Cross-Modal Detection and Analysis of Task-Unrelated Thoughts

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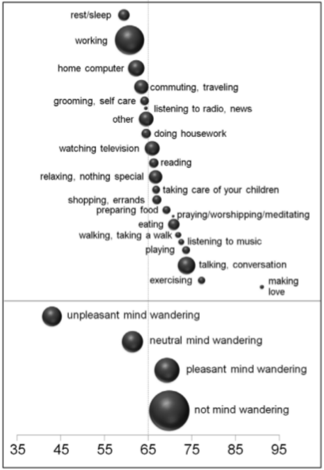
Mind-Wandering is an ubiquitous phenomenon...



- iPhone-app: people are continuously queried about what they are doing
- frequency of mind-wandering: 40-50% independent of current activity

$\rightarrow$If we spend half our waking time day-dreaming, can we assume that our experimental subjects are task-centered at all times?

Killingsworth & Gilbert, 2010, Sciene

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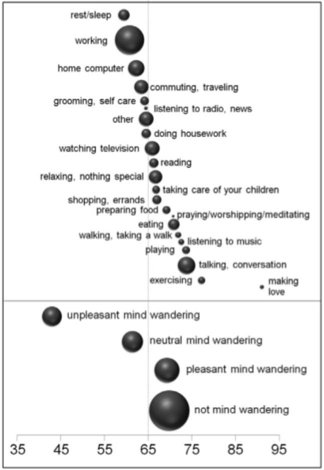

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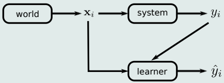
→If we spend half our waking time day-dreaming, can we assume that our experimental subjects are task-centered at all times?

- Mind-Wandering (MW)
- Task-Unrelated Thought (TUT)
- Stimulus-Independent Thought (SIT)
- Attentional Lapses
- . . .

Modelling TUTs

Two Perspectives

Predicting TUTs

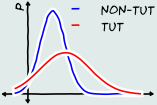


Machine-Learning Approach

$\rightarrow$ include large number of features from different modalities (neuroimaging measures, pupil-diameter, behaviour, ...)

$\Updownarrow$

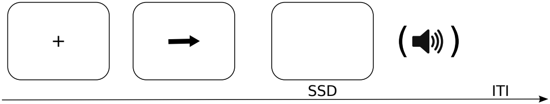
Analyzing TUTs



Data-model based approach (e.g. Drift-Diffusion Model)

$\rightarrow$ theoretical conclusions can be derived from model-fits

Experimental Setup

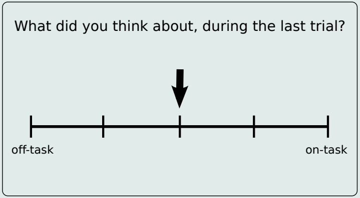


Stop-Signal Task

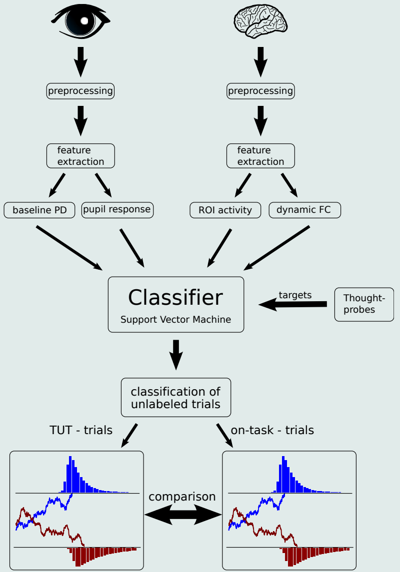
- left/right arrows, response left/right
- beep indicates stop
- stop-signal delay (SSD) adjusted to produce 50% errors

Acquired data

- 16 subjects
- fMRI (3T, 2 TR, $3 \times 3 \times 3$ mm voxel size)
- eyetracker (pupil dilation; 1000 Hz)
- behaviour: RT, errors, thought-probes



