# Topographic Factor Analysis: inferring brain networks from fMRI data

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#### Introduction & overview

Detecting brain networks using fMRI typically requires focusing on a set of "seed" voxels, or a restricted set of brain regions.

Topographic Factor Analysis (TFA) provides an efficient technique that leverages full brain images to discover the locations and sizes of the brain structures activated during a given task, and the interactions between those structures.



Figure 1. A. Sample image. B. Reconstructed image. C. An inferred 10-node network.

# General approach

We decompose each brain image into a weighted combination of spherical sources (factors).

The sources are held fixed across images, and the weights vary by image.

Applying TFA to an fMRI dataset reveals the most probable locations and sizes of the spherical sources and the per-image source weights.

We can assess functional connectivity by examining how the source weights covary across images.



Figure 3. Factors obtained using various techniques. A. Original image. B. PCA factor. C. ICA factor D. TFA factor

## Model specification

We formulate TFA as a probabilistic model by defining a joint distribution over the data (brain images) and hidden variables (the source centers, widths, and weights) given a set of fixed hyperparameters (which reflect our prior assumptions).

The generative process defined below describes how we can draw samples from this joint distribution. Each sample contains a set of N images and the associated sources and weights.

The graphical model defines conditional dependencies in the joint distribution.



Figure 4. TFA's generative process (left) and graphical model (right)

#### Fitting the model

Our goal is to compute the posterior distribution over the hidden variables given the brain images. Computing this posterior exactly is intractable, so we approximate it instead.

We begin by initializing the source centers and widths using the mean image and the weights using linear regression.

We use mean field variational inference to adjust an approximate posterior over each hidden variable.



Figure 5. Initializing the source centers, widths, and weights. A. Original (synthetic) mean image. B. We "fold" the mean image by subtracting the mean and taking the absolute value. C. We place the first source at the position displaying the maximal activation, and adjust its width using convex optimization. D. We fit the next source to the residual image. E. We repeat this process until K sources are placed. F. We estimate the source weights using linear regression.

#### Results

We applied TFA to two fMRI datasets, collected by Mitchell et al. (2008) and Wang et al. (2013). The Mitchell et al. (2008) dataset comprises 9 participants who viewed stimuli drawn from 12 categories, and the Wang et al. (2013) dataset comprises 18 participants who viewed pictures of faces and scenes.

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We tested the quality of the reconstructions and the reliability of the inferred category-specific networks.



Figure 6. A coronal slice from one participant, and the associated reconstruction varying numbers of sources.



Figure 7. A. Observed and estimated covariance of a set of held-out voxels. B. The mean correlation (across participants) between observed and estimated covariance of held-out voxels as a function of the number of sources.





from one participant's data using 10 sources. We used split-halves cross validation to assess network reliability across categories: t(142) = 1.93, p = 0.056. **B.** We fit the hierarchical model to data from 18 participants using 50 sources. The figure shows source interactions that were reliably stronger when participants were viewing scenes (red) or faces (blue); ps < 0.01.

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## **Euture** directions

TFA may be integrated into cognitive models.

We are also exploring the use of non-spherical sources to enable the model to fit irregularly shaped patterns with fewer sources. Figure 9. Combined neural-behavioral model

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