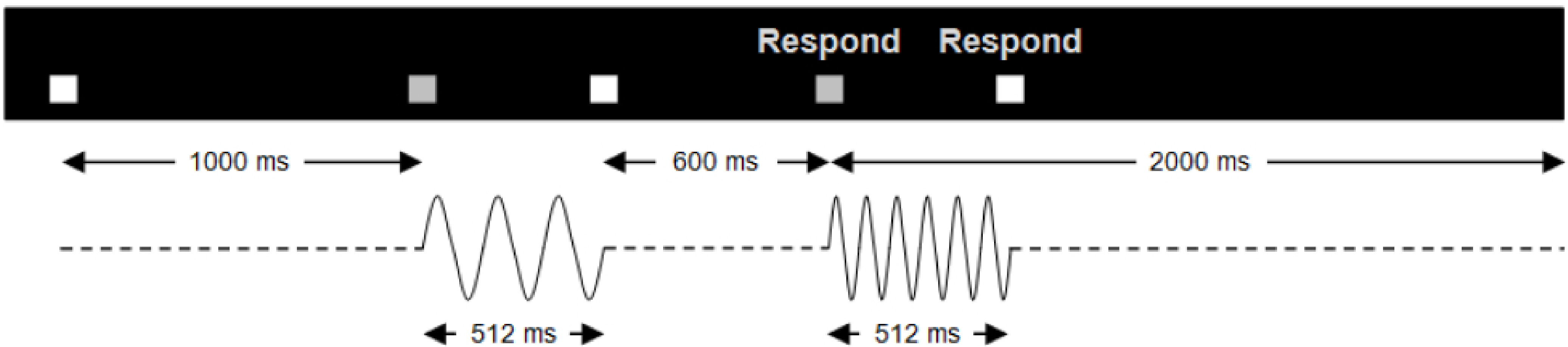

Two-alternative forced choice:

1: Same or Different?
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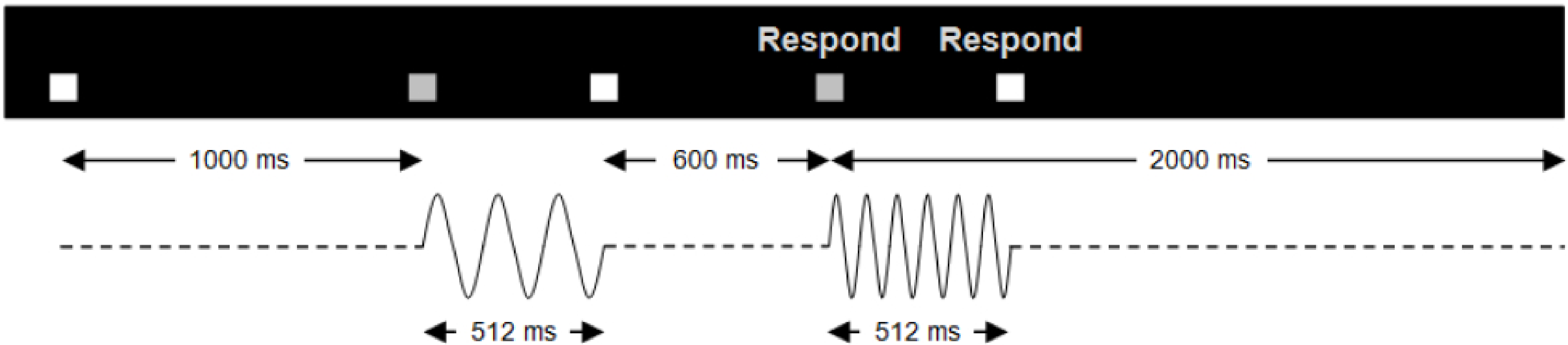
Perceptual decision-making task

Vibrotactile discrimination task



Two-alternative forced choice:

1: Same or Different? S D

2: f2>f1? Y N

Subtraction

Subtraction weighted by precision of stimulus representation

outline

- Same or Different? S D

  Effective connectivity

  Behavioral, fMRI, DCM

- f2>f1? Y N

  Time-order effect

  Behavioral, Bayesian approach

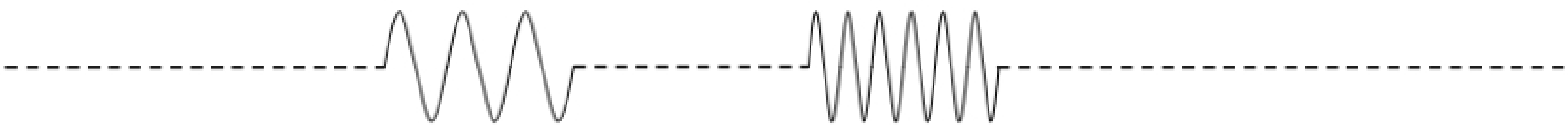
Vibrotactile discrimination task

Experiment 1: Same or Different?

Conditions:

1. Different or same frequencies – adaptation

repetition suppression

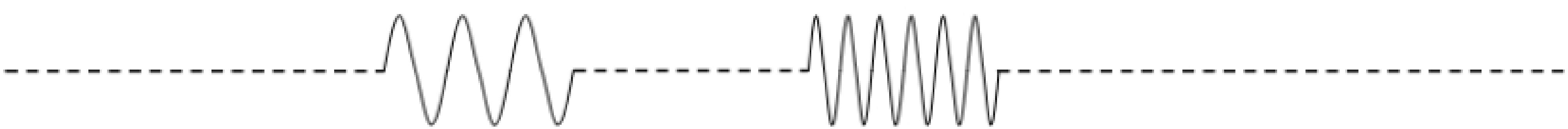


Vibrotactile discrimination task

Conditions:

1. Different or same frequencies – adaptation
2. Pure or noisy sinusoidal shape –

   what is the role of noise in the input frequency?



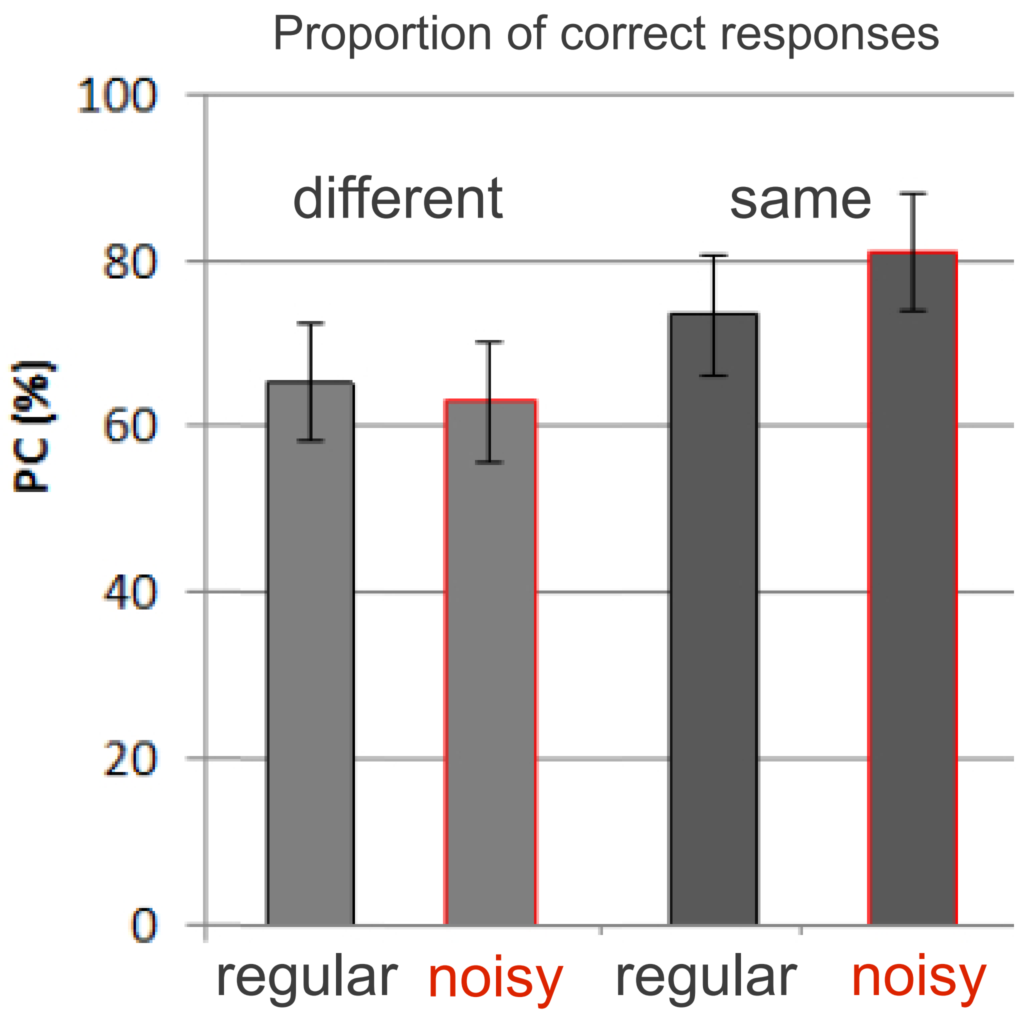
Vibrotactile discrimination task

Conditions:

1. Different or same frequencies – adaptation
2. Pure or noisy sinusoidal shape –

   what is the role of noise in the input frequency?

Behavioral data

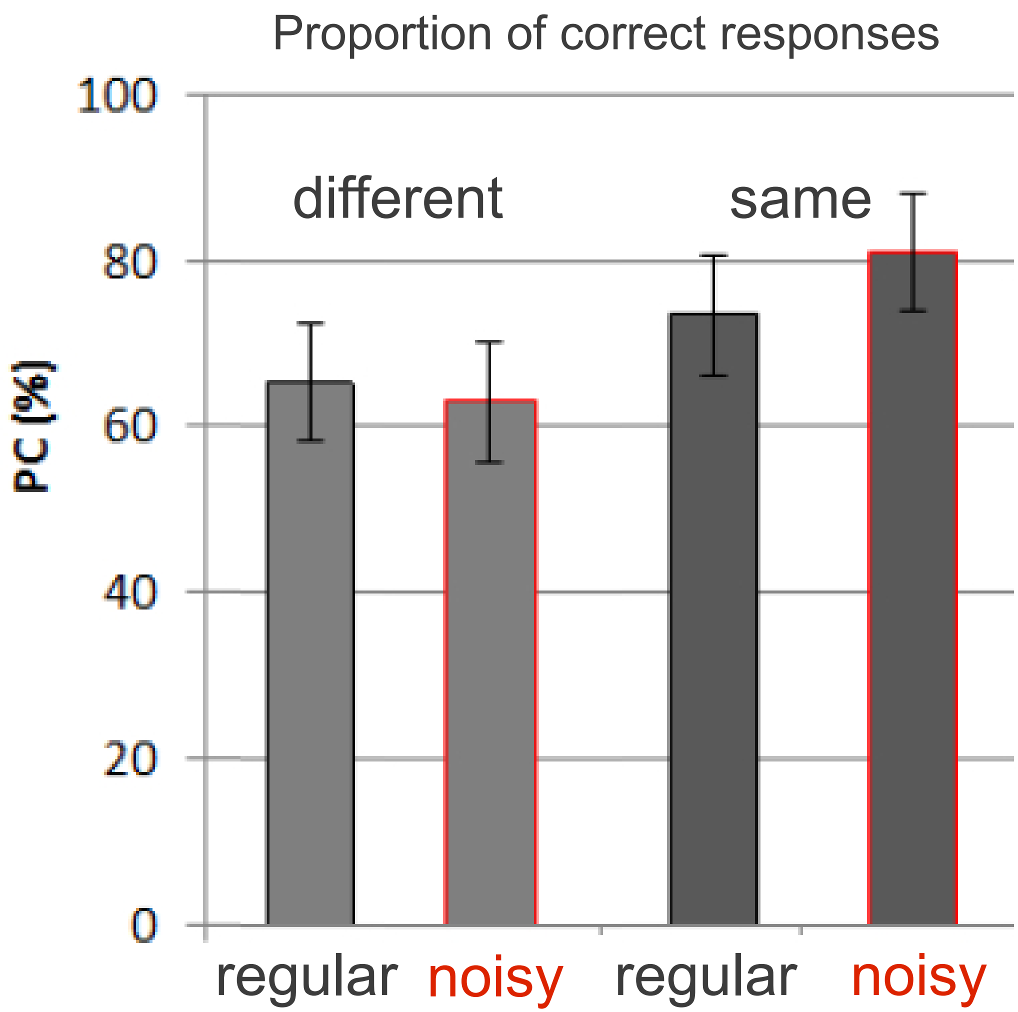


Noise reduces precision of stimulus representation

Karim et al. 2012

Role of input noise

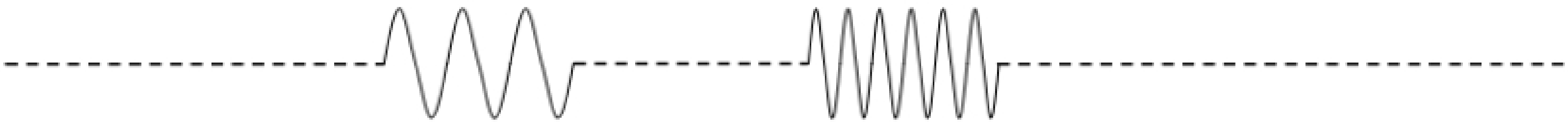
Behavioral data

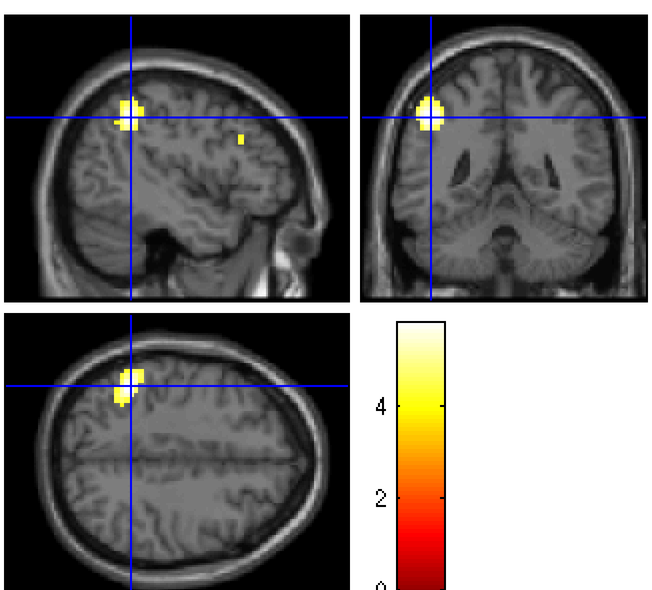


Noise degrades the perception of different trials and improves the perception of same trials (interaction: $p=0.0007$, $F_{1,15}=17.927$)

