

Risk Patterns and Correlated Brain Activities

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Motivation

- Which part of our brain is activated during *risky decisions* ?
- Can statistical analysis help to detect this area?
- Can we provide an *integrated* analysis of the brain?

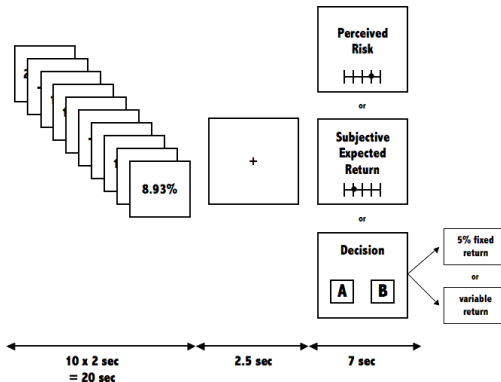


Experiment participants

- 22 volunteers (age 18-35 years), 11 females, 11 males
- no history of neurological or psychiatric diseases
- flat payment (10 EUR) \pm outcome resulting from the participant's decision and modeling problems)



Risk Perception and Investment Decision

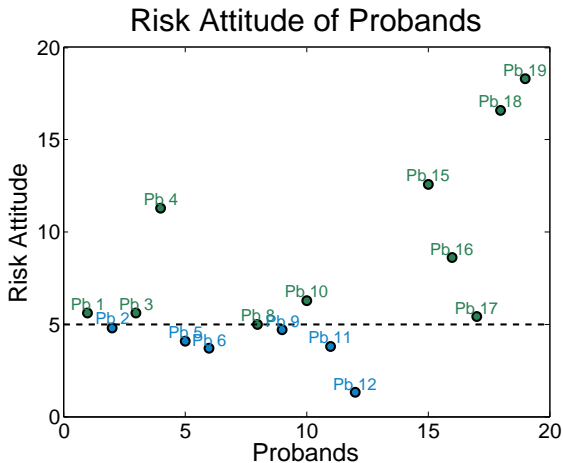


Returns

Pause

Decision





fMRI

functional Magnetic Resonance Imaging

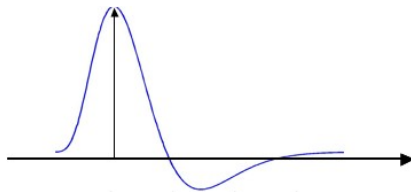


measures the oxygen level in the blood every 2-3 sec

Risk Patterns and Correlated Brain Activities



fMRI



Is there a significant reaction to specific stimuli in the hemodynamic response?

Voxel X



Data Set

Series of 3-dim images

- each scan transformed on the resolution $2 \times 2 \times 2mm^3$
- 91 slices
- observed every 2.5 seconds
- data set: series of $T = 1360$ images with $91 \times 109 \times 91$ voxels

High-dimensional, high frequency & large data set.



fMRI methods

- existing methods to analyze these data: voxel-wise GLM
 - ▶ strong a priori hypothesis necessary
- new statistical method: DSFM
 - ▶ dimension reduction keeping the data structure
 - ▶ exploratory analysis



- Which part of our brain is activated during *risky decisions* ?
- Can statistical analysis help to detect this area?
- Is there a significant reaction to specific stimuli in the hemodynamic response?
- Can we classify the risk attitudes of probands *without* using probands' answers?



Outline

1. Motivation ✓
2. Statistical Model
3. Results vs. Proband's Behaviour
4. Conclusion
5. Future Perspectives



Panel Dynamic Semiparametric Factor Model (Panel DSFM)

$$X_{t,j} = (X_{t,1}, \dots, X_{t,J})^\top$$

$$Y_{t,j} = (Y_{t,1}, \dots, Y_{t,J})^\top$$

$$Z_{t,j} = (Z_{t,1}, \dots, Z_{t,L})^\top$$

$$(\bar{m}_0, \dots, \bar{m}_L)$$

$$\varepsilon_{t,j} \sim (0, \sigma_{t,j}^2)$$

observable covariates defined on \mathbb{R}^d

observable random vector on \mathbb{R}^d

unobservable L -dimensional process

unknown real-valued functions defined on a subset of \mathbb{R}^d

errors with $\sigma_{t,j}^2 < \infty$



Panel DSFM

- assume *fixed effects* α_i for individual i with $\sum_{i=1}^n \alpha_i = 0$
- the “average brain”:

$$\bar{Y}_{t,j} = \bar{m}_0(X_{t,j}) + \sum_{l=1}^L \bar{Z}_{t,l} \bar{m}_l(X_{t,j}) + \varepsilon_{t,j}, \quad 1 \leq j \leq J \quad (\text{DSFM})$$

