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1 Intention to submit document for the Work with  
2 US researchers BBSRC-NSF/BIO lead agency  
3 2024 funding opportunity

4 Enabling Naturalistic, Long-Duration and  
5 Continual Neuroscience Experimentation with  
6 Advanced Machine Learning

7  
8 October 17, 2024

9 **1 Summary**

10 Word limit: 2 A summary is not required for this section, please write 'N/A' in  
11 the textbox. Please still include a title for your project.  
12 N/A

## 2 Core team

List the key members of your team and assign them roles from the following:

- project lead (PL)
- project co-lead (UK) (PcL)
- specialist
- professional enabling staff
- research and innovation associate
- technician
- researcher co-lead (RcL)

Only list one individual as project lead.

The core team section must only contain details of the UK applicants. The US applicant information should be listed in the 'US applicants' section.

Find out more about UKRI's core team roles in funding applications.

**project lead (PL)** Prof. Maneesh Sahani

**project co-lead (UK) (PcL)** Prof. Tiago Branco, Prof. Thomas Mrsic-Flogel

**researcher co-lead (UK) (RcL)** Dr. Joaquin Rapela, Dr. Dario Campagner

## 3 Application questions

### 3.1 Research theme

Word limit: 5 Please state the research theme you are applying under. Choose one of the following research themes:

1. biological informatics
  2. understanding host-microbe interactions
  3. synthetic cells and cellular systems
  4. synthetic microbial communities
- biological informatics

## 1 3.2 Vision

2 Word limit: 500

3 What are you hoping to achieve with your proposed work?

4 What the assessors are looking for in your response

5 Your vision should clearly address:

- 6 • one of the opportunity research themes (biological informatics, under-  
7 standing host-microbe interactions, synthetic cells and cellular systems or  
8 synthetic microbial communities)
- 9 • the remit of the BBSRC and the NSF/BIO division associated with your  
10 chosen research theme

11 References may be included within this section, but this will count towards  
12 your word count.

13 Images are not required for this section.

### 14 3.2.1 Context

15 Conventional systems neuroscience experiments are typically short in duration  
16 and often place significant constraints on subject behavior to simplify data anal-  
17 ysis. However, these restrictions may limit our ability to observe critical aspects  
18 of brain function and behavior that only manifest in more naturalistic and ex-  
19 tended conditions.

20 At the Sainsbury Wellcome Centre (SWC) for Neural Circuits and Be-  
21 haviour, we are pioneering Naturalistic, Long-Duration, and Continual (NaLo-  
22 DuCo) foraging experiments in mice that span weeks to months. During these  
23 extended experiments, we collect high-resolution recordings of both behavioral  
24 and neural activity in naturalistic settings. In collaboration with the Gatsby  
25 Computational Neuroscience Unit (GCNU), we are developing novel analytical  
26 methods to interpret this new class of data.

27 This novel experimental approach will enable researchers to explore neural  
28 mechanisms underlying behavior over extended periods for the first time, of-  
29 fering the possibility of uncovering insights across a wide range of phenomena,  
30 including long-term behavioral adaptation, neural plasticity, and learning. The  
31 data generated from NaLoDuCo experiments represent an entirely new resource  
32 in neuroscience, with the potential to drive breakthroughs and discoveries that  
33 are beyond the reach of traditional experiments.

34 Our vision is to empower research centers worldwide to adopt this ground-  
35 breaking approach. However, the scale and complexity of the data generated  
36 pose significant challenges in data acquisition, visualisation, and analysis. In  
37 this proposal, we will address these challenges, developing and sharing openly  
38 the necessary expertise, hardware, and software to enable this transformative  
39 type of experimentation on a global scale.

### 1 3.2.2 Focus areas

2 Below, we outline the key focus areas we aim to address (Figure 3), along  
3 with their associated challenges. These challenges primarily revolve around the  
4 collection and analysis of continuously recorded, extremely large datasets—on  
5 the order of hundreds of terabytes—gathered from experiments spanning weeks  
6 to months.