Karim et al. 2014

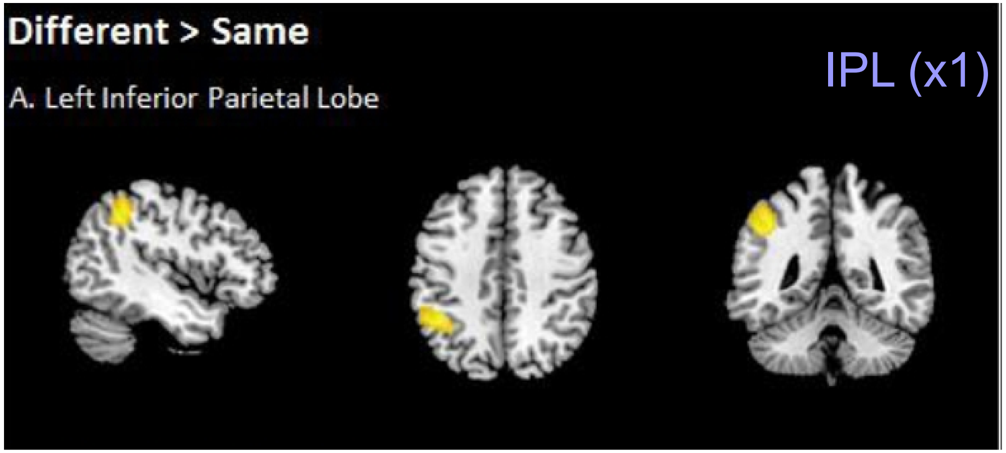
Perceptual decision-making task





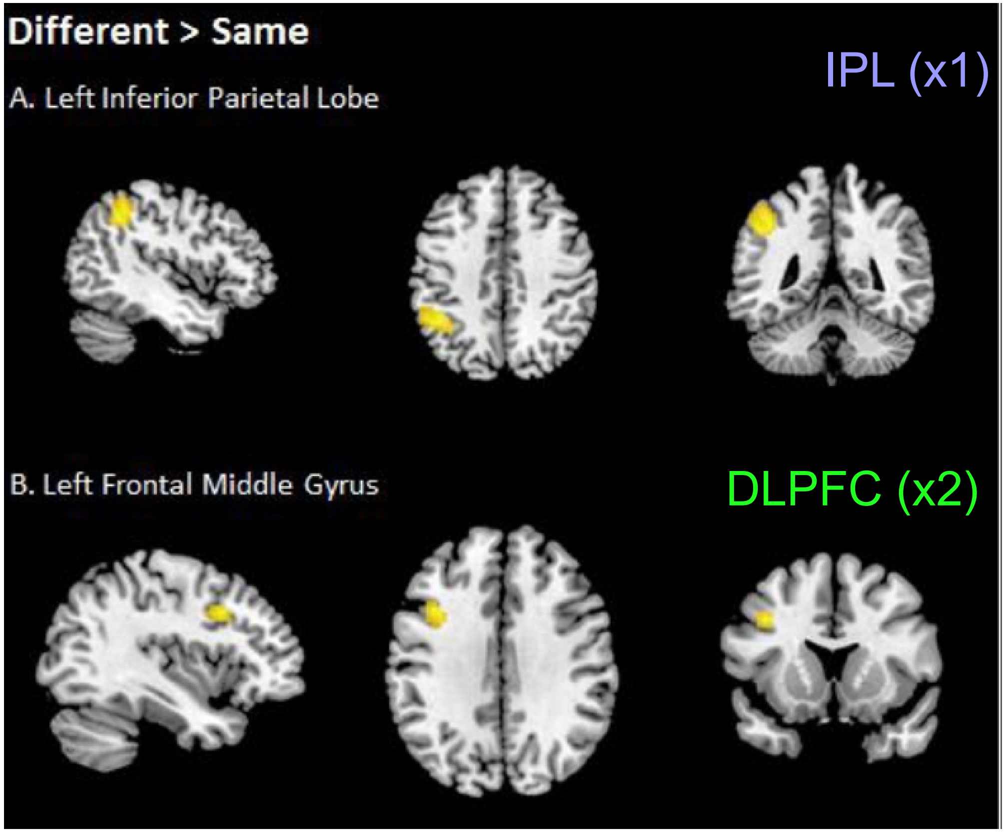
Inferior parietal lobe

Greater activity for different
than for same input frequencies



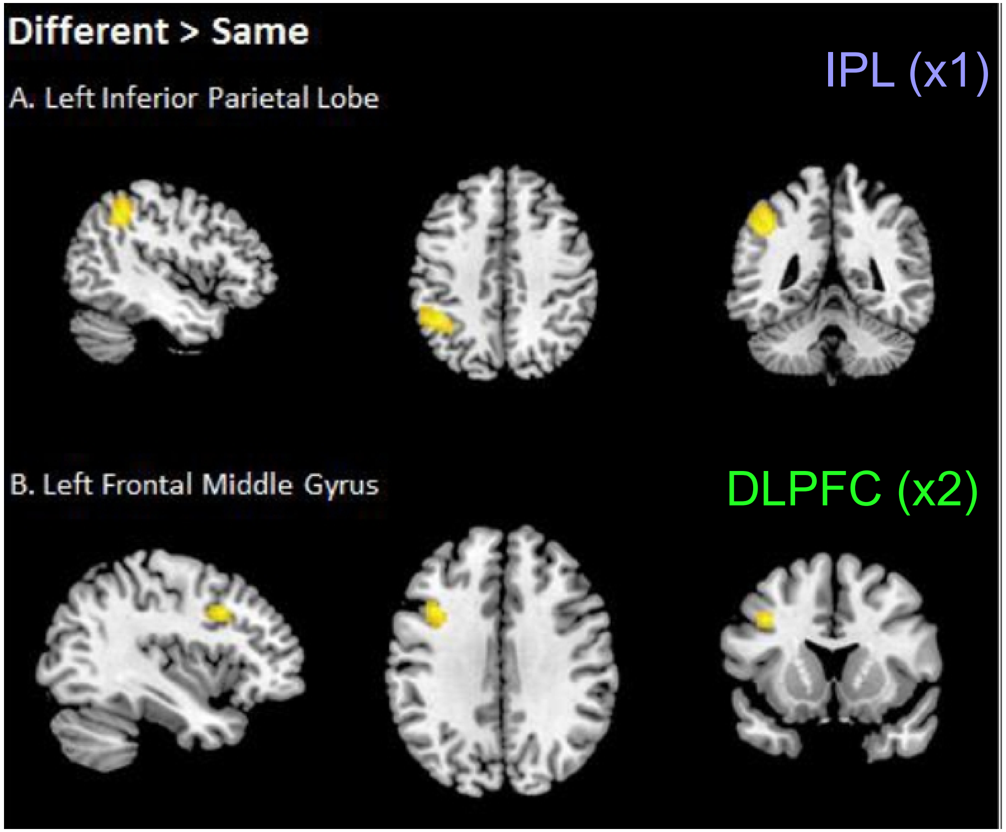
Inferior parietal lobe

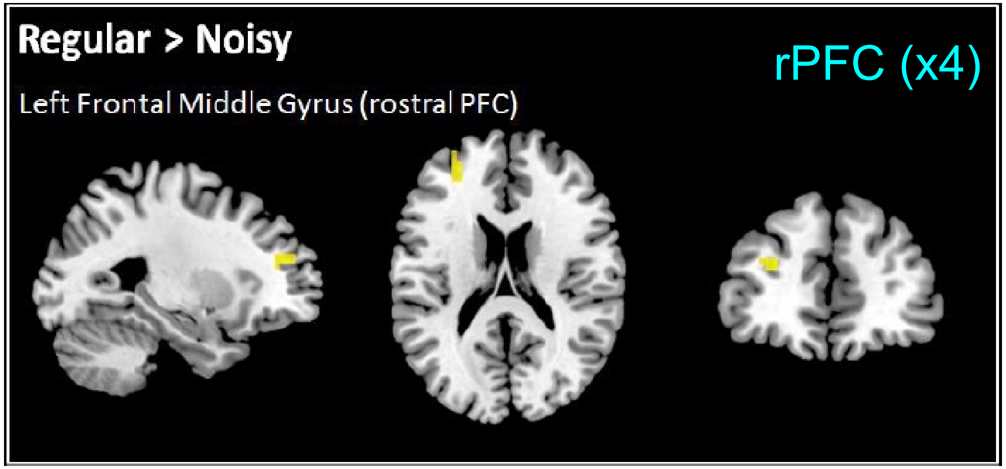
Different > Same



Dorsal lateral prefrontal cortex

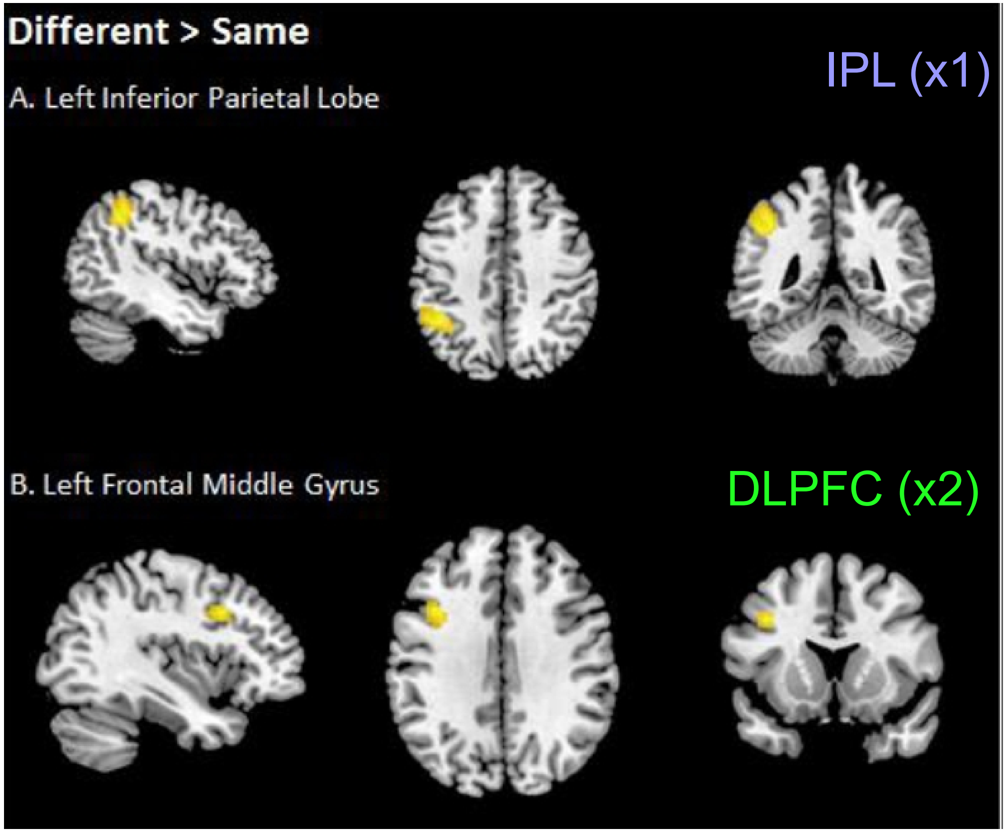
Different > Same

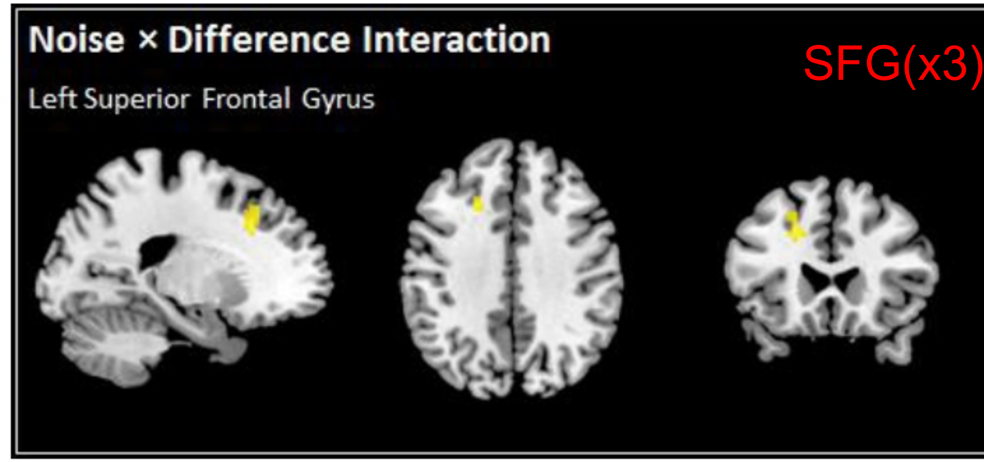


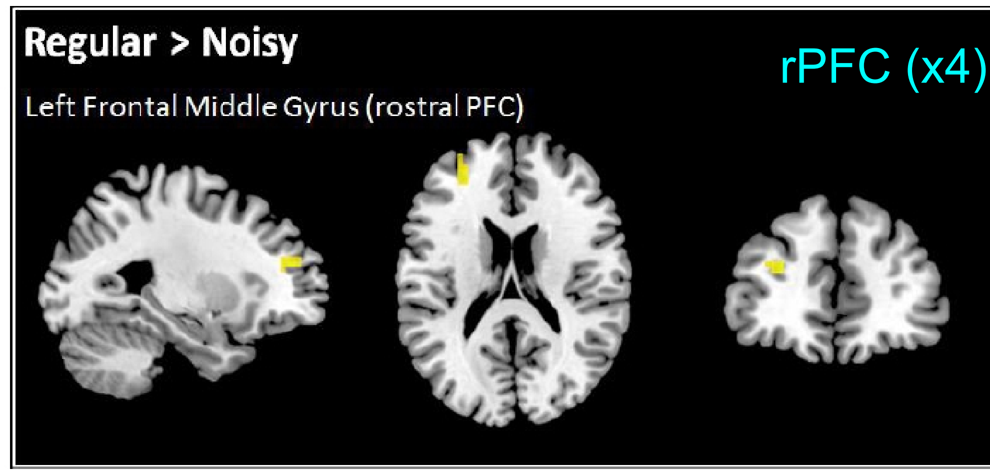


Rostral prefrontal cortex

Regular > Noisy

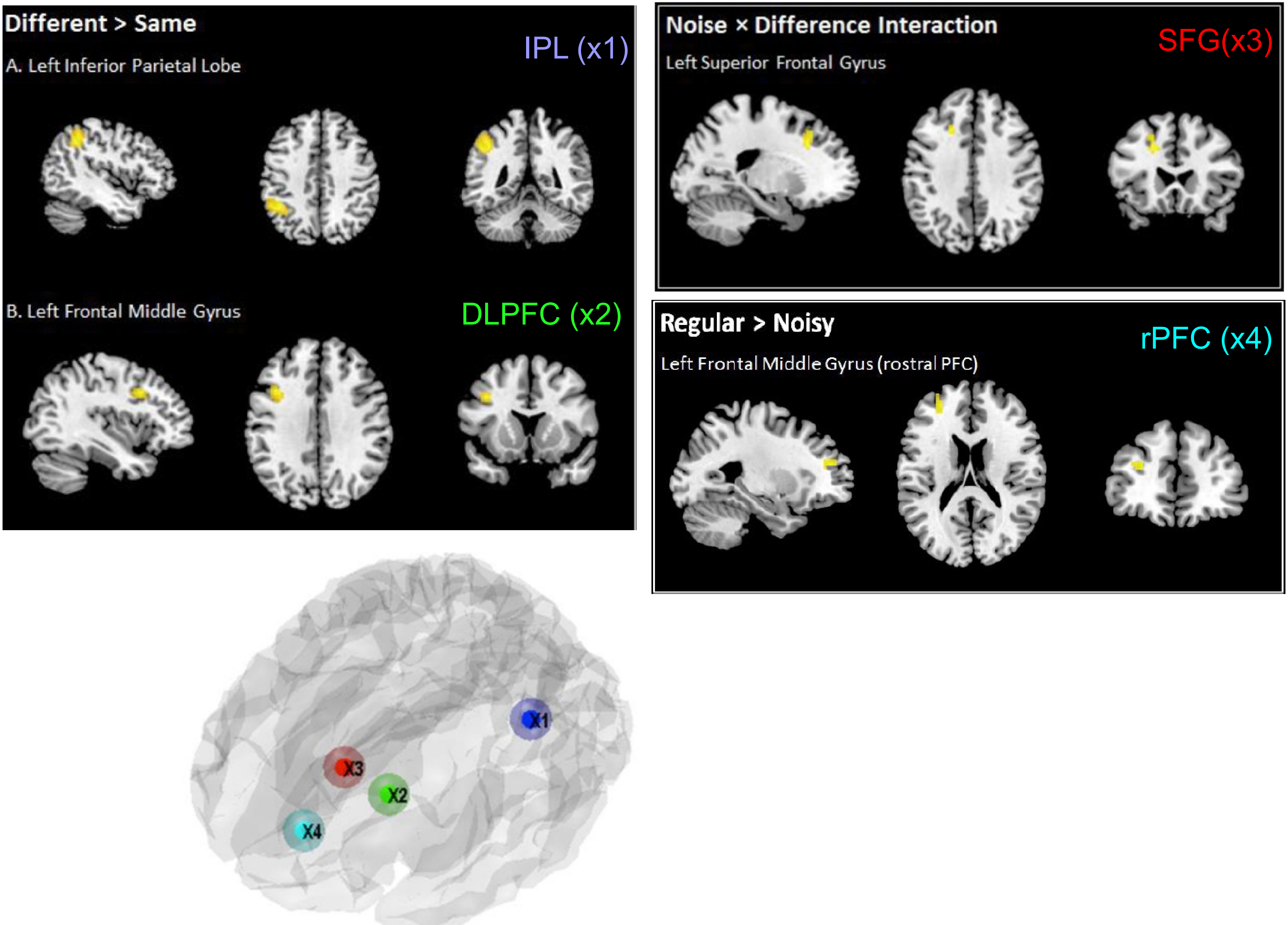




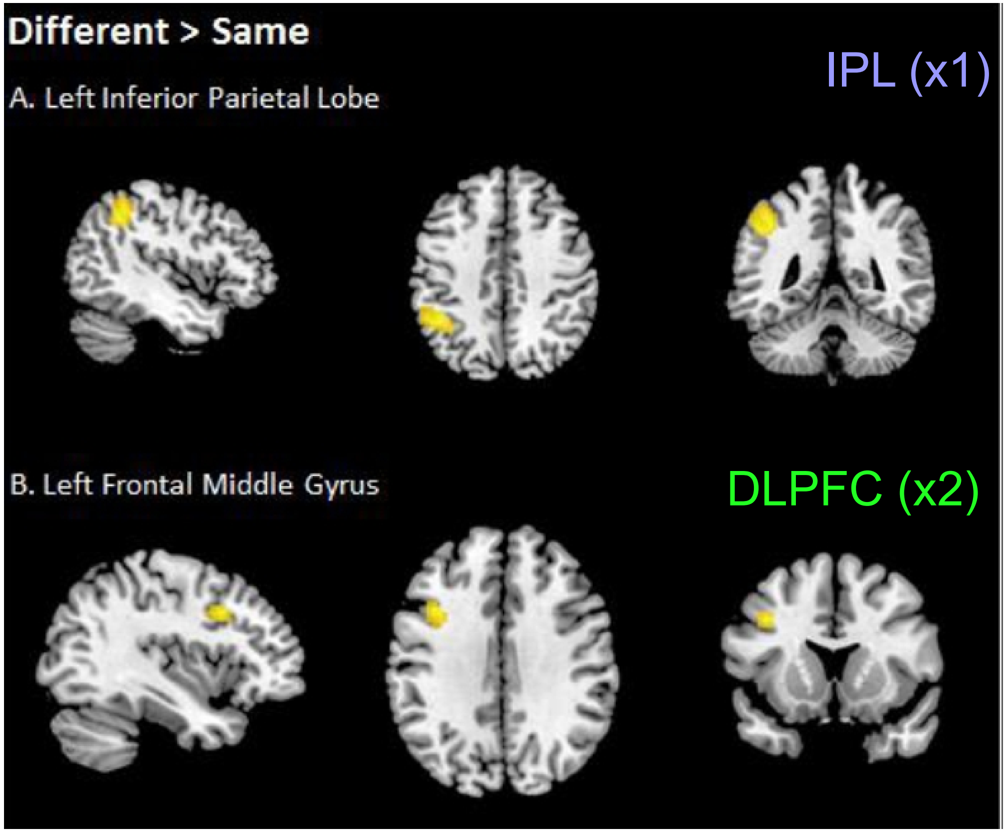


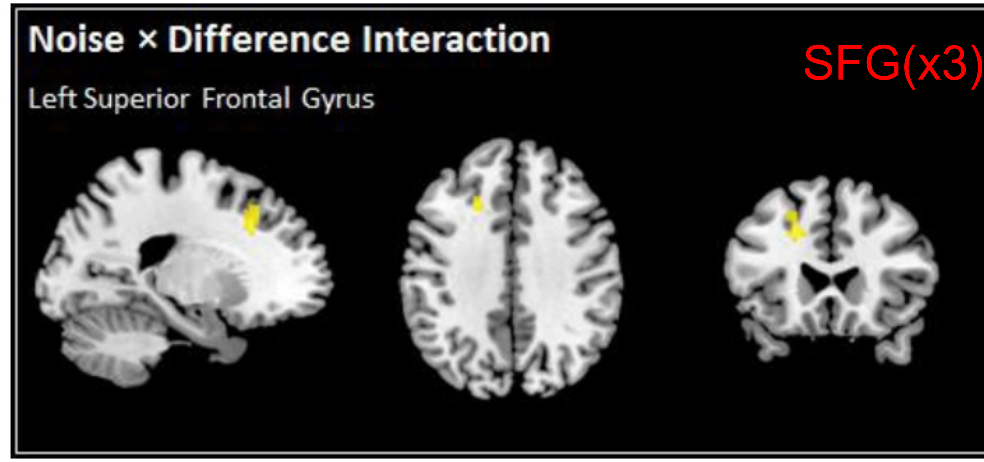
Superior frontal gyrus

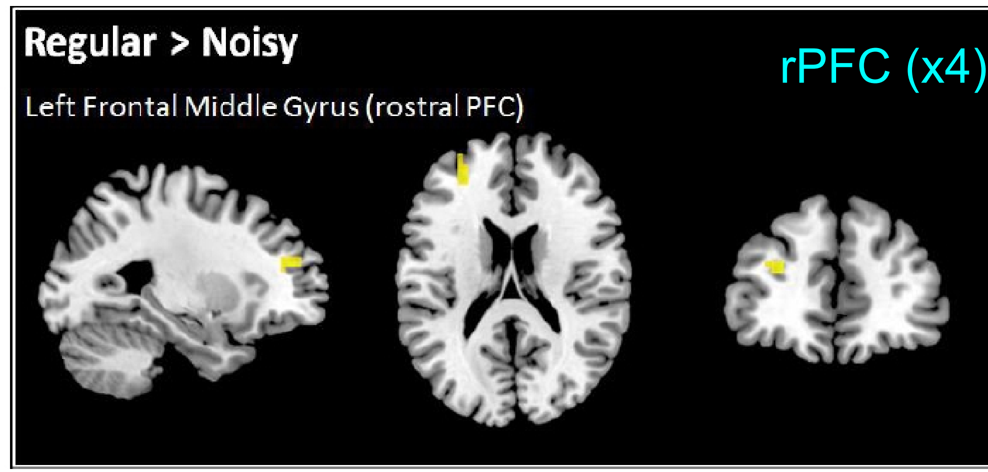
Interaction effect

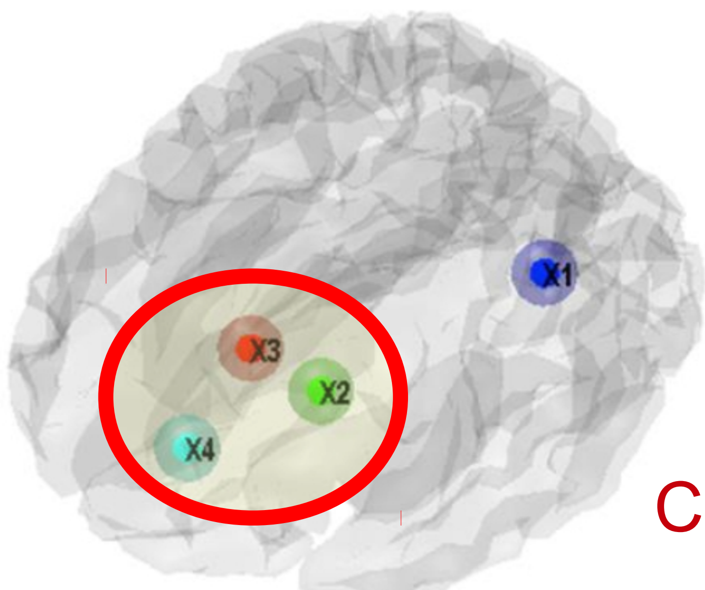


Different > Same
IPL (x1)
A. Left Inferior Parietal Lobe
B. Left Frontal Middle Gyrus
DLPFC (x2)
Noise × Difference Interaction
SFG(x3)
Left Superior Frontal Gyrus
Regular > Noisy
rPFC (x4)
Left Frontal Middle Gyrus (rostral PFC)
X1
X3
X2
X4

