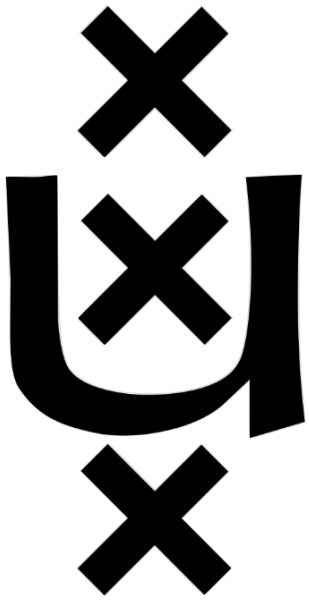
Graduate School of Psychology

University of Amsterdam

Research Master's Psychology Thesis Proposal Form

Author:
Lukas Snoek

Version:
Final version



July 13, 2015

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1 Who and Where?

Student

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Within ResMas (obligatory)	:	Dr. H.S. Scholte
Specialisation	:	Brain & Cognition
Second assessor	:	Prof. dr. R. Ridderinkhof

Misc.

Research center / location	:	Spinoza centre for neuroimaging
Number of credits	:	28
Ethics committee reference code	:	2015-BC-4371

2 Title

Investigating the representational dimensionality and spatial distribution of functional neural networks.

3 Summary of proposal - max 150 words

In the past decade, cognitive neuroscience witnessed a paradigm shift from functional localization to distributed representations of psychological processes in the brain. Multivariate analyses have been a popular choice to

investigate these distributed representations. In the psychological literature, however, the term "distributeness" has been used ambiguously and inconsistently, as multivariate representations may be present locally within cortical areas or globally across the entire brain. While local and global multivariate representations are likely encoded at different levels of organisation (across voxels versus across brain areas, respectively), most multivariate analyses are performed without taking the representation's multivariate dimensionality in account. This research proposal aims to investigate the multivariate dimensionality of emotional valence, which is hypothesized to be encoded over brain regions, and contrast this with the locally encoded representations involved in categorical processing. Furthermore, this proposal will exploratively examine how the attribution of valence develops in the brain.

Word count: 473

4 Project description - max 1200 words

4.1 Prior research

A key question in the field of cognitive neuroscience is how the brain represents information. A traditional approach in the neuroimaging community is to investigate the representations of psychological concepts and processes as significant activations or deactivations of parts of the brain using functional magnetic resonance imaging (fMRI). This type of analysis is commonly referred to as "univariate", because it models each unit of measurement (i.e. voxels) in the brain separately and independently. Effectively, these types of studies aim to localize psychological concepts and functions to particular brain areas. Consequently, researchers implicitly engage in a type of "neophrenology" in which unique function-structure mappings are pursued (**?**). For example, the amygdala has become the "fear area" (**?**) and a particular part of the fusiform gyrus has become the "face area" (and was, in fact, later named the *fusiform face area*).

In the light of our current understanding of the organization of the

human brain, these function-structure mappings are unwarranted. First, for every purportedly selective function-structure mapping, several counter-examples exist (**?**). The amygdala has, for instance, been implicated in processing stimulus novelty (**?**) and the fusiform face area has, for instance, been associated more generally with processing highly familiar objects (**?**). Second, and most importantly, significant *(de)activation* does not imply *representation*; the fact that a brain area activates in response to a certain stimulus does not mean that it represents (processing of) this stimulus.

In the early 21st century, the cognitive neuroscience community gradually moved from this functional localization perspective to a more network-oriented perspective (**??**). Instead of studying *which* regions (de)activate during a particular psychological process, they started investigating *how* brain areas or a network of brain areas encode and represent this particular process. Rather than treating individual voxels as independent sources of information, researchers realized that by modeling psychological concepts and processes as multivariate representations consisting of interdependent voxels, they could investigate how the brain represents, instead of responds to, information.

One of the first studies to show that the human brain encodes psychological concepts as distributed, multivariate representations was described in the seminal paper by **?**. They showed that different object categories are represented in a distributed fashion across the ventral visual cortex, regardless of mean activation level. Their approach, for which they used the term Multivariate Pattern Analysis (MVPA), gained popularity quickly as it appeared to provide a more sensitive analysis as opposed to univariate analyses (**??**) and was consistent with and complemented the emerging network-oriented theoretical framework (**?**). Several new types of multivariate analyses were developed in the succeeding years, including the successful application of machine learning classifiers to distinguish neural representations (e.g. **?**) and representational similarity analyses to characterize relations between neural patterns in a continuous, rather than discrete, manner (**?**).