7 While experiments in neuroscience that are naturalistic, long-duration, or  
8 continuous have been conducted in the past (e.g., Jhuang et al., 2010; Mao  
9 et al., 2021; Voloh et al., 2023), to the best of our knowledge, we are the first  
10 to integrate all three of these features in a single experimental paradigm. This  
11 combination introduces unprecedented complexities in data processing, as we  
12 aim to capture behavior and brain activity in their most ecologically valid,  
13 extended, and uninterrupted forms.

14 The focus areas of the proposed project are (Figure 3):

15 **Data Collection & Management** Efficiently gathering and organizing mas-  
16 sive datasets over extended periods.

17 **Data Sharing** Providing easy access to large-scale datasets to researchers around  
18 the globe using cloud-based technologies.

19 **Data Visualization** Developing efficient web-based tools to visualize very large  
20 behavioral and neural datasets.

21 **Spike Sorting** Assigning spikes to neurons reliably, and tracking individual  
22 neurons across long-periods of time in real time.

23 **Data Analysis** Evaluating existing methods, and developing new ones, when  
24 necessary, to address key problems in behavioral and neural data analysis  
25 (Figure 2).

26 **Inference-Driven Experimentation** Creating a new type of experimenta-  
27 tion driven by real-time behavioral and neural inferences.

28 These focus areas represent key technical and analytical challenges that, once  
29 addressed, will facilitate a transformative shift in neuroscience research.

## 30 3.3 Approach

31 **Word limit: 500**

32 **How are you going to deliver your proposed work?**

33 **What the assessors are looking for in your response**

34 **Your approach should give an overview highlighting:**

- 35 • a clear description of the objectives and methodology for the proposed
- 36 work, including the contributions of the UK and US teams
- 37 • the potential outputs and outcomes of the proposed work

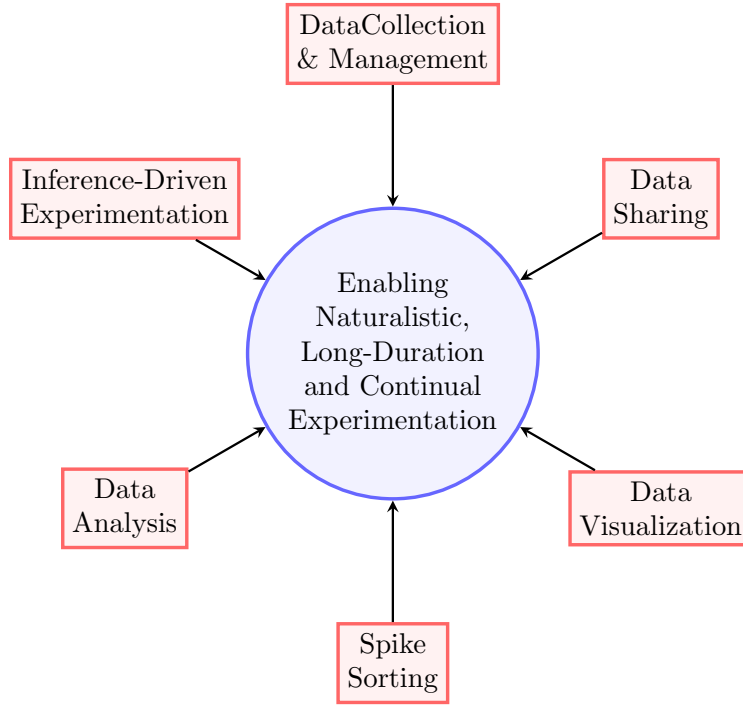


Figure 1: Project theme (blue) and focus areas (red).

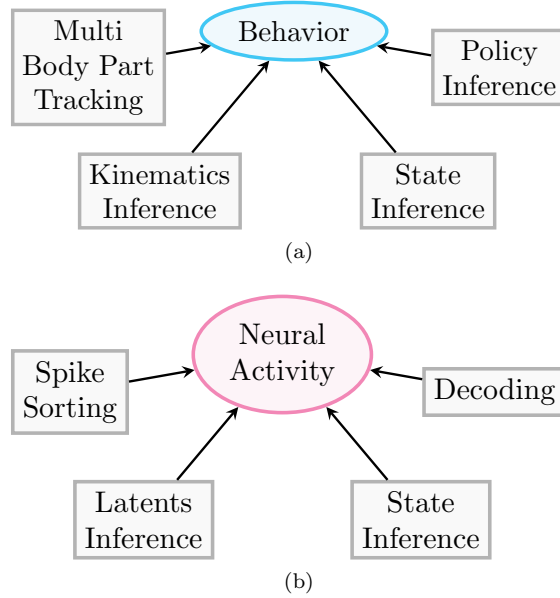


Figure 2: Behavioral (a) and neural (b) data analysis problems to address.