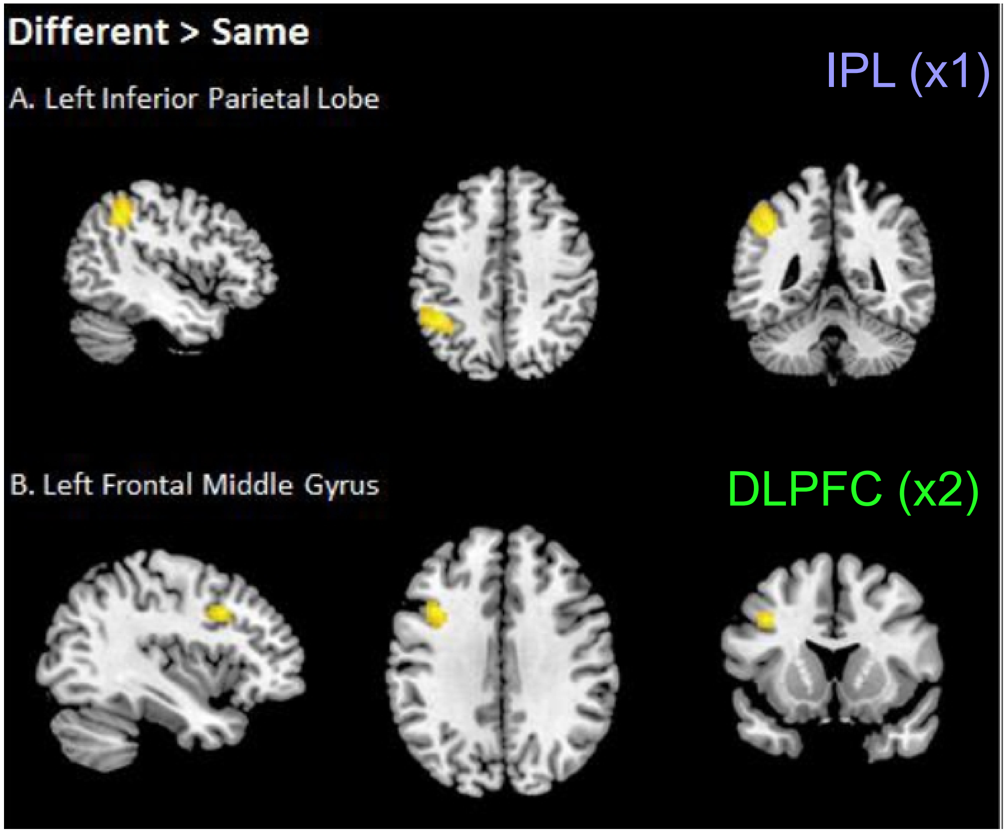


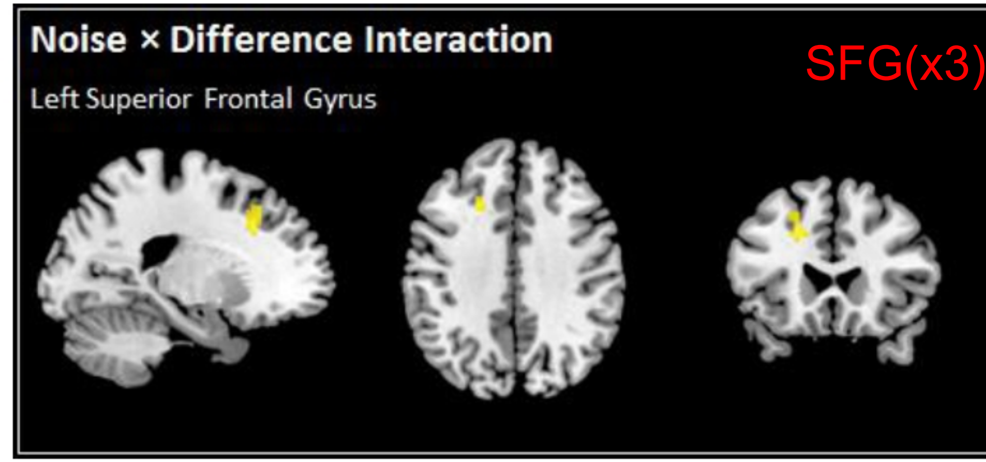


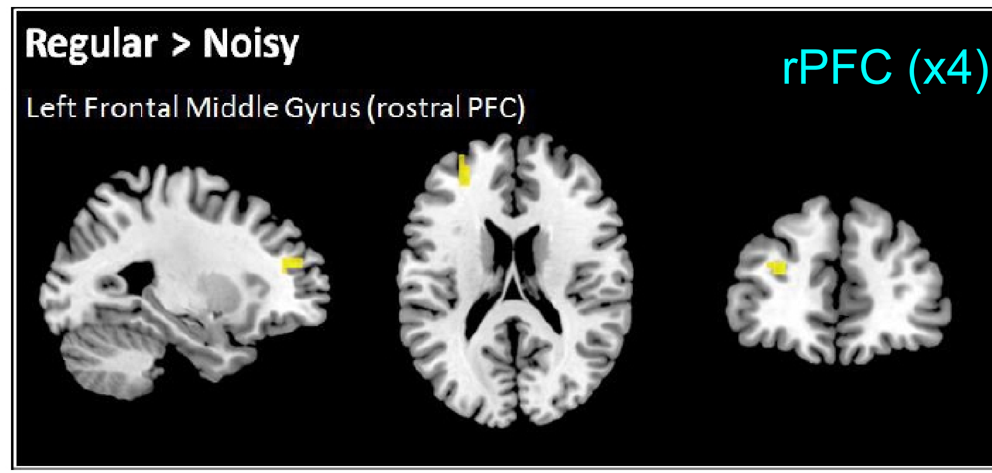


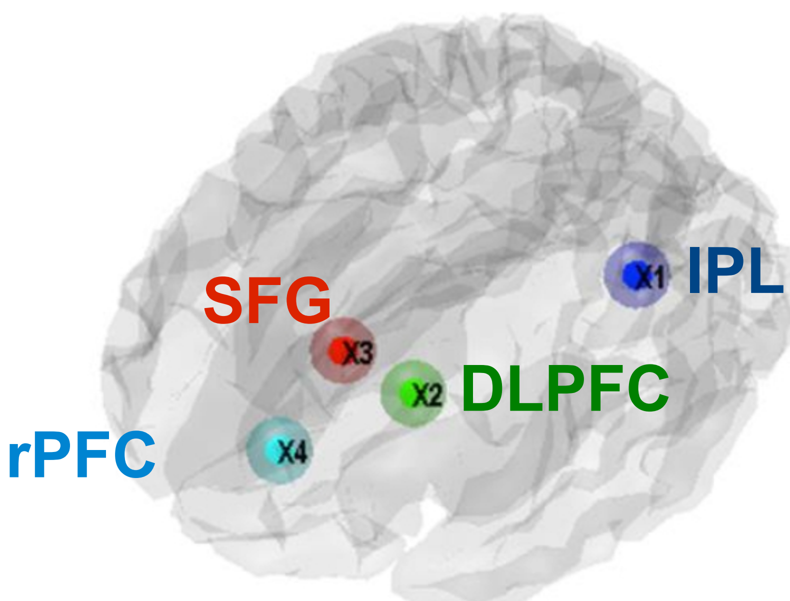


Constellation of prefrontal regions



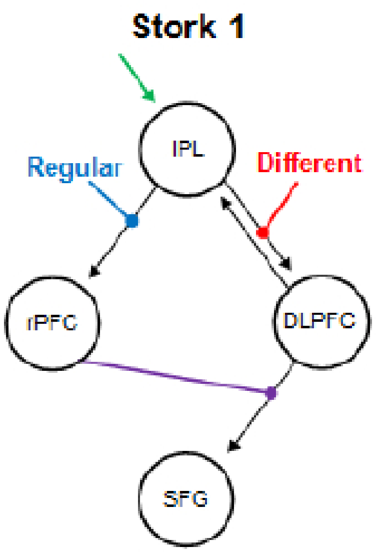


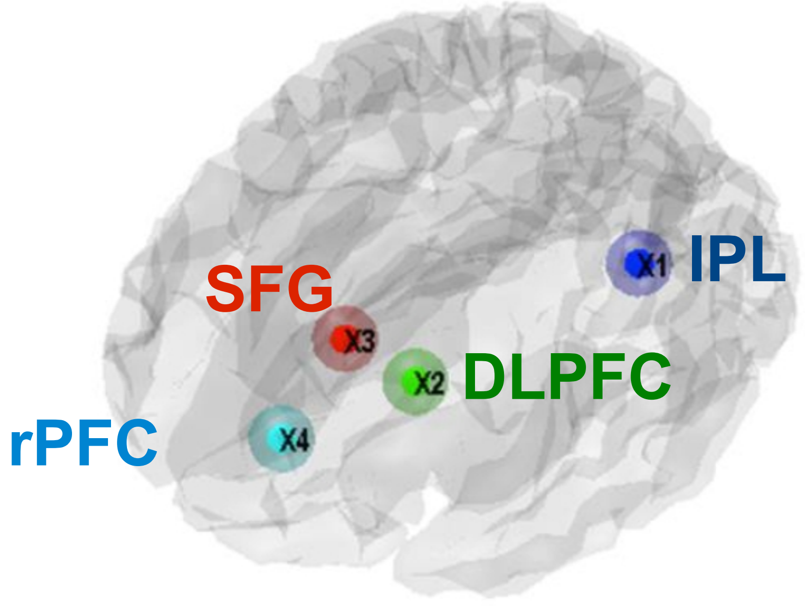




How do these regions interact?

Effective connectivity: Dynamic causal modelling

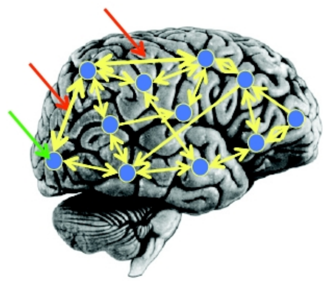




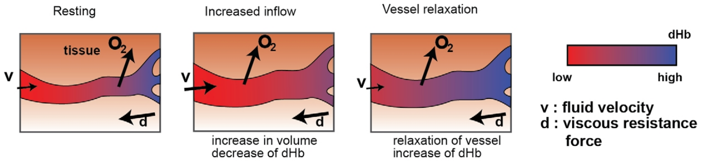
How do these regions interact?

Dynamic causal modelling

Model



$$\dot{x} = F(x, u, \theta)$$ neural state equation



$$y = H(x, u, \theta) + \epsilon$$

hemodynamic state equations

Prediction

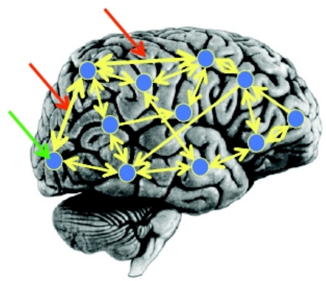
estimated BOLD response

forward model

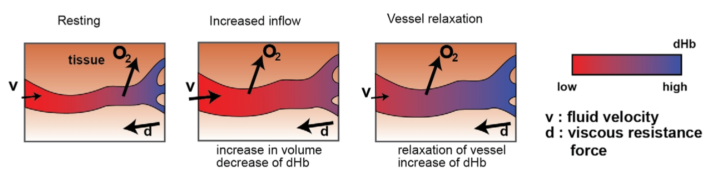
Friston et al. (2003) Neuroimage

Dynamic causal modelling

Model



$$\dot{x} = F(x, u, \theta)$$



$$y = H(x, u, \theta) + \epsilon$$

Prediction

forward model

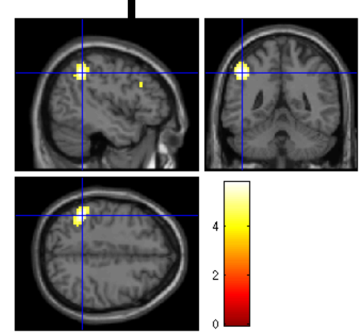
Model evidence

$$p(y|m) = \int p(y|\theta, m)\, p(\theta|m)\, d\theta$$

Probability of observing the data y given the model m

variational Bayes

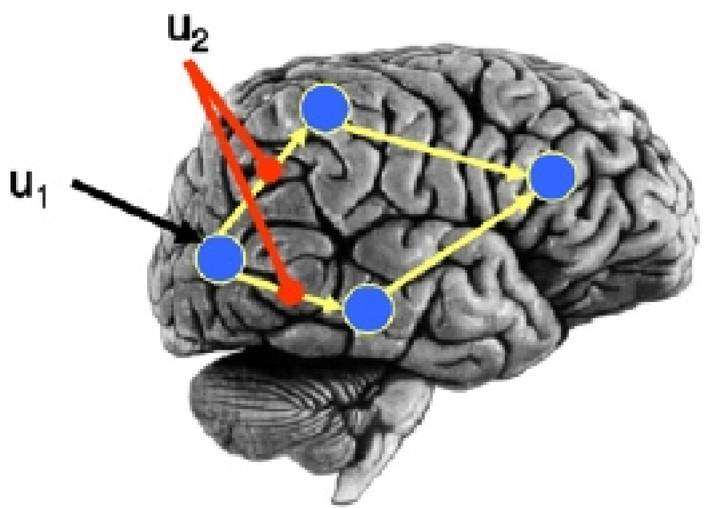
Empirical effect



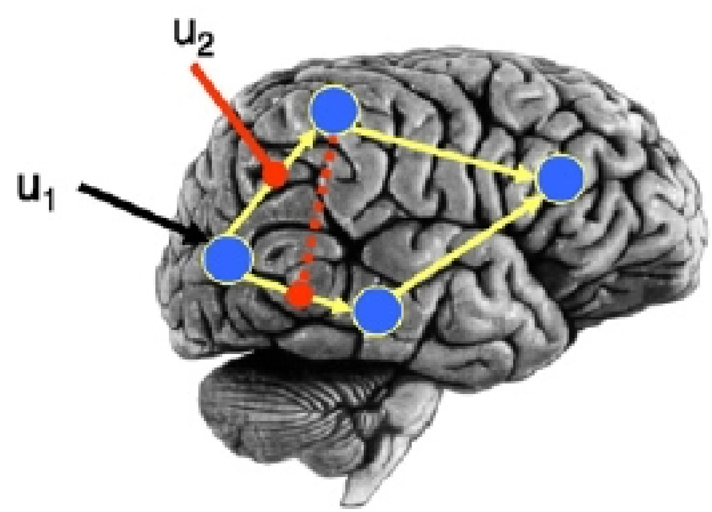
model inversion

Friston et al. (2003) Neuroimage

bilinear DCM



nonlinear DCM



Bilinear state equation

$$\frac{dx}{dt} = \left(A + \sum_{i=1}^{m} u_i B^{(i)}\right)x + Cu$$

state changes

effective connectivity

modulation

input

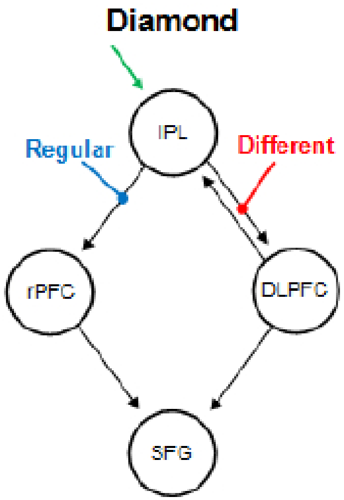
Nonlinear state equation

$$\frac{dx}{dt} = \left(A + \sum_{i=1}^{m} u_i B^{(i)} + \sum_{j=1}^{n} x_j D^{(j)}\right)x + Cu$$

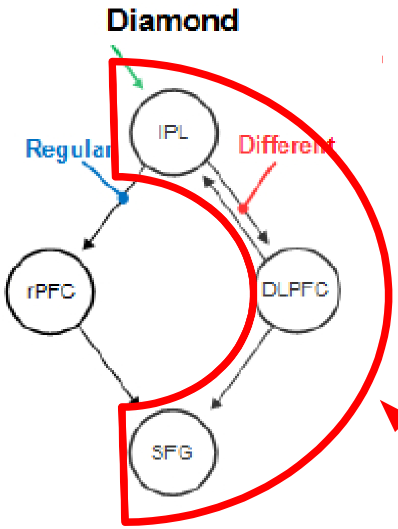
voltage dependent gating
(via NMDA receptors)