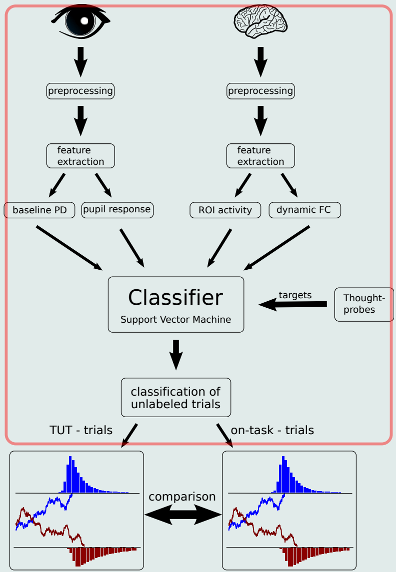
Multi-Modal Framework



Approach

- extract features from non-behavioural (neural/eye-tracking) data
- train classifier on labeled trials ($\approx 10\%$)
- classify unlabeled trials
- analyse Error/RTs in TUT vs. on-task trials in a Decision-model framework and identify cognitive processes involved in mind-wandering

Multi-Modal Framework



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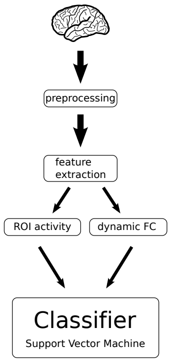
Theory: fMRI and Mind-Wandering

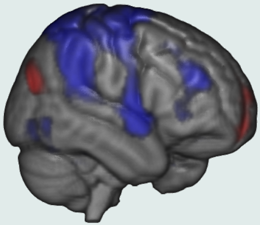


potential fMRI correlates

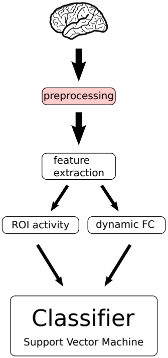
- Default-Mode Network (DMN) and Anticorrelated-Network (ACN)

→ DMN activity reduced prior to TUT measured by probe (Christoff et al., 2009, PNAS)

- DMN/ACN dynamic functional connectivity (dFC) related to vigilance (Thompson et al., 2013, HBM)



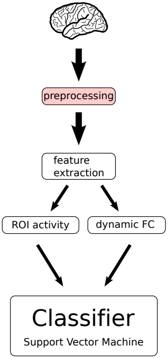
Preprocessing: functional connectivity



Residual General Linear Model

- voxel activity $y_i = \beta_1 x_1 + \cdots + \beta_m x_m + \epsilon$ using task, motion, blinkrate, white-matter, CSF and whole brain activity as regressors.
- subtract estimate from data to obtain residuals $\rho_i = y_i - \sum_i \beta_i x_i$
- pairwise correlations $corr(\rho_i, \rho_j)$ reveal fcMRI

Preprocessing: extracting DMN/ACN

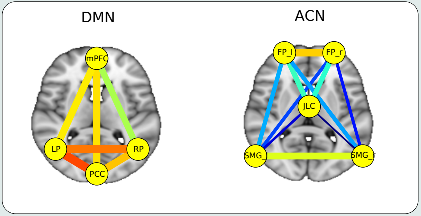


ROI definition

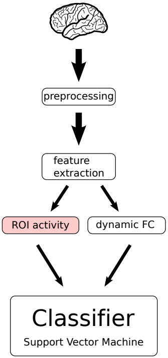
- PCC seed-map (van Maanen et al., 2011, JoN)

$\rightarrow$ global correlation map

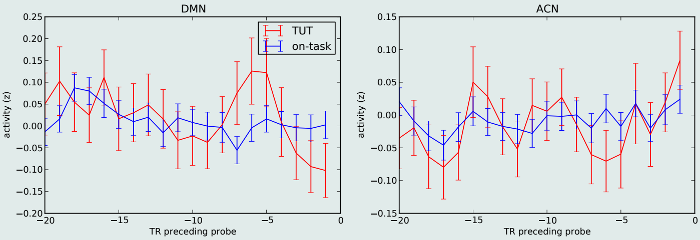
- thresholding and segmentation
- per-subject definition of ROIs as $3 \times 3 \times 3$ cubes around minimum voxel within or close to the defined regions (gradient-descent)



Results: DMN/ACN activity



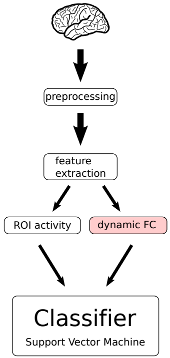
Activity before Thought-Probes



→ effects in resting-state activity up to $\approx 20s$ back $(= 10\,TR)$

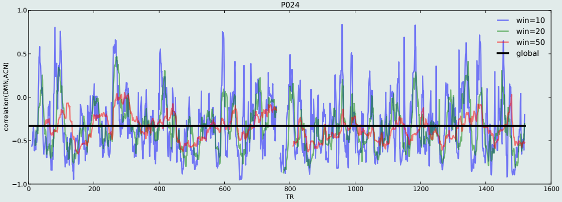
→ use integrated activity over that window for classification