1       References may be included within this section, but this will count towards  
2 your word count.

3       Images are not required for this section.

### 4   **3.4   US applicants**

5   Word limit: 200

6       Please provide the following details of the US applicants on this application:

- 7       1. name
- 8       2. institute
- 9       3. job title
- 10      4. role in project (for example, project lead or project co-lead)
- 11      5. email address

12       Please also indicate who the lead US applicant will be.

13       NSF will use this information to confirm applicant eligibility.

14       Please do not include details of US applicants in the ‘Core team’ section.

### 15   **3.5   Resources**

16   Word limit: 200

17       Please provide the following:

- 18       • overall estimates for costings and staffing full time equivalent (FTE) for  
19       both the UK and US components
- 20       • clear separation of UK and US costings, in pounds sterling and US dollars  
21       (USD) respectively

22       The overall budget should be below the maximum £2 million combined fun-  
23 der contribution

24       If there is more than one UK or US team associated with the application,  
25 please combine their estimates together.

26       A detailed calculation and breakdown of resources is not required at this  
27 stage, nor is a justification of costs.

28       The following is an example of how this might look.

29       UK Resources:

30       Total cost estimate: £600,000

31       Research council contribution: £480,000

32       0.2 FTE time, 1.0 FTE PDRA, 0.5 FTE technician

33       US Resources:

34       Total cost estimate: \$300,000

35       1.0 FTE PDRA or 1.0 FTE doctoral researcher

36       Total funder contribution estimate:

37       £716,475 (£480,000 + £236,475 (\$300,000 at exchange rate 0.79))

## 1 A More details about the vision

### 2 A.1 Context

3 Conventional systems neuroscience experiments are typically short in duration  
4 and often place significant constraints on subject behavior to simplify data anal-  
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40



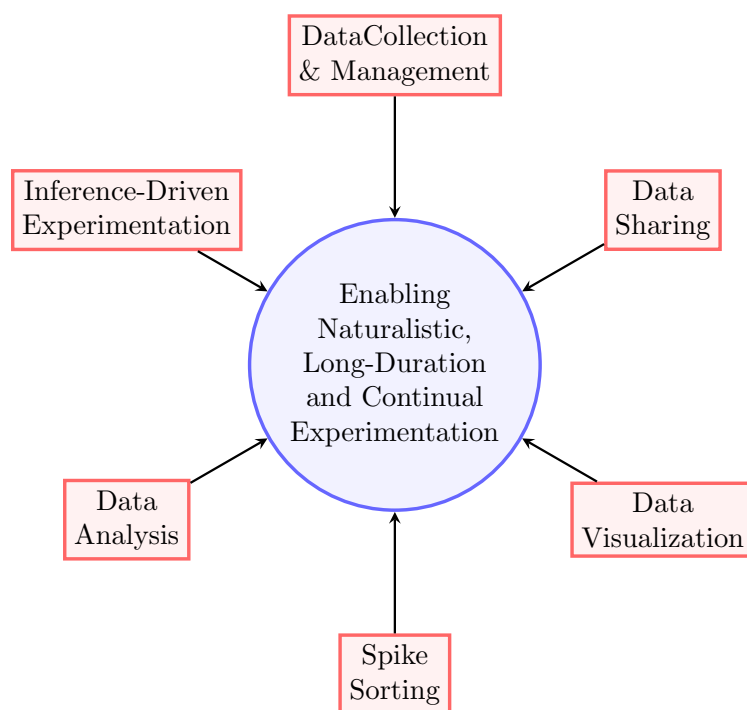


Figure 3: Project theme (blue) and focus areas (red).