Stephan et al. (2008) Neuroimage

Set of minimal models

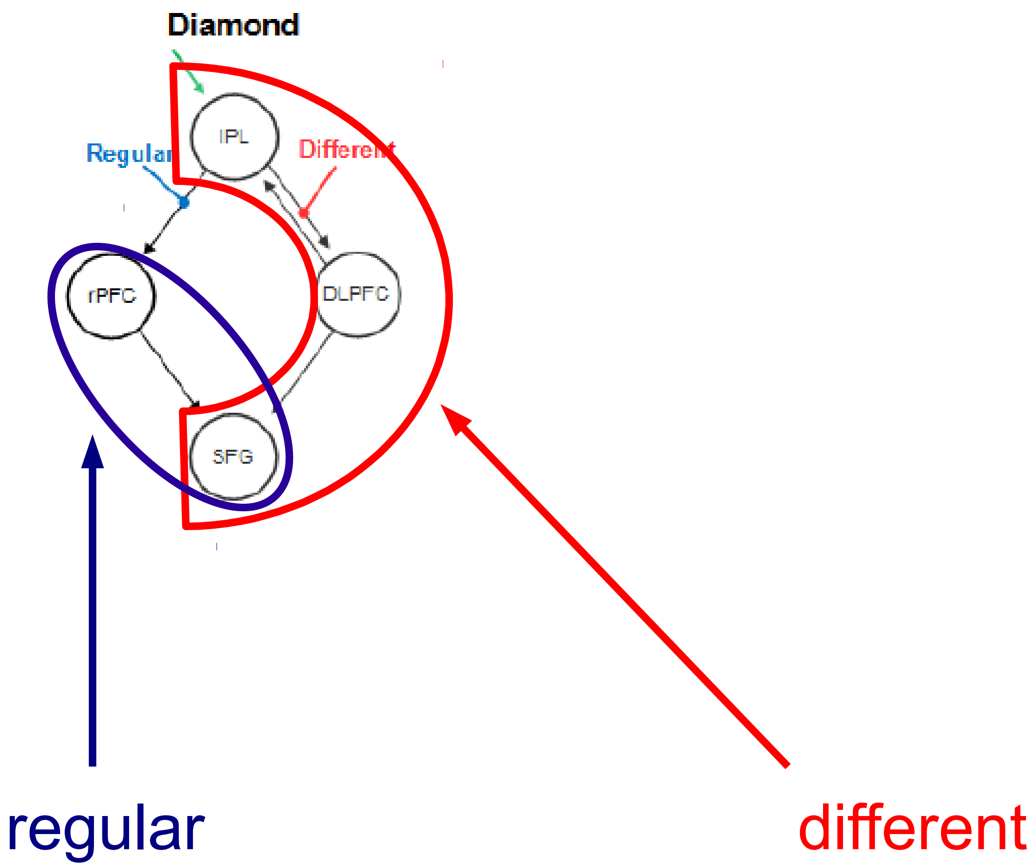


Set of minimal models

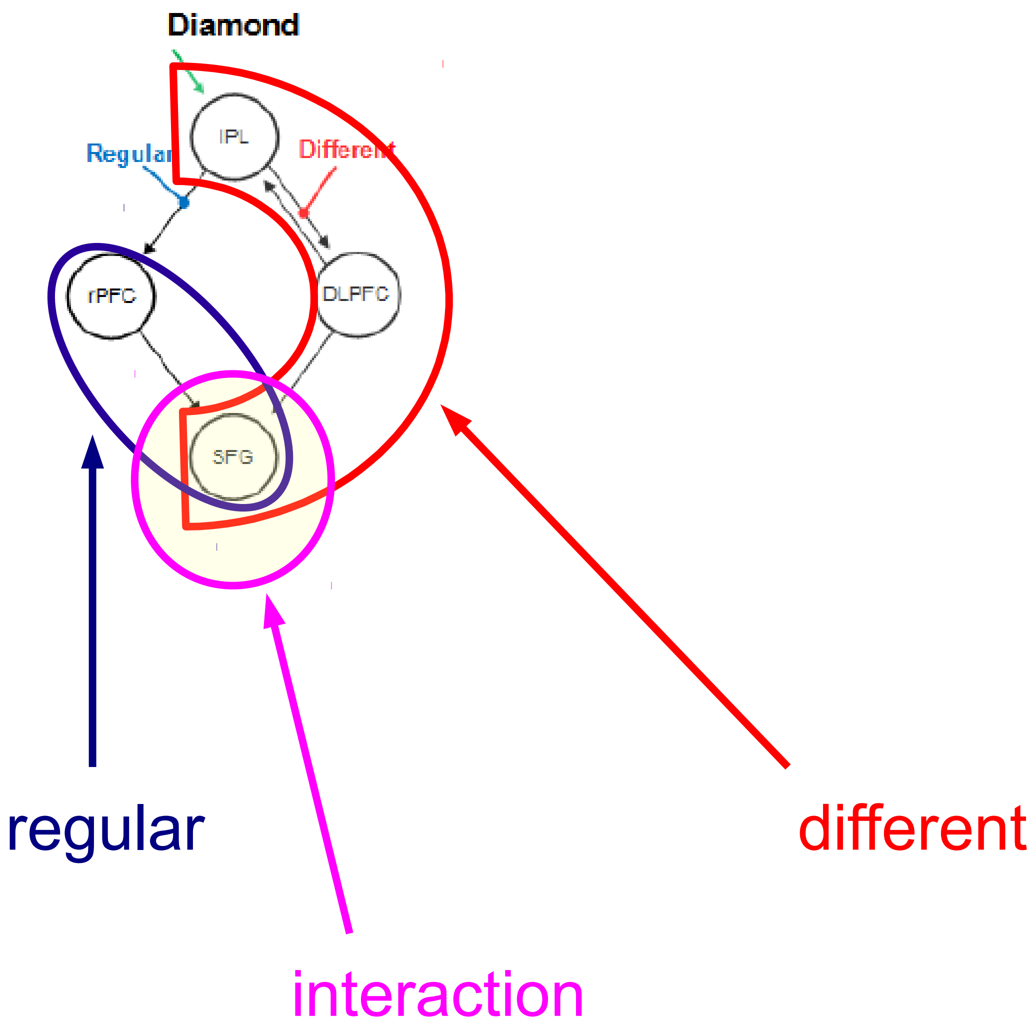


different

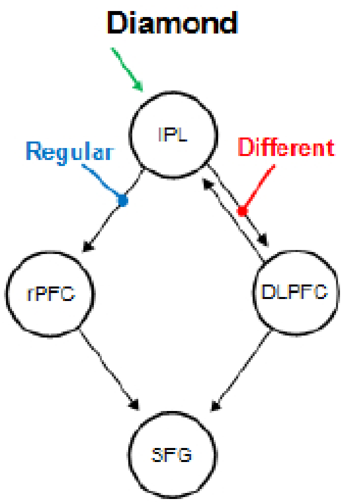
Set of minimal models



Set of minimal models

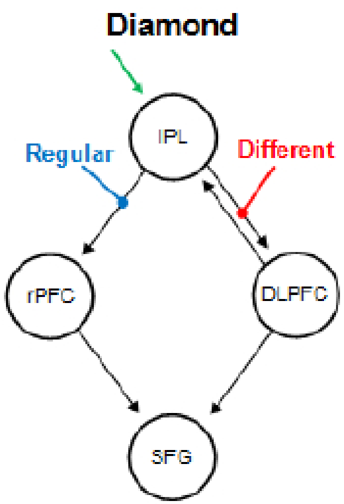


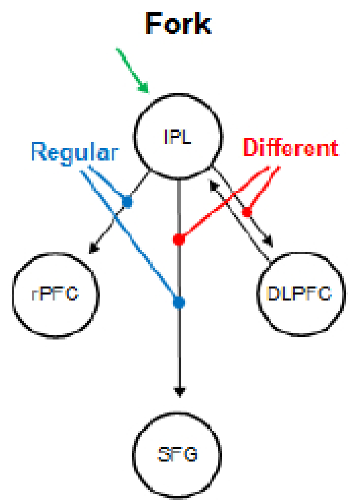
Set of minimal models



Serial

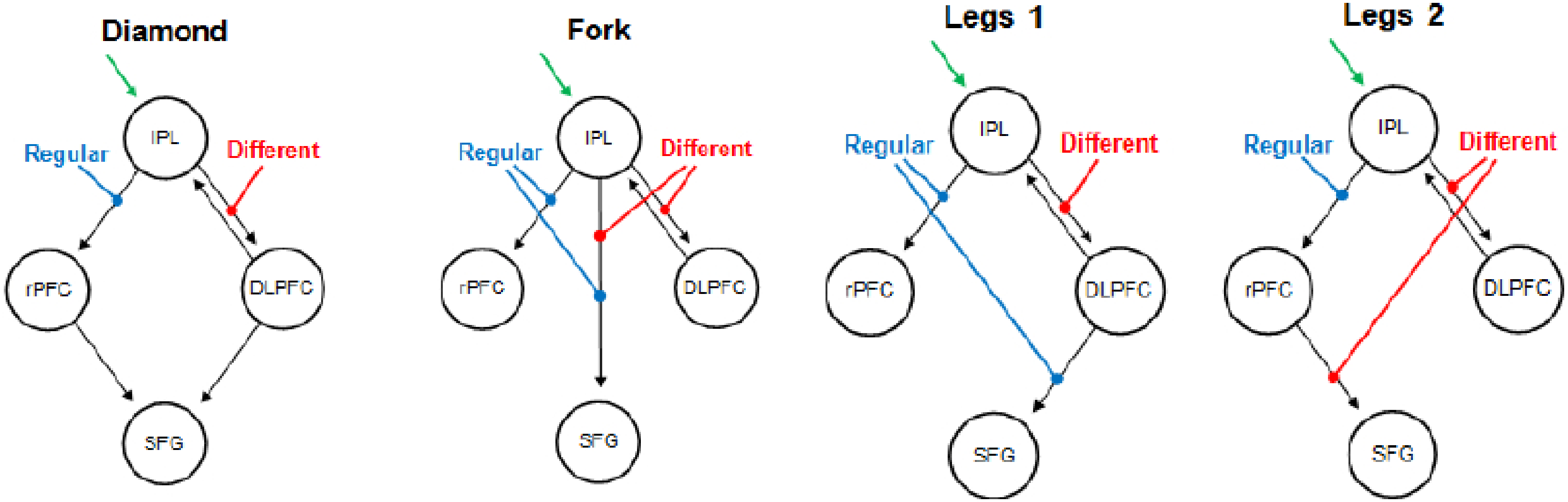
Set of minimal models





Parallel

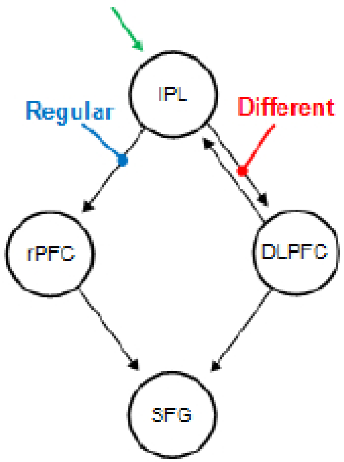
Set of minimal models



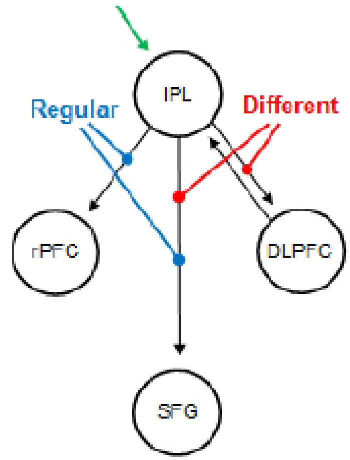
Hierarchical (bilinear)

Set of minimal models

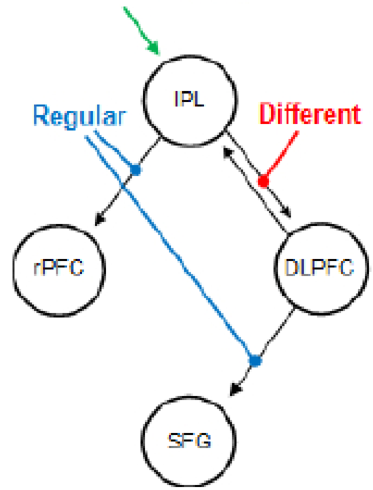
Diamond



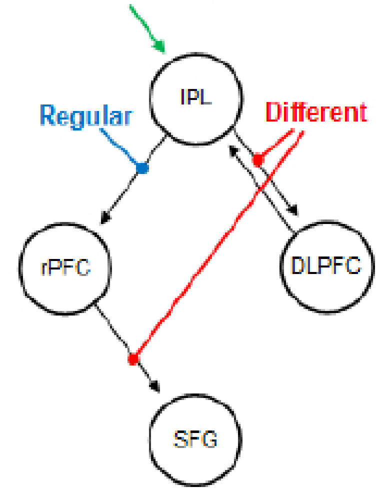
Fork



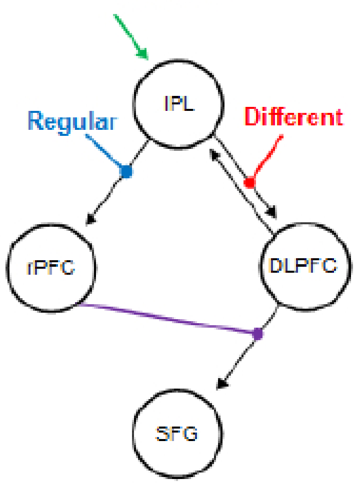
Legs 1



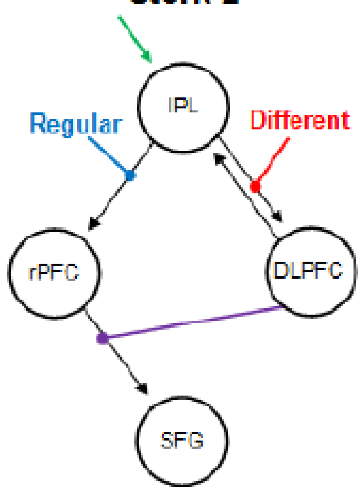
Legs 2



Stork 1

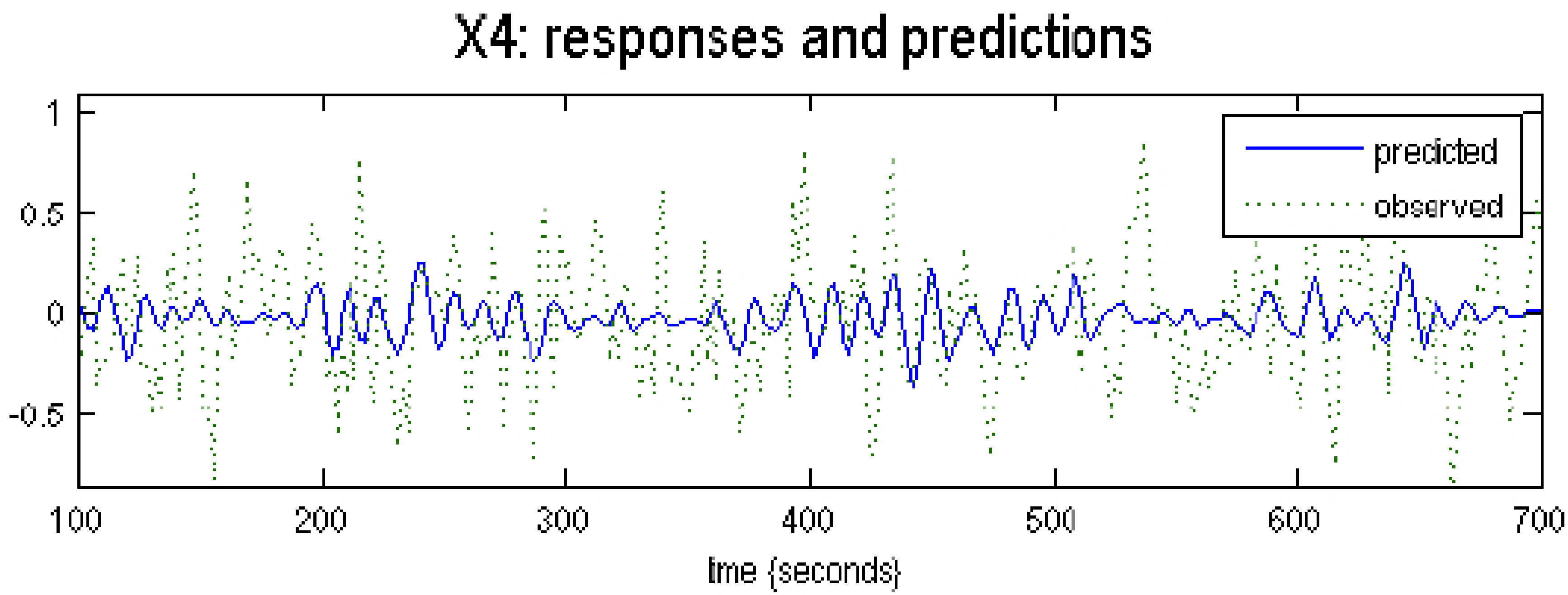


Stork 2



Hierarchical (nonlinear)

