When the brain takes a break: A model-based analysis of mind wandering

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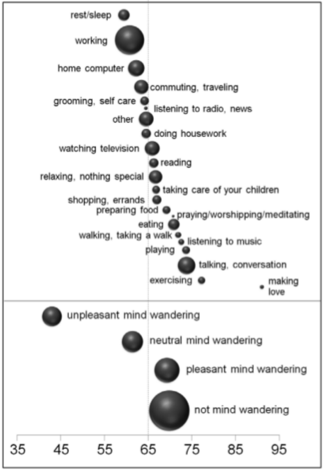
Mind-Wandering is an ubiquitous phenomenon…



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

→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

What is Mind-Wandering?

Different experimental contexts

1. task-unrelated thoughts (TUT)
2. attentional lapses (failure to perceive/respond)
3. stimulus-independent thoughts (SIT)
4. tuning out vs. zoning out (with and without meta-awareness)
5. ...

Experimental Findings

Mind-wandering

1. decreases with growing task-difficulty
2. increases with growing practice on task (automatization)
3. increases with current concerns (baseline thought-production)
4. increases with alcohol consumption
5. increases with nicotine craving
6. increases with fatigue
7. decreases with working-memory capacity
8. is increased in ADHD-patients
9. is increased in mild depression patients
10. is decreased in older adults

Why and How?

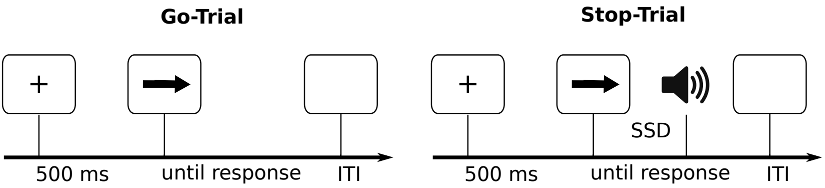
Why? (functions of Mind Wandering)

- future planning (internal practice)
- creativity
- attentional cycling (inherent tendency to shift attention)
- dishabituation (mind wandering as break from current task)

How? (what mechanism is involved)

- executive control is involved (failure vs. resource)
- what kind of control?

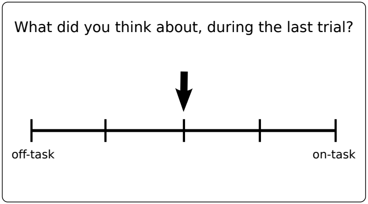
Experimental Setup



Stop-Signal Task

- allows to distinguish between different aspects of executive control (“goal-monitoring” and “stopping”)
- left/right arrows, response left/right
- beep indicates stop the current response
- stop-signal delay (SSD) adjusted to produce 50% errors
- measures: fMRI, pupil, behaviour

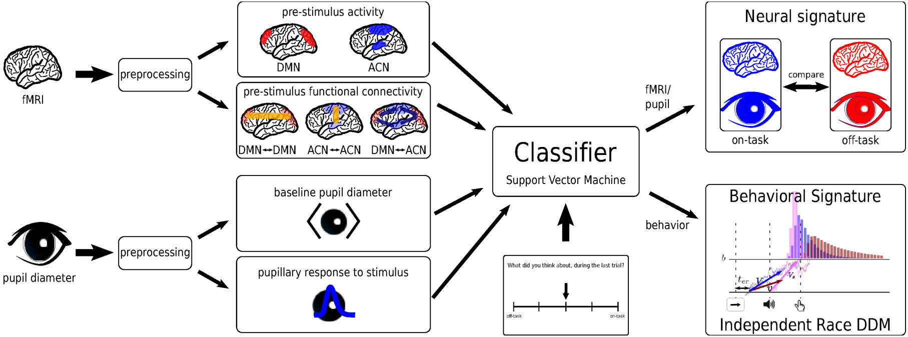
Experimental Setup



Thought-probes

- randomly presented during the course of the experiment (ca. 1 per minute)
- 5-point Likert-scale
- common operationalization of mind-wandering in attention experiments

Goals of this project

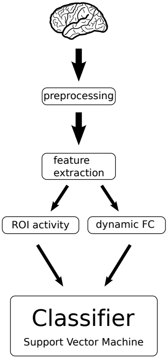


Outline

- identify mind-wandering **on a single-trial level**
- analyse the neural and behavioural signature of Mind-Wandering

→ identify which cognitive processes are impaired using **cognitive models of behaviour**

