Integrated accounts of behavioral and neuroimaging data using flexible recurrent neural network models

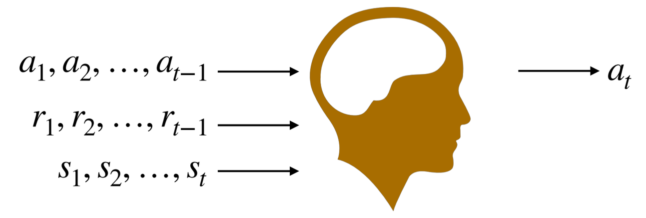
Amir Dezfouli[1,2*], Richard Morris[3], Fabio Ramos[4,5], Peter Dayan[6], Bernard W. Balleine[2]

[1]Data61, CSIRO, Australia [2]School of Psychology, UNSW, Sydney, Australia [3]Centre for Translational Data Science, University of Sydney, Sydney, Australia [4]School of Information Technologies, University of Sydney, Sydney, Australia [5]NVIDIA [6]Max Planck Institute for Biological Cybernetics, Tübingen, Germany

*akdezfuli@gmail.com

Introduction

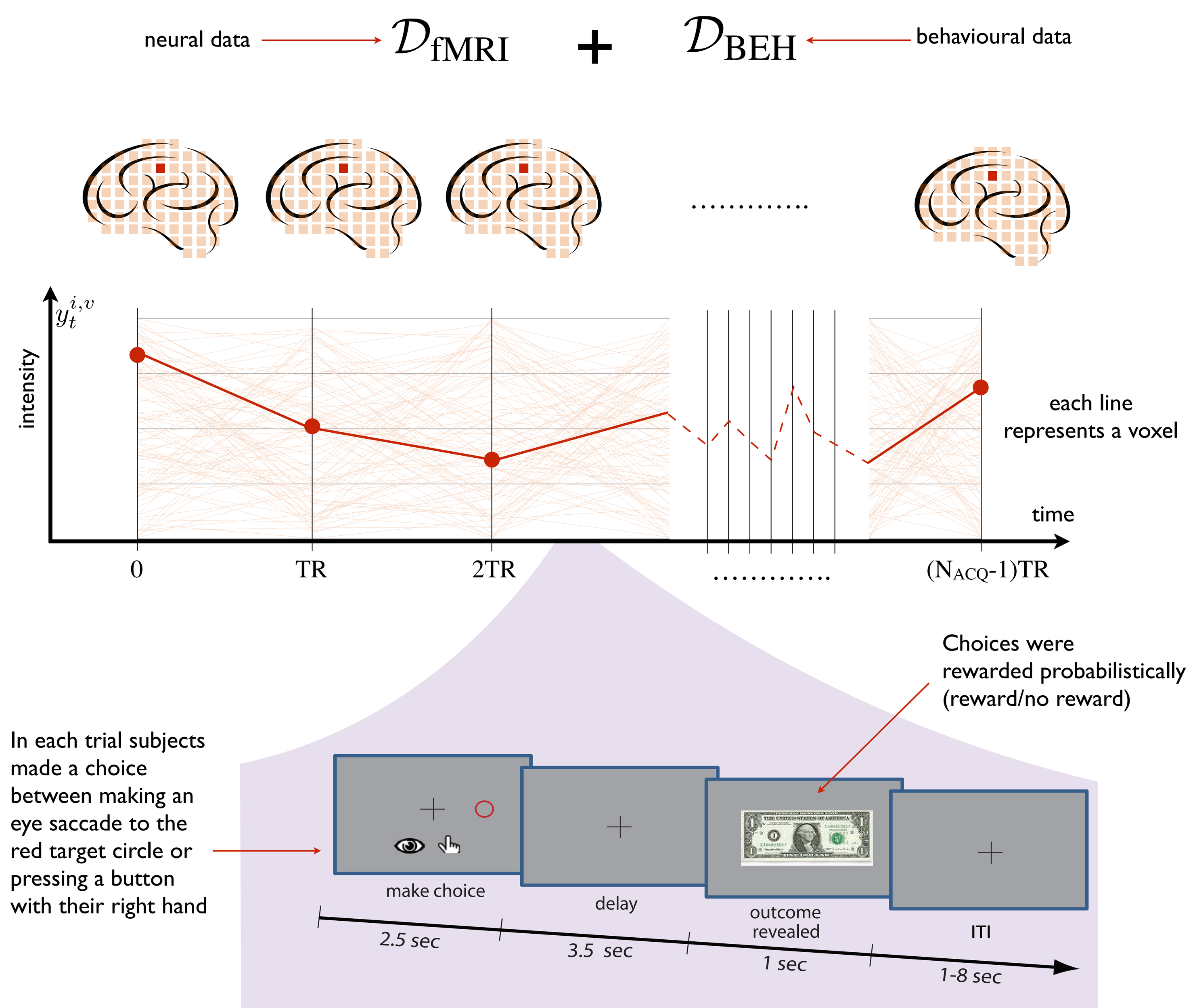
- **Understanding the decision-making system in the brain is important** since it is the substrate for human and animal choice abilities, and has close associations with psychiatric and neurological disease.
- **The main challenge: Decisions and their related brain activities are dependent on the history of previous experiences.** That is, decisions and thus the neural activity that causes them are not only affected by the immediate events in the task, but are also affected by a potentially long history of previous inputs, such as rewards, actions and environmental cues.