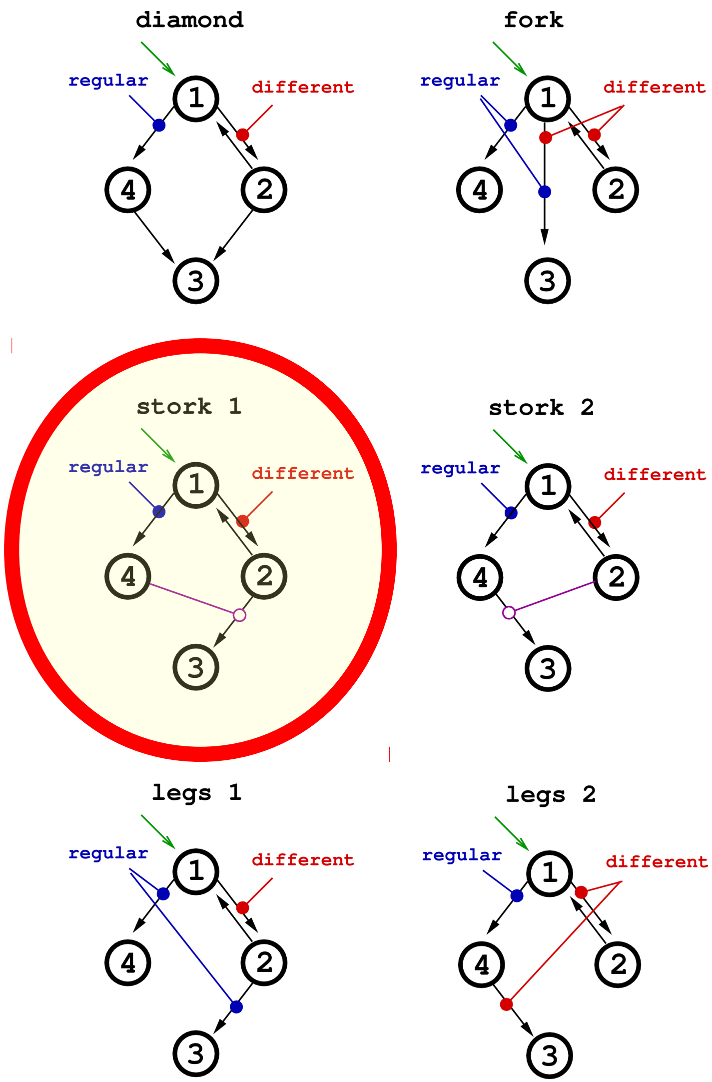
Example time series

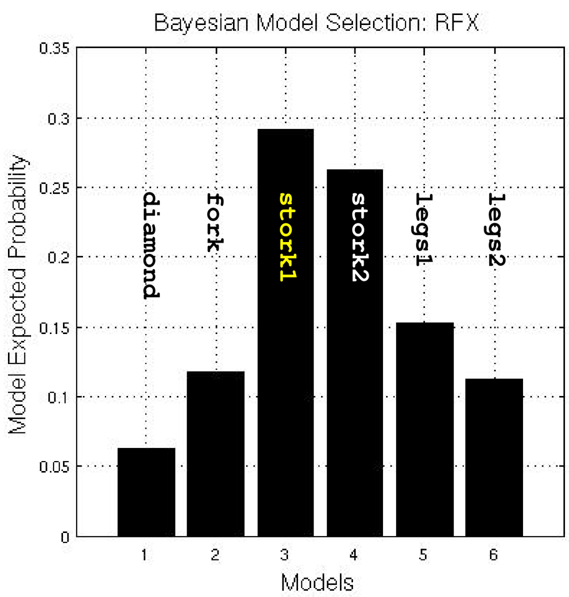


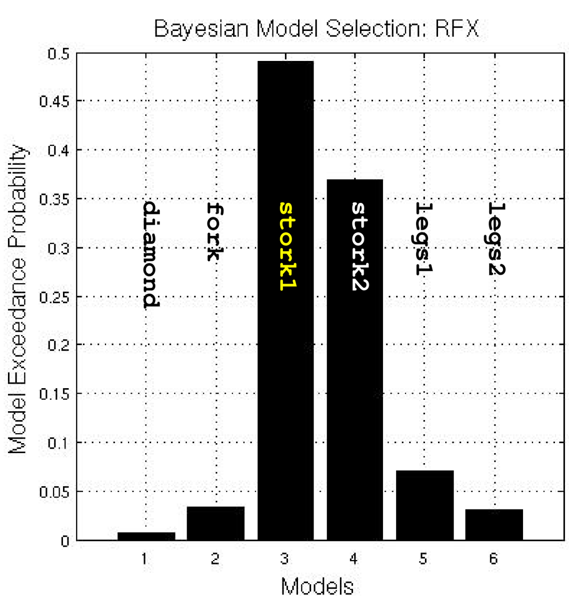
Expectation maximisation optimises the posterior likelihood of each model given the data

Stork 1

Model comparison

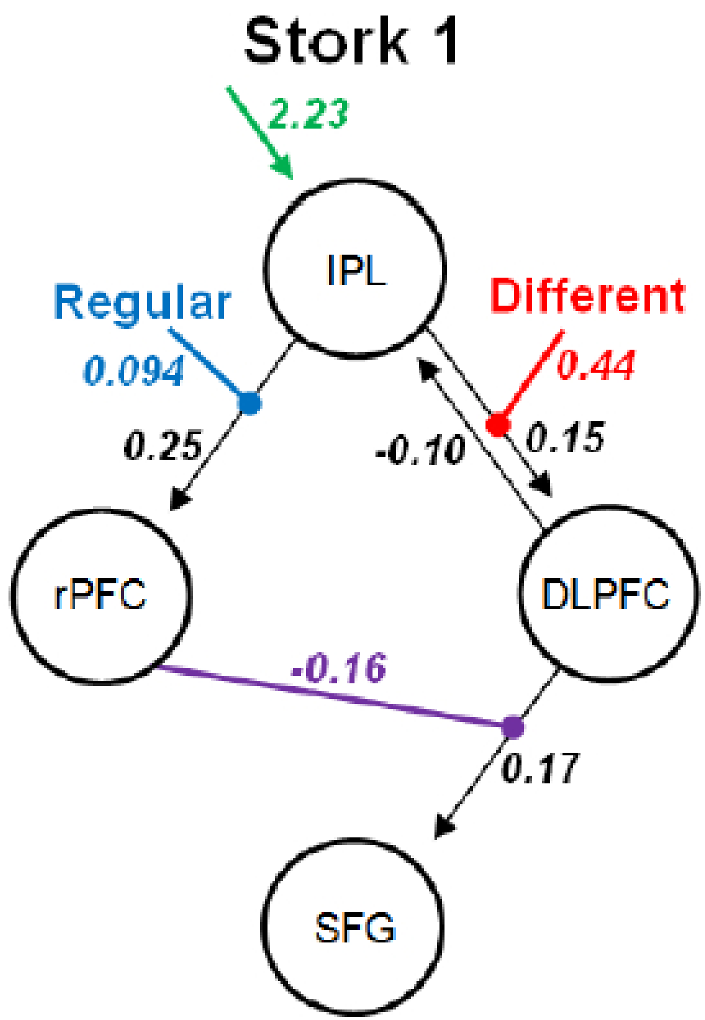






Karim et al. 2014

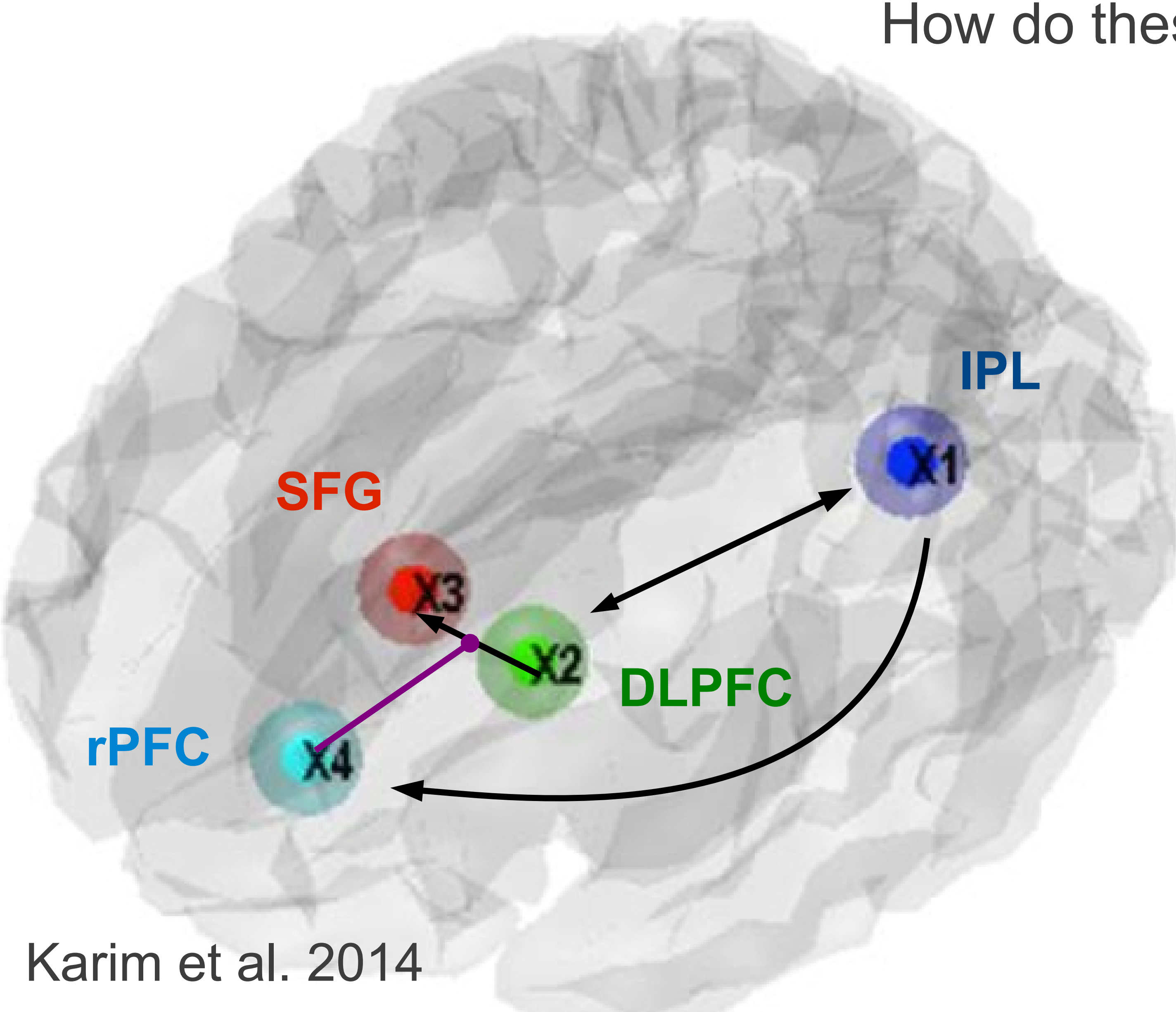
The nonlinear hierarchical model which best describes the data

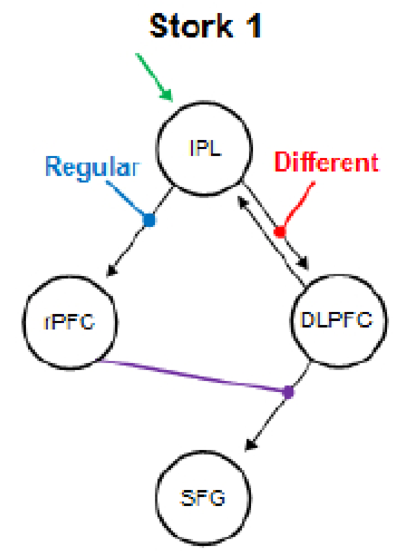


Karim et al. 2014

The nonlinear hierarchical model which best describes the data

How do these regions interact?





Karim et al. 2014

outline

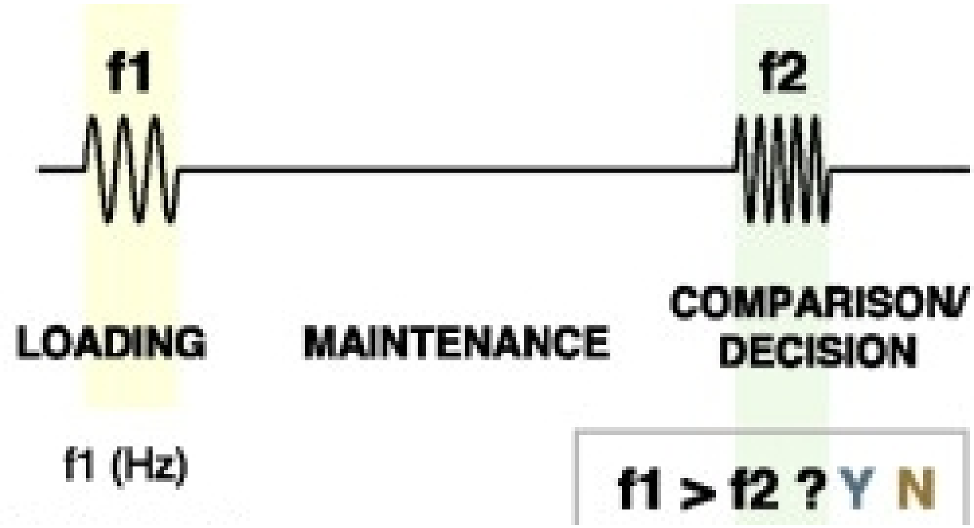
- Same or Different? Effective connectivity

  Behavioral, fMRI, DCM

- f2>f1? Time-order effect

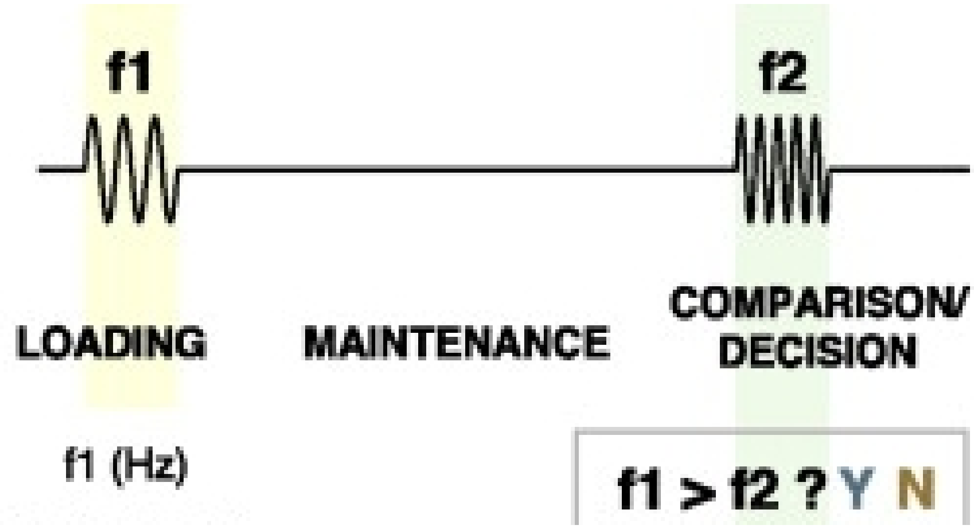
  Behavioral, Bayesian approach

Modeling time-order effect



Delayed vibrotactile discrimination task

Modeling time-order effect

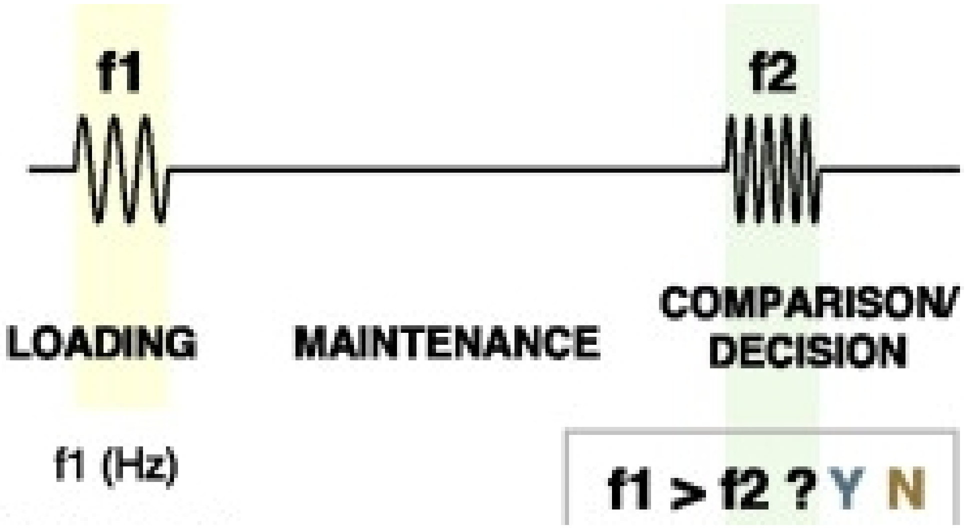


Delayed vibrotactile discrimination task

f1=A; f2=B $\longrightarrow$ Accuracy AB

f1=B; f2=A $\longrightarrow$ Accuracy BA ≠ Accuracy AB

Modeling time-order effect



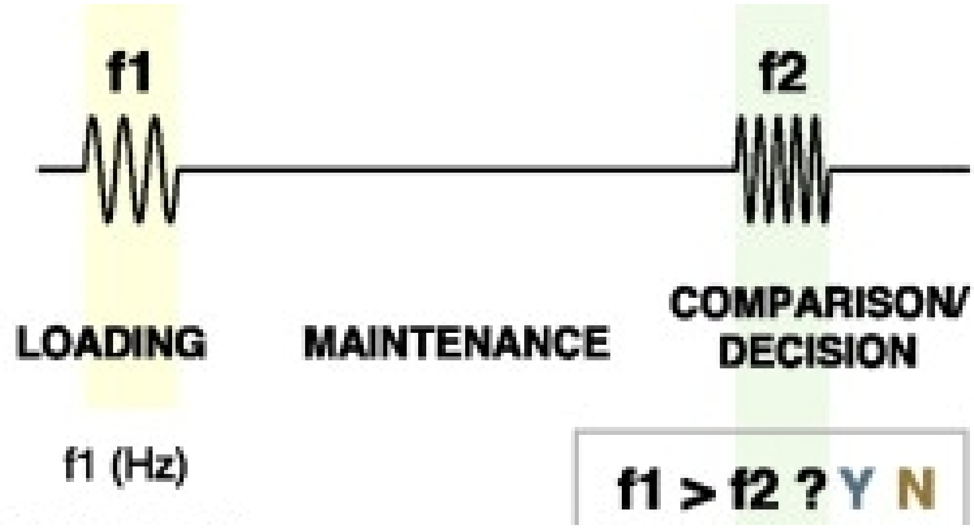
Delayed vibrotactile discrimination task

f1=A; f2=B → Accuracy AB

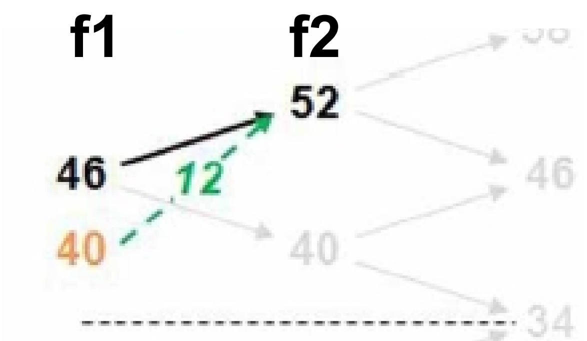
f1=B; f2=A → $\boxed{\text{Accuracy BA} \neq \text{Accuracy AB}}$