Theory: fMRI and Mind-Wandering

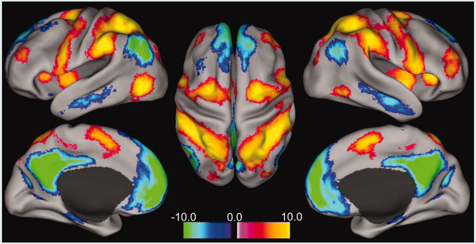


potential fMRI correlates

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

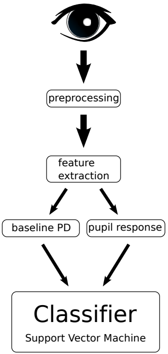
→ DMN activity increased prior to mind-wandering (Christoff et al., 2009, PNAS)

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



Fox et al. (2005), PNAS

Theory: Pupil Data

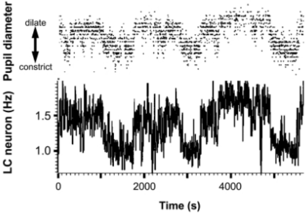


Potential Correlates

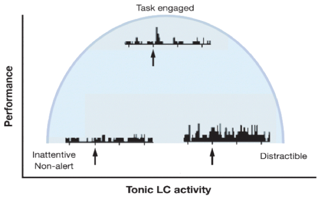
- pupil diameter possibly correlated with locus coeruleus-norepinephrine (LC-NE) activity
- Adaptive Gain Theory (AGT, Aston-Jones et al., 2005)

→ tonic LC-activity: baseline pupil diameter

→ phasic LC-responses: pupil-response function



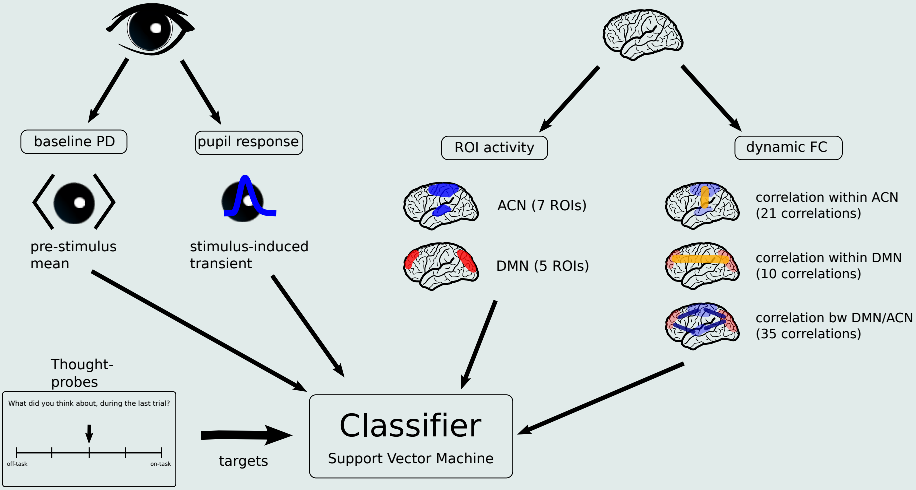
(Rajkowski et al.,1993)



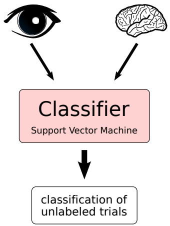
(Aston-Jones & Cohen, 2005)