- **Previous approach: Model-based analysis of fMRI data**, which involves training a computational model using behavioral data, and then searching the brain for regions whose BOLD activity is related to the internal signals and variables of the model.
    - **Problem:** Even if the model produces actions similar to the subjects, the variables and summary statistics that the brain explicitly tracks might not transparently represent the ones the hypothetical model represents. In this case, either the relevant signals in the brain will be missed in the analysis, or the model will have to be altered (manually) in the hope that the new signals in the model resemble neural activity in the brain.
- **We propose a new approach using a recurrent neural network** as a type of model that is sufficiently flexible to represent the potentially complex neural computations in the brain, while also closely matching subjects' choice behavior.
- **We show how to interpret the model** by unrolling it over space and time to determine the role of each brain region at each time slice in the path from reward processing to action selection.

Data

- The data used here were previously published in Wunderlich et al. [2009].



$$\mathcal{D}_{\text{fMRI}} = \{y_t^{i,v}\}, t = 0, \text{TR}, 2\text{TR}, \ldots, (N_{\text{ACQ}}-1)\text{TR}, i = 1 \ldots N_{\text{SUBJ}}, v = 1 \ldots N_{\text{VOX}}$$

intensity; time between image acquisitions; number of image acquisitions; number of subjects; number of voxels

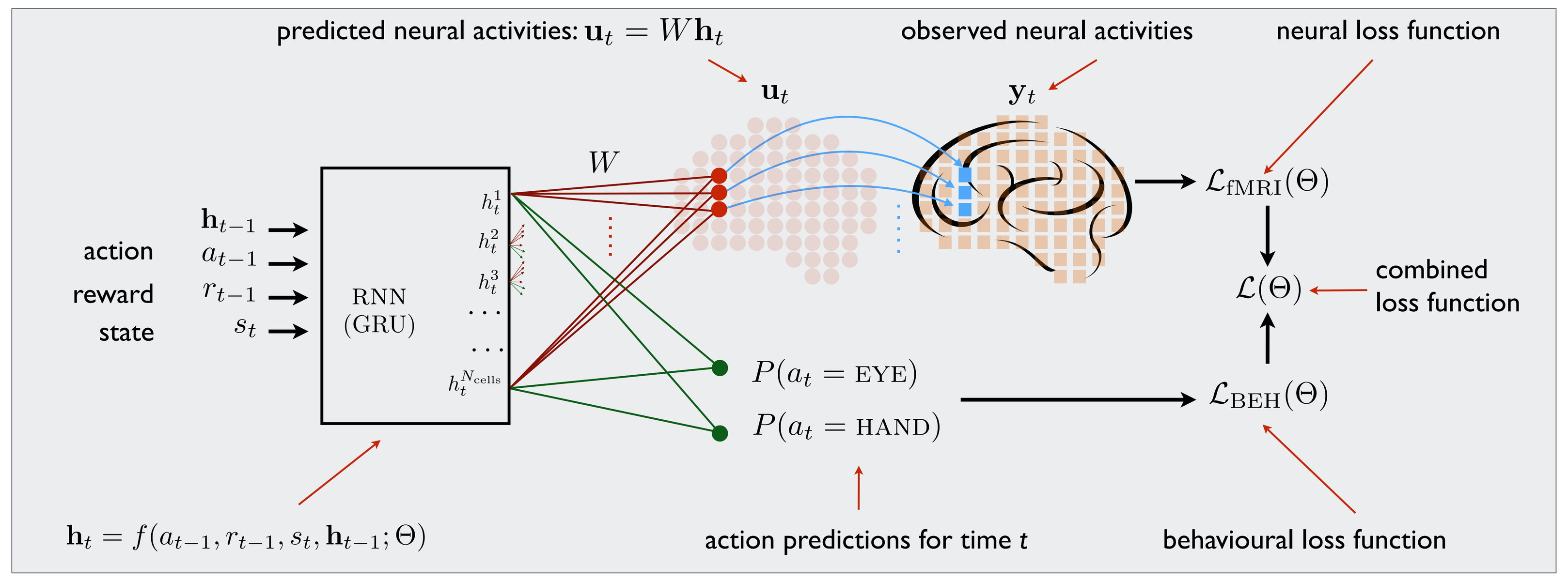
$$\mathcal{D}_{\text{BEH}} = \{(s^i_{t^i}, a^i_{t^i}, r^i_{t^i}) \mid i = 1 \ldots N_{\text{SUBJ}}, t^i \in T^i\}$$

