The MABe22 Benchmarks for Representation Learning of Multi-Agent Behavior

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Abstract

Real-world behavior is often shaped by complex interactions between multiple agents. To scalably study multi-agent behavior, advances in unsupervised and self-supervised learning have enabled a variety of different behavioral representations to be learned from trajectory data. To date, there does not exist a unified set of benchmarks that can enable comparing methods quantitatively and systematically across a broad set of behavior analysis settings. We aim to address this by introducing a large-scale, multi-agent trajectory dataset from real-world behavioral neuroscience experiments that covers a range of behavior analysis tasks. Our dataset consists of trajectory data from common model organisms, with 9.6 million frames of mouse data and 4.4 million frames of fly data, in a variety of experimental settings, such as different strains, lengths of interaction, and optogenetic stimulation. A subset of the frames also consist of expert-annotated behavior labels. Improvements on our dataset corresponds to behavioral representations that work across multiple organisms and is able to capture differences for common behavior analysis tasks.

1 Introduction

The study of behavior in multiple interacting agents is an element of diverse scientific and engineering applications, from designing safer autonomous vehicles [11, 69], to simulating realistic behavior in virtual worlds [25, 28, 83], to understanding the biological underpinnings of neurological disorders [63, 78]. Across disciplines, there is a need for new techniques to characterize the structure of multi-agent behavior with greater precision, sensitivity, and detail. Towards this, many works [45, 30, 67, 5] have made efforts to discover behavioral representations with unsupervised or self-supervised learning, often without manual annotations. To evaluate progress in learning behavioral representations, we introduce a new benchmark of multi-agent behavior in mice and fruit flies, two common model organisms from neuroscience and biology.
Behavioral Representation

Mouse Triplet  Fruit Fly Group
Chase
Strain  Light Cycle
Huddle
…
…
Sequence-level tasks
Frame-level tasks

Figure 1: Overview of MABe2022. We aim to benchmark representation learning for behavior analysis using model organisms across different experimental setups from behavioral neuroscience. Our evaluation procedure consists of a broad range of hidden tasks, such as biological variables (ex: strain), environmental manipulations (ex: optogenetic stimulation), and annotated behaviors (ex: aggression), used to evaluate behavioral representations. In comparison, past behavior analysis datasets usually focus on a specific experimental setup with specific behaviors of interest.

Historically, animal behavior has been investigated by collecting video recordings and producing manual frame-by-frame annotations of animals’ actions, a costly and time-consuming process that has been a bottleneck in behavior analysis. New advances in machine learning and computer vision have more recently enabled the automated tracking and quantification of animal behavior, promising to overcome the annotation bottleneck in behavioral experiments. In scientific domains, the promise of these automated methods has fueled a new interest in long-term, high volume recording of animal behavior.

Still, extracting behavior annotations from behavioral videos or tracked animal poses is not trivial. Due to issues such as cost and subjectivity in obtaining supervised behavior labels, many research groups have studied unsupervised or self-supervised methods to identify animal behavior from trajectory data, without human labels. However, due to a lack of standardized benchmark datasets or metrics in this emerging field, each group typically develops and evaluates methods on its own in-house data: there is no consensus as to what constitute a "good" unsupervised representation of animal pose and movement. As a result, it is difficult to evaluate progress in unsupervised and self-supervised representation learning methods for behavior analysis.

To address this challenge, we have developed a novel dataset and benchmark for representation learning of multi-agent behavior. We take a utilitarian approach that is informed by current common objectives of automated behavior analyses performed in biology and neuroscience. Specifically, our benchmark scores the "quality" of a learned representation of animal behavior in terms of its performance on a gauntlet of downstream tasks, modeled after common scientific applications. Similar evaluation methods has been used in other domains for evaluating visual representations and neural mechanistic models.

We present the 2022 Multi-Agent Behavior (MABe22) Dataset, a dataset of tracked social behavior trajectories using common model organisms in behavioral neuroscience: groups of the vinegar fly Drosophila melanogaster and triplets of laboratory mice Mus musculus. Our initial benchmarking efforts include both standard baseline methods as well as novel methods solicited from the Multi-Agent Behavior Challenge hosted at CVPR 2022, using MABe2022. Improvements of learned representations on our benchmark corresponds to representations that are more discriminative of common behavior analysis tasks, and evaluating on multiple settings and organisms tests the general applicability of the representation learning method.

2 Related Work

Behavior Modeling. Multi-agent behavior modeling is studied across a variety of fields, such as autonomous vehicles, sports analytics, and biology. Recently, in biology and neuroscience, behavioral models have made great progress towards automated behavioral quantification, a task that previously relied on manual effort by domain experts. Computational models of behavior have the potential to significantly reduce human effort and provide more...
detailed descriptions of behavior \[56\]. These models can be used to study the relationship between neural activity and behavior \[46, 63\], characterize behaviors of different species and strains \[27, 45\], and quantify the effect of pharmacological perturbations \[75\].

Both supervised and unsupervised approaches to behavior analysis have been developed. Supervised behavior models are trained to identify human-defined behaviors-of-interest \[8, 29, 63, 66\], often using frame-by-frame behavior annotations from domain experts. Another group of work discovers behaviors without human annotations, using unsupervised and self-supervised methods \[30, 74\], based on learning latent structures from behavioral data. The learned representation may be continuous \[67\], or discrete, such as when discovering behavior motifs \[45, 74\]. There currently does not exist a unified behavioral representation learning dataset that can compare these models across a broad range of behavior analysis settings. Here, we propose a new dataset with multiple organisms and analysis tasks based on scientific applications for evaluating the performance of self-supervised and unsupervised learning methods.

**Representation Learning.** Representation learning for visual \[23, 13, 53, 42, 26\] and trajectory data \[67\] has led to effective representations for a variety of tasks, such as for image classification \[13\], speech recognition \[53\], and behavior classification \[67\]. In these works, many different unsupervised and self-supervised methods have been developed, such as classifying image rotations \[23\], predicting future observations \[53\], contrastive learning with image augmentations \[13\], and decoding programmatic attributes \[67\]. The quality of learned representations is often evaluated on downstream tasks.

For behavior analysis, applications of representation learning include discovering behavior motifs \[5, 45\], identifying internal states \[9\], and improving classification sample-efficiency \[67\]. These works have used methods such as VAEs \[38\], AR-HMMs \[74\], and Umap \[49\] to study the latent structure of behavior. Notably, many groups have proposed methods for unsupervised behavior discovery \[5, 40, 74, 45, 30, 47\]. These works use different methods to model the temporal structure of behavior, such as wavelet transforms \[5\], autoregressive hidden Markov models \[74\], and recurrent neural networks \[45\], as well as different methods for segmenting behavior, such as GMMs \[30\], k-means clustering \[45\], and watershed transforms \[5\]. Our goal is to develop a standardized dataset for evaluating these representation learning models on a common set of behavior analysis tasks.

**Related Datasets.** The goal of our dataset is to benchmark representation learning models for behavior analysis, using data from mice and flies. There are other datasets for studying animal social behavior, including CRIM13 \[8\], Fly vs. Fly \[20\], and CalMS21 \[66\], which contains human-annotated behavior labels with a focus on supervised classification. These datasets often focus on a single organism and setting. While not the focus of our dataset, we note that there are also datasets for multi-animal pose estimation \[48\] and tracking \[55\]. Our dataset instead defines a range of downstream tasks across organisms based on common applications for behavior analysis, in order to evaluate different properties of representation learning models. Current representation learning benchmarks consists of visual representations \[71, 79, 24\] or multi-modal representations \[43\], and to the best of our knowledge, our dataset is the first for studying behavioral representation learning based on a broad set of scientific behavior analysis tasks.

While our dataset is composed of multi-agent data from biology, there are also multi-agent behavior datasets from other domains, such as from autonomous driving \[11, 69\], sports analytics \[77, 15\], and video games \[60, 25\]. These datasets often focus on forecasting, motion planning, and reinforcement learning, whereas our dataset is used for studying representation learning methods based on tasks from scientific applications, such as distinguishing animal strains via observed behaviors.

### 3 Dataset Design and Collection

Our dataset is intended for development and evaluation of new representation learning methods for multi-agent behavior. The agents in our dataset are common model organisms in behavioral neuroscience: mice and flies (Figure 2). We curated 968 30-second clips for flies at 150Hz and 5336 60-second clips for mice at 30Hz, sub-sampled from a larger repository of video data. Agents’ postures and movements in each clip are provided in the form of trajectory data: we track a set of anatomically defined keypoints on each agent (Figure 2(e)), and also track identity across time. Pose estimates are derived from top-view video using either an HRNet-based approach for mouse \[64\] or FlyTracker for flies \[20\].
Figure 2: Video and Tracking for Mouse and Fly. The top and bottom row corresponds to mice triplet and fly group respectively. (a) Example video frame. (b) Video frame superimposed with tracked keypoints. (c) Zoom in of (b). (d) Visualization of the tracked keypoints. (e) The keypoints track anatomical body parts of the agents with 12 keypoints for mouse and 19 keypoints for fly.

Figure 3: Task Subset Label Distribution. Task label distribution on a subset of hidden tasks, where the top row corresponds to mouse and bottom row corresponds to fly. Note that the task distribution for fly is computed only for frames where the task is applicable (ex: frames from other lines are ignored for classifying pC1D activation). The full task set is available in the Appendix.

For each dataset, we constructed a collection of hidden labels, with 13 for mice and 50 for flies (Figure 3). These labels include manual or semi-automated behavior annotations as well as experimental setup in a particular video that we expect to have an effect on animal behavior. Examples of tasks include biological variables (e.g. animal sex or strain), experimental manipulations (e.g. optogenetic stimulation of a population of neurons known to elicit a behavior), or environmental variables (e.g. light cycle, habituation to an environment, or time of day). These hidden labels are defined either at the sequence level (one label per sequence, as in the case of animal strain) or at the frame level (one label per frame, as in the case of behavior annotations).

For the purpose of establishing a benchmark, we defined a "good" learned representation of animal behavior as one from which we can decode these biologically meaningful hidden labels. Specifically, given a learned representation of each frame of a dataset, we trained a linear classifier to predict, for each frame, the value of each hidden label given the representation of that frame. Importantly, hidden labels are not used during training the representation learning model itself.

To encourage exploration of different representation learning methods, our evaluation procedure does not have requirements on the method or form of the learned representation, aside from placing an upper limit on the dimensionality of the representation of each frame (128 for mice and 256 for flies, where there were more agents present).

3.1 Mouse Social Interactions

Data Description. The mouse dataset consists of a set of trajectories from three interacting mice, recorded from an overhead camera in an open field measuring 52cm x 52cm, with a grate located at the northern wall of the arena giving access to food and water. Animals were introduced to the arena one by one over the first ten minutes of recording, and were recorded continuously for four days at
a framerate of 30Hz and camera resolution of 800 x 800 pixels. Illumination was provided by an overhead light on a 24-hour reverse light cycle (lights off during the day and on at night); mice are nocturnal, and thus are most active during the dark. Behavior was recorded using an IR-pass filter so that light status could not be detected by eye in the recorded videos.

The pose estimation model [64] is based on HRNet [68] with an identity embedding network to track long-term identity (see Appendix). Similar mouse datasets have been used for studies in neuroscience, pharmacology, and biomechanics, for example in quantifying gait differences across strains [64], effects of pharmacological manipulation [75], and the relationship between neural activity and behavior [46]. For similar datasets in single animals, representation learning methods have been shown to produce behavior motifs that agree with human-identifiable animal actions [45, 74], thus increasing quantitative precision and resolution and reducing human effort for behavior analysis. These models can also help create data-efficient classifiers for supervised behavior analysis [67].

Tasks. The representations on the mouse dataset are evaluated on a set of 13 tasks that capture information about animal background, environment, and behavior. These tasks were selected based on their relevance to common scientific applications such as identifying the behavioral effects of differences in animals’ genetic backgrounds or experimenter-imposed changes in their environment. In this dataset, we examined capacity of learned representations to determine animal strain, as well as environmental factors such as whether room lights were on or off (a proxy for day/night cycles, which modulate animal behavior). We also included two tasks to predict the day of the trajectory relative to the start of recording (animal behavior changes across days as they habituate to a new environment [41]), and the time of day of the trajectory (animal behavior changes over the course of a day, driven by circadian rhythms.)

A learned representation of behavior should also be rich enough to recapitulate human-produced labels of animals’ moment-to-moment actions. Therefore our evaluation tasks include detection of specific behaviors, such as bouts of chasing between mice, or periods of huddling. These behaviors were annotated programatically, using heuristics generated by trained human experts: for example, chasing is defined as periods when two animals are within a distance D, moving at a speed of at least S, for a duration of at least T frames, with no fewer than G "gap" frames in that duration that do not meet distance and speed criteria. A full description of each behavior is provided in the Appendix.

The majority of tasks are binary classification problems, such as distinguishing between two strains of mice or detecting the presence or absence of a given behavior. The two exceptions, the day of recording task and the time of day task are regression problems. Because we observed occasional identity swaps between mice in the tracking dataset, behavior-based tasks were not animal-specific, but rather were based on detecting whether a given behavior was occurring at all.

3.2 Fly Social Interactions

Data Description. The dataset consists of trajectories of groups of \( \approx 10 \) *Drosophila melanogaster* interacting in a 5cm-diameter dish. The trajectories were derived from 96 videos of length 50k-75k frames, collected at 1024x1024 pixels and 150 frames per second. The flies’ bodies and wings are tracked using FlyTracker [20] and landmarks on body were tracked using the Animal Part Tracker (APT) [34] for a total of 19 points (Figure 2).