Summary: Classification

Trial-wise features for Classification

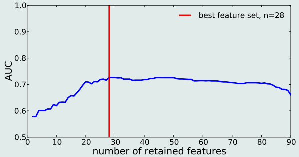


Results: Classification

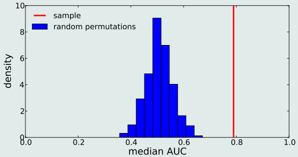


Classifier optimization

Feature Selection



Random Permutation Test

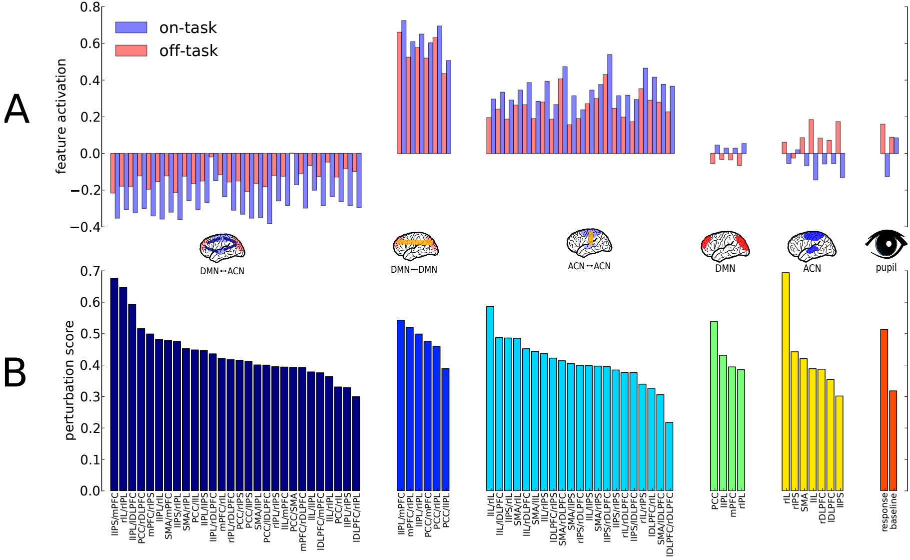


- Support-vector machine with gaussian radial basis functions
- optimize RBF-SVM parameters (C, γ) using AUC criterion
- recursive feature elimination
- Cross-Subject Crossvalidation Accuracy: **79.5%**

$\Rightarrow$ **single-trial** probability of mind wandering for each trial

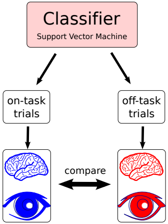
Results: Classification

Feature Importance/Activation

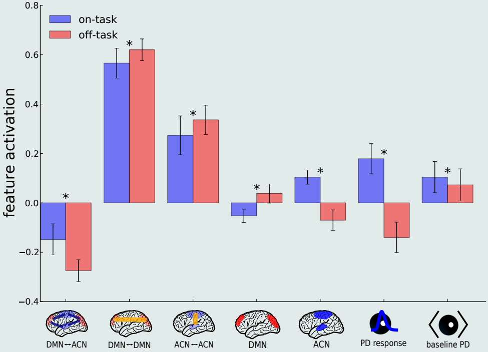


Results: Classification

Feature Activation

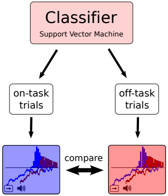


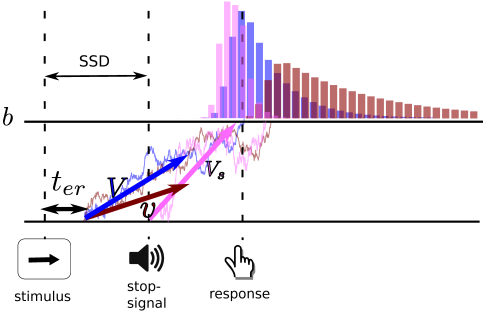
Feature activation on vs. off-task



- DMN activity predicts off-task, ACN predicts on-task
- absolute connectivity during off-task stronger
- PD baseline and response reduced during off-task

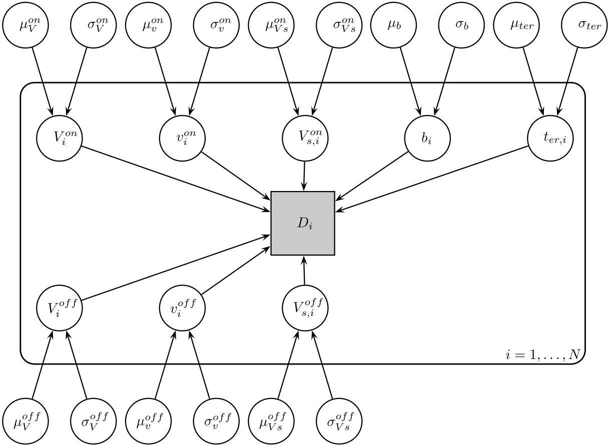
Cognitive Model





Independent Race Drift-Diffusion Model

- allows to decompose reaction times into cognitive processes (parameters):
  - efficiency of go/stop processes (drift rates, V, v)
  - caution (boundary separation, b)
  - duration of perception/motor (nondecision time, t_{er})
- goal-monitoring vs. inhibitory processes



$D_i \sim \text{IndependentRace}(V_i^{on}, V_i^{off}, v_i^{on}, v_i^{off}, V_{s,i}^{on}, V_{s,i}^{off}, b_i, t_{er,i})$