number of subjects

- Each subject made ~300 choices.

Model

- The model learns to learn the task such that (a) its output matches subjects' choices; and (b) its internal mechanism tracks subjects' brain activity.
- A model trained using this approach ideally provides an end-to-end characterisation of the neural decision-making system.



model-parameters; observed action at time t

$$\mathcal{L}_{\text{BEH}}(\Theta) = -\sum_{t \in T'} \log \pi_t(a_t)$$

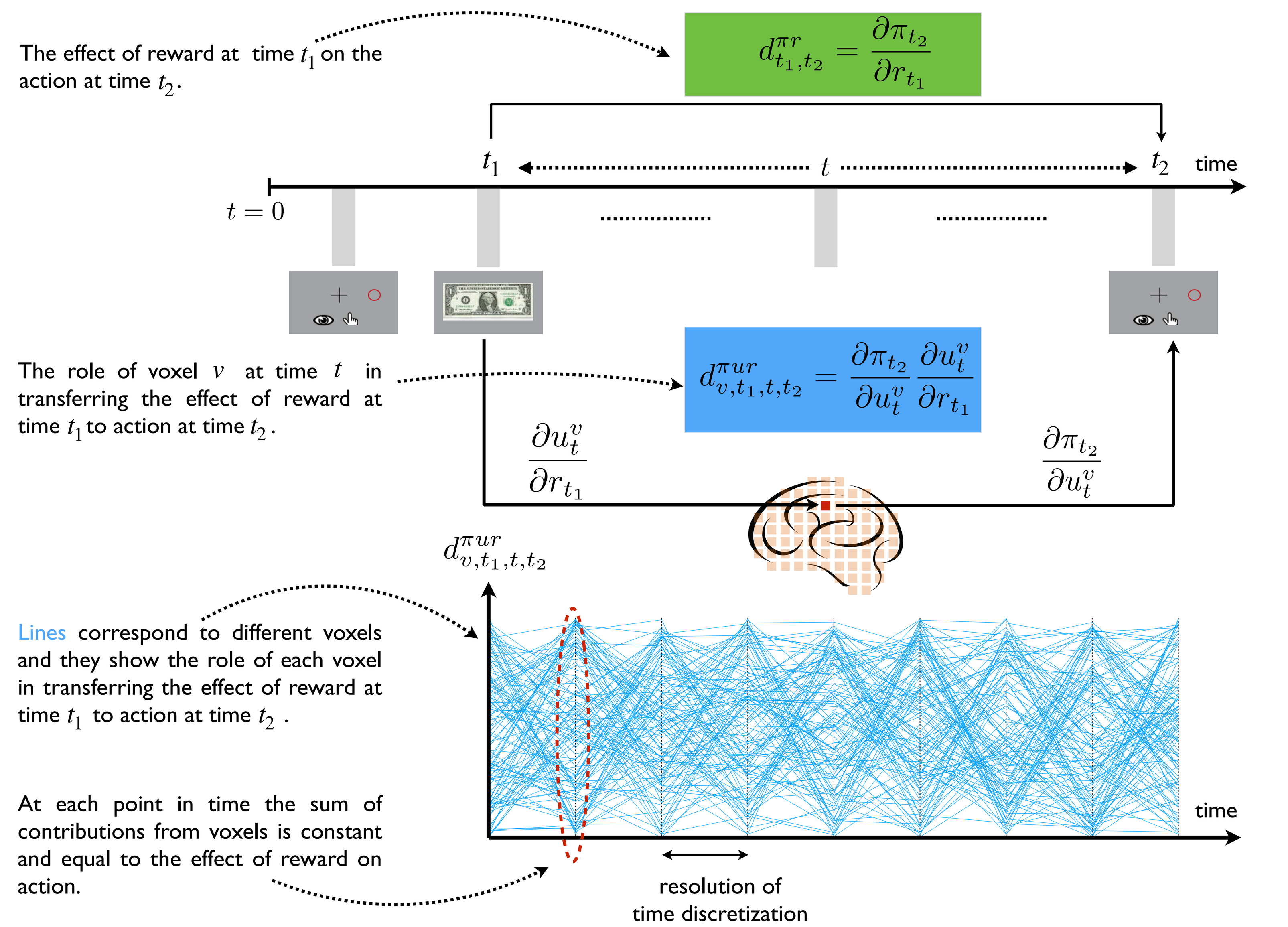
$$\mathcal{L}_{\text{fMRI}}(\Theta) = \sum_t \|\mathbf{u}_t \circledast \text{HRF} + \mathbf{b} - \mathbf{y}_t\|^2$$