Currently, MVPA analyses are widespread in almost all domains of cognitive, affective, and social neuroscience. For example, in vision research, MVPA has been applied to correctly decode stimulus orientation in subre-

gions of V1 (**?**). At a coarser scale, researchers have shown that it is possible to decode episodic memory traces across the human hippocampus (**?**). More recently, MVPA has surfaced in the social and affective neuroscience literature, in which it has been used to investigate representations of social and emotional processes. For example, **?** has shown that MVPA can be used to decode brain-wide representations of different emotions. It thus seems that MVPA is a useful analysis at different levels of representation, from local (e.g. V1) to global (e.g. emotion networks), and across a range of disciplines.

Despite the apparent utility of MVPA for different types of research, little is known about how to apply this analysis optimally in different research contexts and disciplines. Currently, most MVPA analyses implicitly assume that representational information is encoded across voxels, meaning that each voxel within a representation carries unique information. While this is likely the case for small-scale, local representations of for example low-level stimulus features such as orientation (**?**) or color (**?**), several lines of research suggest that with increases in "globality" of representations, information from individual voxels becomes less important. In other words, in global representations, information is likely encoded across informational units *larger* than voxels.

The study by **?** directly tested this hypothesis by examining the effect of spatial smoothing on voxel patterns within the ventral visual cortex. They showed that spatial smoothing removes information about low-level stimulus features (in this case, spatial frequency) but leaves higher-level category information intact, suggesting different spatial scales for representations of different types of information. Another line of evidence comes from the observation that many MVPA studies in social and affective neuroscience find representations of globally distributed *clusters* of voxels (e.g. **???**). This clustering is unlikely if individual voxels within these clusters indeed carry unique information. This dependence between voxels within clusters has been further supported by the fact that spatial smoothing (**??**) does not affect the representation.

This apparent positive association between the globality of representations and the spatial scale of information encoding motivates further inves-

tigation on the dimensionality of global versus local representations in the brain. It appears that local representations, e.g. low-level stimulus features such as orientation and color, are indeed encoded across voxels, while more global representations, such as emotion networks, are more likely encoded at a larger scale across clusters of voxels or even entire brain areas. Taken together, it could thus be said that representations may be "local multivariate" (i.e. encoded locally across voxels), "global multivariate" (i.e. encoded globally across voxels), or "global univariate" (i.e. encoded globally across clusters or brain areas). Figure 1 graphically displays these three types of representations. In the current research, we propose to investigate at which level global representations are encoded.

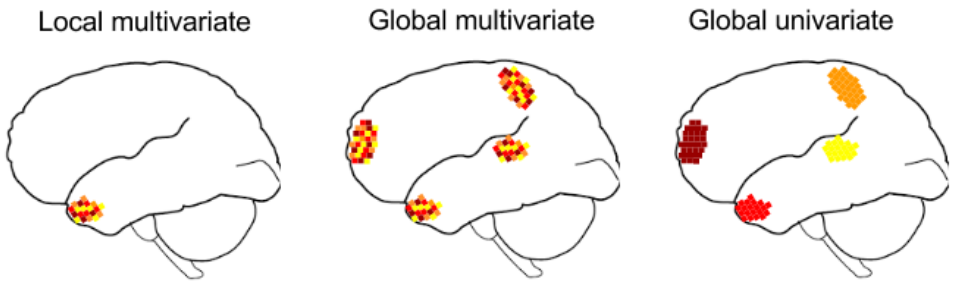


Figure 1: Three basic types of representations, which vary in spatial distribution (local versus global) and level of encoding (univariate, implying uniformity/redundancy between spatially clustered voxels, versus multivariate, implying encoding of unique information across voxels). Strictly speaking, all patterns are multivariate, but the level of encoding here refers to dimensionality of clusters within global representations.