Similar to mice, flies are also often used as a model organism in neuroscience [59], genetics [65], pharmacology [34], and biomechanics [70] studies. Unsupervised methods to study latent structure in fly behavior [5, 4] have provided insights into the organization of fly movements and stereotyped structure of behavior. Learned representations can also lead to more data-efficient classifiers [67].

As the brain controls behavior, a good representation of behavior should change with neural activity. Thanks to its tractable genetics, precise neural activity manipulations are straightforward for Drosophila. We thus chose to perform experiments using optogenetic (light activated, via Chrimson) [39] and thermogenetic (heat activated, via TrpA) [59] activation of selected sets of neurons. We chose neurons (and the associated GAL4 lines) previously identified as controlling social behaviors including courtship, avoidance [59], and female aggression [61]. For thermogenetic experiments, neural activation is constant and continuous for the entire video. Our optogenetic experiments consisted of activation for short periods of time at weak and strong intensities interspersed with periods of no activation (see Appendix). We combined these neural manipulations with genetic mutations.
and rearing conditions. Specifically, we selected populations of flies with the norpA mutation which induces blindness [6], and either raised groups of flies together, or separated by sex.

Tasks. The representations on the fly dataset are evaluated on a set of 50 tasks. Many of these tasks differentiate which populations of neurons are activated, and how they are activated. For example, Task 5 compares groups of 5 female and male flies for which courtship neurons targeted by the R71G01 GAL4 line to all other fly types. Task 31 compares how neurons were activated – it compares strong and weak activation of aIPg neurons, which regulate female aggression. Besides neural activation, tasks also differentiate flies based on sex, how the flies were raised, which strain they are from, and genetic mutations. A full list of tasks and the types of flies used is in the Appendix.

Each task is based on binary classification. For some frames, the task was irrelevant, and we indicated these frames by setting the task annotation to nan, meaning no data. These frames were not used in evaluation for the task. When comparing across fly lines, we only used frames during activation periods, and frames outside of activation periods were set to nan. For comparing behavior during activation (lights on) periods to not activation (lights off) periods for a given line, the task was nan for all other lines. Videos were either of ≈ 5 males and ≈ 5 females or ≈ 10 females. Mixed sex flies were either raised together or separately. A full list of the types of comparisons is in the Appendix.

Besides biological differences, we also include tasks based on manual annotations of the flies’ behavior for the following social behaviors: any aggressive behavior toward another fly, chasing another fly, any courtship behavior toward another fly, high fencing, wing extension, and wing flick. We annotated behaviors sparsely across all videos with human experts using JAABA [35], with the goal of including annotations in a wide variety of flies and videos.

4 Benchmarks on MABe2022

We develop an initial benchmark based on standard sequence representation learning methods, as well as include top performing methods on our dataset from the MABe Challenge at CVPR 2022. We outline our evaluation procedure on the set of behavior analysis tasks (Section 4.1), describe benchmark models (Section 4.2), then present results on the set of hidden tasks (Section 4.3).

4.1 Evaluation Procedure

From an input sequence of trajectory data of $N$ frames ($N=1800$ for mice and 4500 for flies), we evaluate models that produce learned representations of size $N \times D$, where $D$ is the dimensionality of the representations. We evaluate the performance of the representations on our set of hidden downstream tasks using a linear classification or regression protocol (Figure 4).

Evaluation tasks are either frame-level, with one label per frame (such as whether a behavior is occurring), or sequence-level, with one label per sequence (such as whether the lights are off or on). For all hidden tasks, we train a linear model using the representation to predict task labels on each frame. To produce an overall evaluation of each model, we averaged performance (computed as the F1 Score, the harmonic mean of Precision and Recall) across classifiers. For two tasks in the mouse dataset (time of day and day of experiment), performance was instead computed in terms of the mean squared error between predicted and actual times.
4.2 Benchmark Models

We benchmark using PCA and TVAE as standard sequence representation learning methods, and T-BERT, T-Perceiver, T-GPT, and T-PointNet based on the top performing models at the MABe2022 challenge. During model development for the challenge, participants had access to unlabelled trajectories in both train and test splits, with most of the downstream tasks hidden and a few publicly available tasks on the train split for validation - two tasks for mice and three for flies (see Appendix).

While most methods were evaluated on both mouse and fly datasets, T-BERT and T-PointNet were only evaluated on the mouse dataset, due to their reliance on hand-crafted features that were designed for the mouse data, and due to the infeasibility of scaling the models to larger number of agents (8-11 flies vs 3 mice). More implementation details of each model are in the Appendix.

- **Base**: A simple baseline model that always predicts the mean (for regression tasks) or always predicts positive (for classification tasks).

- **PCA**: We perform a frame-wise PCA as a simple baseline. Principal components were computed from the centered and normalized pose of each mouse, or from the centered pose of each fly and its two nearest neighbors, giving a 60-dim representation for mouse and 253-dim representation for fly.

- **TVAE**: As a second baseline, we use a trajectory VAE [14], where the encoder and decoder are both recurrent neural networks trained to reconstruct short fixed-length snippets of pose data called "trajectories". Each timestep in one trajectory consists of the agent poses (stacked for mice, individually embedded for fly), and a trajectory length of \( T = 21 \) frames was used for each species. This trajectory is embedded to a representation of dimension 32 for mice, and 121 for flies.

- **T-Perceiver**: We adapt the Perceiver model [32] to map a \( T = 512 \) sequence of trajectory features to 128-dim for mouse and 256-dim for fly at each frame. First, high-dimensional hand-crafted features are extracted from the trajectory data, then the features are compressed to the final embedding size using a shallow neural network before feeding into the Perceiver model. The model is trained on (1) masked modeling where up to 80% of the sequence is masked and predicted to recover the high-dimensional features, and (2) using the two publicly available tasks in each domain as additional supervision.

- **T-GPT**: We adapt GPT [7] for trajectory modeling using keypoint sequences stacked over all agents of length of \( T = 50 \). The embedding after the transformer layers is 128-dim for mouse and 256-dim for fly with a shallow decoder to train using the next frame prediction task. This task minimizes the difference between the keypoint coordinates of the prediction and the next frame given past frames, and is run both forwards and backwards in time.

- **T-PointNet**: We model trajectory features using PointNet [58]: 10 hand-crafted features similar to [67] are computed based on mouse pairs, where each pair is treated as a “point”, and embedded using PointNet. The model is trained using cosine similarity loss, where similar examples are from the same video clip while different examples are from random clips. The PointNet embeddings is concatenated with the PCA of agent poses and individual mouse features. The final embedding size is 59-dim per frame for mouse.

- **T-BERT**: We extend BERT [17] to learn separate embeddings (42-dim on mouse) for each agent, which are then concatenated for the group embedding (126-dim on mouse) used for evaluation. The input to BERT is a trajectory of length \( T = 80 \), where the trajectory and features of single agents is combined in time using a [SEP] token between each agent. We train the model using four tasks: (1) masked modeling where 70% of the sequence is masked and predicted by BERT; (2) hand-crafted feature predictions similar to that of [67]; (3) contrastive learning using positives from the same video clip, (4) the publicly available “chase” annotations.

4.3 Behavioral Representation Results

Taking into account all tasks across both datasets, the current best performing models are based on transformer architectures (Table 1). These models (T-GPT, T-Perceiver, T-BERT) generally outperform the TVAE, which is based on an RNN architecture. Interestingly, T-PointNet, which
All F1 Frame F1 Sequence F1 | All F1 Frame F1 Sequence F1
---|---|---|---|---|---|---
Base | 0.943 ± 0.000 | 0.161 ± 0.001 | 0.121 ± 0.001 | 0.531 ± 0.002 | 0.425 ± 0.004 | 0.230 ± 0.002 | 0.452 ± 0.005
PCA | 0.942 ± 0.001 | 0.227 ± 0.001 | 0.155 ± 0.001 | 0.549 ± 0.003 | 0.370 ± 0.009 | 0.222 ± 0.011 | 0.390 ± 0.009
T-Perceiver | 0.933 ± 0.004 | 0.271 ± 0.005 | 0.176 ± 0.004 | 0.697 ± 0.009 | 0.448 ± 0.012 | 0.197 ± 0.018 | 0.482 ± 0.014
T-GPT | 0.933 ± 0.002 | 0.274 ± 0.002 | 0.191 ± 0.002 | 0.649 ± 0.004 | 0.458 ± 0.005 | 0.245 ± 0.014 | 0.487 ± 0.005
T-PointNet | 0.930 ± 0.001 | 0.282 ± 0.001 | 0.196 ± 0.002 | 0.666 ± 0.002 | - | - | -
T-BERT | 0.927 ± 0.003 | 0.297 ± 0.004 | 0.199 ± 0.002 | 0.737 ± 0.013 | - | - | -

Table 1: MABe2022 Benchmark Results. Task-averaged MSE and F1 score are from mean and standard deviation over five runs. We additionally average over only sequence-level or only frame-level tasks. The best performing model is in bold.

Figure 5: Correlation between Performance and Training Amount. We plot the amount of positive training examples in each task compared to test performance in terms of F1 error. We show all classification tasks for mouse and sequence level classification tasks for fly, due to many frame level fly tasks with < 1000 frames in the training split. The dotted line represents the line of best fit for each model.

models trajectory features using point clouds, is competitive on the mouse triplet data. Further work to extend this model to account for more agents could improve its fly group performance. For both mouse and fly, PCA performance was very close to the Base model. However in both cases, the top performing model showed a significant improvement in performance, demonstrating that we can learn representations that improve behavior analysis performance, even without knowledge of the downstream evaluation tasks.

All models perform better on sequence-level tasks than frame-level tasks. This is likely due to the rarity of many behaviors, as shown in Figure 3. Frame-level tasks are also more difficult due to the greater need to capture local temporal information. To test for a correlation between number of positive training frames and the model performance, we plotted the two against each other (Figure 5), and instead found a trend of decreasing error with an increase in the number of training samples for the visualized models. Representations that can further improve data efficiency of downstream classifiers or better capture local temporal information could help improve the performance of tasks in low data regimes.

5 Discussion

Benchmarks have facilitated research in machine learning and computer vision for decades, such as for image classification [16], 3D human pose estimation [31], and human action recognition [36]. Benchmarks establish consensus metrics and datasets with which different methods can be compared; they also help focus research efforts on a defined question of interest, in order to identify the critical challenges in a field, and areas where collection of additional data could lead to model improvement. While there is a growing adoption of machine learning tools for quantification of animal behavior in the biological sciences, there does not exist a unified benchmark in the field to facilitate method development and quantitative evaluation across a broad range of behavior analysis tasks.

To address these limitations, we have introduced MABe2022, a novel multi-agent behavior dataset and benchmark for studying representation learning. We additionally benchmark four top-performing
models identified via a competition hosted at CVPR 2022, which substantially outperform simple PCA or VAE-based baselines. However, there is still room for improvement on hidden evaluation tasks, particularly for detection of labels in low data regimes and frame-level behaviors. We note that frame-level tasks are generally rare compared to sequence-level tasks, and so learning representations that can faithfully capture rare events may present a key challenge for future method development.

Interestingly, three out of the four top models make use of transformer networks. Transformers have seen widespread use in natural language processing and more recently, in modeling visual tasks. Though different in form from multi-animal trajectories, language is also sequential and is ultimately another kind of social behavior. While transformers have not been widely used in behavioral sciences, these results suggest that they may be worth further exploration in the field.

Limitations and Next Steps. The current dataset focuses on analysis of animal pose in terms of anatomically defined keypoints. However, in some applications, pose estimates are not available or may not adequately capture information about behavior. A second round of our competition is currently under way, to determine whether the methods that perform best on pose data will also dominate in datasets of behavioral videos. Our competition has focused on animal behavior on a specific temporal and spatial resolution, in top-view videos with limited occlusion between animals. Other settings to consider for future work include more complex environments, additional types of agents (such as other organisms or autonomous vehicles), and three-dimensional pose tracking.

Broader impact. While the "quality" of a learned representation will ultimately depend the downstream use, we provide a resource for general assessment of representation utility by scoring learned representations on a large array of hidden tasks, based on common scientific applications. We note that methods that perform best on our benchmark are not guaranteed to be the best choice for all possible downstream uses of representation learning. Our goal is to provide a unified set of tasks across a range of behavior analysis settings that can enable quantitative comparison of representation learning methods, in order to facilitate research and method development for quantitative behavior analysis. Additionally, we value any input from the community on MABe2022 and benchmarking behavior models; you can reach us at mabe.workshop@gmail.com.

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Appendix for MABe2022

The sections of our appendix are organized as follows:

- **Section A** contains dataset hosting and licensing information.
- **Section B** contains dataset documentation and intended uses for MABe2022, following the format of the Datasheet for Datasets[21].
- **Section C** describes the data format (.npy).
- **Section D** and **Section E** describe how mouse and fly behavior data was recorded and processed respectively.
- **Section F** shows the evaluation metrics for MABe2022, namely the F1 score and Mean Squared Error.
- **Section G** contains additional implementation details of our models.
- **Section I** addresses benchmark model reproducibility, following the format of the ML Reproducibility Checklist[57].

A  MABe2022 Hosting and Licensing

The MABe2022 dataset is available at https://data.caltech.edu/records/20186 (DOI: https://doi.org/10.22002/D1.20186), and is distributed under a CreativeCommons Attribution/Non-Commercial/Share-Alike license (CC-BY-NC-SA).