Method: dynamical functional connectivity (dFC)



Sliding-Window Approach

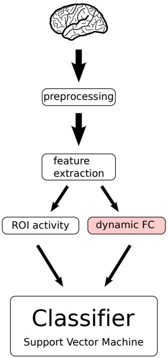
- given the residuals of two voxels $\rho_i(t)$ and $\rho_j(t)$, calculate the sliding-window correlation $corr_w(\rho_i(t), \rho_j(t))$ for $t \in W_k = \{k, \dots, k+w\}$
- Problem: what is the "correct" window size w?



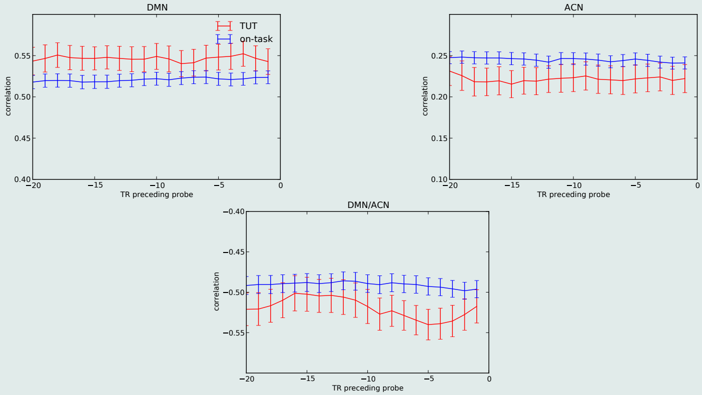
$\rightarrow$ 30-60 s windows seem appropriate (Shirer et al., 2012, CB)

$\rightarrow$ use 40s window

Results: Dynamical FC

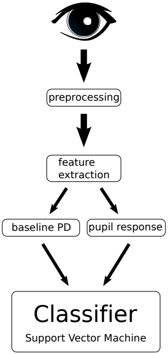


Dynamical FC preceding Thought-Probe



→ use integrated dFC over 10 TR preceding probe as feature

Theory: Pupil Data

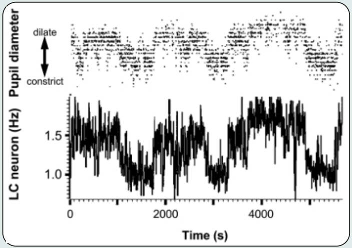


Potential Correlates

- pupil diameter related to the locus coeruleus-norepinephrine (LC-NE) system via the Adaptive Gain Theory (AGT, Aston-Jones et al., 2005)

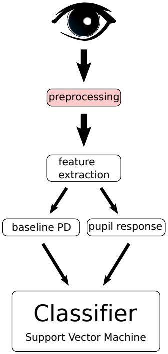
→ tonic LC-activity: baseline pupil diameter

→ phasic LC-responses: pupil-response function



(Rajkowski et al.,1993)

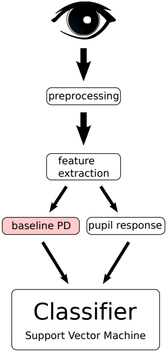
Preprocessing: Pupil Diameter



Preprocessing Steps

- clean data from blinks and surrounding artifacts ($[-100, 100]ms$)
- linearly interpolate missing data
- downsampling to 100 Hz

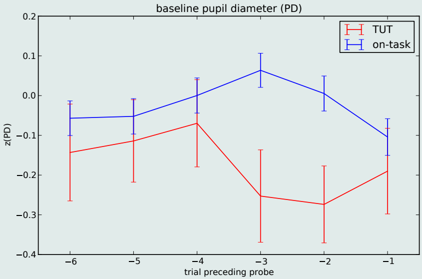
Results: Baseline Pupil Diameter



Baseline Pupil-Diameter

- mean PD $[1000, 0]$ ms before trial onset

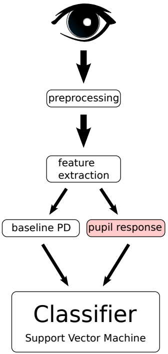
Baseline-PD preceding TUT trials



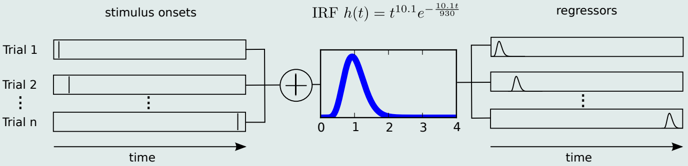
- reflected in mean baseline PD (up to 4 trials back)