4.2 Key questions

In the proposed research, we want to investigate how the level of encoding varies with the globality of representations by contrasting the dimensionality of the representation of category processing, which is known to be (relatively) local multivariate, with the dimensionality of the representation of emotional valence, as emotional valence is known to robustly elicit a brain-wide network of highly clustered, spatially dependent voxels (**??**).

To investigate whether emotional valence is encoded as a globally uni-

variate or multivariate representation, we will analyze its representation both as a multivariate pattern of voxels and as a multivariate pattern in which spatial dependence between voxels, i.e. clusters, are taken into account by averaging activity of voxels within clusters. Given these two representations, we will investigate at what spatial scale – across voxels or across clusters of voxels – valence information is encoded. Given the observed strong clustering of spatially dependent voxels in brain-wide representations of higher-level psychological processes, we hypothesize that valence information is encoded across voxel clusters instead of individual voxels.

Furthermore, as an exploratory addition to this research, we want to examine how and where the representation of valence develops in the brain over time. Questions that will be addressed, but do not bear any a priori hypotheses, include whether valence is represented as a global functional network from the beginning or gradually develop in a local-to-global fashion, and at what rate valence develops. Together with this study's confirmatory part, we hope to contribute to a better understanding of the level of encoding of higher-level psychological processes as well as to show how the development of these representations can be investigated over time.

Word count: 473

5 **Procedure** – approx. 1000 words

5.1 Operationalisation

5.1.1 Experimental design

In order to assess the spatial scale of valence representations, we will compare representations of stimuli before and after we experimentally manipulate their emotional valence in a "pre-test" and "post-test" respectively. The data from the pre-test, in which stimuli do not bear any a priori emotional valence, serves as a control dataset to which the post-test can be compared. The data from the post-test, in which stimuli contain emotional valence, will be used to

investigate the dimensionality of valence representations as part of the confirmatory analyses. The stimuli in the pre- and post-test are presented in a slow event-related design for two seconds with a fixed inter-stimulus interval (ISI) of six seconds. Each stimulus is presented eight times. After each stimulus-presentation (including ISI) in both the pre- and post-test, the subject will rate the "positivity" and "negativity" they associate with the stimuli on a bipolar five-point scale ("very negative", "somewhat negative", "neutral", "somewhat positive", "very positive"), using their right hand (as described in **?**). This will function as a behavioral index of stimulus-valence and provides an additional manipulation check next to the classification scores.

We have decided to manipulate valence of two distinct types of stimuli: faces and visual scenes. We use two types of different stimuli for two reasons; first, to ensure that we measure a representation of valence that is independent of stimulus category, and second, to allow for a factorial design in which we can contrast local representation of categorical processing (i.e. representations of faces versus visual scenes) with global representation of emotional valence (i.e. postive versus negative valence). Figure 2 summarizes how the data from different runs (pre-test, valence development run, and post-test) relate to this study's analyses.

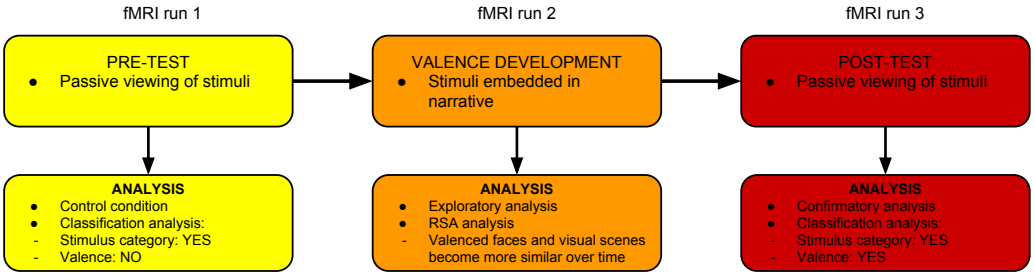


Figure 2: The different runs in the proposed study. The pre- and post-test are part of the confirmatory analyses while the valence development run is part of the exploratory analyses.

5.1.2 Valence development: A new experimental paradigm

To investigate the neural representation (confirmatory analyses) and development (exploratory analyses) of valence in the brain, we want to create a novel experimental paradigm that aims to manipulate emotional valence in an ecologically valid way. To date, most studies on representation of positive and negative emotions have used stimuli with established valence, for example pictures of mutilations, violence, nudity, or emotional facial expressions (**???**). Unfortunately, this strategy does not allow for a dynamic investigation of valence development. Paradigms that specifically target valence development have, so far, only focused on neutral stimuli that are paired with electric shocks (**??**). In both cases, positive and negative valence is already established or is explicitly reinforced, which is not representative for affective development (**?**).