MABe2022 is hosted via the Caltech Research Data Repository at data.caltech.edu. This is a static dataset, meaning that any changes (such as new tasks, new experimental data, or improvements to pose estimates) will be released as a new entity; these updates will typically accompany new iterations of the MABe Challenge. News of any such updates will be posted to the dataset website https://sites.google.com/view/computational-behavior/our-datasets/mabe2022-dataset and on the data repository page at https://data.caltech.edu/records/20186.

Code for all benchmarked models are available in Section H.

B  MABe2022 Documentation and Intended Uses

This section follows the format of the Datasheet for Datasets[21].

B.1  Mouse Triplet Datasheet

| Motivation |
|------------|

**For what purpose was the dataset created?** Was there a specific task in mind? Was there a specific gap that needed to be filled? Please provide a description.

Automated animal pose estimation has become an increasingly popular tool in the neuroscience community, fueled by the publication of several easy-to-train animal pose estimation systems. Building on these pose estimation tools, pose-based approaches to supervised or unsupervised analysis of animal behavior are currently an area of active research. New computational approaches for automated behavior analysis are probing the detailed temporal structure of animal behavior, its relationship to the brain, and how both brain and behavior are altered in conditions such as Parkinson’s, PTSD, Alzheimer’s, and autism spectrum disorders. Due to a lack of publicly available animal behavior datasets, most new behavior analysis tools are evaluated on their own in-house data. There are no established community standards by which behavior analysis tools are evaluated, and it is unclear how well available software can be expected to perform in new conditions, particularly in cases where training data is limited. Labs looking to incorporate these tools in their experimental pipelines therefore
often struggle to evaluate available analysis options, and can waste significant effort training and testing multiple systems without knowing what results to expect.

The Multi-Agent Behavior 2022 (MABe22) dataset is a new pair of animal tracking, pose, and behavior datasets, intended to serve as a benchmark dataset for evaluation of unsupervised/self-supervised behavior representation learning and discovery methods. This datasheet is specific to the Mouse Triplets dataset, which consists of snippets of tracking and pose data from triplets of interacting mice. Accompanying the tracking data is a collection of 13 “hidden labels”: for each video frame of the dataset, we provide annotations of animal strain, time of day, light cycle, and a set of behaviors. These hidden labels can be used to evaluate the quality of learned representations of animal behavior, by asking how well the information they represent can be decoded from a given representation.

Who created this dataset (e.g., which team, research group) and on behalf of which entity (e.g., company, institution, organization)?

The MABe22 Mouse Triplets dataset was collected and analyzed in the laboratory of Vivek Kumar at Jackson Labs (JAX), and was assembled by Ann Kennedy at Northwestern University. Mice were bred and videos of interacting mice were collected by Tom Sproule at JAX. The video dataset was tracked, and behavior annotations algorithmically generated, by Brian Geuther and Keith Sheppard at JAX, with pose estimation performed using a modified version of HRnet described in [64]. Tracking and video data were screened for tracking quality and segmented into one-minute “sequences” by Ann Kennedy. The evaluation tasks were designed by Ann Kennedy using behavior annotations generated by Brian Geuther and Keith Sheppard.

Who funded the creation of the dataset? If there is an associated grant, please provide the name of the grantor and the grant name and number.

Acquisition of behavioral data was supported by NIH grants DA041668 (NIDA), DA048034 (NIDA), and Simons Foundation SFARI Director’s Award (to VK). Curation of data task design was funded by NIMH award #R00MH117264 (to AK) and NSERC Award #PGSD3-532647-2019 (to JJS).

Any other comments?

None.

Composition

What do the instances that comprise the dataset represent (e.g., documents, photos, people, countries)? Are there multiple types of instances (e.g., movies, users, and ratings; people and interactions between them; nodes and edges)? Please provide a description.

The core element of this dataset, called a sequence, captures the tracked postures and actions of three mice interacting in a 52cm x 52cm arena, filmed from above at 30Hz. All three mice are adult males from the same strain, namely C57Bl/6J or BTBR. Postures of animals are estimated in terms of a set of twelve anatomically defined “keypoints” that capture the detailed 2d pose of the animal. Because the three mice are indistinguishable, temporal filtering methods are used to track the identity of animals across frames. Because both of these processing steps are automated, some errors in pose estimation or swaps of mouse identity do occur in the dataset.

Accompanying each sequence are frame-by-frame annotations for 13 “hidden tasks” capturing experimental conditions, animal background, and animal behavior. The 13 hidden tasks for this dataset include four “sequence-level” tasks where annotation values are the same for all frames in a one-minute sequence, and nine “frame-level” tasks where annotation values vary from frame to frame. Descriptions of each task are provided in Table 2; all behaviors are defined between any given pair of animals.

The core element of a sequence is called a frame; this refers to the posture of the three animals on a particular frame of video, as well as annotations for the 13 hidden tasks.

How many instances are there in total (of each type, if appropriate)?

This dataset is composed of 5336 one-minute-long sequences filmed at 30 Hz.

Does the dataset contain all possible instances or is it a sample (not necessarily random) of instances from a larger set? If the dataset is a sample, then what is the larger set? Is the sample representative of the larger set (e.g., geographic coverage)?

This dataset is composed of 5336 one-minute-long sequences filmed at 30 Hz.
| Task Name              | Type   | Values | Description                                                                                                                                 |
|-----------------------|--------|--------|--------------------------------------------------------------------------------------------------------------------------------------------|
| Experiment day        | Sequence | 1-4    | Mice were filmed interacting for four days after introduction to a new arena; task is to determine which day a sequence comes from.          |
| Time of day           | Sequence | 0-1440 | Mice show circadian changes in their level of activity; task is to infer time of day from behavior.                                         |
| Strain                | Sequence | 0 or 1 | Mice are from either C57Bl/6J or BTBR genetic background. Strain field is 1 for BTBR and 0 for C57Bl/6J.                                   |
| Lights                | Sequence | 0 or 1 | Mice are more active when the lights are off, which occurs between 6am and 6pm; task is to infer light condition from behavior.            |
| Approach              | Frame   | 0 or 1 | Mice move from at least 5 cm apart to less than 1 cm apart at closest point, over a period of at least 10 seconds at a maximum speed of 2 cm/sec. |
| Chase                 | Frame   | 0 or 1 | Mice are moving above 15 cm/sec, with closest points less than 5 cm apart, and angular deviation between mice is less than 30 degrees, for at least 80% of frames within at least one second. Merge bouts less than 0.5 seconds apart. |
| Close                 | Frame   | 0 or 1 | Closest points of mice are less than 3 cm apart. Merge bouts less than 2 seconds apart.                                               |
| Contact               | Frame   | 0 or 1 | Closest points of mice are less than 1 cm apart. Merge bouts less than 2 seconds apart.                                               |
| Huddle                | Frame   | 0 or 1 | Closest points of mice are less than 1 cm apart for at least 10 seconds, during which mice show less than 3 cm displacement. Merge bouts less than 2 seconds apart. |
| Oral-ear contact      | Frame   | 0 or 1 | Nose and ear of mice are less than 1.5 cm apart for at least 50% of frames within a window of 0.25 seconds or more. Must occur less than 5 seconds after an approach. Merge bouts less than 0.5 seconds apart. |
| Oral-genital contact  | Frame   | 0 or 1 | Nose and tail base of mice are less than 1.5 cm apart for at least 50% of frames within a window of 0.25 seconds or more. Must occur less than 5 seconds after an approach. Merge bouts less than 0.5 seconds apart. |
| Oral-oral contact     | Frame   | 0 or 1 | Noses of mice are less than 1.5 cm apart for at least 50% of frames within a window of 0.25 seconds or more. Must occur less than 5 seconds after an approach. Merge bouts less than 0.5 seconds apart. |
| Watching              | Frame   | 0 or 1 | Mice are more than 5 cm apart but less than 20 cm apart, and gaze offset of one mouse is less than 15 degrees from body of other mouse, for a minimum duration of 3 seconds. Merge bouts less than 0.5 seconds apart. |

Table 2: Format of hidden tasks for mouse dataset.

The dataset is derived from a larger experiment, in which three mice were allowed to freely interact in an open arena for a period of four days. Videos were recorded from an overhead camera in an open field measuring 52 cm x 52 cm, with a grate located at the northern wall of the arena giving access to food and water. Animals were introduced to the arena one by one over the first ten minutes of recording, and were recorded continuously for four days at a framerate of 30 Hz and camera resolution of 800 x 800 pixels.

To generate the trajectories used for this dataset, we randomly sampled up to five one-minute intervals from each recorded hour of approximately 12 such four-day experiments. In initial sampling, we observed that during the lights-on phase of the light/dark cycle the mice spent the majority of the time huddled together sleeping. As this does not generate particularly interesting behavioral data, we randomly discarded 80% of sampled one-minute intervals in which no substantial movement of the animals occurred, and replaced these with substitute samples drawn from the same one-hour time period. If after five attempts we could not randomly draw a replacement...
sample containing movement, we omitted the trajectory from the dataset. As a result, the dataset contains a higher proportion of trajectories with movement than is present in the source videos, and a slightly lower proportion of trajectories sampled from the light portion of the light/dark cycle.

**What data does each instance consist of?** “Raw” data (e.g., unprocessed text or images) or features? In either case, please provide a description.

Each sequence has two elements. 1) **Keypoints** are the locations of twelve body parts on each mouse: the nose tip, left and right ears, base of neck, body centroid, base, middle, and tip of tail, and the four paws. Keypoints are estimated using a modified version of HRnet documented in [64]. 2) **Annotations** are sequence-level or frame-level labels of experimental conditions or animal’s actions. Definitions of these annotations are provided in Table 3. The behavior labels were generated using a series of short scripts based on features of detected animal poses; it is therefore possible that some mis-identification of behaviors occurs.

Note that this dataset does not include the original raw videos from which pose estimates were produced. This is because the objective of releasing this dataset was to determine the accuracy with which animal behavior could be detected using tracked keypoints alone.

**Is there a label or target associated with each instance?** If so, please provide a description.

Yes: each annotation (as described above) is provided for every frame in the dataset.

**Is any information missing from individual instances?** If so, please provide a description, explaining why this information is missing (e.g., because it was unavailable). This does not include intentionally removed information, but might include, e.g., redacted text.

There is no missing data.

**Are relationships between individual instances made explicit (e.g., users’ movie ratings, social network links)?** If so, please describe how these relationships are made explicit.

Each instance (sequence) is to be treated as an independent observation with no relationship to other instances in the dataset. Although the identities of the interacting animals are the same in some sequences, this information is not tracked in the dataset.

**Are there recommended data splits (e.g., training, development/validation, testing)?** If so, please provide a description of these splits, explaining the rationale behind them.

The dataset includes a recommended train/test split which was used for the Multi-Agent Behavior Challenge. Data was randomly split into training, test, and private-test sets (where the private test set was withheld from challenge evaluation until the end of the competition period, to avoid overfitting.)

**Are there any errors, sources of noise, or redundancies in the dataset?** If so, please provide a description.

Pose keypoints in this dataset are produced using automated pose estimation software. The dataset was screened to remove sequences with poor pose estimation, detected as large jumps in the detected location of an animal, however some errors in pose estimation, missing keypoints, and noise in keypoint placement still occur. These are most common on frames when the two animals are in close contact or moving very quickly.

Frame-by-frame annotations of behavior were generated using a series of scripts that were manually tuned by a human expert. Pose estimation errors can contribute to missed bouts or false positives for behaviors in these annotations.

**Is the dataset self-contained, or does it link to or otherwise rely on external resources (e.g., websites, tweets, other datasets)?** If it links to or relies on external resources, a) are there guarantees that they will exist, and remain constant, over time; b) are there official archival versions of the complete dataset (i.e., including the external resources as they existed at the time the dataset was created); c) are there any restrictions (e.g., licenses, fees) associated with any of the external resources that might apply to a future user? Please provide descriptions of all external resources and any restrictions associated with them, as well as links or other access points, as appropriate.

The dataset is self-contained.

**Does the dataset contain data that might be considered confidential (e.g., data that is protected by legal privilege or by doctor-patient confidentiality, data that includes the content of individuals non-public communications)?** If so, please provide a description.
No.

Does the dataset contain data that, if viewed directly, might be offensive, insulting, threatening, or might otherwise cause anxiety? If so, please describe why.

No such material; dataset contains only tracked posture keypoints (no video or images) and text labels pertaining to mouse social behaviors.

Does the dataset relate to people? If not, you may skip the remaining questions in this section.

No.

Does the dataset identify any subpopulations (e.g., by age, gender)? If so, please describe how these subpopulations are identified and provide a description of their respective distributions within the dataset.

n/a

Is it possible to identify individuals (i.e., one or more natural persons), either directly or indirectly (i.e., in combination with other data) from the dataset? If so, please describe how.

n/a

Does the dataset contain data that might be considered sensitive in any way (e.g., data that reveals racial or ethnic origins, sexual orientations, religious beliefs, political opinions or union memberships, or locations; financial or health data; biometric or genetic data; forms of government identification, such as social security numbers; criminal history)? If so, please provide a description.

n/a

Any other comments?

None.

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### Collection Process

**How was the data associated with each instance acquired?** Was the data directly observable (e.g., raw text, movie ratings), reported by subjects (e.g., survey responses), or indirectly inferred/derived from other data (e.g., part-of-speech tags, model-based guesses for age or language)? If data was reported by subjects or indirectly inferred/derived from other data, was the data validated/verified? If so, please describe how.

Sequences in the dataset are derived from video of triplets of socially interacting mice in an open arena. Video data was processed to extract pose estimates and track identity of the animals, and to generate automated annotations of several behaviors of interest, included in the hidden labels in this dataset.