Time-order effect

Modeling time-order effect



Delayed vibrotactile discrimination task

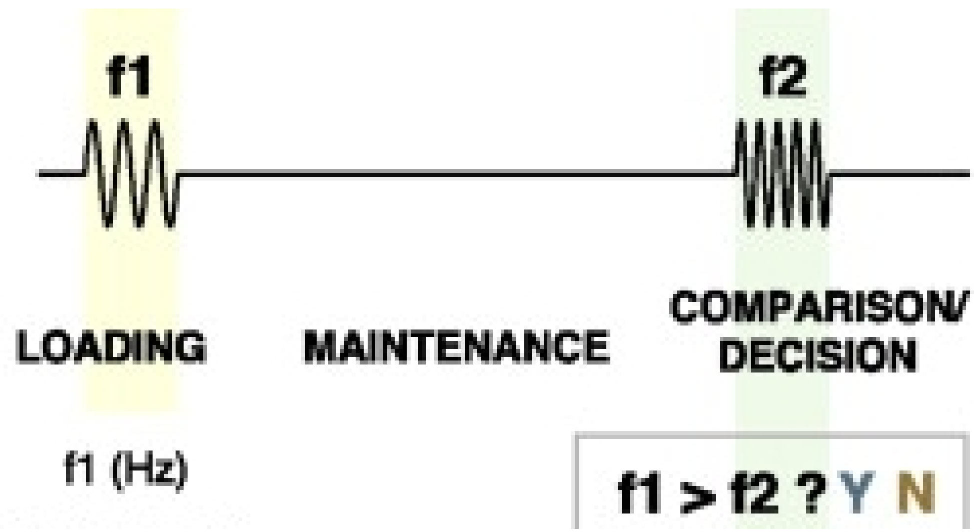


Preferred order improves accuracy

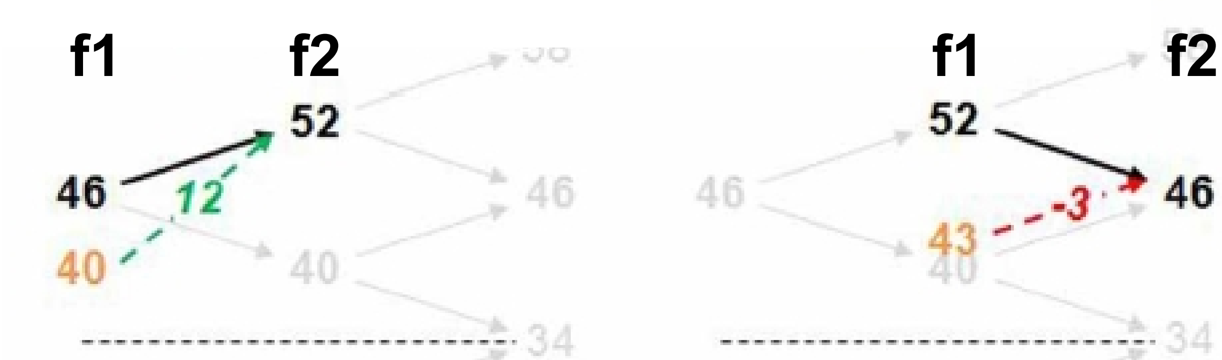
Global mean = 34 Hz

Karim et al. 2013

Modeling time-order effect



Delayed vibrotactile discrimination task



Global mean = 34 Hz

Preferred order improves accuracy

Nonpreferred order reduces accuracy

Karim et al. 2013

Bayesian approach

$$p(x|s)=p(x)\ p(s|x)\ /\ p(s)$$

Bayesian approach

Gaussian assumption: p(x|s)=p(x) p(s|x) / p(s)

Prior belief:

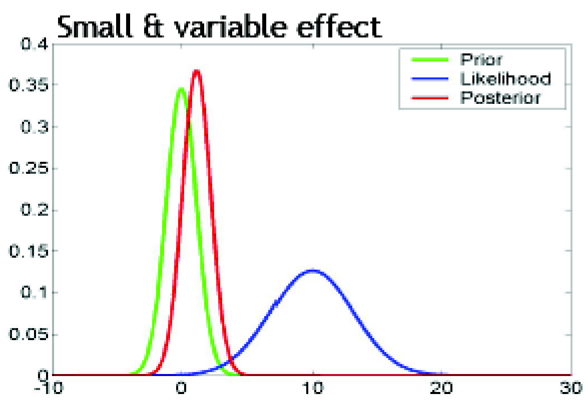
$$p(x) = \frac{1}{\sqrt{2\pi}\sigma_0} \exp\left(\frac{-(x - x_0)^2}{2\sigma_0^2} \right)$$

Likelihood:

$$p(s \mid x) = \frac{1}{\sqrt{2\pi}\sigma_s} \exp\left(\frac{-(x - x_s)^2}{2\sigma_s^2} \right)$$

Posterior belief:

$$p(x \mid s) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(\frac{-(x - \hat{x})^2}{2\sigma^2} \right)$$



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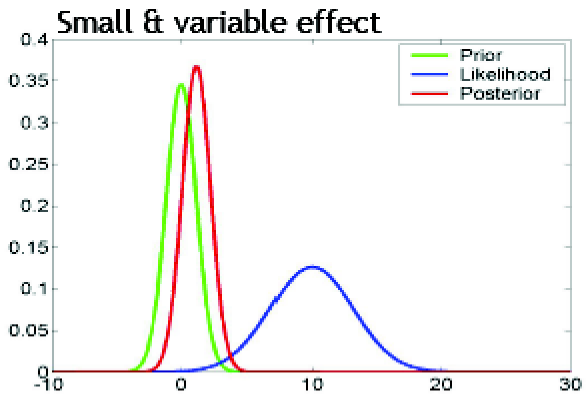
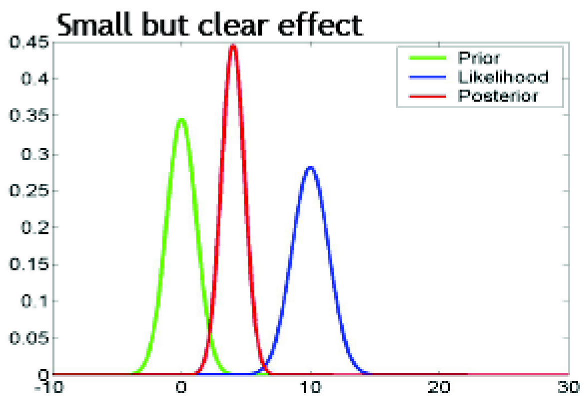
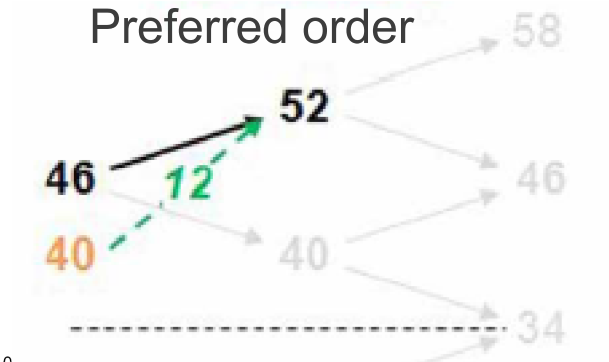
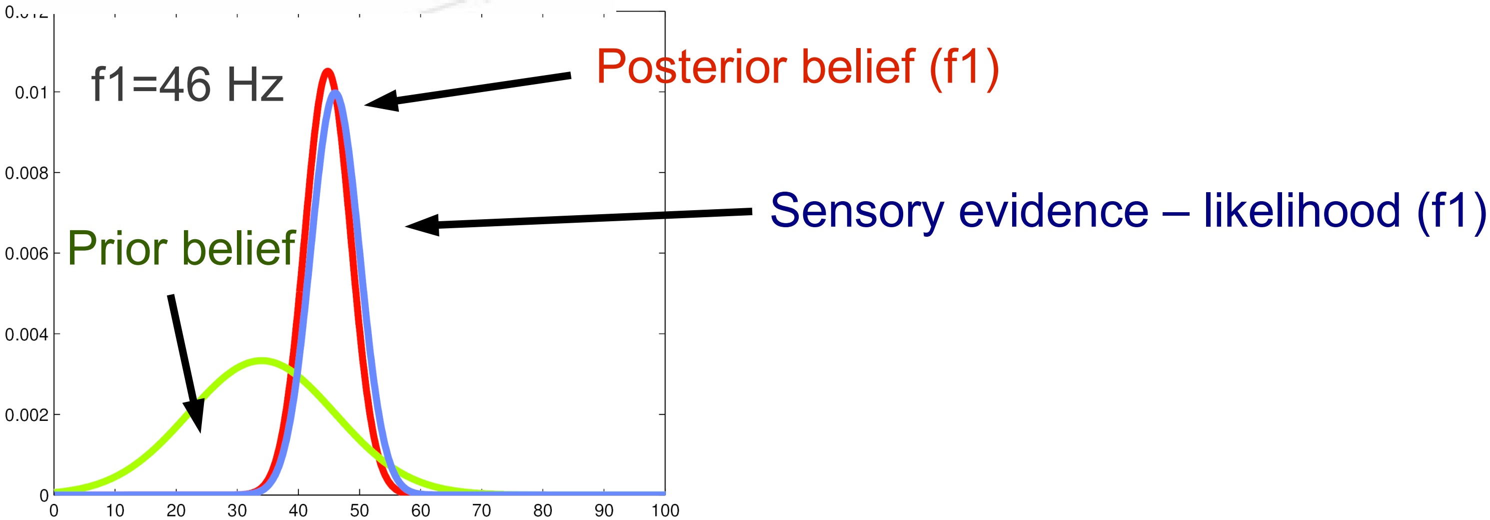




Without precision fade

$$p(x|s)=p(x)\,p(s|x)\,/\,p(s)$$





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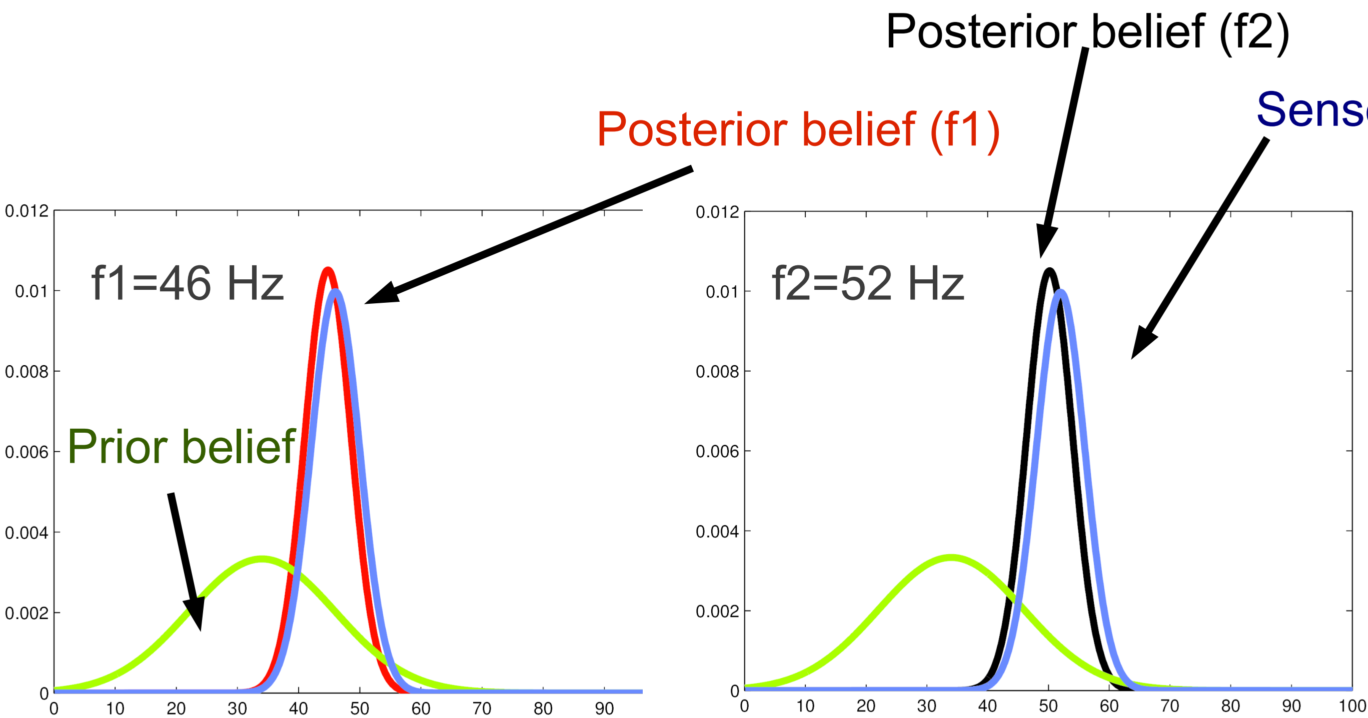

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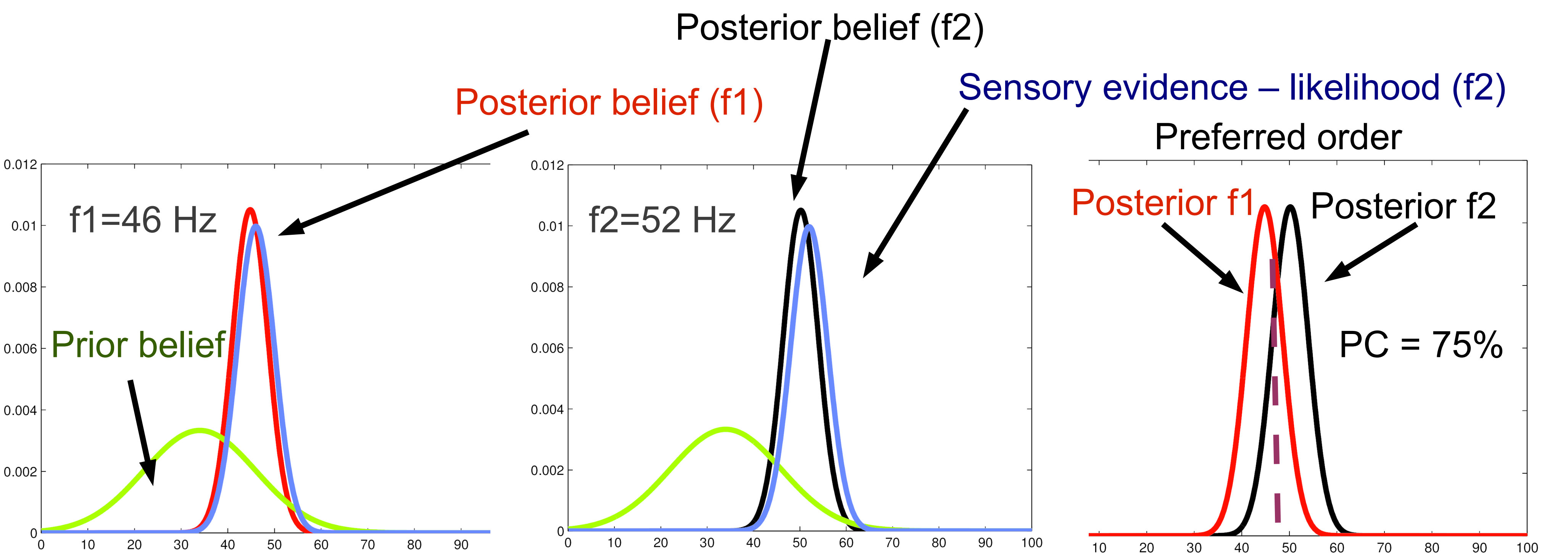

Without precision fade

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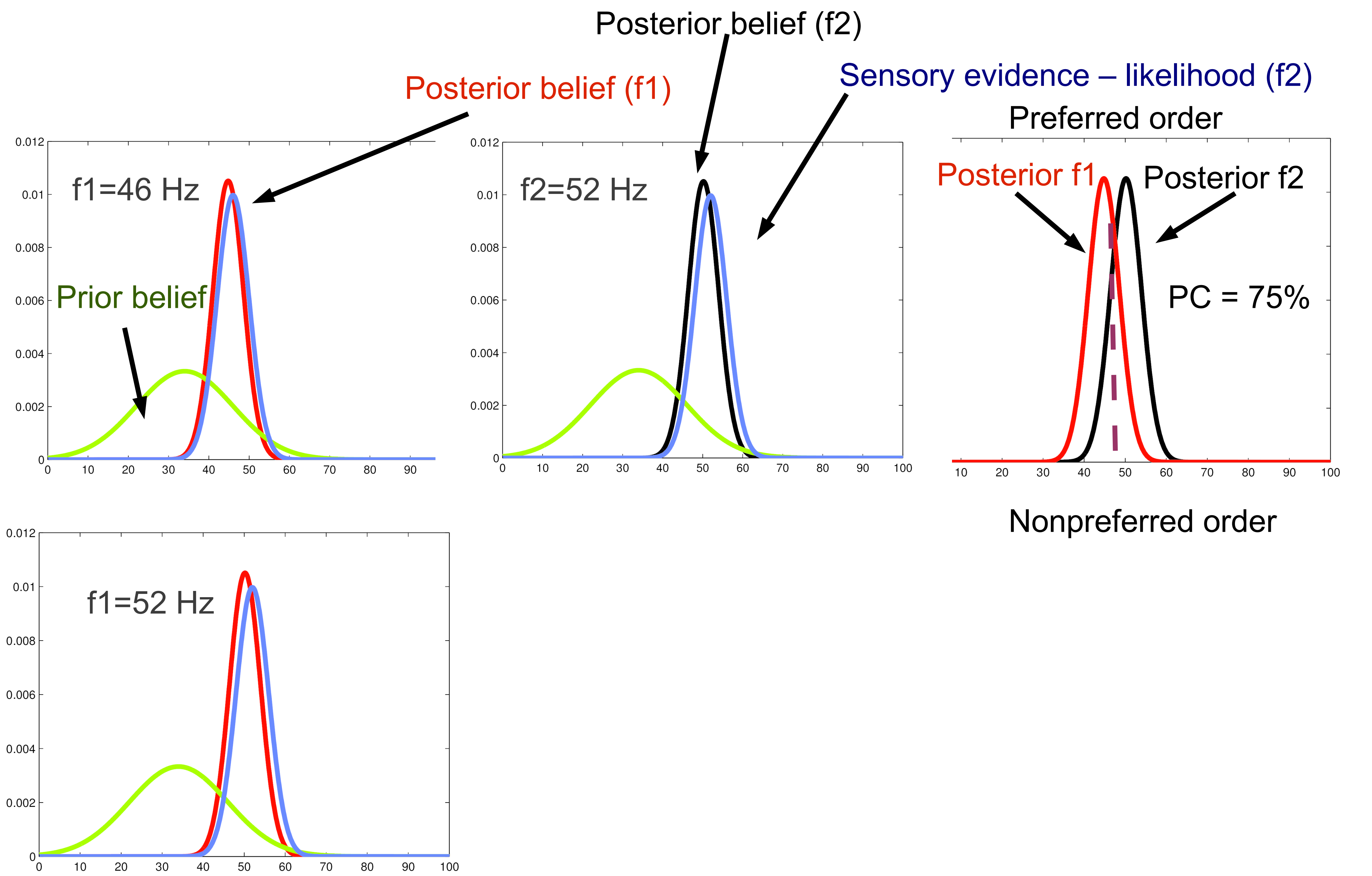