In the proposed experimental paradigm, subjects are shown images of three neutral faces and three neutral locations during fMRI acquisition. We present both faces and locations to examine valence development irrespective of stimulus identity (cf. **?**). The stimuli will be embedded in an auditory fictional narrative that will function as an ecologically valid context in which valence can be dynamically manipulated. Within the narrative, the neutral faces are associated with either positive or negative valence by characterizing the faces as the narrative's "hero" or "villain" respectively. One face is consistently paired with neutral information. The locations are similarly coupled with either a positive or negative valence by portraying one location as a stereotypical "safe place" while the second location is portrayed as a "dangerous place". One location is consistently paired with neutral information. Importantly, the stimuli are associated with with positive or negative contextual information from the narrative in only 50% of the trials. In the other 50% of the trials, these stimuli are coupled with neutral information. Note that the face and visual scene which are neutral throughout the entire narrative are always coupled with neutral information. This *partial reinforcement scheme* allows us to model learned emotional valence separately from the instantaneous auditory content of the narrative (cf. **?**). Figure 3

represents the set-up of the valence development paradigm and how it relates to the pre- and post-test of the stimuli.

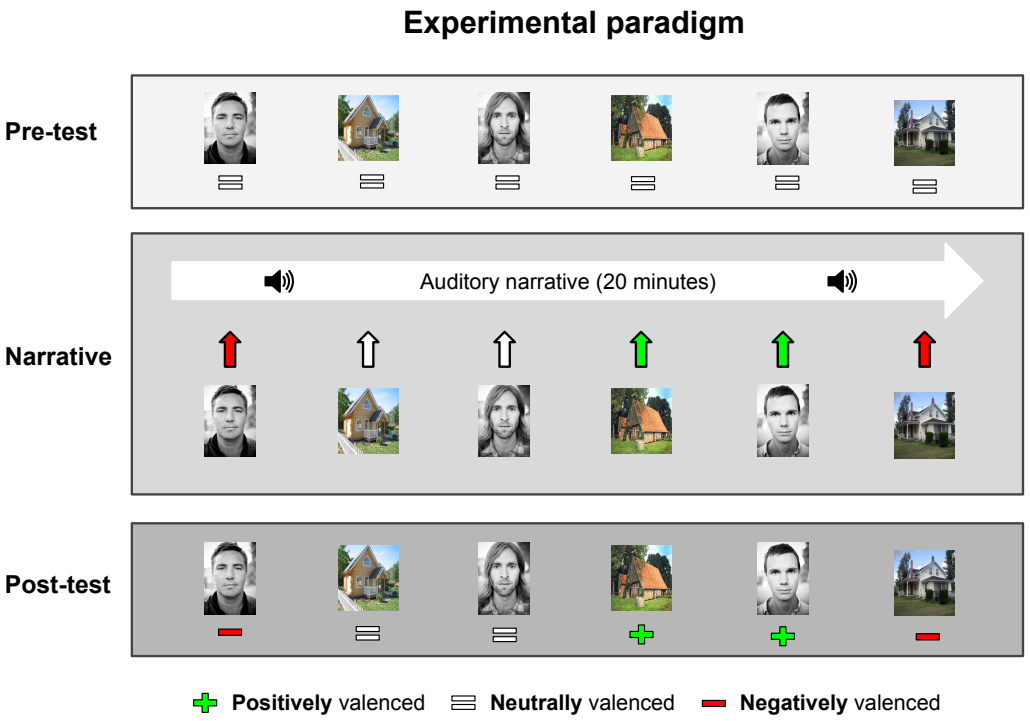


Figure 3: The proposed valence development paradigm. The continuous narrative is interlaced with the presentation of static images of the faces or visual scenes, whenever respectively the characters or places come up in the narrative. For reasons of clarity, this figure does not show the paradigm as a partial reinforcement scheme. The images are presented for two seconds and are followed by an inter-stimulus interval of at least six seconds.