- individual i :

$$Y_{t,j}^i = \bar{m}_0(X_{t,j}) + \sum_{l=1}^L Z_{t,l}^i \bar{m}_l(X_{t,j}) + \varepsilon_{t,j}^i \quad (\text{LS})$$

with the general basis functions \bar{m}_l



Theorem

Under regularity assumptions, for $h \geq 0$

$$\begin{aligned} & \frac{1}{T} \sum_{t=\max[1, -h+1]}^{\min[T, T-h]} \tilde{Z}_{c,t}^i \left(\tilde{Z}_{c,t+h}^i - \tilde{Z}_{c,t}^i \right)^\top \\ & - \frac{1}{T} \sum_{t=\max[1, -h+1]}^{\min[T, T-h]} Z_{c,t}^i \left(Z_{c,t+h}^i - Z_{c,t}^i \right)^\top = \mathcal{O}_P(T^{-1/2}) \end{aligned}$$

with $Z_{c,t}^i$ & $\tilde{Z}_{c,t}^i$ being the (rescaled) real low-dimensional time series and their estimates respectively for individual i .



Fitting fMRI Data

- concentrate on parts with brain scan
- reduction of the original data by taking every second slice in each direction and the first part of experiment only
- voxel's index (i_1, i_2, i_3) as covariate X_j
- BOLD signal as $Y_{t,j}$
- summary: $J = 36 \times 46 \times 46$ and $T = 722$



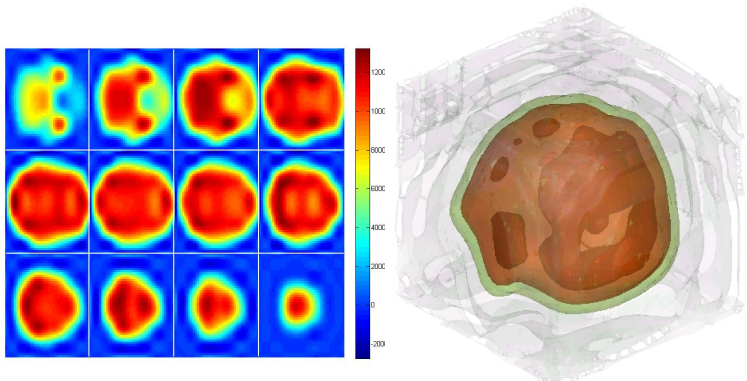
Estimation of DSFM

- choose $K = 7 \times 8 \times 8 = 448$ parabolic tensor B-splines to estimate \hat{m}

$$1 - RV(L) = \frac{\sum_t^T \sum_j^J \{Y_{t,j} - \hat{m}_0(X_{t,j}) - \sum_l^L \hat{Z}_{t,l} \hat{m}_l(X_{t,j})\}^2}{\sum_t^T \sum_j^J (Y_{t,j} - \bar{Y})^2}$$

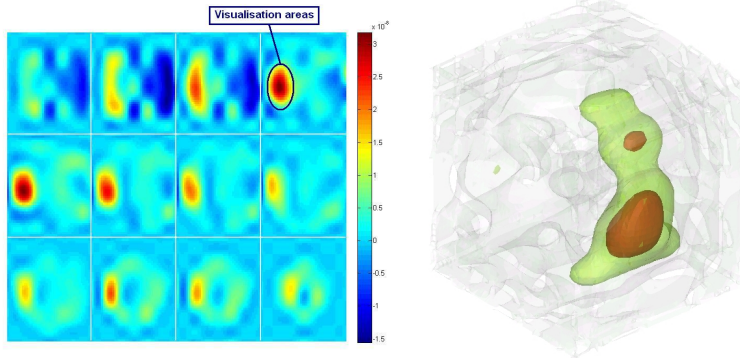
No. of factors	$L = 2$	$L = 3$	$L = 4$	$L = 5$
$1 - \overline{RV}(L)$ in %	88.85	88.88	88.91	88.94





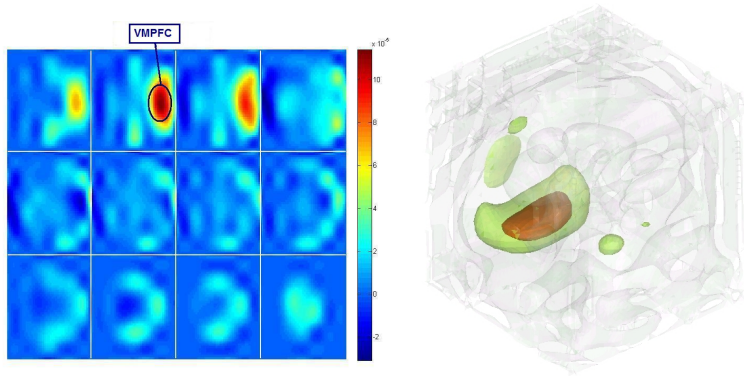
Estimated factor loading \hat{m}_0 with $L = 4$.





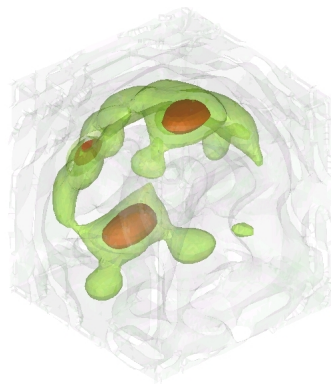
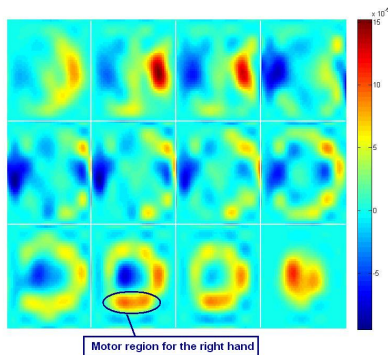
Estimated factor loading \hat{m}_1 with $L = 4$.





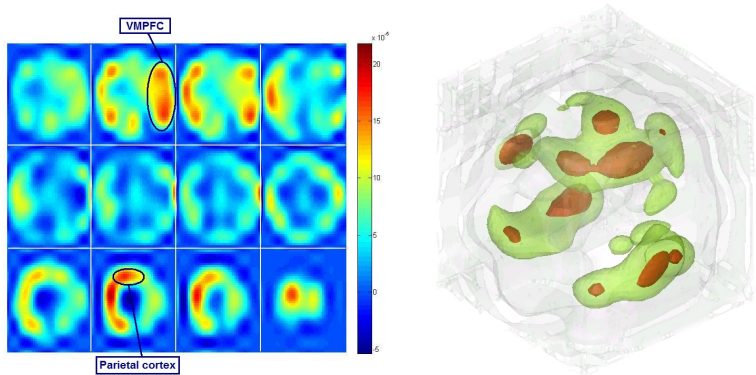
Estimated factor loading \hat{m}_2 with $L = 4$.
(VMPFC = Ventromedial prefrontal cortex)





Estimated factor loading \hat{m}_3 with $L = 4$.

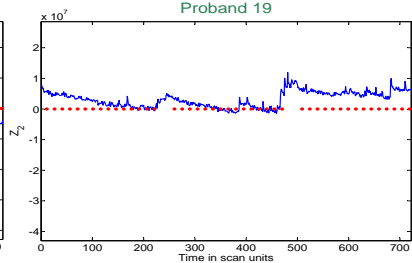
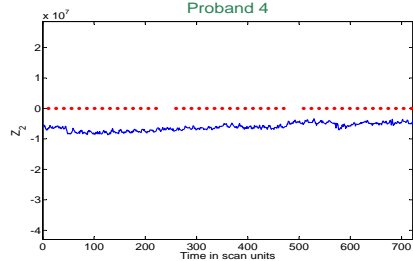
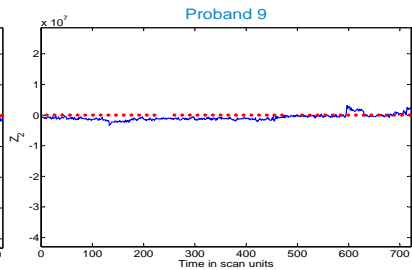
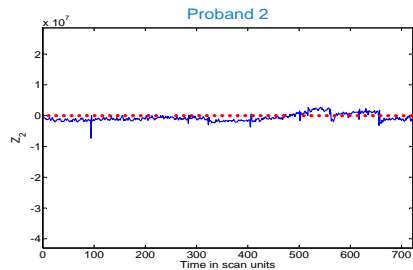




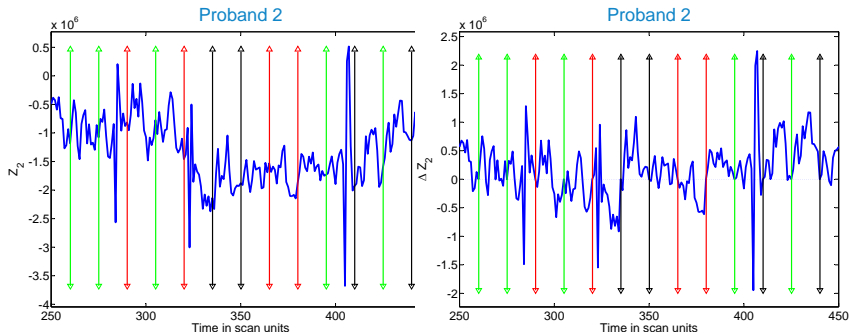
Estimated factor loading \hat{m}_4 with $L = 4$.



Factor \hat{Z}_2



Reaction to stimuli



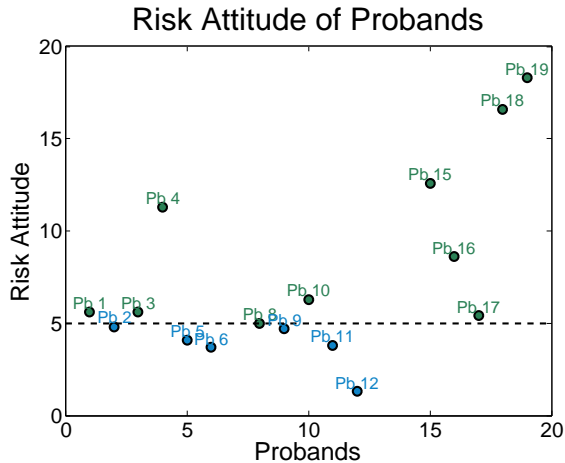
Lines correspond to the time points of judgement tasks: **decision**, **return**, risk.



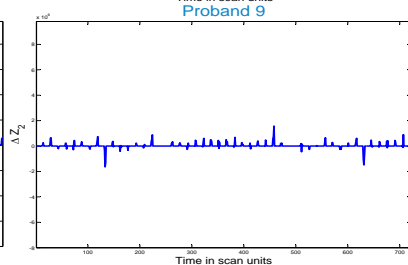
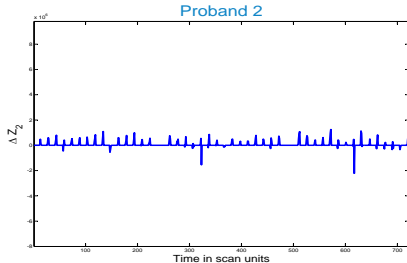
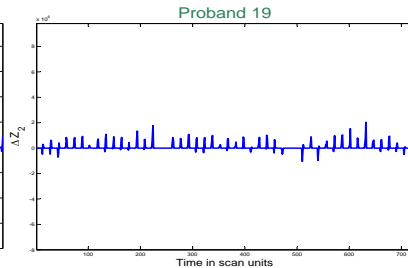
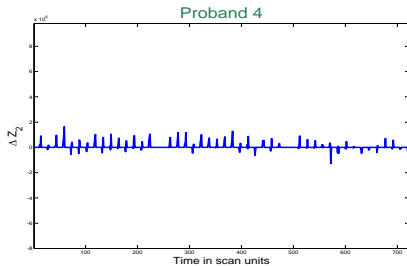
Risk attitude

- modeled by the softmax function from individuals' decisions
- estimated by the Maximum Likelihood Method
- details in: Mohr, Biele, Krugel, Li & Heekeren, *Neuroimage*.(2010)





Reaction to stimuli in factor \hat{Z}_2

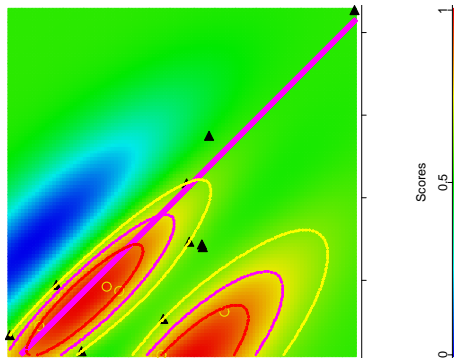


SVM Classification Analysis

- observation: weakly (strongly) risk-averse individuals have smaller (larger) volatilities of Z_t^i inside each trial
- SVM based on:
 - X_1 : mean (median/upper quartile) of the 15 volatilities (of Z_t^i in each separated trial w.r.t. question type 1)
 - X_2 : ... w.r.t. question type 2
 - X_3 : ... w.r.t. question type 3



SVM Classification (mean of volatilities)



Classification Rates

	rate	r	C
mean	0.7500	0.250 – 0.350	20 – 90
median	0.6875	0.355 – 0.455	10 – 90
upper quartile	0.6875	0.400 – 0.550	20 – 90

The rates hold over a wide range of parameters!



Classification Rates

Mean		Estimated	
Data	Strongly	0.85	0.15
	Weakly	0.42	0.58

Median		Estimated	
Data	Strongly	0.90	0.11
	Weakly	0.67	0.33



Conclusion

- basis functions identify activated areas, neurological reasonable
- volatility of estimated factors show differences for individuals with different risk attitudes (2 vs. 19)
- estimated factors show similarities for probands with close risk attitudes (2 and 9)
- SVM classification analysis of measurements in Z_2 after stimulus can distinguish weakly and strongly risk-averse individuals



Future Perspectives

- ▣ Comparison with the PCA/ICA (PARAFAC) approach
- ▣ Analysis of the second part of the experiment (under assumption of independency) to "generate" larger number of subjects
- ▣ Improvement of the classification criterion
- ▣ Penalized DSFM with seasonal effects



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