**What mechanisms or procedures were used to collect the data (e.g., hardware apparatus or sensor, manual human curation, software program, software API)? How were these mechanisms or procedures validated?**

Behavioral data was collected in the JAX Animal Behavior System [3]. Video was recorded at 30Hz using a Basler acA1300-75gm camera with Tamron 4-12mm lens and 800nm longpass filter to exclude visible light. The camera was mounted 105+/−5 cm above the arena floor. Pose estimation was performed using a modified version of HRnet documented in [64]. Automated annotation was performed using custom python scripts created by trained human experts.

**If the dataset is a sample from a larger set, what was the sampling strategy (e.g., deterministic, probabilistic with specific sampling probabilities)?**

Repeated from a previous section: to generate the trajectories used for this dataset, we randomly sampled up to five one-minute intervals from each recorded hour of approximately 12 such four-day experiments. In initial sampling, we observed that during the lights-on phase of the light/dark cycle the mice spent the majority of the time huddled together sleeping. As this does not generate particularly interesting behavioral data, we randomly discarded 80% of sampled one-minute intervals in which no substantial movement of the animals occurred, and replaced these with substitute samples drawn from the same one-hour time period. If after five attempts we could
not randomly draw a replacement sample containing movement, we omitted the trajectory from the dataset. As a result, the dataset contains a higher proportion of trajectories with movement than is present in the source videos, and a slightly lower proportion of trajectories sampled from the light portion of the light/dark cycle.

**Who was involved in the data collection process (e.g., students, crowdworkers, contractors) and how were they compensated (e.g., how much were crowdworkers paid)?**

Behavioral data collection and annotation was performed by graduate student, postdoc, and technician members of the Kumar lab at Jackson Laboratories, as a part of another ongoing research project studying animal gait and behavior. (No videos or annotations were explicitly generated for this dataset release.) Lab members are full-time employees of Jackson Labs, and their compensation was not dependent on their participation in this project.

**Over what timeframe was the data collected? Does this timeframe match the creation timeframe of the data associated with the instances (e.g., recent crawl of old news articles)?** If not, please describe the timeframe in which the data associated with the instances was created.

Source experiments associated with this dataset were performed in 2019, with pose estimation and automated annotation performed in 2019-2020. This dataset was assembled from December 2021 - March 2022.

**Were any ethical review processes conducted (e.g., by an institutional review board)?** If so, please provide a description of these review processes, including the outcomes, as well as a link or other access point to any supporting documentation.

All experiments included here were performed in accordance with NIH guidelines and approved by the Institutional Animal Care and Use Committee (IACUC) and Institutional Biosafety Committee at Jackson Labs. Review of experimental design by the IACUC follows the steps outlined in the NIH-published Guide for the Care and Use of Laboratory Animals. All individuals performing behavioral experiments underwent animal safety training prior to data collection. Animals were maintained under close veterinary supervision.

**Does the dataset relate to people?** If not, you may skip the remaining questions in this section.

No.

**Did you collect the data from the individuals in question directly, or obtain it via third parties or other sources (e.g., websites)?**

n/a

**Were the individuals in question notified about the data collection?** If so, please describe (or show with screenshots or other information) how notice was provided, and provide a link or other access point to, or otherwise reproduce, the exact language of the notification itself.

n/a

**Did the individuals in question consent to the collection and use of their data?** If so, please describe (or show with screenshots or other information) how consent was requested and provided, and provide a link or other access point to, or otherwise reproduce, the exact language to which the individuals consented.

n/a

**If consent was obtained, were the consenting individuals provided with a mechanism to revoke their consent in the future or for certain uses?** If so, please provide a description, as well as a link or other access point to the mechanism (if appropriate).

n/a

**Has an analysis of the potential impact of the dataset and its use on data subjects (e.g., a data protection impact analysis) been conducted?** If so, please provide a description of this analysis, including the outcomes, as well as a link or other access point to any supporting documentation.

n/a

**Any other comments?**

None.
Preprocessing/cleaning/labeling

Was any preprocessing/cleaning/labeling of the data done (e.g., discretization or bucketing, tokenization, part-of-speech tagging, SIFT feature extraction, removal of instances, processing of missing values)? If so, please provide a description. If not, you may skip the remainder of the questions in this section.

No preprocessing was performed on the sequence data released in this dataset.

Was the “raw” data saved in addition to the preprocessed/cleaned/labeled data (e.g., to support unanticipated future uses)? If so, please provide a link or other access point to the “raw” data.

n/a

Is the software used to preprocess/clean/label the instances available? If so, please provide a link or other access point.

n/a

Any other comments?
None.

Uses

Has the dataset been used for any tasks already? If so, please provide a description.

Yes: this dataset was released to accompany the three tasks of the 2022 Multi-Agent Behavior (MABe) Challenge, posted [here](https://sites.google.com/view/computational-behavior/our-datasets/mabe2022-dataset). This competition was aimed at generating learned representations of animals’ actions using unsupervised or self-supervised techniques.

Is there a repository that links to any or all papers or systems that use the dataset? If so, please provide a link or other access point.

Papers that use or cite this dataset may be submitted by their authors for display on the MABe22 website at [https://sites.google.com/view/computational-behavior/our-datasets/mabe2022-dataset](https://sites.google.com/view/computational-behavior/our-datasets/mabe2022-dataset)

What (other) tasks could the dataset be used for?

While this dataset was designed for development of methods for representation learning, the annotations can also be used for supervised learning tasks.

Is there anything about the composition of the dataset or the way it was collected and preprocessed/cleaned/labeled that might impact future uses? For example, is there anything that a future user might need to know to avoid uses that could result in unfair treatment of individuals or groups (e.g., stereotyping, quality of service issues) or other undesirable harms (e.g., financial harms, legal risks) If so, please provide a description. Is there anything a future user could do to mitigate these undesirable harms?

Occasional errors and identity swaps during pose estimation may impact future use of the dataset for some purposes.

Are there tasks for which the dataset should not be used? If so, please provide a description.

None.

Any other comments?
None.

Distribution

Will the dataset be distributed to third parties outside of the entity (e.g., company, institution, organization) on behalf of which the dataset was created? If so, please provide a description.

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Yes - the train split is already available to download. The hidden test labels for the dataset will become publicly available for download by all interested third parties following the completion of the MABe Challenge on July 3rd, 2022.

**How will the dataset be distributed (e.g., tarball on website, API, GitHub)** Does the dataset have a digital object identifier (DOI)?

The dataset is available on the Caltech public data repository at [https://data.caltech.edu/records/20186](https://data.caltech.edu/records/20186), where it will be retained indefinitely and available for download by all third parties. The data.caltech.edu posting has accompanying DOI [https://doi.org/10.22002/D1.20186](https://doi.org/10.22002/D1.20186).

The dataset as used for the MABe Challenge (lacking hidden task labels) is available for download on the AIcrowd page, located at [https://www.aicrowd.com/challenges/multi-agent-behavior-challenge-2022/problems/mabe-2022-mouse-triplets](https://www.aicrowd.com/challenges/multi-agent-behavior-challenge-2022/problems/mabe-2022-mouse-triplets).

**When will the dataset be distributed?**

The train split is already available to download. The hidden test labels for the dataset will become publicly available for download by all interested third parties following the completion of the MABe Challenge on July 6th, 2022.

**Will the dataset be distributed under a copyright or other intellectual property (IP) license, and/or under applicable terms of use (ToU)?** If so, please describe this license and/or ToU, and provide a link or other access point to, or otherwise reproduce, any relevant licensing terms or ToU, as well as any fees associated with these restrictions.

The MABe22 dataset is distributed under the CreativeCommons Attribution-NonCommercial-ShareAlike license (CC-BY-NC-SA). The terms of this license may be found at [https://creativecommons.org/licenses/by-nc-sa/2.0/legalcode](https://creativecommons.org/licenses/by-nc-sa/2.0/legalcode).

**Have any third parties imposed IP-based or other restrictions on the data associated with the instances?** If so, please describe these restrictions, and provide a link or other access point to, or otherwise reproduce, any relevant licensing terms, as well as any fees associated with these restrictions.

There are no third party restrictions on the data.

**Do any export controls or other regulatory restrictions apply to the dataset or to individual instances?** If so, please describe these restrictions, and provide a link or other access point to, or otherwise reproduce, any supporting documentation.

No export controls or regulatory restrictions apply.

**Any other comments?**

None.

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**Maintenance**

**Who will be supporting/hosting/maintaining the dataset?**

The dataset is hosted on the Caltech Research Data Repository at [data.caltech.edu](https://data.caltech.edu). Dataset hosting is maintained by the library of the California Institute of Technology. Long-term support for users of the dataset is provided by Jennifer J. Sun and by the laboratory of Ann Kennedy.

**How can the owner/curator/manager of the dataset be contacted (e.g., email address)?**

The managers of the dataset (JJS and AK) can be contacted at mabe.workshop@gmail.com or AK can be contacted at ann.kennedy@northwestern.edu and JJS can be contacted at jjsun@caltech.edu

**Is there an erratum?** If so, please provide a link or other access point.

No.

**Will the dataset be updated (e.g., to correct labeling errors, add new instances, delete instances)?** If so, please describe how often, by whom, and how updates will be communicated to users (e.g., mailing list, GitHub)?
Users of the dataset have the option to subscribe to a mailing list to receive updates regarding corrections or extensions of the MABe22 dataset. Mailing list sign-up can be found on the MABe22 webpage at https://sites.google.com/view/computational-behavior/our-datasets/mabe2022-dataset.

Updates to correct errors in the dataset will be made promptly, and announced via update messages posted to the MABe22 website and data.caltech.edu page.

Updates that extend the scope of the dataset, such as additional hidden tasks, or improved pose estimation, will be released as new named instantiations on at most a yearly basis. Previous versions of the dataset will remain online, but obsolescence notes will be sent out to the MABe22 mailing list. In updates, dataset version will be indicated by the year in the dataset name (here 22). Dataset updates may accompany new instantiations of the MABe Challenge.

If the dataset relates to people, are there applicable limits on the retention of the data associated with the instances (e.g., were individuals in question told that their data would be retained for a fixed period of time and then deleted)? If so, please describe these limits and explain how they will be enforced.

N/a (no human data.)

Will older versions of the dataset continue to be supported/hosted/maintained? If so, please describe how. If not, please describe how its obsolescence will be communicated to users.

Yes, the dataset will be permanently available on the Caltech Research Data Repository (data.caltech.edu), which is managed by the Caltech Library.

If others want to extend/augment/build on/contribute to the dataset, is there a mechanism for them to do so? If so, please provide a description. Will these contributions be validated/verified? If so, please describe how. If not, why not? Is there a process for communicating/distributing these contributions to other users? If so, please provide a description.

Extensions to the dataset will take place through at-most-yearly updates. We welcome community contributions of behavioral data, novel tracking methods, and novel hidden tasks; these may be submitted by contacting the authors or emailing mabe.workshop@gmail.com. All community contributions will be reviewed by the managers of the dataset for quality of tracking and annotation data. Community contributions will not be accepted without a data maintenance plan (similar to this document), to ensure support for future users of the dataset.

Any other comments?

If you enjoyed this dataset and would like to contribute other multi-agent behavioral data for future versions of the dataset or MABe Challenge, contact us at mabe.workshop@gmail.com!

B.2 Fly Group Datasheet

| Motivation |
|---|

For what purpose was the dataset created? Was there a specific task in mind? Was there a specific gap that needed to be filled? Please provide a description.

The prospect of discovering structure previously unknown to humans from large datasets has tremendous potential, particularly for science. However, progress has been inhibited by a lack of common datasets and quantitative evaluation criteria for assessing and comparing different algorithms. In the field of video-based behavior analysis, there has been a lot of progress in tools for tracking the pose of people and animals. To make use of these methods in biology, we now need computational methods to probe the temporal structure in these still large time-series datasets, and learn representations amenable to comparison and further study.

The MABe 2022 dataset is a new animal behavior dataset, intended to a) serve as a benchmark dataset for comparison of unsupervised or self-supervised behavior analysis tools, and establish community standards for evaluation of unsupervised techniques, b) highlight critical challenges in computational behavior analysis, particularly pertaining to unsupervised representation learning, and c) foster interaction between behavioral biologists and the greater machine learning community. This datasheet is specific to the Fly Group dataset, which consists of tracking data for a group of 8 to 11 fruit flies with 50 “hidden labels” for evaluating the quality of the learned representation.

Also see MABe 2022 mouse triplet data sheet (Section B.1) for more details.
Who created this dataset (e.g., which team, research group) and on behalf of which entity (e.g., company, institution, organization)?

The MABe 2022 fly dataset was created as a collaborative effort between Kristin Branson, Alice Robie, and Catherine Schretter at HHMI Janelia Research Campus within the labs of Kristin Branson and Gerry Rubin. Fly lines were generated by Gerry Rubin with the help of the Janelia Fly Core, PTR, and Fly Light project teams. Fly crosses and offspring were set up and collected by Alice Robie and Catherine Schretter, the behavior rig was developed by Alice Robie and Kristin Branson, and video were recorded by Alice Robie and Catherine Schretter, with help from Janelia Shared Resources. Analysis was done by Kristin Branson, Alice Robie, and Catherine Schretter, with help from Adam Taylor. The dataset tasks were designed by Kristin Branson, Alice Robie, and Catherine Schretter.

Who funded the creation of the dataset? If there is an associated grant, please provide the name of the grantor and the grant name and number.

Acquisition of behavioral data was funded by the Howard Hughes Medical Institute.

Any other comments?

None.

### Composition

What do the instances that comprise the dataset represent (e.g., documents, photos, people, countries)? Are there multiple types of instances (e.g., movies, users, and ratings; people and interactions between them; nodes and edges)? Please provide a description.

The core element of this dataset, called a sequence, captures the tracked postures of \( \approx 10 \) flies over 30s (4,500 frames) on a 5-cm-diameter domed plate filmed from above at 150Hz.

The core element of a sequence is called a frame; this refers to the posture of all animals on a particular frame of video, as binary categorization for each of the 50 tasks.

Tasks were based on the genotype, rearing, mutation, and environmental conditions of the flies. Flies from the following genotypes were assayed: dTrpA1 x pBDPGAL4U (Control) [59], dTrpA1 x R71G01 (R71G01) [59], dTrpA1 x R65F12 (R65F12) [59], 20xCsChrimson x SS36551 (aIPg) [61], NorpA,20xCsChrimson x NorpA;SS36564 (Blind aIPg), 20x CsChrimson x SS56987 (pC1d) [61], 20x CsChrimson x BPp65AD-x-BPZpGal4DBD (Control 2) [61], NorpA,20xCsChrimson x NorpA;BPp65AD-x-BPZpGal4DBD (Blind control). Neural populations in CsChrimson flies were activated by periods of red light illumination from an LED panel below the flies. Neural populations in dTrpA1 flies were activated by performing the experiments at the permissive temperature for TrpA. In addition, we manually annotated 6 social behaviors sparsely across the dataset.

How many instances are there in total (of each type, if appropriate)?

Instances for each dataset are shown in Table 3, divided into user train, evaluator train, test 1, and test 2 sets. Number of instances is reported as frames. As frames within a sequence are temporally contiguous and sampled at 150Hz, they are not statistically independent observations.

Does the dataset contain all possible instances or is it a sample (not necessarily random) of instances from a larger set? If the dataset is a sample, then what is the larger set? Is the sample representative of the larger set (e.g., geographic coverage)? If so, please describe how this representativeness was validated/verified. If it is not representative of the larger set, please describe why not (e.g., to cover a more diverse range of instances, because instances were withheld or unavailable).

We used all videos from chosen genotypes and conditions containing at least 9 flies. Frames for manual annotation of behavior were chosen using JAABA's interactive system [55] to help find instances of rare behaviors. When cutting a video into sequences, we chose segments to avoid obvious identity tracking errors (trajectory births or deaths). We left gaps of a randomly chosen length between .5 and 2s (75 and 300 frames) between sequences.

What data does each instance consist of? “Raw” data (e.g., unprocessed text or images) or features? In either case, please provide a description.
Table 3: Number of frames in each split set for each task and category.

| Task                                | Category 1 | Category 0 |
|-------------------------------------|------------|------------|
|                                    | User train | Eval train | User train | Eval train |
| Female vs male                      | 13,808,901 | 7,696,105  | 5,155,335  | 6,452,311  |
| Control 1                           | 1,363,000  | 279,000    | 364,491    | 405,000    |
| Control 1 sex separated             | 405,000    | 364,491    | 405,000    | 364,500    |
| Control 2                           | 726,798    | 514,548    | 287,012    | 283,151    |
| pC1d                                | 1,160,877  | 418,714    | 262,500    | 520,350    |
| Blind aIPg                          | 520,770    | 516,990    | 518,450    | 518,890    |
| Blind control vs off                | 911,001    | 543,361    | 236,961    | 468,234    |
| Blind control vs off                | 1,011,001  | 534,781    | 236,961    | 468,234    |
| Blind control vs off                | 505,372    | 272,425    | 118,314    | 232,335    |
| Blind control vs weak               | 505,372    | 272,425    | 118,314    | 232,335    |
| Blind control vs weak               | 505,372    | 272,425    | 118,314    | 232,335    |
| Blind control vs first              | 169,813    | 88,736     | 38,970     | 78,507     |
| Blind control vs first              | 726,798    | 516,548    | 287,012    | 283,151    |
| Blind control vs first              | 365,783    | 258,405    | 143,836    | 141,922    |
| Blind control vs weak               | 365,783    | 258,405    | 143,836    | 141,922    |
| pC1d                                | 477,331    | 389,800    | 260,930    | 271,073    |
| Blind aIPg                          | 477,331    | 389,800    | 260,930    | 271,073    |
| Blind control vs off                | 505,372    | 272,425    | 118,314    | 232,335    |
| Blind control vs off                | 505,372    | 272,425    | 118,314    | 232,335    |
| Blind control vs off                | 505,372    | 272,425    | 118,314    | 232,335    |
| Blind control vs weak               | 505,372    | 272,425    | 118,314    | 232,335    |
| Blind control vs weak               | 505,372    | 272,425    | 118,314    | 232,335    |
| Blind control vs first              | 169,813    | 88,736     | 38,970     | 78,507     |
| Blind control vs first              | 726,798    | 516,548    | 287,012    | 283,151    |
| Blind control vs first              | 365,783    | 258,405    | 143,836    | 141,922    |
| Blind control vs weak               | 365,783    | 258,405    | 143,836    | 141,922    |
| Blind aIPg                          | 477,331    | 389,800    | 260,930    | 271,073    |
| Blind aIPg                          | 477,331    | 389,800    | 260,930    | 271,073    |
| Any courtship                       | 4,927,499  | 1,733,014  | 1,579,509  | 1,575,009  |
| Any control                         | 4,005,799  | 2,153,800  | 1,299,464  | 1,525,885  |
| Any blind                           | 3,996,333  | 1,324,217  | 756,051    | 1,017,266  |
| Any aIPg                            | 2,422,189  | 1,199,074  | 782,190    | 1,685,342  |
| Any agegression                     | 2,422,189  | 1,199,074  | 782,190    | 1,685,342  |
| Any seg separated                   | 3,073,505  | 769,509    | 769,509    | 810,011    |
| Any segmentation                    | 810,008    | 364,800    | 769,500    | 769,500    |
| Aggression manual annotation        | 610        | 972        | 1,279      | 890        |
| Courshipal manual annotation        | 1,496      | 15,351     | 105        | 141        |
| High fence manual annotation        | 188        | 157        | 106        | 138        |
| Wing ext. manual annotation         | 0          | 1,594      | 1,523      | 3,130      |
| Wing flick manual annotation        | 230        | 149        | 95         | 116        |
Each sequence has three elements. 1) Tracking features consist of, for each of the \( \approx 10 \) flies, the locations of 19 body parts (left wing tip, right wing tip, antennae midpoint, right eye, left eye, left front of thorax, right front of thorax, base of thorax, tip of abdomen, right middle femur base, right middle femur-tibia joint, left middle femur-base, left middle femur-tibia joint, right front leg tip, right middle leg tip, right rear leg tip, left front leg tip, left middle leg tip, left rear leg tip), information about an ellipse fit to the fly body (Fit ellipse center, orientation, major and minor axis length), and information about the segmented animal (body and foreground area, image contrast). Tracking features are estimated using the Animal Part Tracker (APT) and the FlyTracker. Videos have between 9 and 11 flies. All data are stored as matrices with space for 11 flies, with NaN values if there are < 11 flies. 2) Task categories are frame- and fly-wise binary categorizations for each of the 50 tasks we defined, and will have values 1, 0, or NaN, with NaN indicating no data (the task is irrelevant or ill-defined for this frame and fly, or this frame and fly was not manually annotated). For some tasks, all flies in the same frame will have the same value. For some tasks, all frames will have the same value for the entire sequence, or for long periods of contiguous time.

Table 4: Number of sequences in each split set for each task and category.

| Task category | Category 0 | Category 1 |
|---------------|------------|------------|
|               | Eval train | Test 1     | Test 2     | User train | Eval train | Test 1 | Test 2 |
| Male R71G01 female control | 11 | 221 | 197 | 221 | 197 | 221 | 197 |
| Male R71G01 control | 11 | 221 | 197 | 221 | 197 | 221 | 197 |
| Control 1 | 50 | 20 | 9 | 10 | 20 | 9 | 10 |
| Control 1 sex separated | 10 | 9 | 10 | 10 | 9 | 10 | 10 |
| Control 2 | 33 | 22 | 11 | 11 | 33 | 22 | 11 |
| Control 2 sex separated | 33 | 22 | 11 | 11 | 33 | 22 | 11 |
| Blind control | 44 | 22 | 11 | 22 | 44 | 22 | 11 |
| Blind control strong vs off | 24 | 12 | 6 | 12 | 24 | 12 | 6 |
| Blind control weak vs off | 20 | 10 | 5 | 10 | 20 | 10 | 5 |
| Blind control strong vs weak | 24 | 12 | 12 | 6 | 12 | 6 | 12 |
| Blind control last vs first | 8 | 4 | 2 | 4 | 8 | 4 | 2 |
| Control 2 on vs off | 33 | 22 | 11 | 11 | 33 | 22 | 11 |
| Control 2 weak vs off | 15 | 10 | 5 | 5 | 15 | 10 | 5 |
| Control 2 strong vs weak | 18 | 12 | 6 | 6 | 15 | 10 | 5 |
| Control 2 last vs first | 6 | 4 | 2 | 2 | 6 | 4 | 2 |
| Blind aIPg on vs off | 44 | 33 | 22 | 22 | 44 | 33 | 22 |
| Blind aIPg strong vs off | 24 | 18 | 12 | 12 | 24 | 18 | 12 |
| Blind aIPg weak vs off | 20 | 15 | 10 | 10 | 20 | 15 | 10 |
| Blind aIPg strong vs weak | 24 | 18 | 12 | 12 | 20 | 15 | 10 |
| Blind aIPg last vs first | 8 | 4 | 4 | 4 | 6 | 4 | 4 |
| aIPg on vs off | 54 | 21 | 11 | 22 | 62 | 23 | 13 |
| aIPg weak vs off | 25 | 10 | 5 | 10 | 62 | 23 | 13 |
| aIPg strong vs weak | 29 | 11 | 6 | 12 | 62 | 23 | 13 |
| aIPg last vs first | 10 | 4 | 2 | 2 | 62 | 23 | 13 |
| pCl on vs off | 22 | 22 | 22 | 22 | 26 | 26 | 26 |
| pCl strong vs off | 12 | 12 | 12 | 12 | 26 | 26 | 26 |
| pCl last vs first | 10 | 10 | 10 | 10 | 26 | 26 | 26 |
| pCl weak vs off | 12 | 12 | 12 | 12 | 26 | 26 | 26 |
| Any courtship | 120 | 45 | 40 | 37 | 304 | 168 | 106 |
| Any control | 137 | 73 | 41 | 53 | 286 | 140 | 105 |
| Any blind | 88 | 35 | 33 | 44 | 330 | 156 | 111 |
| Any aggression | 120 | 76 | 55 | 66 | 298 | 135 | 89 |
| Any R71G01 | 77 | 20 | 21 | 20 | 348 | 192 | 125 |
| Any sex-separated | 21 | 10 | 20 | 20 | 397 | 202 | 125 |
| Aggression manual annotation | 11 | 46 | 13 | 17 | 10 | 20 | 17 |
| Aggression control annotation | 11 | 46 | 13 | 17 | 10 | 20 | 17 |
| Courtship control annotation | 6 | 4 | 4 | 4 | 6 | 4 | 4 |
| High fence manual annotation | 12 | 17 | 13 | 17 | 23 | 27 | 16 |
| Wing ext. manual annotation | 0 | 4 | 8 | 8 | 0 | 52 | 49 |
| Wing flick manual annotation | 28 | 19 | 16 | 28 | 19 | 16 | 28 |

Is there a label or target associated with each instance? If so, please provide a description.
The annotation field for a given sequence consists of frame- and fly-wise categorizations for each of the 50 tasks. For fly-frames for which the task is irrelevant or ill-defined, or no manual annotation was made, this label will be missing (indicated by nan). In the MABe 2022 challenge, these task annotations were kept secret, and used for evaluation purposes, not for training.

Is any information missing from individual instances? If so, please provide a description, explaining why this information is missing (e.g., because it was unavailable). This does not include intentionally removed information, but might include, e.g., redacted text.

As described above, all data are stored as matrices with space for 11 flies, with nan values if there are < 11 flies. Annotations will be nan if the task is irrelevant or ill-defined for this frame and fly, or this frame and fly was not manually annotated.

Are relationships between individual instances made explicit (e.g., users’ movie ratings, social network links)? If so, please describe how these relationships are made explicit.

Each instance (sequence) is to be treated as an independent observation. Some sequence come from the same groups of flies in the same video. Each sequence is at least 0.5s (75 frames) from another sequence. Frames within a sequence are temporally contiguous, and highly correlated.

Are there recommended data splits (e.g., training, development/validation, testing)? If so, please provide a description of these splits, explaining the rationale behind them.

The dataset includes a recommended split into User train (for unsupervised representation learning), Evaluator train (for training evaluator classifier), Test 1 (for validating the classifier), and Test 2 (for final evaluation score) sets. Each set containing distinct videos and flies. The splits were designed to provide a roughly consistent, small amount of training data for each task.

Are there any errors, sources of noise, or redundancies in the dataset? If so, please provide a description.

Tracking in this dataset are produced using automated tracking software (FlyTracker and APT). In addition, manual annotations of animal behavior are inherently subjective, and individual annotators show some variability in the precise frame-by-frame labeling of behavior sequences.

Is the dataset self-contained, or does it link to or otherwise rely on external resources (e.g., websites, tweets, other datasets)? If it links to or relies on external resources, a) are there guarantees that they will exist, and remain constant, over time; b) are there official archival versions of the complete dataset (i.e., including the external resources as they existed at the time the dataset was created); c) are there any restrictions (e.g., licenses, fees) associated with any of the external resources that might apply to a future user? Please provide descriptions of all external resources and any restrictions associated with them, as well as links or other access points, as appropriate.

The dataset is self-contained.

Does the dataset contain data that might be considered confidential (e.g., data that is protected by legal privilege or by doctor-patient confidentiality, data that includes the content of individuals non-public communications)? If so, please provide a description.

No.

Does the dataset contain data that, if viewed directly, might be offensive, insulting, threatening, or might otherwise cause anxiety? If so, please describe why.

No such material; dataset contains only trajectories (no video or images) and text labels pertaining to fly social behaviors.

Does the dataset relate to people? If not, you may skip the remaining questions in this section.

No.

Does the dataset identify any subpopulations (e.g., by age, gender)? If so, please describe how these subpopulations are identified and provide a description of their respective distributions within the dataset.

n/a
Is it possible to identify individuals (i.e., one or more natural persons), either directly or indirectly (i.e., in combination with other data) from the dataset? If so, please describe how.

n/a

Does the dataset contain data that might be considered sensitive in any way (e.g., data that reveals racial or ethnic origins, sexual orientations, religious beliefs, political opinions or union memberships, or locations; financial or health data; biometric or genetic data; forms of government identification, such as social security numbers; criminal history)? If so, please provide a description.

n/a

Any other comments?

None.

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**Collection Process**

How was the data associated with each instance acquired? Was the data directly observable (e.g., raw text, movie ratings), reported by subjects (e.g., survey responses), or indirectly inferred/derived from other data (e.g., part-of-speech tags, model-based guesses for age or language)? If data was reported by subjects or indirectly inferred/derived from other data, was the data validated/verified? If so, please describe how.

See above for details on collection process. All data pertains to groups of interacting flies in carefully controlled environments.

What mechanisms or procedures were used to collect the data (e.g., hardware apparatus or sensor, manual human curation, software program, software API)? How were these mechanisms or procedures validated?

Details of fly genotypes and rearing are above. Flies were recorded in our custom developed behavior rig, which consists of a custom LED panel for back-illumination for recording in NIR and timed optogenetic activation in red, a custom 5-cm-diameter domed circular dish designed to reduce interactions with the arena wall and ceiling, a visual surround to isolate the flies, and a camera with an NIR-pass filter (FLIR Flea3) recording at 1024x1024 at 150Hz. We used data capture software based on the FlyBowlDataCapture system [59] and the Basic Image Acquisition System (BIAS, IORodeo). As described above, manual annotations were made using JAABA.

If the dataset is a sample from a larger set, what was the sampling strategy (e.g., deterministic, probabilistic with specific sampling probabilities)?

As described above, we included videos with at least 9 flies in them. When cutting a video into sequences, we chose segments to avoid obvious identity tracking errors (trajectory births or deaths). We left gaps of a randomly chosen length between .5 and 2s (75 and 300 frames) between sequences.

Who was involved in the data collection process (e.g., students, crowdworkers, contractors) and how were they compensated (e.g., how much were crowdworkers paid)?

Full-time employees of Janelia’s Shared Resources teams (Fly Core, Fly Light, Media, and Project Technical Resources) were involved in producing and maintaining flies.

Over what timeframe was the data collected? Does this timeframe match the creation timeframe of the data associated with the instances (e.g., recent crawl of old news articles)? If not, please describe the timeframe in which the data associated with the instances was created.

Videos associated with this dataset were collected between December 2020 and September 2021. Tracking and annotation was performed in October 2021 - February 2022.

Were any ethical review processes conducted (e.g., by an institutional review board)? If so, please provide a description of these review processes, including the outcomes, as well as a link or other access point to any supporting documentation.

No.

Does the dataset relate to people? If not, you may skip the remaining questions in this section.
No.

Did you collect the data from the individuals in question directly, or obtain it via third parties or other sources (e.g., websites)?
n/a

Were the individuals in question notified about the data collection? If so, please describe (or show with screenshots or other information) how notice was provided, and provide a link or other access point to, or otherwise reproduce, the exact language of the notification itself.
n/a

Did the individuals in question consent to the collection and use of their data? If so, please describe (or show with screenshots or other information) how consent was requested and provided, and provide a link or other access point to, or otherwise reproduce, the exact language to which the individuals consented.
n/a

If consent was obtained, were the consenting individuals provided with a mechanism to revoke their consent in the future or for certain uses? If so, please provide a description, as well as a link or other access point to the mechanism (if appropriate).
n/a

Has an analysis of the potential impact of the dataset and its use on data subjects (e.g., a data protection impact analysis) been conducted? If so, please provide a description of this analysis, including the outcomes, as well as a link or other access point to any supporting documentation.
n/a

Any other comments?
None.

### Preprocessing/cleaning/labeling

Was any preprocessing/cleaning/labeling of the data done (e.g., discretization or bucketing, tokenization, part-of-speech tagging, SIFT feature extraction, removal of instances, processing of missing values)? If so, please provide a description.

If not, you may skip the remainder of the questions in this section.

No preprocessing was performed on the *sequence* data released in this dataset.

Was the “raw” data saved in addition to the preprocessed/cleaned/labeled data (e.g., to support unanticipated future uses)? If so, please provide a link or other access point to the “raw” data.

n/a

Is the software used to preprocess/clean/label the instances available? If so, please provide a link or other access point.

n/a

Any other comments?
None.

### Uses

Has the dataset been used for any tasks already? If so, please provide a description.

Yes: this dataset was released to accompany the three tasks of the 2022 Multi-Agent Behavior (MABe) Challenge, posted [here](#). In this challenge, competitors are provided video of multiple interacting animals and
tasked with learning a general-purpose, low-dimensional representation of the video. They upload their learned representations to the evaluation site, which then trained simple linear classifiers on the set of secret tasks described above, and returns accuracy measures.

Is there a repository that links to any or all papers or systems that use the dataset? If so, please provide a link or other access point.

Papers that use or cite this dataset may be submitted by their authors for display on the MABe22 website at [https://sites.google.com/view/computational-behavior/our-datasets/mabe2022-dataset](https://sites.google.com/view/computational-behavior/our-datasets/mabe2022-dataset)

What (other) tasks could the dataset be used for?

Besides unsupervised representation learning, this dataset could also be used for supervised representation learning, using the hidden labels as supervision.

Is there anything about the composition of the dataset or the way it was collected and preprocessed/cleaned/labeled that might impact future uses? For example, is there anything that a future user might need to know to avoid uses that could result in unfair treatment of individuals or groups (e.g., stereotyping, quality of service issues) or other undesirable harms (e.g., financial harms, legal risks)? If so, please provide a description. Is there anything a future user could do to mitigate these undesirable harms?

No.

Are there tasks for which the dataset should not be used? If so, please provide a description.

None.

Any other comments?

None.

### Distribution

**Will the dataset be distributed to third parties outside of the entity (e.g., company, institution, organization) on behalf of which the dataset was created?** If so, please provide a description.

Yes - the train split is already available to download. The hidden test labels for the dataset will become publicly available for download by all interested third parties following the completion of the MABe Challenge on July 6th, 2022.

**How will the dataset be distributed (e.g., tarball on website, API, GitHub)?** Does the dataset have a digital object identifier (DOI)?

The dataset is available on the Caltech public data repository at [https://data.caltech.edu/records/20186](https://data.caltech.edu/records/20186), where it will be retained indefinitely and available for download by all third parties. The data.caltech.edu posting has accompanying DOI [https://doi.org/10.22002/D1.20186](https://doi.org/10.22002/D1.20186)

The dataset as used for the MABe Challenge (lacking hidden task labels) is available for download on the AIcrowd page, located at [https://www.aicrowd.com/challenges/multi-agent-behavior-challenge-2022/problems/mabe-2022-fruit-fly-groups](https://www.aicrowd.com/challenges/multi-agent-behavior-challenge-2022/problems/mabe-2022-fruit-fly-groups).

**When will the dataset be distributed?**

The train split is already available to download. The hidden test labels for the dataset will become publicly available for download by all interested third parties following the completion of the MABe Challenge on July 6th, 2022.

**Will the dataset be distributed under a copyright or other intellectual property (IP) license, and/or under applicable terms of use (ToU)?** If so, please describe this license and/or ToU, and provide a link or other access point to, or otherwise reproduce, any relevant licensing terms or ToU, as well as any fees associated with these restrictions.

The MABe22 dataset is distributed under the CreativeCommons Attribution-NonCommercial-ShareAlike license (CC-BY-NC-SA). The terms of this license may be found at [https://creativecommons.org/licenses/by-nc-sa/2.0/legalcode](https://creativecommons.org/licenses/by-nc-sa/2.0/legalcode)


**Have any third parties imposed IP-based or other restrictions on the data associated with the instances?** If so, please describe these restrictions, and provide a link or other access point to, or otherwise reproduce, any relevant licensing terms, as well as any fees associated with these restrictions.

There are no third party restrictions on the data.

**Do any export controls or other regulatory restrictions apply to the dataset or to individual instances?** If so, please describe these restrictions, and provide a link or other access point to, or otherwise reproduce, any supporting documentation.

No export controls or regulatory restrictions apply.

**Any other comments?**

None.

---

## Maintenance

**Who will be supporting/hosting/maintaining the dataset?**

The dataset is hosted on the Caltech Research Data Repository at [data.caltech.edu](http://data.caltech.edu). Dataset hosting is maintained by the library of the California Institute of Technology. Long-term support for users of the dataset is provided by Jennifer J. Sun and by the laboratory of Ann Kennedy.

**How can the owner/curator/manager of the dataset be contacted (e.g., email address)?**

The managers of the dataset (JJS and AK) can be contacted at [mabe.workshop@gmail.com](mailto:mabe.workshop@gmail.com) or AK can be contacted at [ann.kennedy@northwestern.edu](mailto:ann.kennedy@northwestern.edu) and JJS can be contacted at [jjsun@caltech.edu](mailto:jjsun@caltech.edu).

**Is there an erratum?** If so, please provide a link or other access point.

No.

**Will the dataset be updated (e.g., to correct labeling errors, add new instances, delete instances)?** If so, please describe how often, by whom, and how updates will be communicated to users (e.g., mailing list, GitHub)?

Users of the dataset have the option to subscribe to a mailing list to receive updates regarding corrections or extensions of the MABe22 dataset. Mailing list sign-up can be found on the MABe22 webpage at [https://sites.google.com/view/computational-behavior/our-datasets/mabe2022-dataset](https://sites.google.com/view/computational-behavior/our-datasets/mabe2022-dataset).

Updates to correct errors in the dataset will be made promptly, and announced via update messages posted to the MABe22 website and data.caltech.edu page.

Updates that extend the scope of the dataset, such as additional hidden tasks, or improved pose estimation, will be released as new named instantiations on at most a yearly basis. Previous versions of the dataset will remain online, but obsolescence notes will be sent out to the MABe22 mailing list. In updates, dataset version will be indicated by the year in the dataset name (here 22). Dataset updates may accompany new instantiations of the MABe Challenge.

**If the dataset relates to people, are there applicable limits on the retention of the data associated with the instances (e.g., were individuals in question told that their data would be retained for a fixed period of time and then deleted)?** If so, please describe these limits and explain how they will be enforced.

N/a (no human data.)

**Will older versions of the dataset continue to be supported/hosted/maintained?** If so, please describe how. If not, please describe how its obsolescence will be communicated to users.

Yes, the dataset will be permanently available on the Caltech Research Data Repository (data.caltech.edu), which is managed by the Caltech Library.

**If others want to extend/augment/build on/contribute to the dataset, is there a mechanism for them to do so?** If so, please provide a description. Will these contributions be validated/verified? If so, please describe how. If not, why not? Is there a process for communicating/distributing these contributions to other users? If so, please provide a description.
Extensions to the dataset will take place through at-most-yearly updates. We welcome community contributions of behavioral data, novel tracking methods, and novel hidden tasks; these may be submitted by contacting the authors or emailing mabe.workshop@gmail.com. All community contributions will be reviewed by the managers of the dataset for quality of tracking and annotation data. Community contributions will not be accepted without a data maintenance plan (similar to this document), to ensure support for future users of the dataset.

Any other comments?

If you enjoyed this dataset and would like to contribute other multi-agent behavioral data for future versions of the dataset or MABe Challenge, contact us at mabe.workshop@gmail.com!

C Data Format

Our dataset is released in .npy format, which can be loaded using the Python Numpy library. We provide sample data loading and visualization notebooks for mice (https://www.aicrowd.com/showcase/getting-started-mabe-2022-mouse-triplets-round-1) and flies (https://www.aicrowd.com/showcase/getting-started-mabe-challenge-2022-fruit-flies-v-0-2-2kb). Each data sequence corresponds to keypoints detected from a video clip, all stored as arrays in a dictionary. The train file additionally contains 2 publicly available labels for mouse and 3 publicly available labels for fly to use during model development. The publicly available tasks are lights and chase task (out of 13 total) for mice, and identity of a genetic control line (pBDPGAL4U), presence of pCl1d neuron stimulation, and aggression behavior (out of 50) for flies. The results are reported on the test file, where only trajectory data is available.

For all MABe2022 data, the npy format is shown in Listing 1.

```json
{
    "vocabulary": a list of public task names [train split only],
    "sequences": {
        "<sequence_id-1>": {
            "keypoints": an array of shape
            (frames, num agents, num keypoints, 2),
            "annotations": an array of shape (num tasks, frames)
            [train split only]
        },
        "<sequence_id-2>": {
            "keypoints": an array of shape
            (frames, num agents, num keypoints, 2),
            "annotations": an array of shape (num tasks, frames)
            [train split only]
        },
        ...
    }
}
```

Listing 1: npy file format.

The keypoints field contains the (x,y) position of anatomically defined pose keypoints for either mice or flies. The dimensions correspond to the number of frames in a sequence, number of tracked agents, keypoint identity, and image (x,y) coordinates in pixels. See Figure 2 for a list of tracked parts for mice and flies.

The annotations field contains the frame-level publicly available labels on the train split only, which is a subset of the hidden tasks.
The vocabulary field contains the task name of the frame-level publicly available labels on the train split only.

D Mouse Dataset Preparation

D.1 Behavior Video Acquisition

This section is adapted from [3, 64, 22]. Experiments were performed in the JAX Animal Behavior System (JABS), consisting of an open field arena measuring 52 cm by 52 cm, with overhead LED ring lighting on a 12:12 light-dark cycle. The arena floor is white PVC plastic covered by a layer of bedding (wood shavings and Alpha-Dri), and food and water are held in a hopper with grate access in one arena wall, and replaced when depleted. For recording videos while lights were off, additional IR LED lighting at 940 nm was added. Video was recorded at 30Hz using a Basler acA1300-75gm camera with 4-12mm lens (Tamron) and 800nm longpass filter (Hoya) to exclude visible light, using a custom recording client developed by JAX (see https://github.com/KumarLabJax/JABS-data-pipeline). Experimental mice were adult males between 10 and 20 weeks old, of genetic background C57Bl/6J or BTBR. Prior to testing, animals were allowed to acclimate to the behavior room for 30-60 minutes, after which three mice were introduced to the JABS arena over a period of several minutes. Behavior was recorded continuously for four days, during which time animal behavior and welfare was monitored remotely. All behavioral tests were performed in accordance with approved protocols from The Jackson Laboratory Institutional Animal Care and Use Committee guidelines.

D.2 Tracking

12 anatomical keypoints on each animal were tracked using a modified version of HRnet (provided at https://github.com/KumarLabJax/deep-hrnet-mouse), with coordinates of keypoints reported in pixels [64]. Occurrence of each anatomically defined keypoint were grouped into up to four animal pose instances (one more than the number of mice present), using associative embedding [50] to evaluate likelihood of keypoint pairs belonging to the same animal. The four candidate pose instances were then assigned animal identities by computing distances between all tracked pose pairs across neighboring video frames, and propagating animal IDs forward in time to the closest pose instance falling within a maximum radius. A second post-hoc pass was then applied to extracted pose tracklets, in which incomplete pose instances were merged when complementary pairs of points were found within a maximum radius, and resulting tracklets were merged based on a minimum distance criterion, to produce the final set of three pose trajectories provided in the dataset.

D.3 Behavior Annotation

Nine behaviors were programmatically annotated using heuristics described below. Note that multiple behavior labels may be positive on a given frame.

- **Approach**: Mice move from at least 5 cm apart to less than 1 cm apart at closest point, over a period of at least 10 seconds at a maximum speed of 2 cm/sec.
- **Chase**: Mice are moving above 15 cm/sec, with closest points less than 5 cm apart, and angular deviation between mice is less than 30 degrees, for at least 80% of frames within at least one second. Merge bouts less than 0.5 seconds apart.
- **Close**: Closest points of mice are less than 3 cm apart. Merge bouts less than 2 seconds apart.
- **Contact**: Closest points of mice are less than 1 cm apart. Merge bouts less than 2 seconds apart.
- **Huddle**: Closest points of mice are less than 1 cm apart for at least 10 seconds, during which mice show less than 3 cm displacement. Merge bouts less than 2 seconds apart.
- **Oral-ear contact**: Nose and ear of mice are less than 1.5 cm apart for at least 50% of frames within a window of 0.25 seconds or more. Must occur less than 5 seconds after an approach. Merge bouts less than 0.5 seconds apart.
• **Oral-genital contact**: Nose and tail base of mice are less than 1.5 cm apart for at least 50% of frames within a window of 0.25 seconds or more. Must occur less than 5 seconds after an approach. Merge bouts less than 0.5 seconds apart.

• **Oral-oral contact**: Noses of mice are less than 1.5 cm apart for at least 50% of frames within a window of 0.25 seconds or more. Must occur less than 5 seconds after an approach. Merge bouts less than 0.5 seconds apart.

• **Watching**: Mice are more than 5 cm apart but less than 20 cm apart, and gaze offset of one mouse is less than 15 degrees from body of other mouse, for a minimum duration of 3 seconds. Merge bouts less than 0.5 seconds apart.

### D.4 Dataset sampling

To generate the trajectories used for this dataset, we randomly sampled up to five one-minute intervals from each recorded hour of approximately 12 four-day experiments in the JABS setup described above. In initial sampling, we observed that during the lights-on phase of the light/dark cycle the mice spent the majority of the time huddled together sleeping. As this does not generate particularly interesting behavioral data, we randomly discarded 80% of sampled one-minute intervals in which no substantial movement of the animals occurred, and replaced these with substitute samples drawn from the same one-hour time period. If after five attempts we could not randomly draw a replacement sample containing movement, we omitted the trajectory from the dataset. As a result, the dataset contains a higher proportion of trajectories with movement than is present in the source videos, and a slightly lower proportion of trajectories sampled from the light portion of the light/dark cycle.

### D.5 Data splitting

Trajectories were randomly assigned into four sets; due to the relatively small number of source experiments, we did not separate sets by animal identity. Percentage of trajectories assigned to each set is given in parentheses.

- **User train (30%)**: data given to the competitor to learn their embedding (note that competitors could also include the submission train, test 1, and test 2 trajectories for training.)
- **Evaluation train (50%)**: data used to train the linear classifiers during evaluation.
- **Test 1 (10%)**: Data used to measure performance of the linear classifiers. Performance on this dataset was presented on the leaderboard during the competition.
- **Test 2 (10%)**: Final set of data used to measure performance of the linear classifiers, and for determining the competition winners.

### E Fly Dataset Preparation

#### E.1 Experimental Setup

Optogenetic experiments used group-housed, mated female flies (4–5 days post eclosion) that were sorted into 10 flies per vial. Flies were reared in the dark in a 12:12 light-dark cycle incubator (25°C, 50% relative humidity) on standard food supplemented with retinal (Sigma-Aldrich, St. Louis, MO) (0.2 and mM all trans-retinal prior to eclosion and 0.4 mM all trans-retinal post eclosion). Control lines, lines labeling cell types involved in the female aggression circuit, and the CsChrimson effector line were described previously [61, 2]. Blind control and blind aP.g lines were generated through crossing established lines with a mutation in norpA [6] and lines described previously [61]. All experiments were performed during the morning activity peak (ZT0-ZT3).

For thermogenetic experiments, flies were reared in a 12:12 light:dark incubator (22°C 50% relative humidity) on a standard molasses food. They were cold anesthetized and sorted into groups of 5 males and 5 females, unless noted as “male71G01 + female control” and “control sex-separated”. These flies were housed separately in groups of 5 males or 5 females prior to the experiments. All flies were food deprived on agar media for 24 hours directly before recording. Experiments were conducted at the permissive temperature for TrpA, 30°C, and 50% relative humidity during the evening activity peak (ZT8-ZT12). Control lines, the TrpA effector line, and lines labeling cell types involved in courtship or avoidance were previously described [59, 76].
Fly type | N. videos | Description
---|---|---
Control 1 | 9 | Groups of 5 female and 5 male flies from control line pBDP-GAL4u x TrpA that were raised together.
Control 1 sex-separated | 4 | Groups of 5 female and 5 male flies from control line pBDP-GAL4u x TrpA that were raised separately, with groups encountering each other for the first time in the videos.
Control 2 | 6 | Groups of 10 female flies from control line JHS_K_85321 x CsChrimson
R71G01 | 13 | Groups of 5 female and 5 male flies from courtship line R71G01 x TrpA
Male R71G01 female control | 5 | Groups of 5 female flies from the control line pBDP-GAL4U x TrpA and 5 male flies from courtship line R71G01 x TrpA
R65F12 | 12 | Groups of 5 female and 5 male flies from courtship line R65F12 x TrpA
R91B01 | 10 | Groups of 5 female and 5 male flies from visual avoidance line R91B01 x TrpA
Blind control | 9 | Groups of 10 blind female flies from control line JHS_K_85321 x ChR with the norpA mutation
aIPg | 9 | Groups of 10 female flies from aggression line SS36564 x ChR, which targets aIPg neurons
pC1d | 8 | Groups of 10 female flies from aggression line SS56987 x ChR, which targets pC1d neurons.
Blind aIPg | 11 | Groups of 10 blind female flies with the norpA mutation from aggression line SS36564, which targets aIPg neurons
Any courtship | 30 | Any of R71G01, Male R71G01 + female control, or R65F12.
Any control | 28 | Any of Control 1, Control 1 sex-separated, Control 2, or Blind control.
Any blind | 20 | Any of Blind control, Blind aIPg.
Any aIPg | 20 | Any of aIPg or Blind aIPg.
Any aggression | 28 | Any of aIPg, pC1d, blind aIPg.
Any R71G01 | 18 | Any of R71G01 or Male R71G01 + female control
Any sex separated | 9 | Any of Control 1 sex-separated or Male R71G01 + female control.

Table 5: Descriptions of types of flies used in each task.

The circular assay chamber was 50 mm in diameter and 3.5 mm tall, with a domed translucent ceiling coated with silicon (Sigma Cote, Sigma Aldridge) to prevent upside-down walking and a translucent acrylic floor. The chambers were illuminated from below with infrared light from custom LED panels and recorded from above with a USB3 camera at 150 fps (Flea3, FLIR) with an 800-nm long-pass filter. Visible white light was present at all times so that the flies could see. Figure 2(a) shows an example video frame.

For optogenetic experiments, neurons expressing CsChrimson were activated with 617-nm red light from custom LED panels. Experiments were run with one of two activation protocols. Protocol 1 consisted of 2 repeats of a 30s (red) lights-off period then a 30s “strong” lights-on period (7 mW/cm², pulsed at 30 Hz with on period 10/33 ms), followed by a 30s lights-off period, then 2 repeats of a 30s lights-off period then a 30s “weak” lights-on period (3 mW/cm² constant illumination), then a 30s lights-off period. In total, these videos were 300s (45000 frames) long. Protocol 2 consisted of 3 repeats of a 30s lights-off period then a 30s “weak” lights-on period (1 mW/cm², constant) followed by 3 repeats of a 30s lights-off period then a 30s “strong” lights-on period (3 mW/cm²). In total, these videos were 390s long (58500 frames). For thermogenetic experiments, videos were recorded for 300 seconds (45000 frames).
| Task type   | Description                                                                                                                                 |
|------------|---------------------------------------------------------------------------------------------------------------------------------------------|
| Fly type   | 1 indicates activation periods (whole video for TrpA, any lights-on periods for ChR) of the selected fly type. 0 indicates activation periods for other lines. nan indicates lights-off periods. |
| On vs off  | 1 indicates activation lights-on periods for the selected fly type, 0 lights-off periods for that fly type. nan indicates other fly types.            |
| Strong vs off | 1 indicates strong activation lights-on periods for the selected fly type, 0 lights-off periods for that fly type. nan indicates other fly types.       |
| Weak vs off | 1 indicates weak activation lights-on periods for the selected fly type, 0 lights-off periods for that fly type. nan indicates other fly types.         |
| Strong vs weak | 1 indicates strong activation lights-on periods for the selected fly type, 0 weak activation lights-on periods for that fly type. nan indicates lights-off periods for that fly type, or any other fly type. |
| Last vs first | 1 indicates the last strong activation lights-on period for the selected fly type, 0 the first strong activation lights-on period for that fly type. nan indicates other lights-on periods or lights off periods for that fly type, or any other fly type. |
| Manual annotation | 1 indicates frames from any fly type manually labeled as the selected behavior, 0 frames manually labeled as not the selected behavior, nan frames that were not labeled. |
| Female vs male | 1 indicate female flies, 0 indicates male flies.                                                                                                                                                 |

Table 6: Descriptions of types of comparisons made in each task.

| Task | Flies/Behavior | Task type               | Task | Flies/Behavior | Task type               |
|------|----------------|-------------------------|------|----------------|-------------------------|
| 1    | All            | Female vs male          | 26   | Blind aIPg     | Strong vs weak          |
| 2    | Control 1      | Fly type                | 27   | Blind aIPg     | Last vs first           |
| 3    | Control 1 sex-separated | Fly type          | 28   | aIPg           | On vs off              |
| 4    | Control 2      | Fly type                | 29   | aIPg           | Strong vs off           |
| 5    | R71G01         | Fly type                | 30   | aIPg           | Weak vs off             |
| 6    | R71G01 female control | Fly type          | 31   | pCl1d          | Strong vs weak          |
| 7    | R65F12         | Fly type                | 32   | aIPg           | Last vs first           |
| 8    | R91B01         | Fly type                | 33   | pCl1d          | On vs off              |
| 9    | Blind Control  | Fly type                | 34   | pCl1d          | Strong vs off           |
| 10   | aIPG           | Fly type                | 35   | pCl1d          | Weak vs off             |
| 11   | pCl1d          | Fly type                | 36   | pCl1d          | Strong vs weak          |
| 12   | Blind aIPG     | Fly type                | 37   | pCl1d          | Last vs first           |
| 13   | Blind control  | On vs off               | 38   | Any courtship  | Fly type                |
| 14   | Blind control  | Strong vs off           | 39   | Any control    | Fly type                |
| 15   | Blind control  | Weak vs off             | 40   | Any blind      | Fly type                |
| 16   | Blind control  | Strong vs weak          | 41   | Any aIPg       | Fly type                |
| 17   | Blind control  | Last vs first           | 42   | Any aggression | Fly type                |
| 18   | Control 2      | On vs off               | 43   | Any R71G01     | Fly type                |
| 19   | Control 2      | Strong vs off           | 44   | Any sex-separated | Fly type            |
| 20   | Control 2      | Weak vs off             | 45   | Aggression     | Manual annotation       |
| 21   | Control 2      | Strong vs weak          | 46   | Chase          | Manual annotation       |
| 22   | Control 2      | Last vs first           | 47   | Courtship      | Manual annotation       |
| 23   | Blind aIPg     | On vs off               | 48   | High fence     | Manual annotation       |
| 24   | Blind aIPg     | Strong vs off           | 49   | Wing ext.      | Manual annotation       |
| 25   | Blind aIPg     | Weak vs off             | 50   | Wing flick     | Manual annotation       |

Table 7: Descriptions of fly tasks.
E.2 Tracking

The body and wings of the flies were tracked using the FlyTracker software [20]. 17 selected landmark points were tracked using the Animal Part Tracker (APT) [34]. Coordinates were converted from pixels to millimeters by detecting the circular arena boundary, with \((0,0)\) corresponding to the arena center. Figure 2 shows an illustration of the pose tracking.