Previous studies have demonstrated that listening to narratives robustly elicit widespread activation patterns in the brain (**??**) akin to networks commonly active during emotional experience (**?**). The gradual development of these emotional associations can be tracked in the brain to characterize how valence development is represented neurally. At the University of Amsterdam, researchers have used a similar experimental setup to investigate the development of fear conditioning (**??**). These previous studies have demonstrated that this paradigm creates robust fear associations over time which

can be reliably measured in the brain.

5.1.3 Pilot and assessment of effectiveness of the paradigm

As the success of the proposed research crucially depends on the effectiveness of the experimental paradigm, we will run an extensive pilot on eight subjects. To determine whether the experimental paradigm effectively manipulates valence, we will perform a classification analysis for each subject in which representations of positive and negative valence is decoded from the fMRI data separately for faces and visual scenes, as well as from these factors combined. As emotional valance is known to be robustly encoded in the brain across large, global networks (see for an extensive meta-analysis **?**), failure to succesfully decode positive and negative valence in the proposed study means that the experimental paradigm failed to manipulate emotional valence. Thus, classification performance represents the study's manipulation check *as well as* the dependent variable of interest. In the pilot, we will operationalize "succesfull decoding" as classification performance significantly above chance using within-subject statistics (one-sample t-test of classification accuracy compared to chance-level accuracy, per subject over cross-validation iterations). As discussed with Dr. Scholte, we will not continue with testing the rest of the subjects if we cannot succesfully decode valence in either category (faces, visual scenes, or both categories collapsed) in less than half of the pilot-subjects (i.e. 3 or less).

In the unfortunate scenario in which we would not be able to succesfully decode valence from the data of the pilot, Dr. Scholte suggested to use the data for investigation of the effectiveness of hyperalignment (**?**) in mitigating inter-individual differences in neural representations of object categories. Hyperaligment is a method that aligns data from multiple subjects in a common *functional* space instead of a common *anatomical* space using a functional "template". In the proposed experiment, the data from the narrative, that is the non-stimulus locked timeseries, provides an appropriate functional template (cf. **?**). Using hyperaligment, we can investigate whether decoding accuracy of representations of stimulus categories (i.e. faces and

visual scenes) improve compared to traditional anatomical aligment. Although this hyperaligment approach substantially deviates from the original research question, we believe that this approach is a thesis-worthy topic and allows me to develop of state-of-the-art skills (i.e. how to use and implement hyperaligment) in cognitive neuroscience.

5.1.4 Procedure

The experimental session will last about an hour per subject. Before fMRI acquisition, subjects sign an informed consent, complete the MRI-safety screening, and are instructed about the task. The fMRI scanning session will consist of three functional runs (apart from the anatomical T1 scan) as discussed previously. The first run is the "pre-test" run with presentation of the stimuli in a slow event-related design (approximately 4 minutes; each stimulus is presented eight times for two second) without narrative. The second run will the be the run with the stimuli embedded in the narrative (approximately 20 minutes; each stimulus is presented ten times for four seconds). The last run will be the post-test, which is identical to the pre-test. During fMRI acquisition, pupil size (using an eyetracker), galvanic skin response (GSR), heart rate (power output using plethysmography), and respiration (using a respiration belt) are additionally measured as an operationalization of arousal (as a potential confounder of valence). After the scanning procedure, subjects are paid €20 and debriefed about the study's research goals.

5.2 Sample characteristics

5.2.1 A priori power analysis

In this study, we will use different multivariate (RSA and MVPA) analyses. Little is known about the optimal parameter settings multivariate analyses due to the the method's novelty. This warrants an approach in which various parameter settings – e.g. smoothing kernel, feature selection methods, and ROI selection – are tested for optimal use of the data (cf. **?**). However, to avoid double-dipping the data, we implement the procedure originally pro-

posed by **?** in which the data is partitioned into an optimization-set and a validation-set (see figure 4). The data from the optimization-set will be used to explore various parameter settings, and when the optimal parameters are established, these will be cross-validated on the validation-set. This way, exploratory and confirmatory research can be combined to use the data optimally without double-dipping.