### 1 **A.2.1 Data acquisition and management**

2 At the SWC we have already performed foraging experiments in mice contin-  
3 uously collecting behavioral and experimental data 24 hours a day for seven  
4 days. We will share openly the specifications of the hardware used to build  
5 these experiments (e.g., instructions for building large foraging arenas, video  
6 cameras specifications, electrophysiological recording hardware), as well as the  
7 software we used for experimental control, data quality control, data access and  
8 management.

9 The data acquisition and management software used in our project is already  
10 publically available in GitHub<sup>1</sup>. This software is already being used by scientists  
11 at the Allen Institue for Neural Dynamics and at Northwestern University. We  
12 will substantially improve its documentation to simplify its usage by external  
13 users.

14 Challenges related to data acquisition and management include data index-  
15 ing to allow fast access to very large amount of saved data, online quality control  
16 and alert systems to guarantee that anomalies in data collection are detected  
17 and corrected with minimal delay, and synchronization between multiple data  
18 streams.

### 19 **A.2.2 Data dissemination**

20 Datasets of the scale of hundreads of terabytes cannot be practically down-  
21 loaded from data repositories. This is specially true for contiguous experiments  
22 where unique insights are extracted by characterizing full datasets, and not only  
23 parts of them. Therefore, we will store data in DANDI, which uses Amazon S3  
24 buckets, and provide software in Amazon EC2 instances to visualize and analyze  
25 data on the cloud, avoiding costly data transfers. That is, the large dataset sizes  
26 of NaLoDuCo experiments make it impractical to distribute data to users and  
27 require to bring users to data. Fortunately, cloud technologies are now mature  
28 to allows this.

29 Importantly, if we distributed these very large datasets to users, only those  
30 in large research centers would have the computing power to process them. But,  
31 by deploying data and computing in the cloud, any person with Internet access  
32 around the world will be able to benefit from them. Storing large datasets in  
33 DANDI is free.

34 Dr. Ben Ditcher, founder of CatalystNeuro, has played a pivotal role in  
35 supporting the development and operations of the DANDI archive.

### 36 **A.2.3 Data visualisation**

37 Visualisations are essential for scientific discovery. For the proposed project  
38 visualisation present two major challenges. First, they need to display very large  
39 datasets at different temporal scales, from milliseconds to weeks and months.  
40 Second, as data and software will be deployed in the cloud, visualisation need

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<sup>1</sup>[https://github.com/SainsburyWellcomeCentre/aeon\\_mecha](https://github.com/SainsburyWellcomeCentre/aeon_mecha)

1 to be web based. Standard visualization tools cannot display terabyte sized  
2 datasets. We will build custom web-based visualization tools to do this.

3 We have substantial experience building web-based visualization tools for  
4 neurophysiological data. Dr. Jeremy Magland is now developing Neurosift<sup>2</sup> a  
5 web-based visualizer for DANDI datasets.

#### 6 **A.2.4 Spike sorting**

7 When electrodes are placed in the brain, they typically record spikes from mul-  
8 tiple nearby neurons. Spike sorting attributes spikes to individual neurons.

9 Spike sorting is specially challenging for NaLoDuCo experiments. First,  
10 because these experiments require to track individual neurons of freely moving  
11 mice for weeks to months. Second, because spike sorting needs to be done  
12 online, to allow experiments driven by real-time machine learning inference, as  
13 described below.

14 Prof. Sahani pioneered the use of Bayesian inference methods for spike sort-  
15 ing (Sahani, 1999). Dr. Jeremy Magland has significantly advanced the field of  
16 spike sorting, particularly through his development of MountainSort<sup>3</sup> and his  
17 contributions to SpikeInterface<sup>4</sup>.

#### 18 **A.2.5 Data analysis**

19 Advanced data analysis methods are indispensable to extract meaning from  
20 NaLoDuCo experimental data. However, analyzing this data is challenging for  
21 at least three reasons. First, important insights will most probably come from  
22 the characterization of complete datasets, and not from subsets extracted from  
23 them. Conventional batch methods cannot be used with datasets of the size  
24 produced by NaLoDuCo experiments. For instance, for learning, batch linear re-  
25 gression cannot load into memory and invert a data matrix with high-resolution  
26 observations from a one-month-long experiment. Thus, **online methods** that  
27 can process infinite data streams become mandatory.