$$\mathcal{L}(\Theta) = \mathcal{L}_{\text{BEH}}(\Theta) + \lambda \mathcal{L}_{\text{fMRI}}(\Theta)$$

weight of neural loss function determined using cross-validation

- Model parameters Θ include W (red lines), parameters in the softmax layer (green lines) and parameters in the RNN layer.
- Hyper-parameter λ determines the balance between neural and behavioral data in the combined loss function.

Interpreting the model



The sum of individual voxel contributions at each point in time is equal to the total behavioural effect of reward:

behavioural $d^{\pi r}_{t_1,t_2}$ **neural** $d^{\pi u r}_{v,t_1,t,t_2}$

$$\frac{\partial \pi_{t_2}}{\partial r_{t_1}} = \sum_{v=1}^{N_{\text{VOX}}} \frac{\partial \pi_{t_2}}{\partial u_t^v} \frac{\partial u_t^v}{\partial r_{t_1}}, t = t_1 + 1 \ldots t_2$$

For the above equation to hold it is necessary for the state of the network to be fully determined by the neural activity (u_t). This can hold in the case of GRU cells (provided that the hidden units do not partition into separate behavioral and neural groups). In contrast, in LSTM cells, the cell states and cell outputs are different and are both required to determine the outputs in the next time-step, and therefore in the case of LSTM cells equations do not hold.

The equation also requires that $W^\top W$ be non-singular.

model settings

- All the methods were implemented in Tensorflow and gradients (for both optimization and interpretation of the model) were calculated using automatic differentiation methods available in this package. RMSProp was used for optimization.
- The time of behavioral data was discretized with resolution dt = 0.6625. $N_{\text{CELLS}} = 48$ $N_{\text{SUBJ}} = 22$ $N_{\text{ACQ}} = 1136$ $N_{\text{VOX}} = 63191$

Conclusion

- We have introduced a new architecture for investigating the neural substrates of decision-making in the brain.
- Our approach does not require manual engineering and is able to learn computational processes directly from the data. We further showed that the model can be interpreted to uncover the temporal engagement of different brain regions in choice and reward processing.
- Besides being used as a standalone analysis tool, this approach can inform model-based fMRI analyses to investigate whether the model correctly tracks the brain's internal mechanisms. That is, if a brain region is found to be important in the current analysis, but not using the model-based fMRI analysis, this could mean that the model used to extract neural information is not representing all of the relevant neural signals involved in decision-making and requires further modification.