This model cross-validation approach, however, comes at the cost of effectively cutting the experiment's power in half. This would results in a sample size of 18 for our multivariate analysis. Currently, there are no guidelines concerning minimum sample size for MVPA-studies. However, our previous MVPA study on emotion-networks (**?**) yielded a satisfactory effect size (i.e. decoding accuracy 30% above chance and a standard deviation of 11%, Cohen's $d = 2.55$) with 12 subjects (see **?**, for a similar effect size). Assuming a similar standard deviation for the results of the proposed study, a sample size of 18 subjects should suffice for finding a similar effect size.

5.2.2 Post-hoc power analysis

As MVPA is a relatively new method and consequently ill-investigated in terms of appropriate sample size for desired effect sizes, the final report will include a table listing the effect size (average classification accuracy over subjects minus chance level) as a function of sample size for both this study and a previous study in which we also used MVPA on a similar fMRI data-set (**?**). To do so, we will calculate the mean effect size with random subsets of subjects of various sizes (e.g. n = 4, n = 8, n = 20) across multiple interations, akin to a statistical bootstrapping procedure. As such, we hope to generate a useful benchmark for minimal sample sizes in affective neuroscience studies employing MVPA analyses.

5.2.3 Exclusion criteria

Participants will be excluded in case of excessive movement during fMRI acquisition (>3 millimeters within runs) and in case of falling asleep during fMRI acquisition. Participants will not be excluded based on their score in

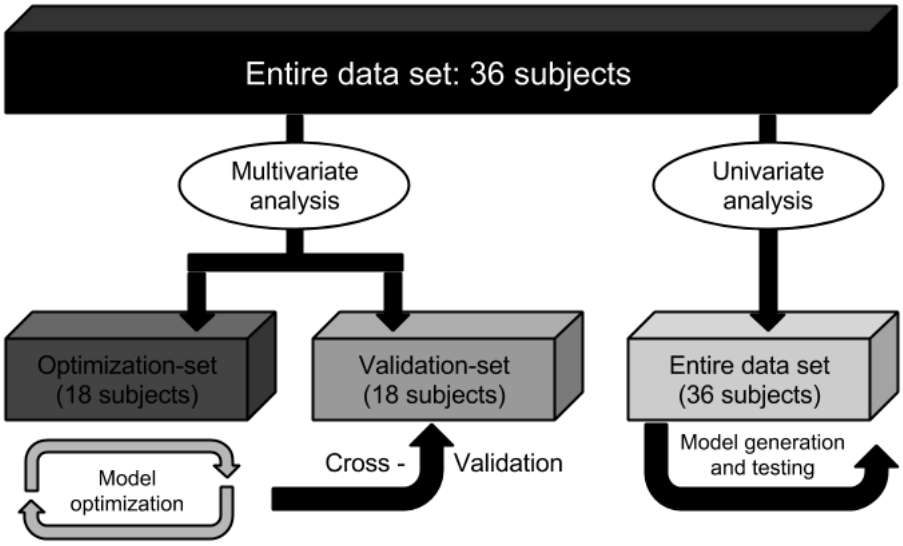


Figure 4: Schematic representation of the model optimization process for the multivariate analysis. A 50/50 partitioning ratio will be used. The univariate analysis will be done *once* with predetermined parameter settings and will thus not be partitioned. N.B.: The univariate analysis will not be part of this study's confirmatory analysis and will thus not be reported in the final thesis article. In case that the results of this analysis are used, it will be reported under the exploratory findings.

the classification analysis, as we argue that individual differences are interesting in itself and are even to be expected in analyses on emotional processes (see e.g. **?**).

5.3 Materials

Images of the three neutral faces will be drawn from the Karolinska Directed Emotional Faces (KDEF) database (**?**), an extensively tested and validated set of pictures including images of people with valence-neutral facial expressions (**?**). The visual scenes will be selected from Google images and validated in terms of valence-neutrality through an online questionnaire. In this questionnaire, subjects will indicate their association with the scenes in terms of valence (does the scene appear positive or negative?). Thirty responses on the online questionnaire will be recorded before assessing their valence-neutrality, which is operationalized as an insignificant difference in valence

compared to neutral. Furthermore, stimulus-valence contingency will be fully counterbalanced between subjects (by creating four different stimulus-valence contingencies), which will eliminate any effect of initial valence.

