Project Final Report – Publishable summary

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Contents

1 Introduction

The contributions of this project consist in modeling, estimating and forecasting multivariate time series that are characterized by two features: *non-stationarity*and *dimension-reduction*. These two ingredients are typically observed, for example, in economic data: *the variability of the series evolves smoothly over time* and *the series have a common behavior*.

The history of economic forecasting suggests that there are some regularities informative about future events, but also major irregularities as well (see Clements and Hendry 1999). To deal with these irregularities we need to face the problem of non-stationarity that characterizes the data.

In addition to non-stationarity, these time series can be highly correlated, which motivates the use of dimension-reduction techniques. Linear factor models have attracted considerable interest over recent years especially in the econometrics literature. One of the characteristics of the traditional factor model is that the process is stationary in the time dimension (see Forni et al. 2000, Bai 2003). This appears restrictive, given the fact that over long time periods it is unlikely that the variability remains constant over time.

Recently we have generalized the theory of Factor Analysis to the non-stationary case from both the identification and the estimation points of view. Given a $N \times 1$ vector of observations $\boldsymbol{Y}$, Motta et al. (2011) consider a model with time-varying factor loadings $\boldsymbol{\Lambda}$ (of size $N \times q$) at time t (where T is the sample size)

$$\boldsymbol{Y}(t) = \boldsymbol{X}(t) + \boldsymbol{Z}(t) = \boldsymbol{\Lambda}(t)\boldsymbol{f}(t) + \boldsymbol{Z}(t), \qquad t = 1, \dots, T, \tag{1}$$

with common components $\boldsymbol{X}$ (of size $N \times 1$), factors $\boldsymbol{f}$ (of size $q \times 1$) and idiosyncratic components $\boldsymbol{Z}$ (of size $N \times 1$). The common component $\boldsymbol{X}$ describes the co-movements of all the series, the idiosyncratic component $\boldsymbol{Z}$ is specific to each particular series. Since q (the number of factors) is smaller than N (the number of observed series), a factor model allows for dimension reduction. In a stationary factor model, the loadings are time-invariant. The non-stationarity in model (1) is captured by the time-varying parameters $\boldsymbol{\Lambda}(t)$. The basic idea is to consider the loadings as smooth functions of rescaled time, rendering the process non-stationary while the factors remain stationary. In particular, the factors $\boldsymbol{f}(t)$ are stationary and *serially uncorrelated*, that is, they have no correlation with their own past values. As a consequence, though model (1) allows for a flexible parametrization of the loadings, it does not allow for prediction. Indeed, as the loadings vary "freely" over time, and the factors are uncorrelated, it is not possible to benefit from past information to the predict the future.

In order to introduces serial correlation in the theory of non-stationary factor models, in Eichler et al. (2011) we have generalize model (1)

$$\boldsymbol{Y}(t) = \boldsymbol{X}(t) + \boldsymbol{Z}(t) = \boldsymbol{\Psi}(t, B)\boldsymbol{f}(t) + \boldsymbol{Z}(t) = \sum_{k=0}^{\infty} \boldsymbol{\Psi}_k(t)\boldsymbol{f}(t-k) + \boldsymbol{Z}(t), \tag{2}$$

where the loadings $\boldsymbol{\Psi}(t, B)$ are time-varying filters (B is the lag operator), and the idiosyncratic components are also allowed to be dynamic and non-stationary. Model (2) generalizes the (non-stationary but) static model in (1) as well as the well-known dynamic (stationary) model by Forni et al. (2000), where the filters $\boldsymbol{\Psi}(B)$ are constant over time. Model (2) is dynamic in the sense that it takes into account also past values of the latent factors. However, the estimation method of model delivers two-sided filters, and thus unsuitable for prediction. In order to predict the future values we would need a one-sided filter that consider, at the end of the observed sample, only previous (and thus observable) values.