$\rightarrow$ use baseline-PD up to 5 trials back as features

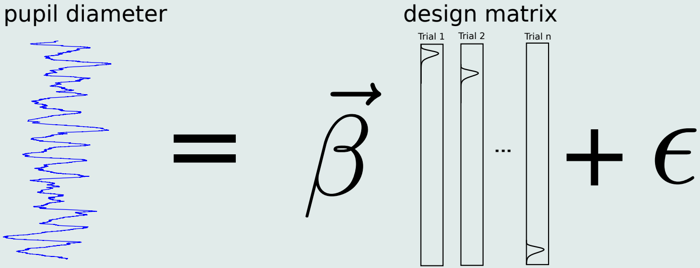
Method: Pupillary Response to Stimulus



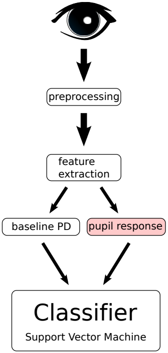
Stimulus Onset-Regressor



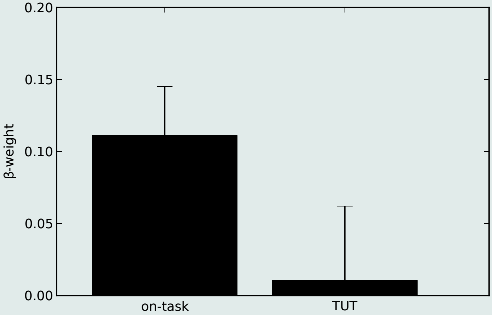
General Linear Model



Results: Pupillary Response



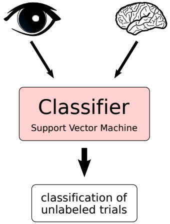
Pupillary Response preceding TUT/on-task trials

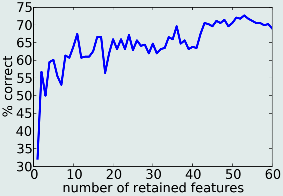


- pupillary response less pronounced during TUT-trials

→ use pupillary response up to 5 trials back as features

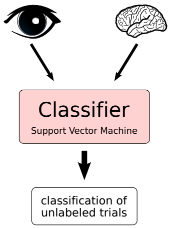
Results: Classification

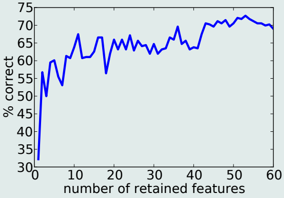




- performance measure: Leave-One-Out Crossvalidation (LOOCV)
- feature selection: train classifier using the *n* most influential features

Results: Classification





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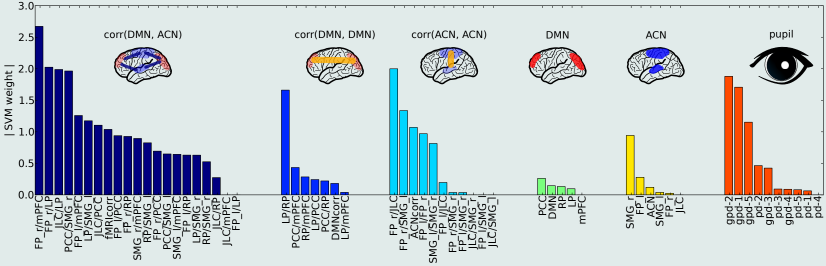
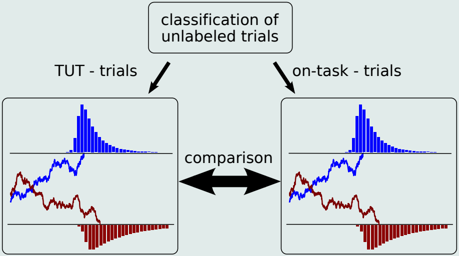
Best classification performance (LOOCV): 73%



Outlook

Analysing labeled trials



- need model that can handle STOP-signal

→ Stop-Signal Linear Ballistic Accumulator (SSLBA), Forstmann et al., submitted

- analysing model parameters between TUT and on-task trials allows inference about underlying cognitive processes

Thanks...

Birte Forstmann

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Institutions

- Cognitive Science Center Amsterdam (CSCA)
- University of Amsterdam (UvA)

Thank you for your attention!