The narrative has yet to be created. The plan is to have a professional storyteller from the Mezrab cultural center (`www.mezrab.nl`) create a narrative tailored to the proposed research. As discussed, the narrative should contain three characters: one who will be developed as a morally good character – the narrative's "hero" –, one who will be developed as a morally evil character – the narrative's "villain", and one who will remain valence-neutral throughout the narrative. As moral goodness and evil is an inherently social concept (**?**), this does not apply to the visual scenes. We argue that characterizing visual scenes as either "safe" or "dangerous" is equivalent to characterizing the narrative's characters as morally good or evil. The details of how to achieve this development of valence for both categories will be decided together with the storyteller.

5.4 Data analysis

The proposed experiment is organized as a factorial design (valence × stimulus identity) in which the representation of object categories and valence can be investigated regardless of stimulus identity. The data analysis plan and predictions will be discussed separately for the multivariate classification analysis and the multivariate RSA analysis.

5.4.1 Confirmatory classification analysis

In our classification analysis, we will use a support vector machine classifier to investigate whether we can distinguish between neural representations of the factors in our factorial design. For this, we will use the data from the pre- and post-test. We will use a fully data-driven feature selection using Fisher selection. On the resulting subset of voxels, we will employ a repeated random subsampling cross-validation approach in which we train the classifier to distinguish either between valence (positive/negative) or between stimulus category (face/visual scene). Subsequently, we average the spatially

dependent voxels (using FSL's Gaussian Random Field cluster-thresholding method) and perform our classification analysis again with the reduced set of parameters (clusters instead of individual voxels). The classification analysis is done fully within subjects. The final results are based on the across-subjects averaged confusion matrix, which is statistically evaluated against chance (i.e. 50%) using permutation statistics (**?**).

5.4.2 Exploratory RSA analysis

The development of valence representations will be investigated using a trial-by-trial representational similarity analysis (RSA; **?**). In this analysis, representational distances (as normalized Euclidian distances) are computed between all trials and stored in a "distance matrix". Then, we will – exploratively – create a model-RSA matrix that aims to explain the observed distance matrix best (as described in **?**). This approach allows us to create a model in which specific components of our factorial design can be specified separately. To test the model, we simply vectorize the components of our factorial model (main effects: valence and category, interaction: valence $\times$ category) and regress this onto the vectorized observed distance matrix. This computation of distance matrices and subsequent model testing will be done for different feature sets (ROIs and brain-wide patterns based on the multivariate classification analysis). Furthermore, as part of the exploratory analysis – if time permits – the covariance of pupil size and SRC, as an index of arousal, with (the development of) representations of valence is investigated.

5.5 Modifiability of procedure

The research project as proposed here can be modified along recommendations from the RMP Thesis Committee and others, in each stage of the project (preparation/stimulus materials, data acquisition, or analyses). Advice on any section of this project is very much appreciated.

Word count: 473

6 **Intended results** - max 250 words

For our confirmatory analysis, we expect to find that our classification analysis of the pre-test reveals a local multivariate network for stimulus category but cannot reveal a valence representation (as this is only developed in the following run). We expect that the classification of the post-test data reveals, again, a local multivariate representation of stimulus category, as well as a global multivariate representation of valence. Furthermore, we hypothesize that classification of valence representations does not decrease when averaging over clusters of spatially dependent voxels within the entire pattern. This finding would be interpreted as evidence for encoding of valence at the level of clusters of voxels instead of individual voxels. If averaging degrades classifier performance, then this could mean that valence information is indeed encoded at the level of voxels, regardless of their clustering. If this coincides with at-chance classification of valence, then it is likely that our experimental paradigm failed to induce valence, in which case no conclusions about the spatial scale of the representation of valence can be drawn.

We believe that the proposed study bears a great potential to improve our fundamental understanding of functional brain networks. Ontologically, we may improve understanding of how the brain is organized functionally by showing how different psychological processes may be encoded on different spatial scales in the brain. Methodologically, we hope to show that the sensitivity of MVPA analysis may improve when a priori specifying the spatial scale on which a representation is expected. Furthermore, we think that our ecologically-valid experimental paradigm is a proper and effective way to investigate the development of any psychological process in the brain.