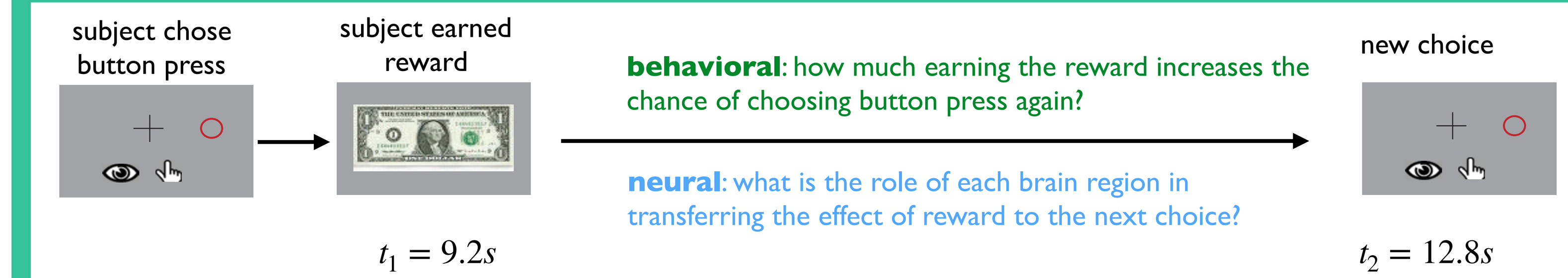
References:

- Klaus Wunderlich, Antonio Rangel, and John P O'Doherty. Neural computations underlying action-based decision making in the human brain. Proceedings of the National Academy of Sciences, 106(40):17199–17204, 2009.
- Amir Dezfouli, Kristi Griffiths, Fabio Ramos, Peter Dayan, Bernard W Balleine. Models that learn how humans learn: the case of decision-making and its disorders.

Acknowledgements:

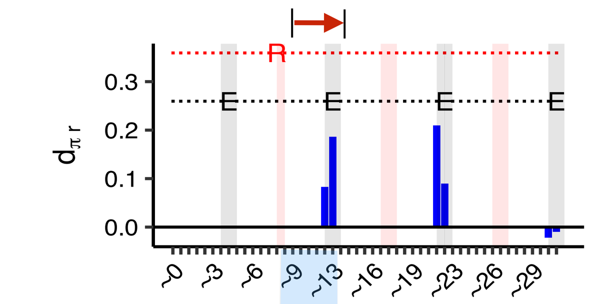
AD and BWB were supported by funding from UNSW Sydney and the National Health and Medical Research Council of Australia GNT1079561. PD was funded by the Gatsby Charitable Foundation. We are grateful to John O'Doherty for sharing the data with us.