2 Main results: theory, methods and applications

In order to find a good forecasting *method*, it is crucial to represent the data with a suitable statistical *model*. The two goals are interdependent: a suitable statistical method strongly depends on the model that is underlying the data.

The two terms 'model' and 'method' should be kept distinct. The model is the statistical tool which is needed to formalize and describe the process which is supposed to generate the data we observe in practice. The method is the estimation technique implemented to estimate the parameters characterizing the model. The behavior of a stationary process can be described by a set of parameters. For example, in an auto-regressive (AR) model the auto-regressive coefficients are parameters describing the dependency of a series on its past. Because of the assumption of stationarity, these coefficients are constant over time. Stationary time series are estimated and predicted with the so-called parametric approach. Though the theory of stationary processes is well-established, many observed time series exhibit a non-stationary behavior, which can be captured by time-varying parameters. These time-varying parameters are smooth functions (curves), that can be estimated by means of nonparametric techniques.

This is the challenge we took up in this project, and it is the most innovative element of our proposal: providing estimation and prediction tools for models allowing for time-varying parameters. The value added of the project compared to other solutions is in the transition between parametric and non-parametric modeling.

We have achieved the tasks of *Model Construction* and *Estimation Method* in different ways, depending on the data at hand. The main contributions of the work we carried out during this period can be categorized into four main directions/fields of applications: Macroeconomic time series, Systemic Risk and Financial cycles, Neuroscience of Brain Signals, and Communication Science of Public Discourse.

2.1 Common non-stationary latent-factors: Macroeconomic data

For **Macroeconomic** data, we have used an approach based on time-varying AR parameters, with the underlying latent process being auto-regressive and non-stationary at the same time

$$\begin{aligned} \boldsymbol{Y}(t) &= \boldsymbol{\Lambda} \boldsymbol{f}(t) + \boldsymbol{Z}(t), \qquad \text{where} \\ \boldsymbol{f}(t) &= \mathbf{A}(t) \boldsymbol{f}(t-1) + \mathbf{V}(t) \boldsymbol{\eta}(t). \end{aligned}$$

Since this latent process is auto-regressive, its structure can be extracted to the future. Hence, this approach allows for prediction while permitting the auto-regressive coefficients to be time-varying. In this way we provide estimation and prediction tools for models with time-varying (rather than time-invariant) AR-parameters.

In Figure 1 (left) we plot fifteen US monthly-rate variables recorded from 1960 to 2003. In particular, the first set of seven variables are Exchange rates, the second set of eight variables are Interest rates. Clearly, there are two factors underlying the whole set of series. At the same time all the series show a time-varying auto-correlation structure $\mathbf{A}(t)$, as well as a time-varying variability $\mathbf{V}(t)$.

The advantage of using a forecasting procedure based on the assumption that the underlying variability is smooth is that we can follow the evolution of the process *locally*. To do this we need a technique to predict the behavior of the smooth curves. In the paper "A semi-parametric approach to dynamic factor models with time-varying AR parameters" (joint with Michael Eichler from Maastricht University) we use the *local linear regression* estimator, which is essentially based on the idea that a (sufficiently smooth) curve can be approximated locally by a straight line. In Figure 1 (right) we give an idea about the performance of our method.

2.2 Systemic risk and Cycles: Financial data

For **Financial** time series data, we have used an approach based on the combination of (i) a time-varying *deterministic* univariate common volatility $\sigma(t)$, and (ii) a *stochastic* and auto-regressive conditionallyheteroskedastic (ARCH) latent factor $\boldsymbol{f}(t)$:

$$\boldsymbol{Y}(t) = \sigma(t)\boldsymbol{\Lambda}\boldsymbol{f}(t) + \boldsymbol{Z}(t).$$

This approach allows for prediction (because of the ARCH structure in the latent factors), while permitting the common cycle to be time-varying. In this way we provide estimation and prediction tools for models with time-varying (rather than time-invariant) volatility.