28 Second, a pervasive assumption in most ML algorithms is stationarity; i.e.,  
29 the assumption that the statistics of data do not change over time. But in long-  
30 duration and continuous experiments this assumption is most often violated  
31 as, for example, the arousal of subjects changes. Hence, the analysis of data  
32 generated by these experiments requires **adaptive methods**.

33 Third, statistical algorithms consist of two key stages: learning (or training)  
34 and inference (or prediction). The learning stage identifies model parameters,  
35 and the inference stage uses the learned model to make predictions, or infer  
36 latent variables, from new unseen data. Frequently training is performed on a  
37 small subset of a dataset, and inference is done on the remaining data. However,  
38 since in long-duration and continual experiments behavior and neural activity  
39 are generally not stationary, it is not optimal to train models on data subsets and

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<sup>2</sup><https://github.com/flatironinstitute/neurosift>

<sup>3</sup><https://github.com/flatironinstitute/mountainsort5>

<sup>4</sup><https://github.com/spikeinterface/spikeinterface>

1 use them to make inferences on the remaining data, since the state of the animal  
2 at training and inference times may be different. To overcome this difficulty we  
3 will use **continual learning methods**.

4 We will evaluate methods to analyze different aspects of behavior and neu-  
5 ral activity (Figure ??). We will test how these methods process very large  
6 datasets, how they handle non-stationary data, and how feasible is to retrain  
7 them to adapt to changing conditions. We will adapt these methods so that they  
8 better address these challenges and, when needed, develop new ones. We will  
9 carefully report the outcomes of these evaluations so that researchers performing  
10 NaLoDuCo experimentation can choose the best methods that suit their needs.

### 11 **A.2.6 Experiments driven by real-time machine learning inference**

12 Small animal experiments are usually controlled by simple static rules or direct  
13 behavioral observations. Funded by a BBSRC award<sup>5</sup> we are developing soft-  
14 ware to allow a new type of experimental control based on statistical inferences  
15 made on behavioral and/or neural measurements.

16 For example, after inferring latent variables from neural activity and observ-  
17 ing that one of these latents have crossed a threshold, we can deliver a reward (as  
18 done in learning to control a BCI; Clancy and Masic-Flogel, 2021), or perform  
19 an action (as done in motor imagery BCI; Lebedev and Nicolelis, 2006), or ma-  
20 nipulate of neural activity (as done when studying the causal relation between a  
21 pattern of brain activity and behavior; Deisseroth, 2015). We propose to further  
22 develop the previous software and use it to test causal effects of neural activity  
23 patterns on foraging decisions using our NaLoDuCo foraging experiments.

24 Building experiments driven by real-time machine learning inferences brings  
25 at least two challenges. The first one is a machine learning problem, how to  
26 build fast inferences that can operate in real time. The second one is a neuro-  
27 science problem, how to identify neuroscience experiments suitable to real-time  
28 control, and then perform the experiment with real-time control. Fortunately  
29 at the Gatsby Unit we are experienced on building advanced machine learning  
30 algorithms to address the first challenge. And at the SWC we perform many so-  
31 phisticated animal experiments that could benefit from real-time experimental  
32 control.

33 In summary, we are pioneering a new paradigm in neuroscience experimen-  
34 tation, driven by advanced inferential methods applied to rich behavioral and  
35 neural recordings. This innovative technology has the potential to transform  
36 the field, enabling experiments that were previously unimaginable. By leverag-  
37 ing these sophisticated inferences, we may unlock new dimensions of knowledge  
38 that could not be achieved through simpler, conventional approaches. This  
39 breakthrough could open doors to insights that redefine our understanding of  
40 brain-behavior relationships.

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<sup>5</sup><https://gow.bbsrc.ukri.org/grants/AwardDetails.aspx?FundingReference=BB%2FW019132%2F1>

## 1   **References**

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3   causally controlled objects. *Neuron*, 109(4):677–689.
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- 11   Mao, D., Avila, E., Caziot, B., Laurens, J., Dickman, J. D., and Angelaki,  
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- 16   Voloh, B., Maisson, D. J.-N., Cervera, R. L., Conover, I., Zambre, M., Hayden,  
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18   cortex of freely moving macaques. *Cell reports*, 42(9).