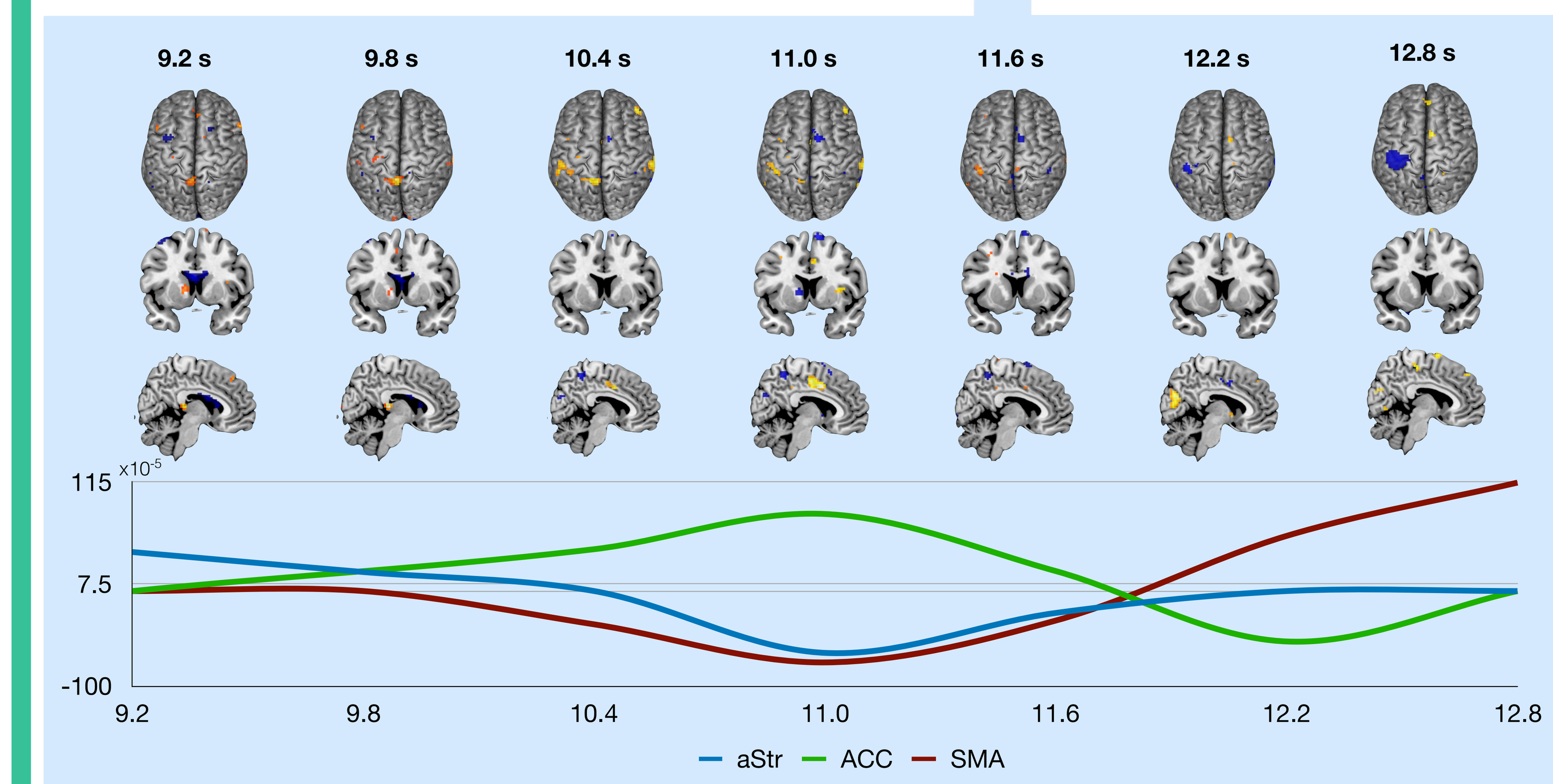
Results



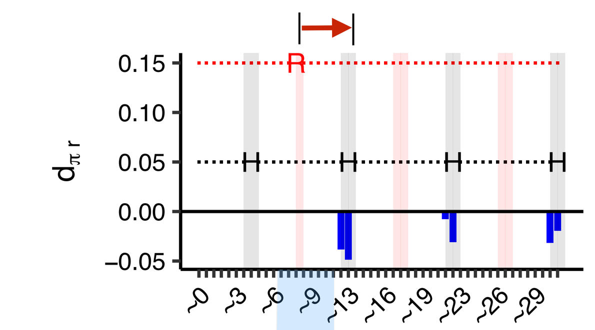
- We calculated $d^{\pi u r}_{v,t_1,t,t_2}$ for every voxel and every time-step between t_1 and t_2, and masked out the voxels that were not in the top one percent. By focusing only on the 99th percentile of $|d^{\pi u r}_{v,t_1,t,t_2}|$, we hoped to limit our analysis to the circuitry known to be involved in decision-making.