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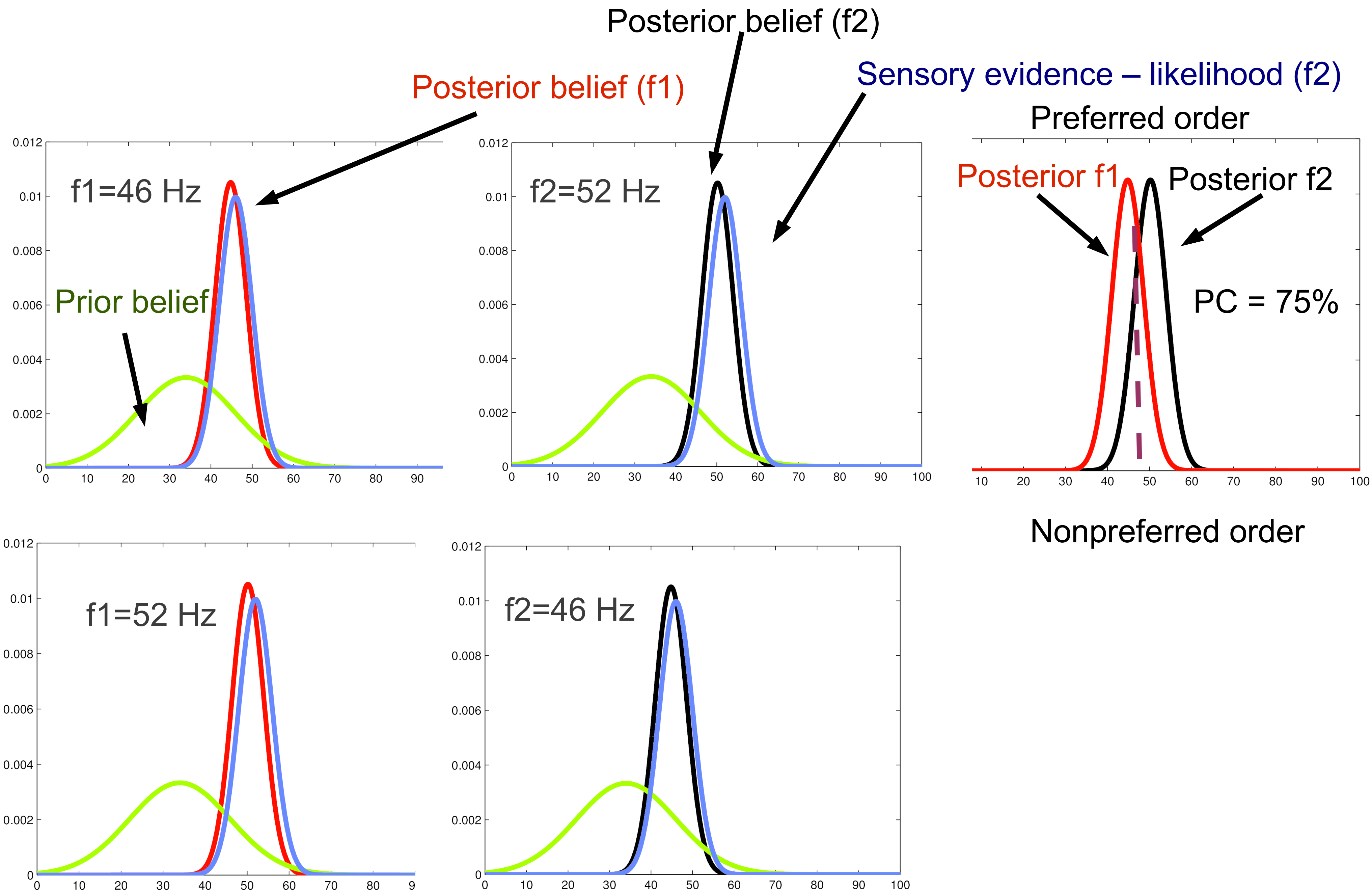

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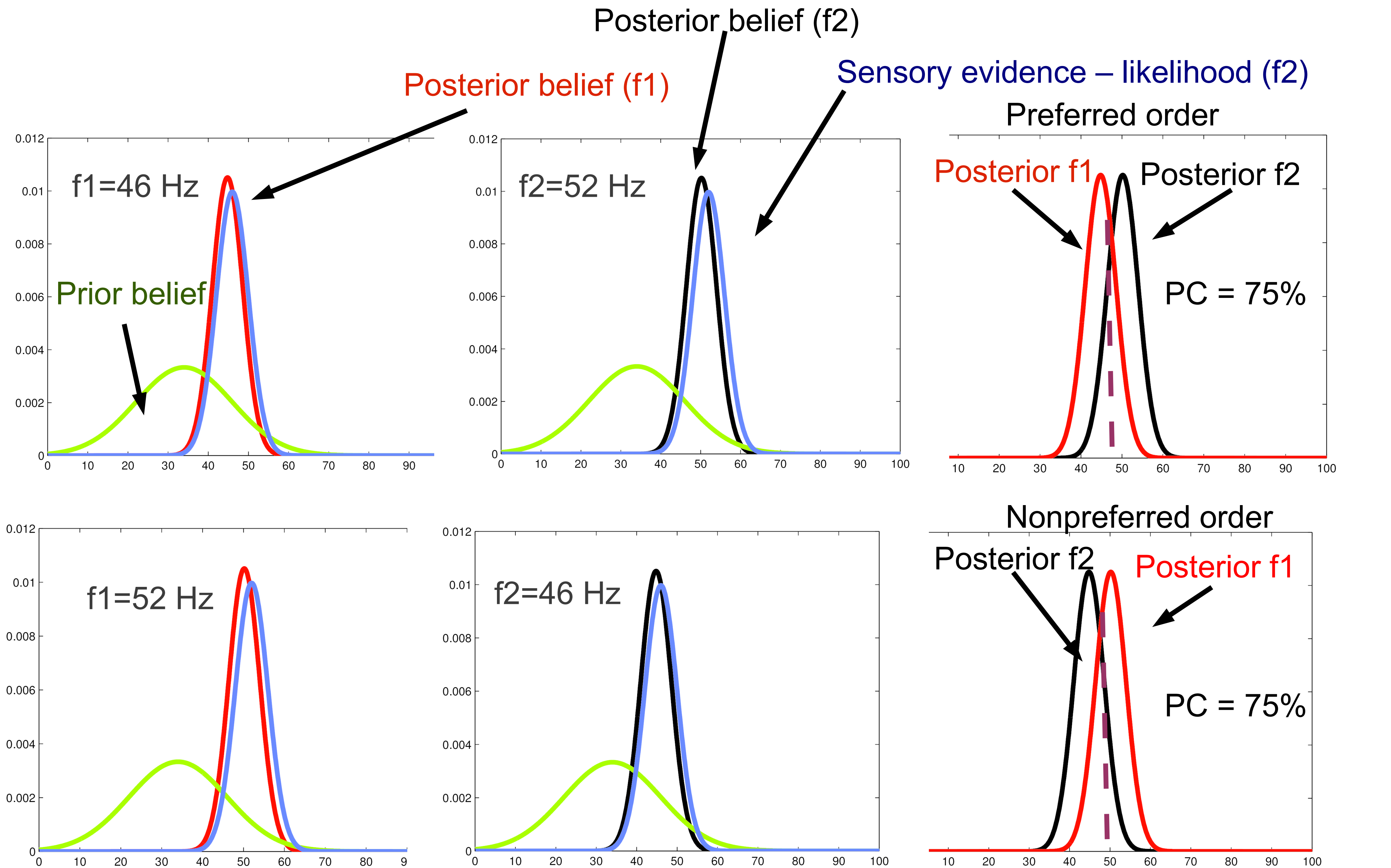

Precision fade

The variance of the sensory evidence of stimulus f1 grows in time

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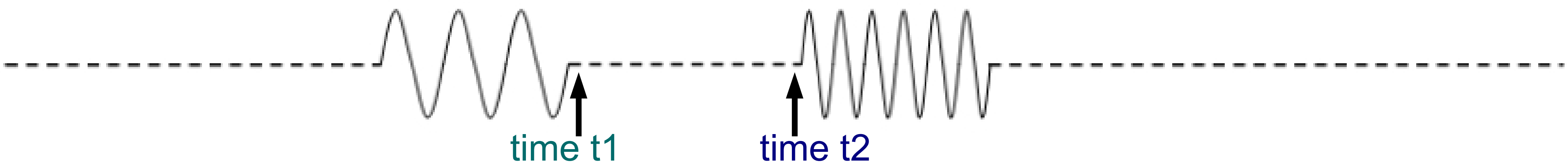

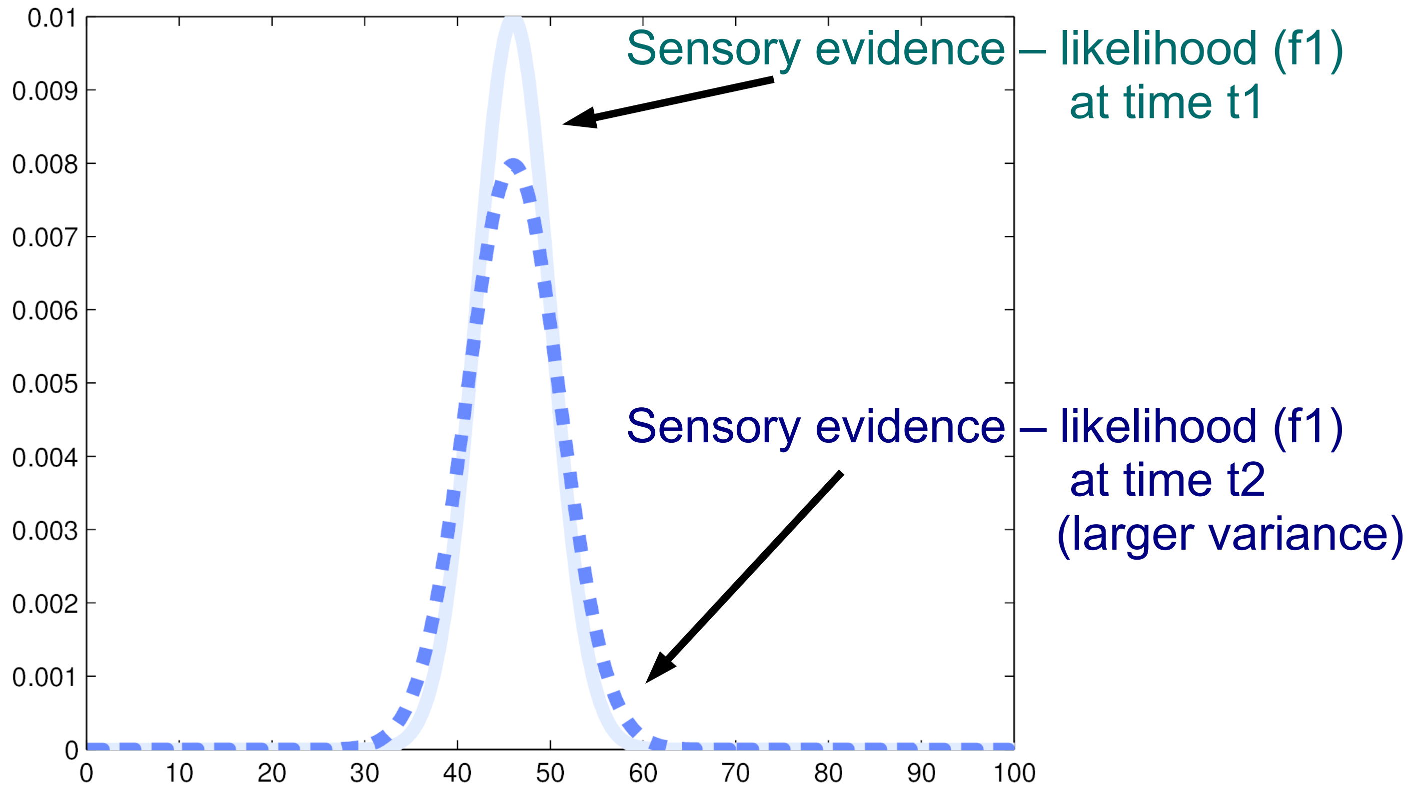

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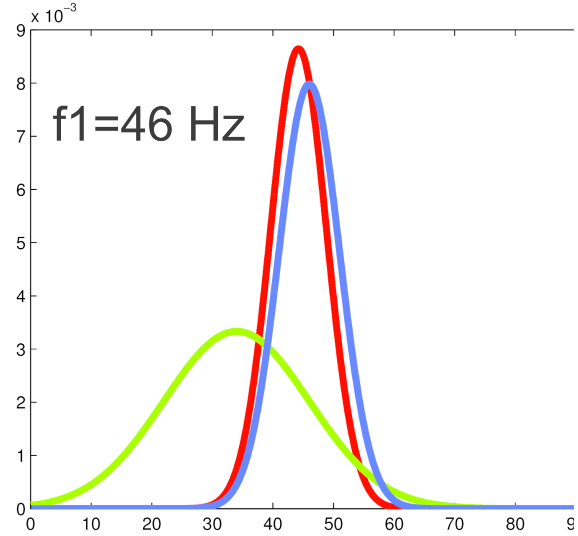

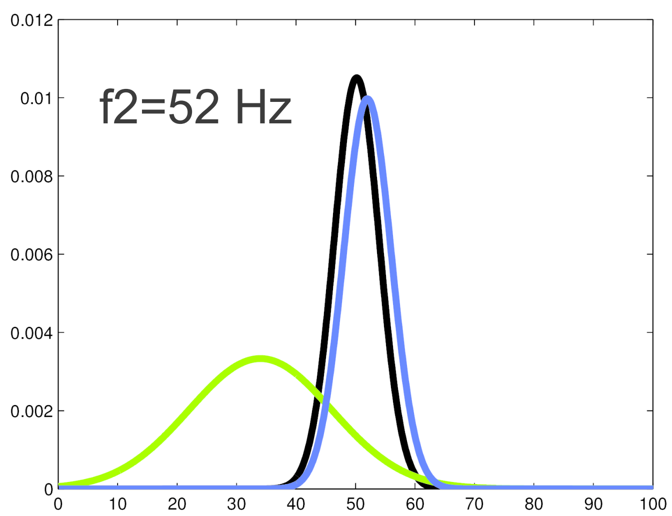

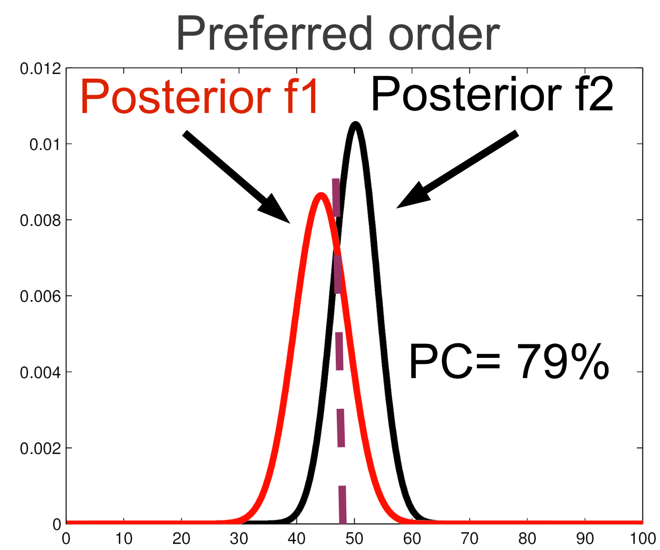

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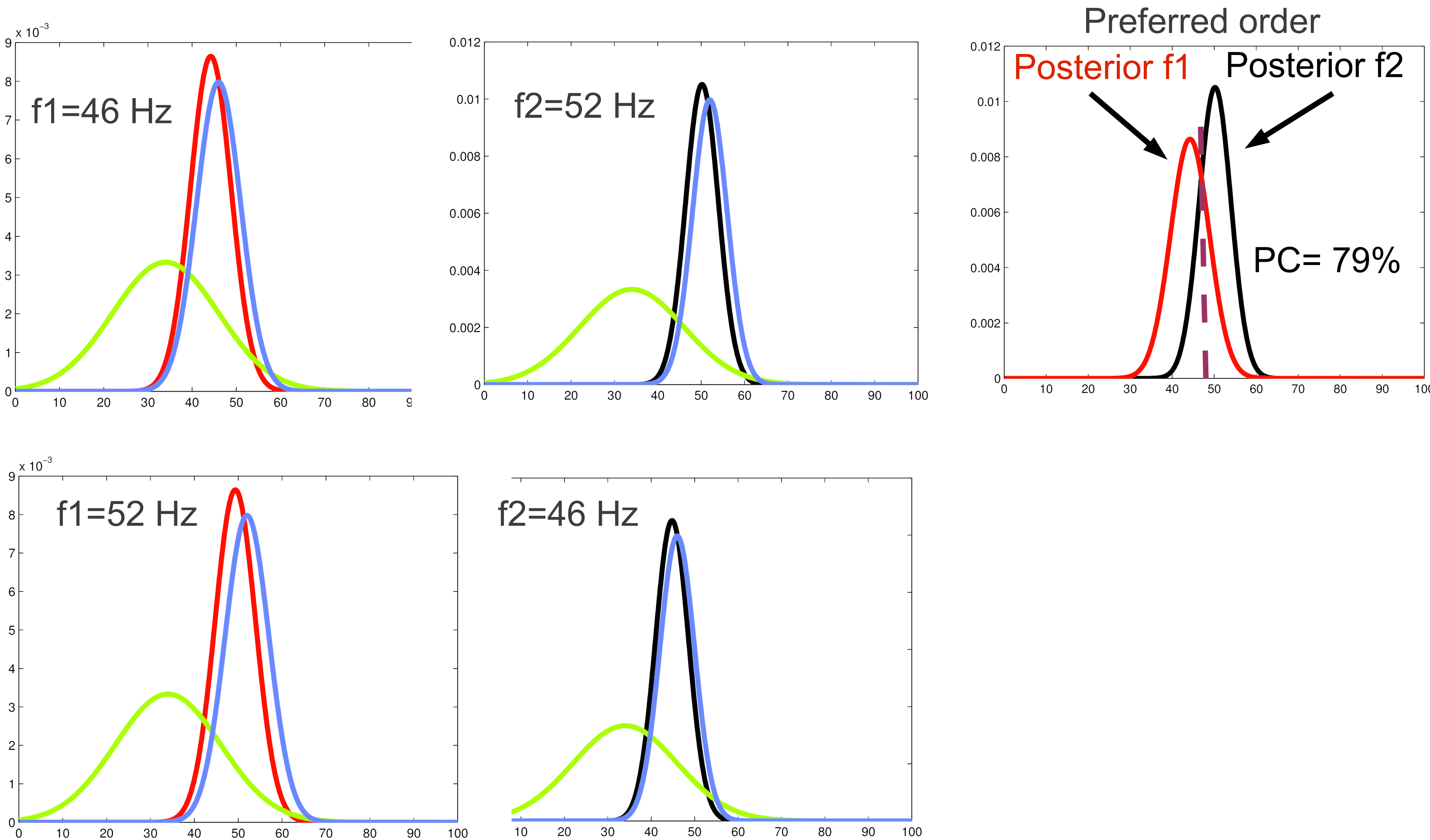