Our results provide several new insights illustrated in Figure 2 (left), which shows the common volatility cycle $\sigma(t)$ estimated for 34 countries (the shaded periods correspond to major international crises). First, we find that *one global factor* is sufficient to capture systemic risk in international equity markets. The advantage of using a GARCH specification for the underlying common factor is the possibility of forecasting future values of the latent process and thus, to forecast future values of the observable process itself. Second, we show that the exposure of an investor's portfolio to systemic risk varies significantly over the last two decades. In particular, global risk displays humps associated with large financial disruptions, such as the 1994-1995 Latin American crisis, the 1997-1998 East Asian crisis, the 2000-2002 dotcom crash, and the 2007-2008 global credit crunch. Finally, we document an upward trend in the rise of exposure to systemic risk during crises: while the crises of the early 1990s and 2000s generate a moderate rise in risk, the 2007-2008 financial crisis produces the historically largest increase, which suggests that the recent crisis has been truly global.

2.3 Statistical methods for Brain Signals: EEG data

For the analysis of **EEG** data, the non-stationarity is fully explained by the factor loadings which are smooth functions of time and estimated by the eigenvectors of a non-parametric estimator of the time-varying covariance matrix. The dataset consists of $N = 62$ channel electroencephalograms (EEGs) recorded from one healthy subject in a hand-guided visual-motor experiment. From this dataset we extract $q = 3$ factors and the corresponding 62×3 matrix of time-varying loadings. Since we know the exact location of the sixty-two electrodes, we can draw conclusions about the locations of the corresponding underlying factor loadings and thus predict the location of the latent factors over space. This is our solution to a well-know problem in Neuroscience called *latent source localization*. It is in this sense that the loadings are (temporally and) spatially varying, see Figure 3.

The weights corresponding to factor 1 appear to be uniformly distributed over the scalp topography. This suggests that factor 1 corresponds to the process that engages the entire brain cortex. Moreover, the weights visually appear to be almost constant over time suggesting that factor 1 can be interpreted to correspond to "baseline" brain activity that is persistent in most cognitive tasks.

In contrast, the weights for factor 2 are concentrated in the temporal and fronto-central regions and provide connections between the left and right brain hemispheres. This interesting result suggests contra-lateral connectivity or co-activation associated with this visuo-motor task. Our model was able to capture this activation in the cortical regions that are primarily involved in visual and motor processing. The weights for factor 3 are concentrated on regions that were not implicated by factor 2 and capture the anterior-posterior pathways – in contrast to the contra-lateral inter-hemispheric pathway captured by factor 2.

The results of the project "Evolutionary Factor Analysis of of Replicated Time Series" (joint with Hernando Ombao from UCI in Irvine, California) have been recently published in *Biometrics*.

2.4 Political Science and Communications: Semantic data

For the analysis of **Semantic** data, we use a one-sided, exponentially discounted kernel for estimation to represent the influence of recent states of the debate, which progressively fade from public memory, while the future of the debate remains unknown:

$$\widetilde{\mathbf{C}}(t) := \sum_{s=1}^{h} \widehat{\mathbf{C}}(t-s)\,\omega(s), \tag{3}$$

where h is the smoothing bandwidth that determines the number of values in the local average. At each time point t, the smooth estimator $\widetilde{\mathbf{C}}(t)$ of the correlation matrix $\mathbf{C}(t)$ is obtained by averaging the raw cosine matrices $\widehat{\mathbf{C}}(s)$ over those values s right before t. In our application we use the local polynomial kernel method of degree p. As shown by Gijbels et al. (1999), this method is a natural extension of equation (3). In particular, we choose a kernel weight of degree $p = 1$ (local linear kernels) and a window of $h = 20$ weeks.

In this way we can analyze the changing interpretations of the EU constitutional treaty in the Dutch news, as well as the evolving understandings of the current financial crisis in the German and Greek mass media. These analyses show, for instance, the strong rise in the consensus and structuring of the previously much more diverse debate on the EU Constitutional around the referendum date: The black line in Figure 4 (top-left), is the amount of variance in advanced interpretations captured by the dominant frame.

Also, we find that such strong consolidation brings an end to the recurrent redefinition of the issue: Figure 4 (bottom-left) shows that, prior to the referendum, major discontinuities in the meaning of the Constitution expressed in the Dutch news occurred at regular intervals, while thereafter, meaning remains very stable (black line is the amount of instability in interpretations over time). Extending the EFA design to compare the structures of the German and Greek debates on the financial crisis, we can identify phases of co-movement, where dynamics are relatively synchronized in both countries, as well as phases where both debates are rather disconnected: the gray areas in Figure 4 (right) indicate co-movement. The same strategy also reveals when one debate leads and exerts structural influence upon the respective other one: In Figure 4 (right), the blue areas indicate that the Greek debate exerts a stronger influence on the German debate than viceversa, thus taking the prerogative in interpreting the financial crisis; the orange areas indicate, conversely, that the German debate shapes the coverage of the financial crisis in the Greek media. The results of the project "Evolutionary Factor Analysis of the Dynamics of Frames" (joint with Christian Baden from Ludwig Maximilians University in Munich) are available in a paper that is now (conditionally) accepted for publication in *Communication Methods and Measures*.

3 Socio-economic impacts of the project

The contribution of this project is twofold. From the scientific point of view, carrying out further research in the field of estimation and forecasting will significantly advance the econometric theory of time series analysis. The main theoretical contribution of the project is provided by the treatment of non-stationarity. This is probably the most original aspect of our project, in which the *non-stationarity* is treated for the first time in a smooth way within the framework of *Factor Analysis*. From the socio-economic viewpoint, the forecasting of how interest rates will develop, for example, can function as an early warning system for economic crises.

3.1 Financial Stability

During the past thirty years, the world's major central banks have been successful at bringing down previously high and volatile inflation. While price stability continues to remain at the core of a healthy economy, a key task facing economists today is to develop an understanding of financial market instability, in order to stand a chance at weathering future financial crises. The project entitled "Common long-run and short-run volatility in international equity markets" (joint with Norbert Metiu from the Research Centre of the Deutsche Bundesbank) addresses an important aspect of global financial market instability: the statistical modeling of global factors, volatility, and systemic risk in international equity markets.

Beyond looking at the global volatility cycle, we also analyze how volatility responds to the arrival of news in the global marketplace. The term "news" is used here in a general context, and is meant to represent any new piece of information that influences equity returns, such as information regarding the profitability of firms' future investment projects, changes in the macroeconomic environment, monetary policy changes, and financial regulation. Typically, a negative correlation between current equity returns and future volatility is observed in equity markets, a phenomenon sometimes called the "leverage effect". The existence of such an effect can provide guidance to monetary policy makers in the optimal design of policies, by facilitating the understanding of the potential impact of policy changes.

We document the existence of an international leverage effect in equity markets. In particular, we find that the arrival of new information has an asymmetric effect on global volatility; adverse news leads to significantly higher subsequent volatility than positive news. This phenomenon is illustrated in Figure 2 (right), which shows so-called "news impact curves" developed by Engle and Ng (1993). The news impact curve is a plot of the global factor at time $t-1$ on the horizontal axis (which represents news in the market) against subsequent volatility at time t on the vertical axis. Figure 2 (right) plots two different news impact curves estimated from two different econometric specifications for the evolution of volatility over time; the dashed line represents a specification with symmetric volatility, while the solid line reflects a specification which allows for asymmetric volatility. Based on a statistical comparison of the two models, the latter one provides a better fit to the data, and therefore it is our preferred model.