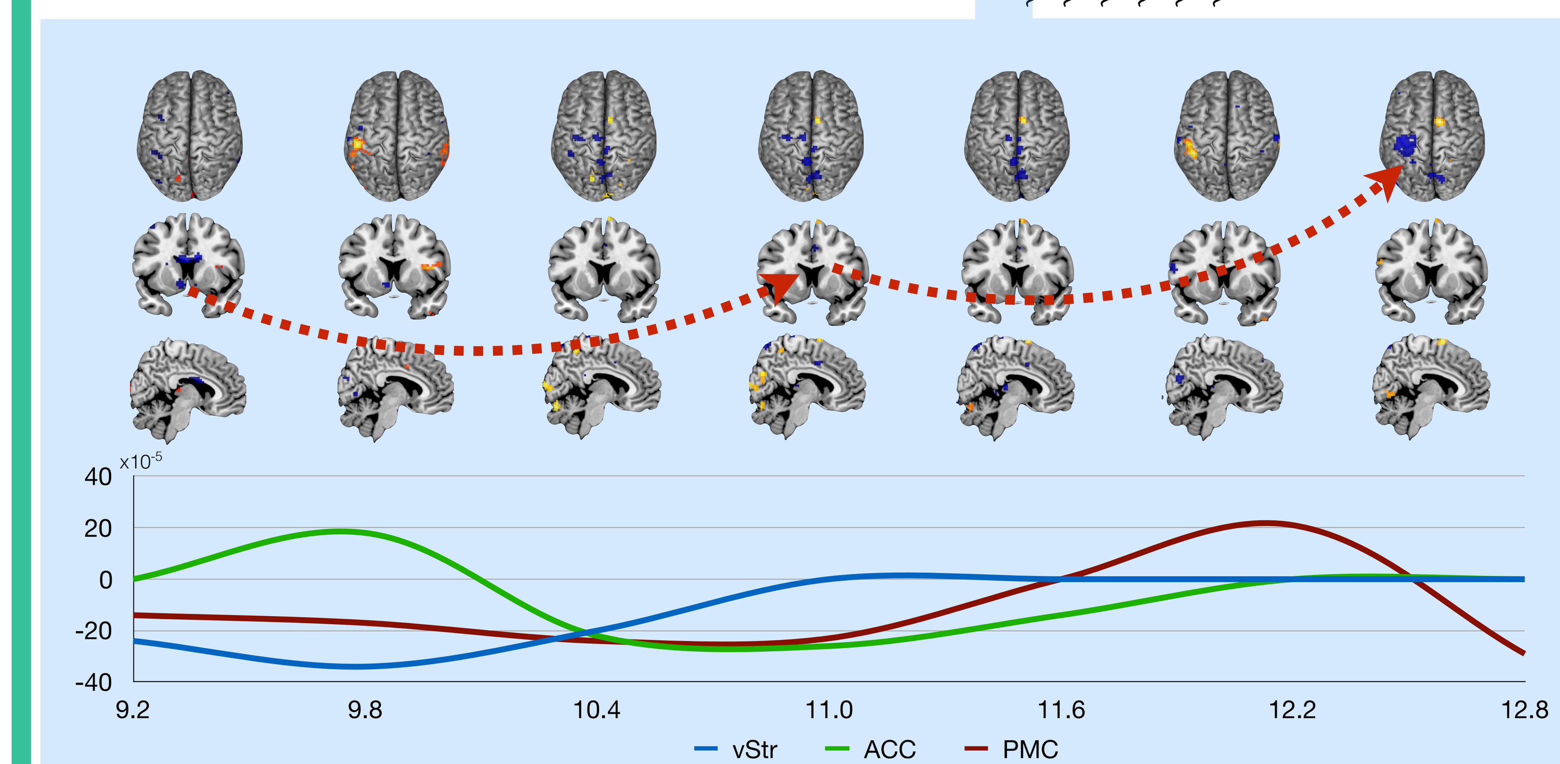
E: EYE action was selected
R: reward was earned
Red patch: outcomes of action are revealed
Grey patch: choice time





H: HAND action was selected
R: reward was earned
Red patch: outcomes of action are revealed
Grey patch: choice time





- The results show that, for each action, the top 1% of voxels contain three key cortical and subcortical brain regions known to be critically involved in reward-processing and decision-making, i.e., (i) striatum (associative aStr; or ventral, vStr), (ii) anterior cingulate cortex (ACC) and (iii) supplementary motor area (SMA).
- These anatomical regions are among the same anatomical regions that Wunderlich et al. [2009] also identified as involved in decision-making in this task.
- The temporal order of engagement of these regions is also consistent with their functional role in decision-making.