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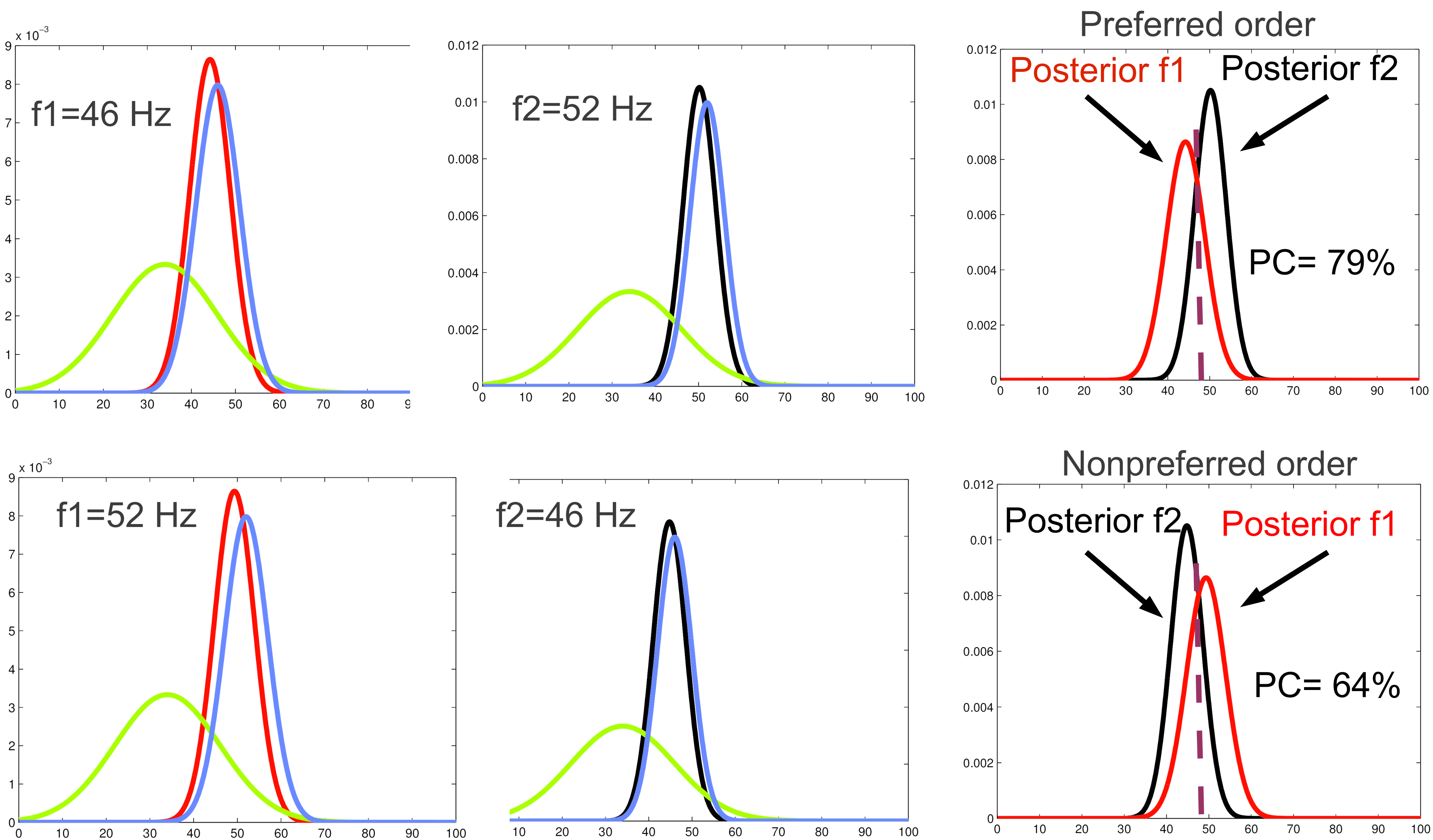
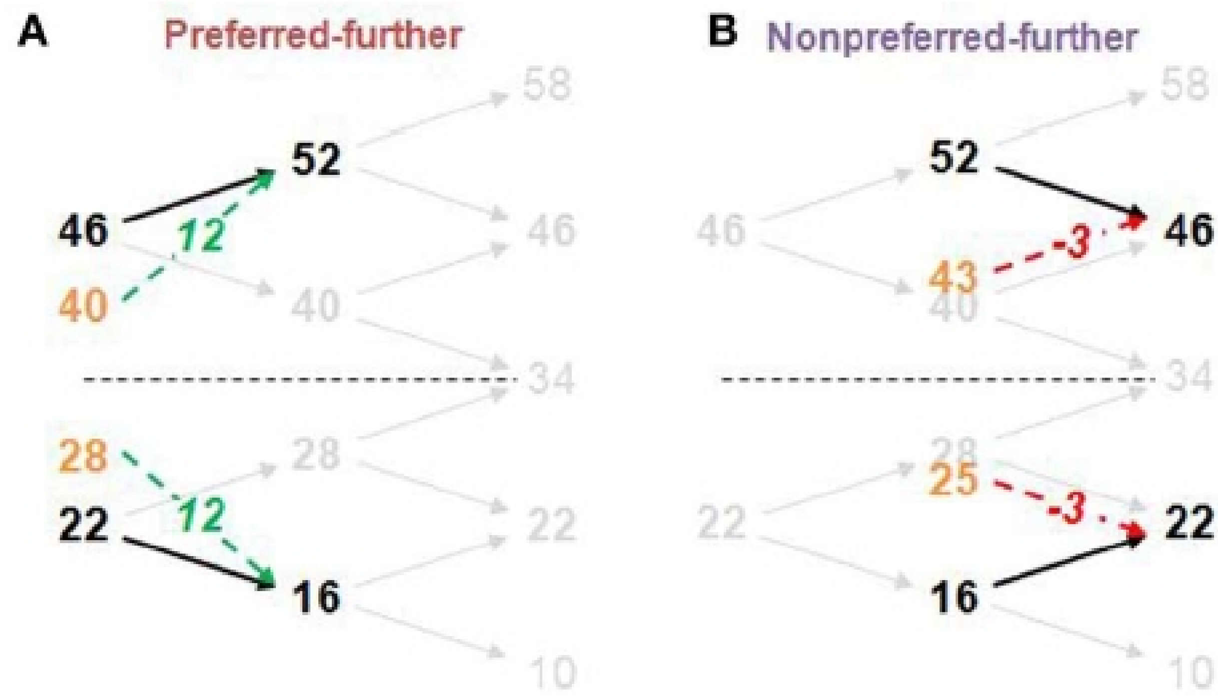
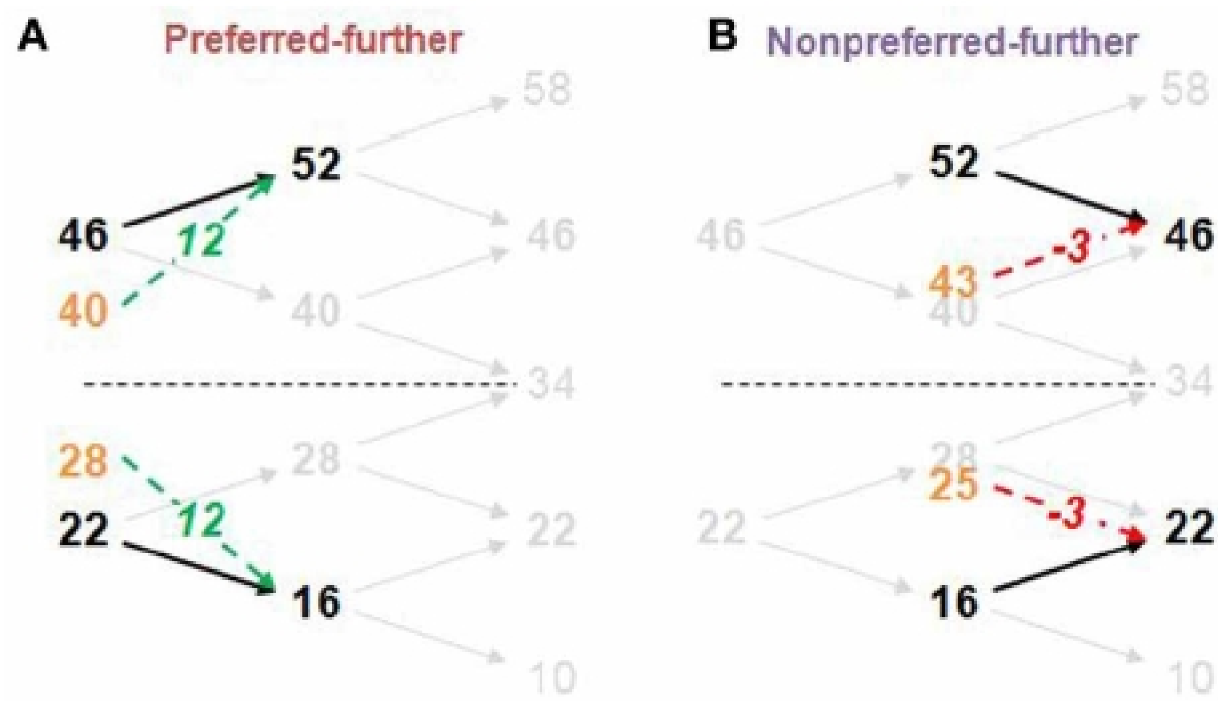
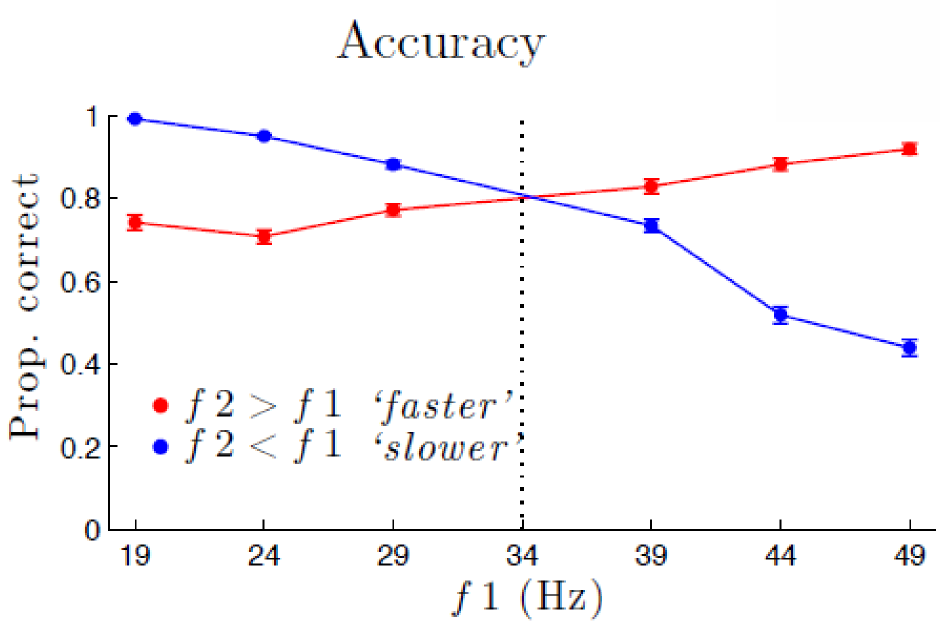




Karim et al. 2013

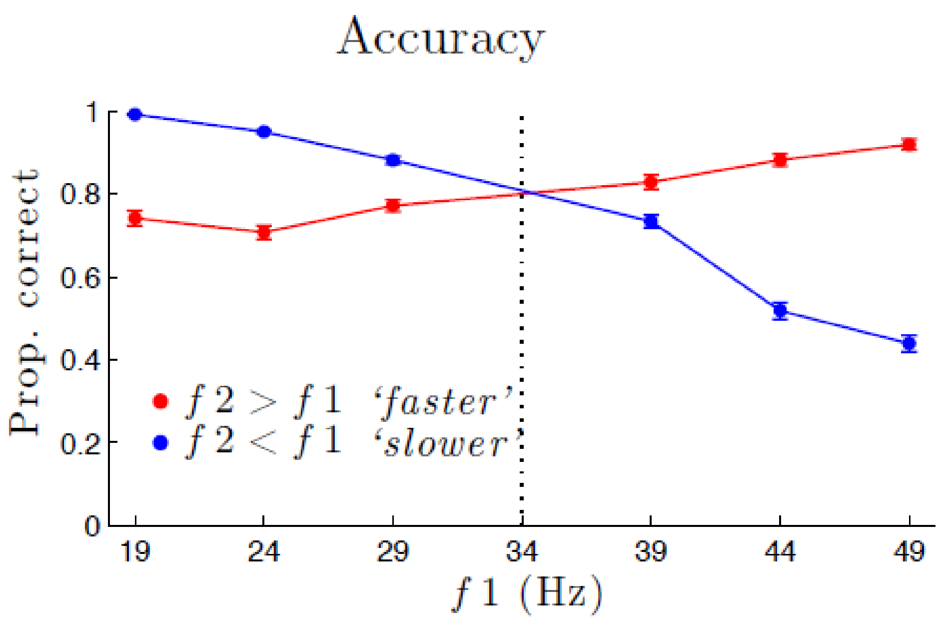


data



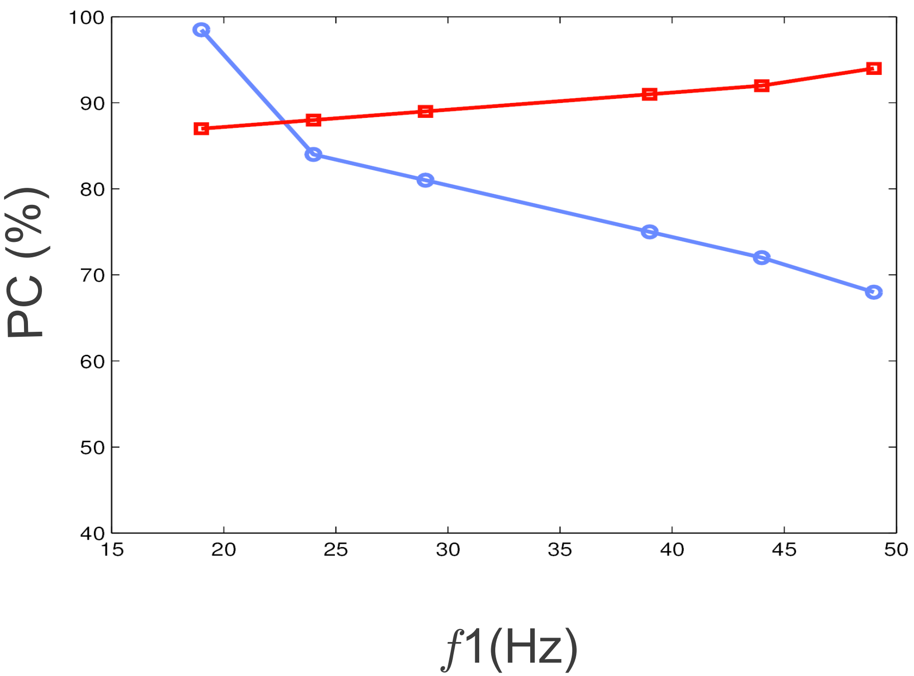
Langdon et al. 2012

data



Accuracy
1
0.8
0.6
0.4
0.2
0
Prop. correct
19
24
29
34
39
44
49
$f\,1$ (Hz)
$f\,2 > f\,1$ 'faster'
$f\,2 < f\,1$ 'slower'

model



100
90
80
70
60
50
40
PC (%)
15
20
25
30
35
40
45
50
f1(Hz)

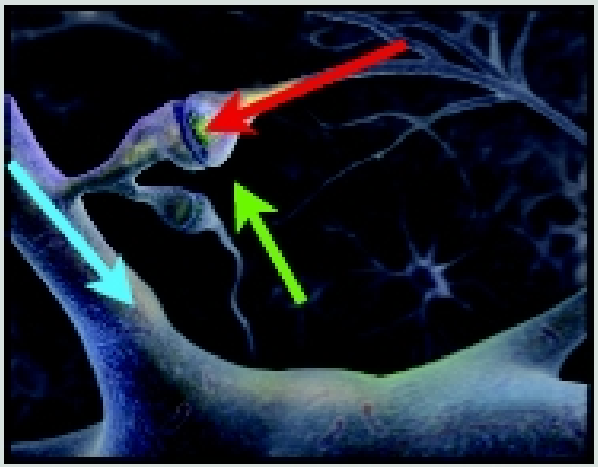
Conclusions

- Vibrotactile decision-making task depends on a constellation of prefrontal cortical areas
- The data is best described by nonlinear hierarchical models
- Time-order effect = estimation + precision fade

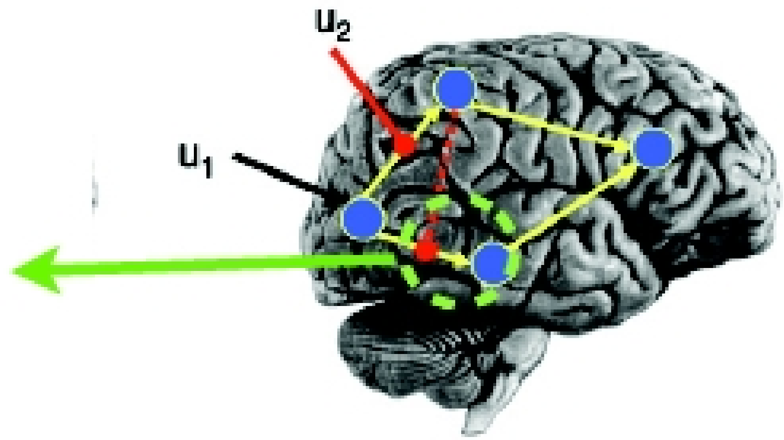
Thank you

Thank you

nonlinear DCM



Stephan *et al* 2008



Nonlinear state equation

$$\frac{dx}{dt} = \left(A + \sum_{i=1}^{m} u_i B^{(i)} + \sum_{j=1}^{n} x_j D^{(j)} \right) x + Cu$$

The nonlinear term in the D matrix embodies a very basic form of neurophysiological gating, namely voltage dependent gating via NMDA receptors