$V_i^{on} \sim \text{Normal}(\mu_V^{on}, \sigma_V^{on})$

$v_i^{on} \sim \text{Normal}(\mu_v^{on}, \sigma_v^{on})$

$V_{s,i}^{on} \sim \text{Normal}(\mu_{Vs}^{on}, \sigma_{Vs}^{on})$

$V_i^{off} \sim \text{Normal}(\mu_V^{off}, \sigma_V^{off})$

$v_i^{off} \sim \text{Normal}(\mu_v^{off}, \sigma_v^{off})$

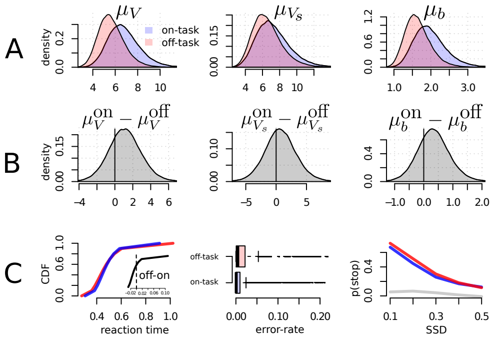
$V_{s,i}^{off} \sim \text{Normal}(\mu_{Vs}^{off}, \sigma_{Vs}^{off})$

$b_i \sim \text{Normal}(\mu_b, \sigma_b)$

$t_{er,i} \sim \text{Normal}(\mu_{ter}, \sigma_{ter})$

Results

Group-level



Mind-Wandering is

- reflected in a combination of decreased drift-rates and decreased boundary (sign. on posterior modes) → goal-monitoring affected

→ more "impulsive" behaviour:
  - behaviour more variable (longer distribution tails)
  - more errors
- inhibitory processes not affected

Conclusion

Conclusion

- Mind wandering can be predicted on the single-trial level (80% accuracy)
- ... using theoretically meaningful, neural variables
- the classification signature agrees with predominant view of DMN influence on MW
- MW affects executive goal-monitoring but not inhibitory processes

Thanks...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Andrew Heathcote

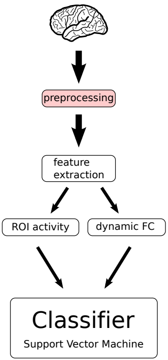

Brandon Turner

Institutions

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

Thank you for abstaining from mind wandering!

Preprocessing: functional connectivity

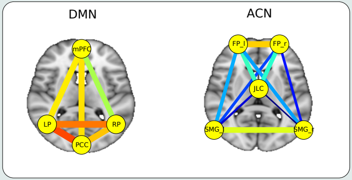


Residual General Linear Model

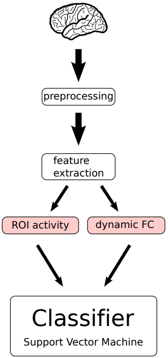
- voxel activity $y_i = \beta_1 x_1 + \cdots + \beta_m x_m + \epsilon$ incl. task, motion, blinkrate, white-matter and CSF
- subtract estimate from data to obtain residuals $\rho_i = y_i - \sum_i \beta_i x_i$

ROI definition

- global correlation map with PCC seed
- per-subject definition of ROIs



Method: fMRI (ROI activity and functional connectivity)



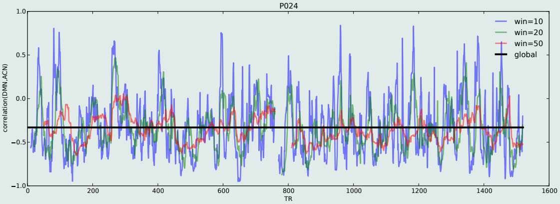
Activity before Thought-Probes

→ effects in resting-state activity up to $\approx 20s$ back

→ use integrated activity over that window

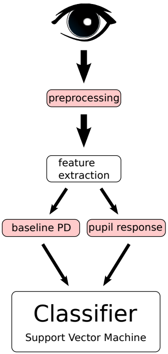
Dynamic functional connectivity

- 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?