Word count: 473

7 **Work plan** – max 500 words

The research project can be conceptually divided into three stages. The preparation stage, spanning from March to mid April, will be centered around

gathering the necessary stimulus materials and programming the Presentation script. This will be done in collaboration with Steven Scholte. Suzanne Oosterwijk will additionally aid in this stage because of her expertise in emotion research. In this stage I will also start programming a fully open-source preprocessing and analysis pipeline in Python, with a focus on transparency and reproducibility (as argued here: `http://tinyurl.com/pmveewc`). Tomas Knapen (VU University), who is very experienced Python programmer, might assist in creating the pipeline if necessary. Early April I will begin recruiting participants.

The data acquisition stage will start mid April, when the 3T scanner at the Spinoza Centre for Neuroimaging will be fully operational again after the hardware upgrade. I plan to scan 36 participants in three weeks time. As the experimental protocol takes about 60 minutes, this will result in approximately 11 hours per week. If there is more time available at the scanner, I will try to scan more people per week. During this stage, I will adapt my existing MVPA scripts to fit the data from the proposed project. The adaptation and formalization of these scripts will be one in part during the Research Master Psychology course "Advanced Programming: The Next Step".

In the first or second week of May (depending when data acquisition is finished), the data analysis stage will start. This stage will be centered around finishing the analysis scripts and subsequently trying out different parameters on the optimization-set. In the first week of June, I hope to execute the final analysis on the validation-set Only if I finish the confirmatory analyses ahead of schedule, I will start with the exploratory RSA analyses. In June, I will also start writing the thesis report. I plan to finish a draft of my report mid July and, after revision, submit a final version at the end of the month.

7.1 Time schedule

The project will amount to a total of 28 EC, or 784 hours. Assuming a standard 40 hours (5 day) working week, the research project will be finished

the 24th of July. This allows for one week of planned vacation. In case of unplanned delay in either stage of the research project, the exploratory analyses will be omitted and the parameter optimization process can be shortened.

7.2 Infrastructure

Data acquisition will take place at the Spinoza Centre for Neuroimaging. As a research assistant, I have access to the centre and its facilities at all times. The centre provides all necessary equipment, including necessary proprietary software (e.g. Presentation).

7.3 Budget

The research project will be financed by funds of Steven Scholte. I will use approximately 30 euros of the Brain & Cognition departmental budget to print a poster which I will present at the annual Research Master's Graduate Conference.

Word count: 473

8 References

9 Further steps

Make sure your supervisor submits an Ethics Checklist for your intended research to the Ethics Committee of the Department of Psychology at http://ce.psy-uva.nl/. Submit the research proposal in PDF by email to researchmaster-psychology@uva.nl. If you have the proposal signed by the supervisor(s) and you have scanned their signatures in the PDF, you only have to hand in a digital version of the proposal. However if the signatures are not on the PDF, please also submit a printed copy of the signed research proposal to the secretariat of the Research Master Psychology:

Universiteit van Amsterdam
Research Master's Psychology
Weesperstraat 4, room 1.02
1018 XA Amsterdam
researchmaster-psychology@uva.nl

A response of the Research Master's Thesis Committee can be anticipated within 10 workdays (i.e. two weeks) after handing in the proposal.

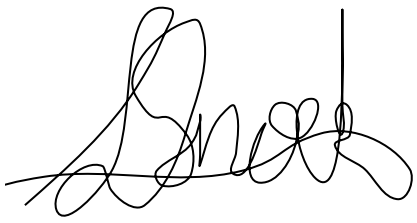
10 Signatures

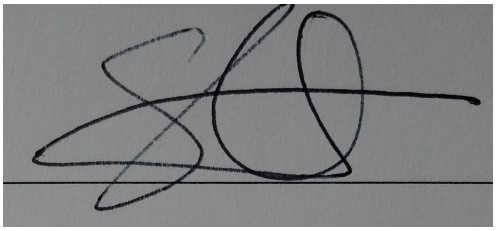
☑ I hereby declare that both this proposal, and its resulting thesis, will only contain original material and is free of plagiarism (cf. Chapter 11 or the Research Master's course catalogue).

☑ I hereby declare that the result section of the thesis will consist of two subsections, one entitled "confirmatory analyses" and one entitled "exploratory analyses" (one of the two subsections may be empty):

1. The confirmatory analysis section reports exactly the analyses proposed in section 4 of this proposal
2. The exploratory analysis section contains additional, and thus exploratory, analyses.

Signature student:





Signature ResMas supervisor: