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Estimating the activity of regions of interest using Expectation Maximization algorithm

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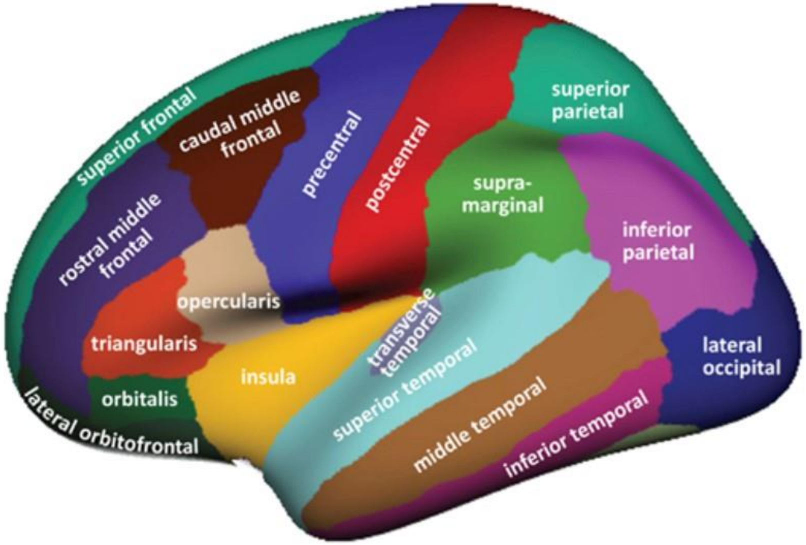
Background 1/3

- The human brain has two functional principles:
  - Functional segregation
  - Functional integration
    - Quantified in terms of functional connectivity which is defined as statistical interdependencies between the functional properties of different brain regions
    - Functional properties can be measured using EEG/MEG

Background 2/3

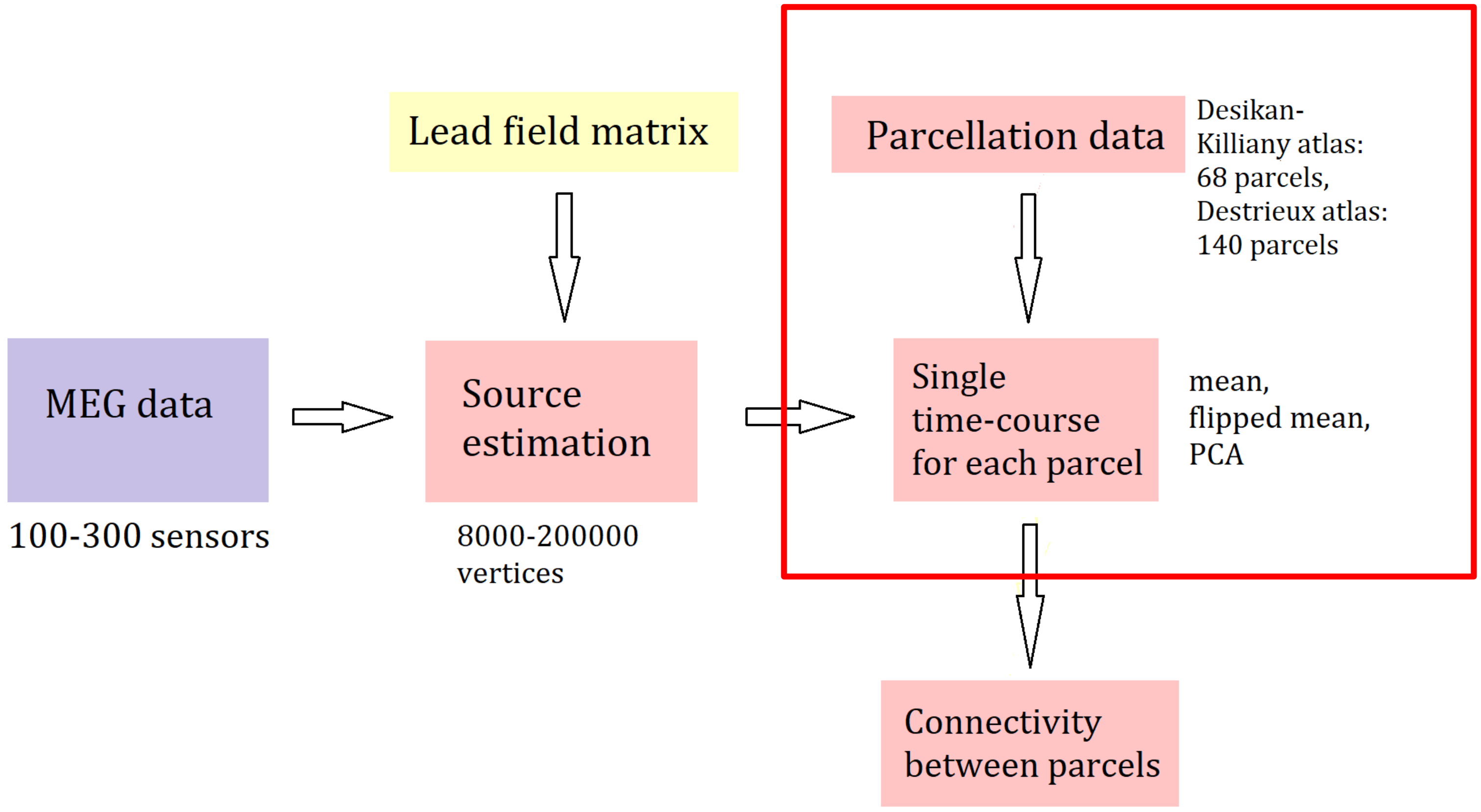
- Due to limited spatial resolution of EEG/MEG, the underlying neural activity is estimated by solving an inverse problem
- The activity of a region is determined by combining the activity of the neural sources within a certain region using some parcellation e.g. Desikan-Killiany



Background 3/3

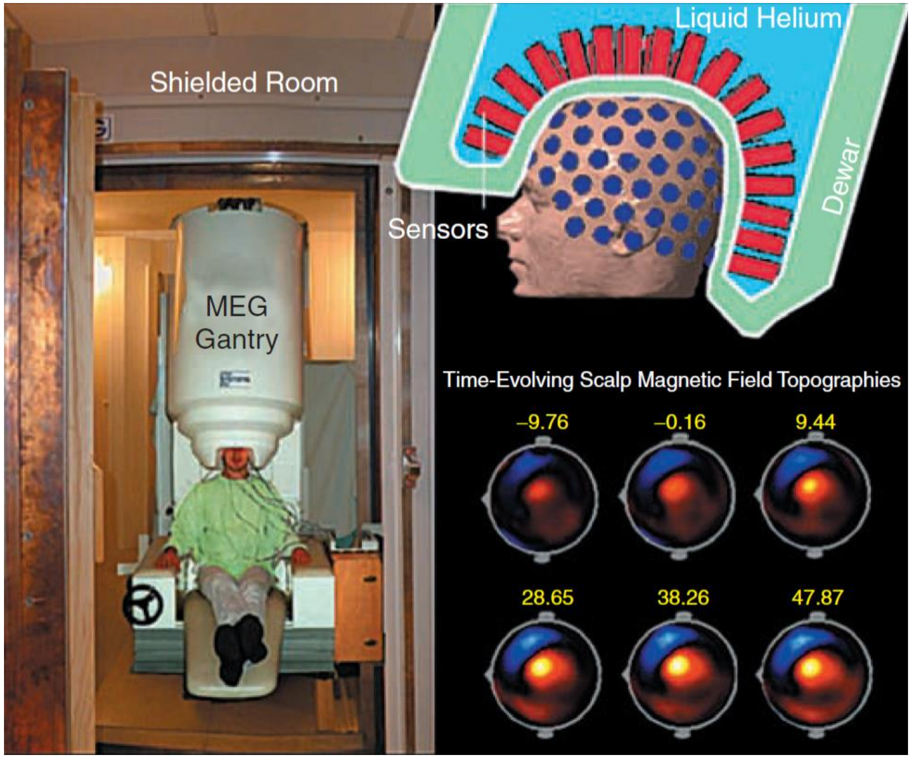
- Functional connectivity is estimated from the activity of the regions using various methods such as correlation or Granger causality
- Currently used methods for combining the activity of neural sources within a region are quite ad hoc e.g. mean, flipped mean or PCA
- This thesis focused on developing a data driven method for estimating the activity of a region

Connectivity estimation pipeline



Measuring the activity

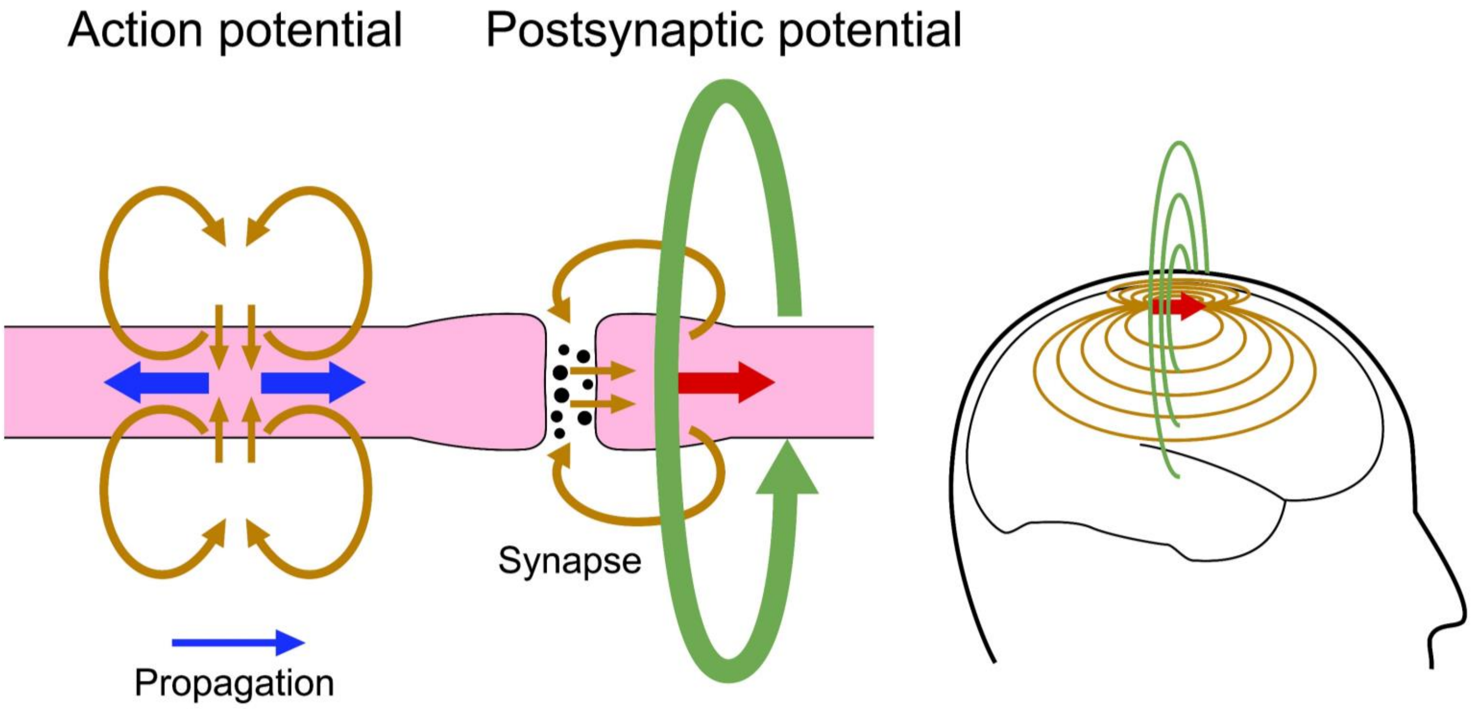
- The activity of the brain can be measured with noninvasive measurement techniques such as EEG and MEG which measure the electromagnetic fields generated by neurons



Sylvain Baillet, John C. Mosher and Richard M. Leahy: Electromagnetic Brain Mapping. IEEE Signal Processing Magazine, November 2001

Approximation of a neural source

- A current dipole is an approximation for multiple closely related coherently behaving neurons



The inverse problem

- The activity of the neural sources can be estimated by solving the equation

$$\bar{y}_t = G\bar{q}_t + \bar{\varepsilon}_t$$

where

$\bar{y}_t$= measured data

G= the lead field matrix

$\bar{q}_t$= activity of the dipoles

$\bar{\varepsilon}_t$= the measurement noise

→ The neural source activity within a region is combined to form a single time series representing the activity of the region

Objective

- Implementing a data driven method to estimate the activity of the regions
- Estimate a matrix, call it L, such that

$$\bar{q}_t = L\bar{u}_t + \bar{\epsilon}_t$$

where

$\bar{q}_t$= the dipole activity

L= the weight matrix

$\bar{u}_t$= the region activity

$\bar{\epsilon}_t$= additional dipole noise

Methods 1/2

- The activity of the brain is modeled using a state-space model

$$\bar{u}_t = A\bar{u}_{t-1} + \bar{\vartheta}_t$$
$$\bar{q}_t = L\bar{u}_t + \bar{\epsilon}_t$$
$$\bar{y}_t = GL\bar{u}_t + \bar{\eta}_t$$

  where $\bar{\eta}_t = G\bar{\epsilon}_t + \bar{\varepsilon}_t$

- Enables to obtain the activity of a region using Kalman filter

Methods 2/2

- Expectation Maximization algorithm is used in the estimation of L
- The expectation of $\bar{u}_t$ is estimated using Kalman smoother
- The maximum a posterior is obtained by

$$\widehat{\mathbf{L}}_{k+1} = \arg\max_{\mathbf{L}} (Q(\mathbf{L}, \mathbf{L}_k) + \ln p(\mathbf{L}))$$

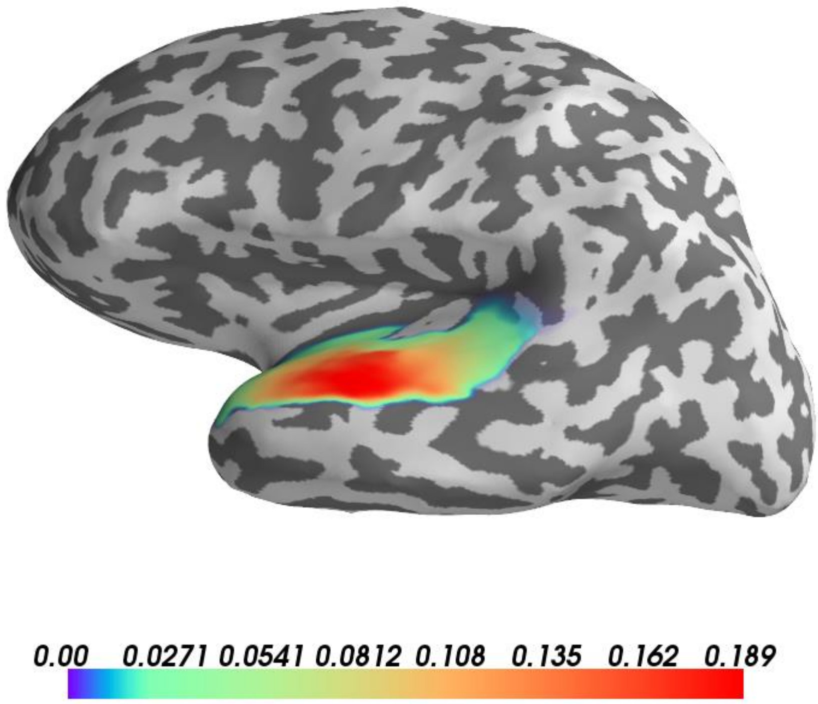
where

$$Q(\mathbf{L}, \mathbf{L_k}) = \int \ln p(\mathbf{u}, \mathbf{y} | \mathbf{L}) p(\mathbf{u} | \mathbf{y}, \mathbf{L_k}) d\mathbf{u}$$

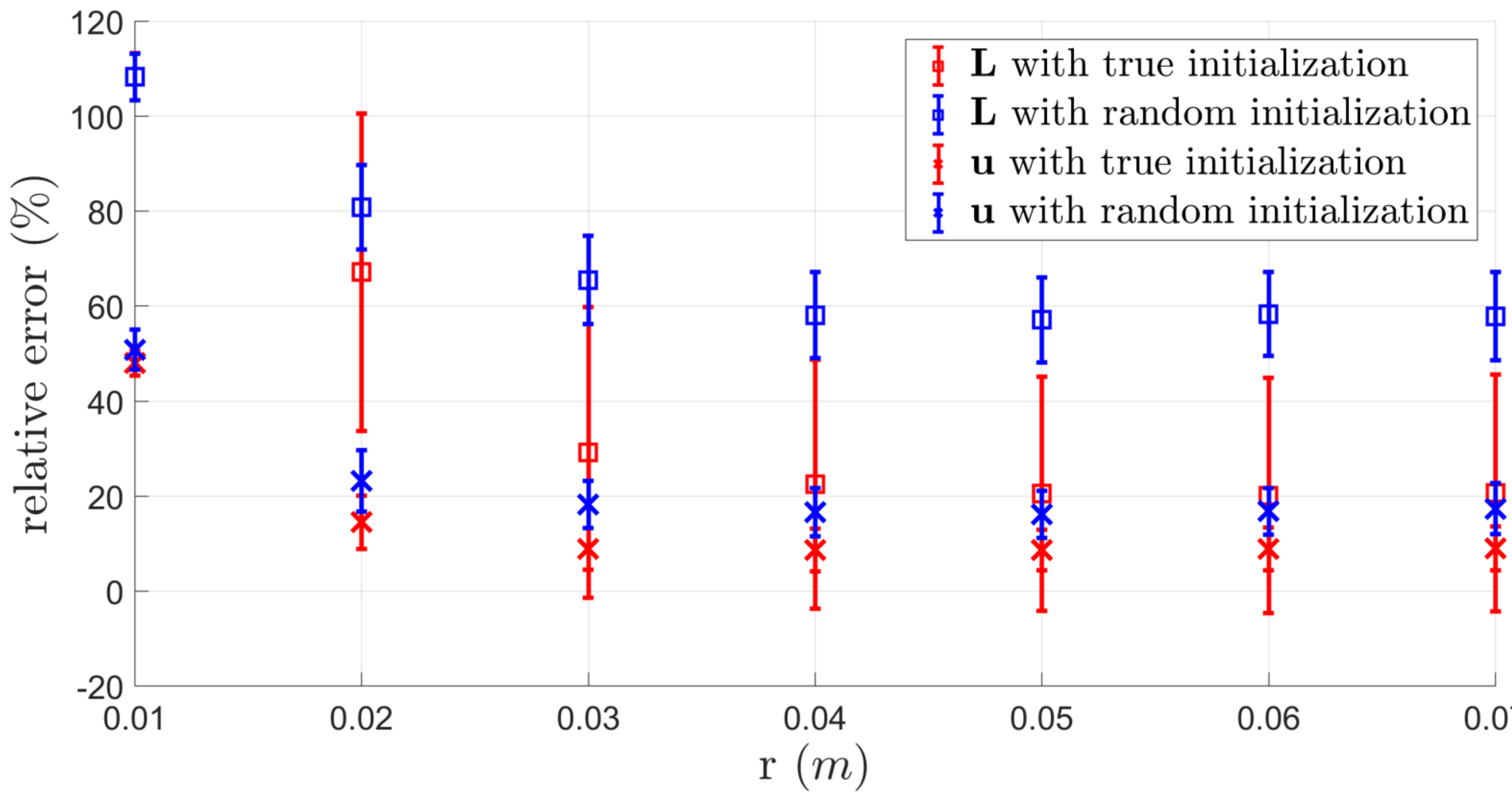
is the expectation of the joint log-likelihood under a posterior

Simulation setup

- The weights in L are designed to have a Gaussian distribution around the most active dipole
- To introduce spatial smoothness, a penalty term is added



Results 1/2



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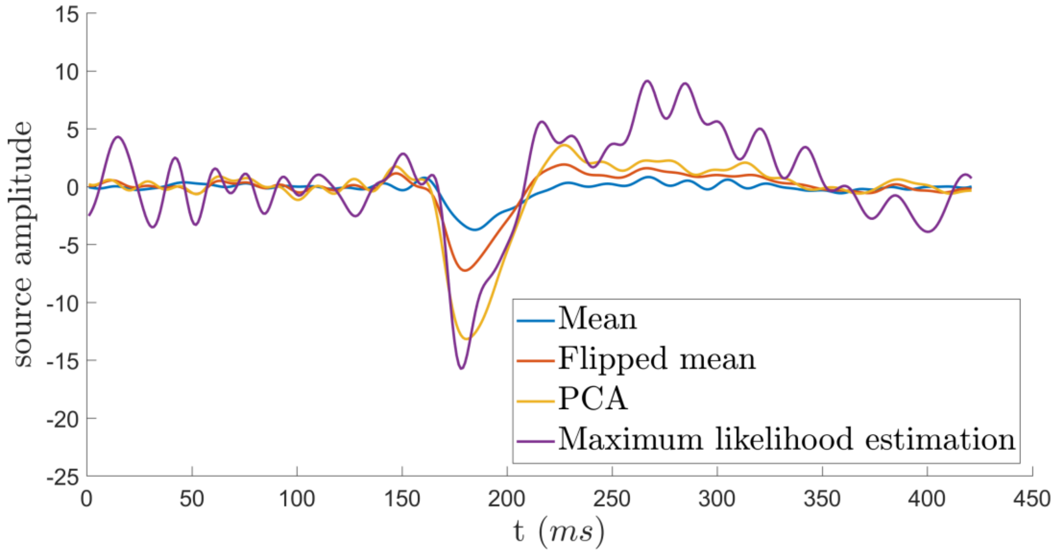
Real data

- Left auditory stimulus MEG-measurement
  - A stronger response in the activity representing the right hemisphere is expected
- From MNE Python library sample data set

Results 2/2



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source amplitude
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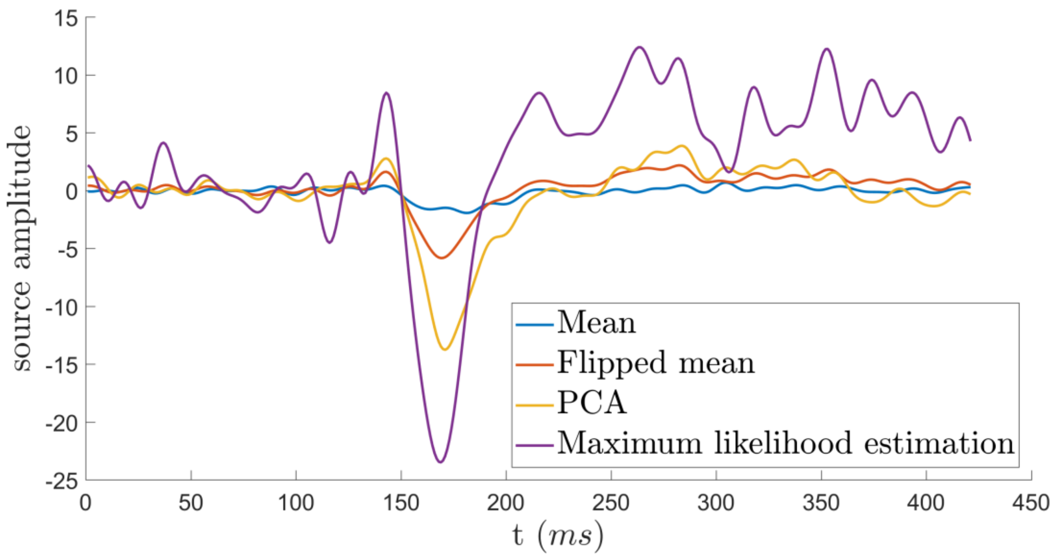
450
t (ms)
Mean
Flipped mean
PCA
Maximum likelihood estimation



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Conclusions

- Simulation results show that a larger radius was needed to obtain decent results and the performance on smaller radius was not good
  - Simulation setup might not be optimal
  - Design of the penalty term
  - Large number of parameters
- Application on real data produced a higher amplitude in the activity meaning a more dipole-like activity
- Carefully designed and implemented data driven method would provide a more accurate approach for estimating the region activity

References

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