→use 40s window (Shirer et al., 2012, CB)

Method: Pupil Diameter

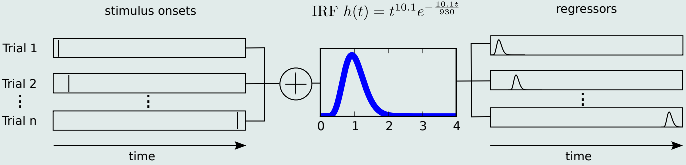


Baseline Pupil-Diameter

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

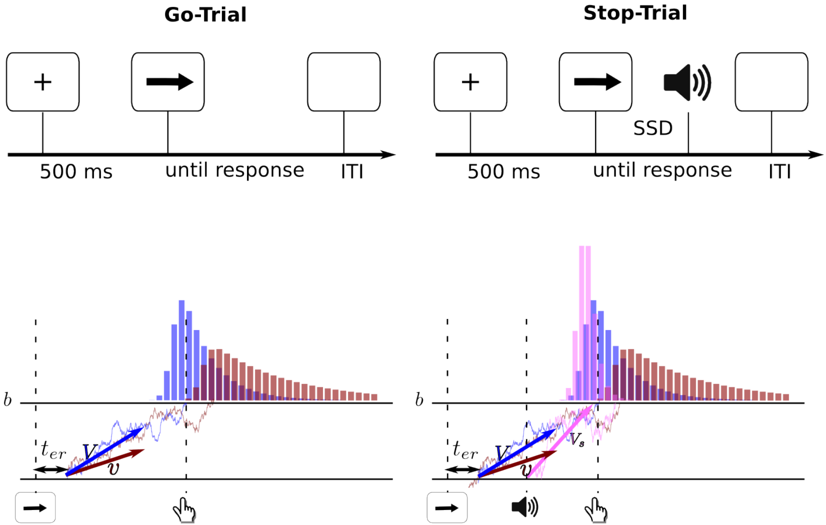
Pupil Response

extrace pupillary response via GLM



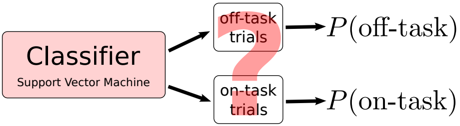
Cognitive Model

Independent Race Drift-Diffusion Model



Cognitive Model

Dealing with Classifier Uncertainty



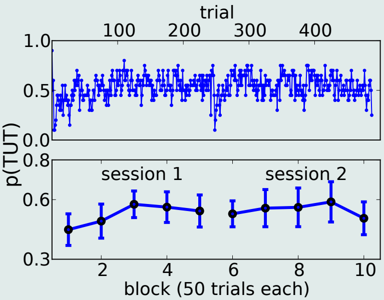
- SVM predicts state sequence for each trial i:
  $\hat{S} = (\hat{S}_1, \ldots, \hat{S}_N), \hat{S}_i \in \{\text{on}, \text{off}\}$
- SVM classification not perfect but: probability for correct prediction
  $P(\hat{S}_i = S_i) := p_{acc}(i)$

→ model uncertainty as a mixture:

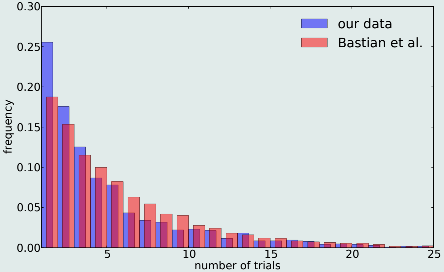
$$p(x_i|\theta) = p_{acc}(i) f(x_i|\hat{S}_i) + (1 - p_{acc}(i)) f(x_i|\neg\hat{S}_i)$$

Analysis of frequency of mind wandering

Probability of Mind-wandering



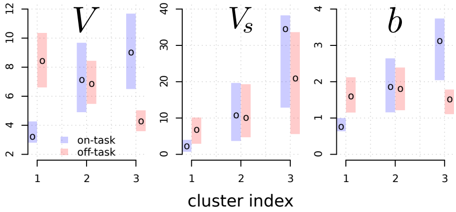
Duration of Mind-Wandering



- TUTs increase with time
- TUTs are mainly short (a few trials)
- good correspondence to previous work (Bastian et al., 2013)

Results

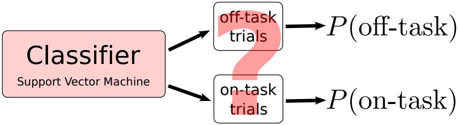
Individual differences



- cluster-analysis reveals 3 clusters of subjects with distinct behavioural patterns
  1. cluster 1 (N=2): inverse goal-monitoring effect
  2. cluster 2 (N=8): no effect
  3. cluster 3 (N=10): goal-monitoring effect
- different “kinds” of mind wandering involved?

Cognitive Model

Dealing with Classifier Uncertainty



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