The solid news impact curve indicates the presence of an international leverage effect. This curve is centered on zero and it has different slopes for its positive and negative sides, with the latter one being steeper. Thus, negative values of the global factor correspond to higher volatility in the subsequent time period than positive values. This is a crucial result for understanding the effects of, for example, unanticipated monetary policy changes, macro-prudential financial sector regulation, or a sudden decline in the macroeconomic environment (such as the collapse of house prices) on international equity market volatility. In particular, it contributes to understanding the mechanism underlying the 2007-2008 global financial crisis, whereby a worldwide decline of equity markets lead to elevated levels of financial market volatility.

The conclusions drawn from the paper leave monetary policymakers with a clear double mandate of price as well as financial stability. The strong links between international financial markets unraveled in the paper motivate a special focus on systemic risk – i.e., risk inherent to the global financial system as a whole – at the international level. Understanding, monitoring, and keeping systemic risk under control is essential for the financial system to perform its role of promoting an efficient capital allocation in the economy. Major steps have already been taken into this direction, marked by a shift in the focus of monetary policy as well as academic research. For example, the Bundesbank (the German central bank) will receive a legal mandate from 2013 onward to perform macro-prudential oversight of the financial system, including responsibility for analysis of issues that are crucial to financial stability and for identifying and assessing systemic risks.

The statistical tools developed in our paper are well-suited to model and monitor systemic risk at the national, European, or global level. The project can directly benefit from the fact that one of the authors in an economist working in the financial stability research group of the Deutsche Bundesbank. Therefore, the model developed could provide the statistical basis of monitoring systemic risk in the financial system and issuing early warning signals if the global volatility cycle is about to reach excessive levels. This tool supplements well the macro-prudential instruments currently operational at the German central bank.

3.2 Political Science and Communications

Since our specific extension of the Evolutionary Factor Analysis (EFA) is a methodological innovation, its main significance lies in the many applications it has within and beyond the field of social sciences. In its narrow application to the analysis of semantic frames in discourses and debates, EFA allows a detailed analysis of a variety of processes in the emergence of social consensus or conflict, the construction and evolution of new issues, and the processes of public communication (in news media, social media, etc) underlying these semantic constructions. Besides advancing theorizing in the study of media and communication (framing theory, agenda-setting theory, deliberative political debates, the structure of public spheres, etc.), a deepened understanding of these dynamic processes of evolving meaning directly affects social behavior and policy in a variety of ways: Based on an EFA of social media dynamics, for instance, social software, search and indexing algorithms can be improved to recognize related debates or critical moments when ongoing debates separate or become relevant to one another. Likewise, internet regulation (e.g., of propaganda, hate speech, or cyber mobbing) can benefit from a more thorough understanding of the dynamics of emerging and evolving debates. On a societal level, knowledge about the self-reinforcing dynamics of stereotyping and the marginalization of specific interpretations can help bolster responsible journalism and media practice. From a policy-making point of view, the dynamics of emerging consent or polarization in a society's debate over current issues provides an important input for responsive decision making and may even provide a warning bell to guard against radical dissent and harmful divisions and decoupling between different societal discourses. Within the field of knowledge and expert systems, crowd computing, artificial intelligence, and related disciplines, EFA can help bridge the gap between externally defined, static (and therefore inflexible and often quickly inappropriate or inefficient) structurings of available data, and the reliance of bottom-up structures within data; understanding the time-changing structures of information content in a knowledge system enables the development of adaptive, demand-driven yet still encompassing macro-level structurings. Likewise, in cases where the emergent structure is the information, EFA can aid the analysis of a large variety of high-dimensional data: Detecting common, yet not time-invariant structures in available data is a common problem specifically in the social sciences: Notably, most social interactions follow latent, overlapping and time-changing organization patterns. EFA can play a role in the analysis of phenomena as diverse as consumer behavior (how do common, transitory fashions and fancies structure their purchasing activities), the behavior of traders on a financial market (how can different sets of information or current convictions about an economic situation temporarily synchronize the behavior of large numbers of independent traders), the practice of cultural rituals (how do social practices in cultural communities change over time, taking into account influences such as social and geographical mobility, diversifying contact with other cultural influences, etc), or political decision making (how does the changing political agenda affect the structure of allegiances and alliances among parliamentarians, political activists, or actors in an intergovernmental negotiation).

Knowledge from such applications of EFA may help inform suitable policy responses (e.g., to avoid herd behavior on financial markets or to mitigate the tensions in a community created by changes in their cultural configuration and cohesion, as for instance in a context of immigration and integration policy), contribute to increasing the efficiency of business planning (e.g., by anticipating regional trends in consumption), and allow a reflexivity of actors that facilitates finding suitable solutions for complex social challenges (e.g., structuring political agendas to prevent or facilitate the formation of cohesive camps). For all social and semantic phenomena listed here, our presented extension to EFA is of crucial importance: Since social actors and discourse participants are aware of the past (but not the future), responding to and building upon it in a path-dependent fashion, the presented technique is capable of realistically modeling the intrinsic logic of reflexive social and semantic processes.

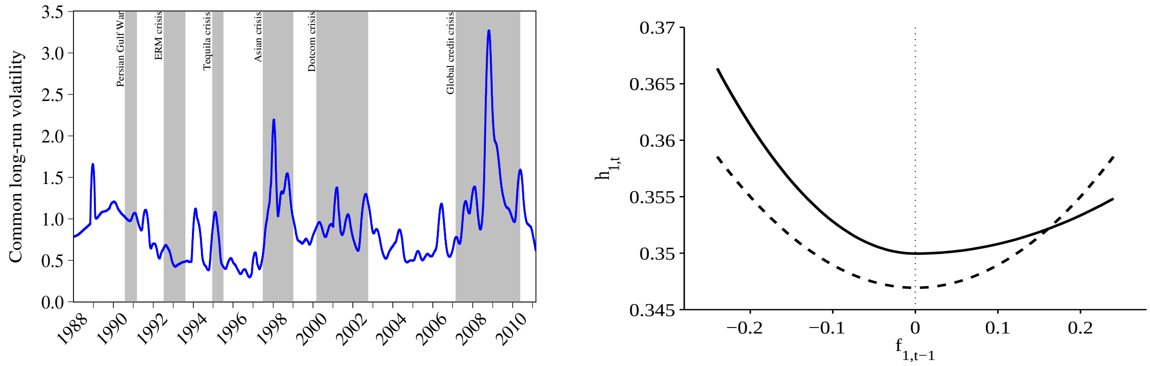

Figure 2: **Left**: Common volatility cycle for 34 countries (shaded periods correspond to major international crises). **Right**: News impact curves.

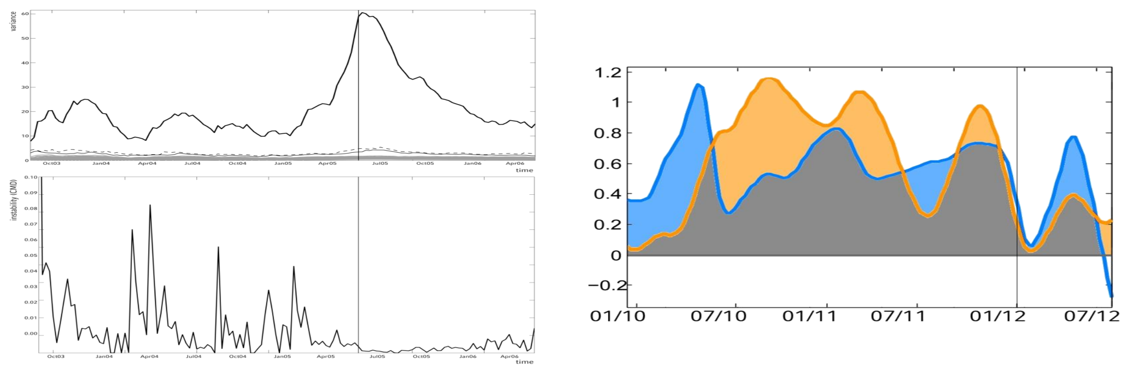

Figure 4: **Top-left**: Structuring of meaning in the Dutch EU Constitutional Debate. **Bottom-left**: Instability of dominant meaning in the Dutch EU Constitutional Debate. **Right**: Co-movement and mutual influences between the Greek and German debates on the Financial Crisis.

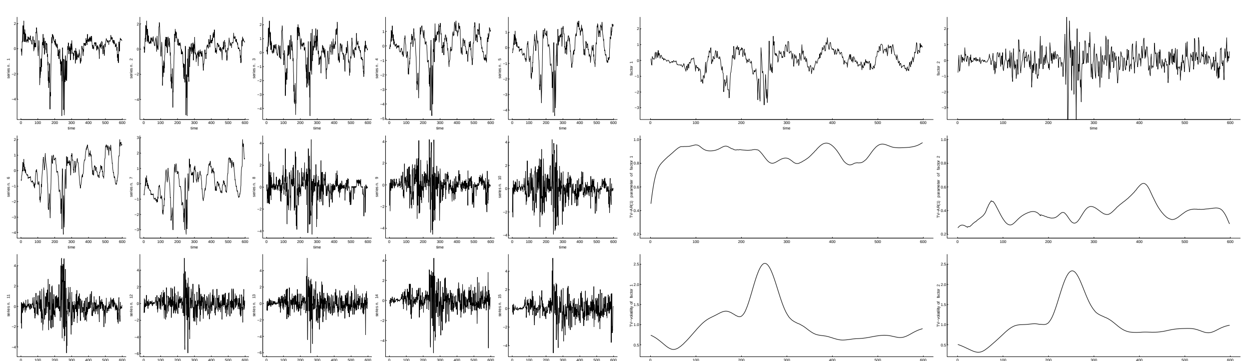

Figure 1: **Left**: 15 US rate variables recorded from 1960 to 2003. **Right**: extracted factors (top), with their time-varying AR-coefficients (center) and time-varying volatility (bottom).

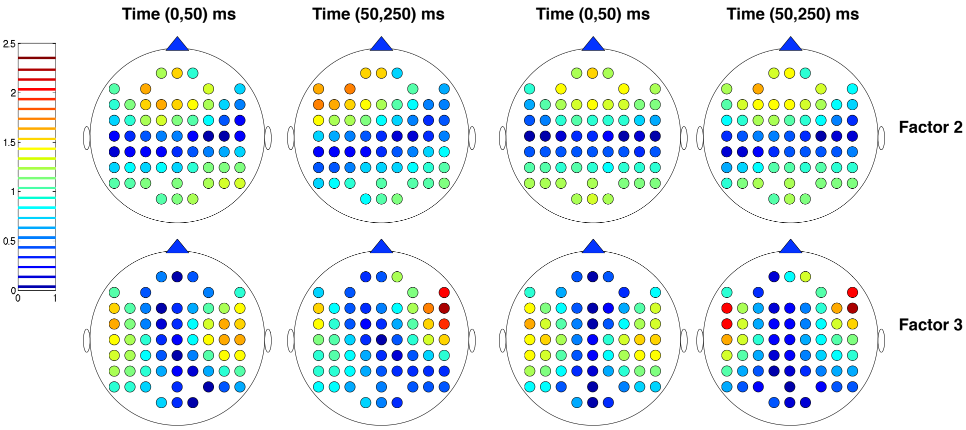

Figure 3: Spatio-temporal factor-loadings. The first row shows the factor loadings that weight the second factor, while the second row shows those weighting the third factor. The first two columns correspond to left-condition, whereas the last two to right-condition.

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