E.3 Behavior Annotation

Using JAABA [35], we annotated 6 behaviors involved in fly courtship and aggression:

- **Aggression**: The focus fly was angled towards another fly and engaged in several touches with \(\geq 2\) limbs to the head, abdomen or thorax of another fly, causing the other fly to move. This behavior included head butting, fencing, and shoving behaviors as defined [52, 61].
- **Chase**: The focus fly was following another moving fly, maintaining a small, somewhat constant distance to it [59].
- **Courtship**: The focus fly was performing any stage of the courtship sequence, including orienting, following, tapping, singing, licking, attempted copulation, or copulation [65].
- **High posture fencing**: The focus fly was angled towards another fly with the mid legs of the fly angled sharply (< 45 degrees), and the forelegs lifted off of the bottom of the arena and touching limbs, head, abdomen or thorax of another fly [52, 61].
- **Wing extension**: The focus fly unilaterally rotates a wing out for an extended period of time. This behavior is likely an indication of the fly producing courtship song with the extended wing [59].
- **Wing flick**: The focus fly rapidly and symmetrically moves its wings out and back in performing a quick scissoring movement several times in a row [59].

As all of the behaviors we annotated occur rarely, we sparsely annotated the data using frames suggested using JAABA’s interactive system. We only annotated frames for which we were confident of the correct class. We annotated frames across all fly types, for many different videos and flies. For all behaviors, the classifiers trained by JAABA using the annotated data looked reasonable, based on casual proofreading.

E.4 Data splitting

We split the data into 4 sets, with each set containing distinct videos and flies.

- **User train**: Data given to the competitor to learn their embedding.
- **Evaluation train**: Data used to train the linear classifier during evaluation.
- **Test 1**: Data used to measure performance of the linear classifier. Performance on this dataset was presented on the leaderboard during the competition.
- **Test 2**: Final set of data used to measure performance on the linear classifier, used for determining the competition winners.

We used simulated annealing to find a way to split the videos so that:

- There were videos from each fly type in each set.
- There were manual labels from each fly type and each behavior category in each set.
- Approximately 60% of videos were in User train, 20% in Evaluator train, 10% in Test 1, and 10% in Test 2.
- For each behavior type and fly type, approximately 40% of manual labels for each behavior were in User train, 30% in Test 1, and 30% in Test 2.

We split each video into segments of length 30s (4500 frames), with gaps of a randomly selected interval between .5s (75 frames) and 2s (150 frames) between segments. Included segments were chosen so that they did not include obvious identity tracking errors (trajectory births or deaths). Flies were shuffled within each segment so that fly \(i\) across segments do not correspond.

F Evaluation
For all tasks, we evaluate representation learning performance using a linear evaluation protocol, by training a linear model on top of the learned representation at each frame for classification and regression on a set of downstream tasks. These downstream tasks are unseen during training of the representation learning model. We train separate linear models per task, and because of the high class imbalance of some tasks, the classes are weighted inverse to class frequencies during training. Our evaluation framework is open for submissions at [https://www.aicrowd.com/challenges/multi-agent-behavior-challenge-2022](https://www.aicrowd.com/challenges/multi-agent-behavior-challenge-2022) for mouse triplet and fly group trajectory representations. Our test labels and evaluation code will be publicly available after the conclusion of the MABe video challenges on July 3rd.

For training the linear models, we use three fixed random 80% of the evaluation train split to train three models. All evaluations are performed on a fixed test set. For classification tasks, majority voting is used to combine the predictions of the three classifiers. For regression tasks, the predictions are averaged. Both merging schemes are done at the frame level. The evaluation metrics are F1 score for classification and Mean Squared Error for regression computed for each sequence, then averaged over the sequences. Note that all sequences given an organism have the same number of frames.

**F1 score.** The F1 score is the harmonic mean of the Precision $P$ and Recall $R$:

$$P = \frac{TP}{TP + FP}$$  \hspace{1cm} (1)

$$R = \frac{TP}{TP + FN}$$  \hspace{1cm} (2)

$$F1 = \frac{2 \times P \times R}{P + R}$$  \hspace{1cm} (3)

Where true positives (TP) is the number of frames that a model correctly labels as positive for a class, false positives (FP) is the number of frames incorrectly labeled as positive for a class, and false negatives (FN) is the number of frames incorrectly labeled as negative for a class.

For F1 score across tasks, we take an unweighted average across classification tasks in either the mouse or fly domain. For our evaluation, the class with the highest predicted probability in each frame was used to compute F1 score, but the F1 score will likely be higher with threshold tuning.

**Mean Squared Error.** For regression tasks, given $n$ data samples, we use the predicted values $\bar{y}$ and the real labels $y$ to compute:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - \bar{y}_i)^2$$  \hspace{1cm} (4)

We normalize the label values for regression to between 0 and 1. In our dataset, the experiment day and time of day tasks are regression tasks, while all other tasks are classification tasks.

### G Implementation Details

Our benchmark models learn from sequences of trajectory data and maps this data to a behavioral representation, which can then be used for a range of downstream tasks. Let $D$ be a set of $N$ unlabelled trajectories. Each trajectory $\tau$ is a sequence of states $\tau = \{s_t\}_{t=1}^{T}$ over time, which represents the data for a variable number of agents across a variable number of timestamps. The state $s_t$ at timestamp $t$ corresponds to the location and pose of the agents at that time, often represented by keypoints. Let $z$ be the behavioral representation. In our framework, models can learn from trajectories across time, but needs to produce a representation at each frame to account for frame-level tasks.

#### G.1 TVAE

The Trajectory Variational Autoencoder (TVAE) is trained in a self-supervised way using trajectory reconstruction (Figure 6). To start, the keypoints of multiple agents is stacked to form the state
Learning Objective. The TVAE is a sequential generative model that uses trajectory reconstruction as the signal during training. Given previous states, the goal is to train the model to predict the next state. This architecture has previously been studied to learn trajectory representations in a variety of domains \cite{14, 81, 67}. We embed the input trajectory using an RNN encoder, \( q_\phi \), and an RNN decoder, \( p_\theta \), to predict the next state. The TVAE loss is:

\[
L_{\text{tvae}} = \mathbb{E}_{q_\phi} \left[ \sum_{t=1}^{T} - \log(p_\theta(s_{t+1}|s_t, z)) \right] + D_{KL}(q_\phi(z|\tau)\|p_\theta(z)).
\]  

We use the unit Gaussian as a prior distribution \( p_\theta(z) \) on \( z \) to regularize the learned embeddings.

To predict behavioral representations at each frame, we form a sliding window of size 21, using 10 frames before and after the current frame. The encoder and decoder are based on Gated Recurrent Units with 256 hidden layers. The training uses the Adam optimizer \cite{37} with a batch size of 512 with learning rate 0.0002.

G.2 T-Perceiver

The T-Perceiver model (Figure 7) has two main steps: (1) we first create a richer representation by augmenting keypoint coordinates with additional hand-crafted features and (2) then we learn the...
temporal relationships and extracted the embedding from a Perceiver model \cite{perceiver}. The model is trained to reconstruct frame-level features from masked input as well as predict any public tasks.

**Hand-crafted feature extraction.** The first step transforms the original keypoint features into a high dimensional frame-level representation of the distances, angles and velocities between the keypoints. Feature extraction was performed algorithmically resulting in a 456 dimensional vector for the mouse dataset, and a 2112 dimensional vector for the fly dataset. The fly dataset has larger feature vectors as there were up to 11 individual flies in each frame, and when there were fewer flies, the vector was padded with zeros. Angles are encoded using \((\sin(\theta), \cos(\theta))\). All features are normalized to have a mean of 0 and a standard deviation of 1.

**Sequence modeling.** The second step is to use an unsupervised sequence to sequence (seq2seq) model to combine these features across frames and map to the desired final embedding dimension. The features are first downsized to the final embedding size using a two layer fully-connected neural network with an intermediate layer size twice the size of the respective final embeddings using a 50% dropout rate and the ELU activation function. This sequence of downsized features are passed through a standard Perceiver model \cite{perceiver} with the number and dimension of latent vectors equal to embedding size and a sequence length of 512. For the fly dataset only, every second frame is dropped for computational reasons due to the high original frame rate.

**Learning Objective.** During training, a variable number of up to 80\% of frames were masked out and there was an additional linear layer to predict the original unmasked high dimensional features as well as labels from the public train split containing a subset of the hidden tasks. The model was trained to simultaneously optimize for two tasks: to minimize the mean square error on the frame-level features and to minimize the cross entropy loss of the label predictions. The first task was given a weight of 10 compared with the second task. The Adam optimizer \cite{kingma2014adam} was used for training with a learning rate of 0.001.

### G.3 T-GPT

The T-GPT model is inspired by the NSP (Next Sentence Prediction) \cite{devlin2018bert} task from natural language processing. We instead propose the NFP (Next Frame Prediction) task, which is a frame-level task for predicting the keypoint coordinates in the next frame based on the observation of the past frames (Figure 8).

Giving a stream of frame-by-frame states \(\tau = \{(s_t)\}_{t=1}^{T}\), we first aggregate information from past frames with a *vanilla* Transformer encoder \cite{vaswani2017attention}: 

\[
\mathbf{z}_t = f(s_1, s_2, ..., s_t)
\]  

(6)

Then a shallow decoder \(h\) (i.e. a two-layer MLP) is used to predict the keypoint coordinates in the next frame:

\[
\hat{s}_{t+1} = h(\mathbf{z}_t)
\]  

(7)
Learning Objective. We compute the reconstruction loss between the decoder output and original keypoint coordinates:

\[ L = \text{MSE}(\hat{s}_{t+1}, s_{t+1}) \]  

(8)

Following our preliminary exploration, we find the representation generalizes better with MSE loss than L1.

We build on the open source implementation of GPT [7]. First, the keypoint coordinates in each frame are converted into a token by flating and normalization, which results in 528-d input tokens. Then the tokens are fed into the encoder network, with a 24-layer Transformer encoder and a projection head. Each Transformer layer has 768 dimensional states and 12 masked attention heads. The one-layer projection head reduces the feature dimension from 768 to 256 for flies and 128 for mice. A two-layer decoder (Linear-LayerNorm-Tanh-Linear) is used to predict the coordinates in the next frame. In order to only attends to the left context, we use the upper triangular matrix attention mask in each self-attention layer when training. In the inference stage, these masks are removed to better aggregate contextual features from the past and future.

At training, we use all the available data and sample 50 consecutive frames each iteration. We randomly flip the coordinates horizontally with a probability of 0.5. The learning rate and batch size are 1e-5 and 2 respectively, with the AdamW optimizer [44]. To make better use of the training data, we do the NFP task in a bidirectional way and the corresponding losses are averaged.

G.4 T-PointNet

We use PointNet [58] alongside hand-crafted features and PCA to extract permutation-invariant features from the keypoint data (Figure 9). As the embedding will be used to train a network for the hidden tasks, its important that embedding vector remains same even the order of the mice is switched. We note that this model is only applied to the mouse data, and not to the fly data, where some of the tasks are fly-dependent.

The hand-crafted features used are similar to the ones from [67], and 10 PCA components are computed for each mice and averaged to generate the group embeddings. Based on the goal of generating permutation-invariant embeddings, we select a PointNet based architecture [58], which has been popular for learning patterns in unordered point cloud datasets. It fundamentally relies on commutative operations like sum, average, max to create permutation invariant features.

Learning Objective. Each “point” fed into PointNet represents one pair of agents, and the coordinates are hand crafted features between each pair such as distance, angle, and speed (each 10 dimensions). PointNet is trained using a cosine similarity loss, where nearby frames in a sequence are treated as positives whereas a random frame chosen from a random sequence is chosen as negatives. The advantage of this network is that the embedding remain same regardless of the input order of the agents. The final combined embedding size is 69 dimensions.

We use the vanilla PointNet network as described by authors in [58] with a reduced set of parameters and filters. The original network is designed for point clouds in order of 1000 and in contrast, in
this application there are only 6 animal pairs corresponding to 6 points, thus we reduce the network capacity to prevent overfitting. Given the novelty of this approach for modeling trajectory data, we experiment with a range of hyperparameters (see Section H.4). This model is trained with an Adam optimizer [37] with learning rate 0.005 and batch size 512.

G.5 T-BERT

We extend BERT [17] to learn separate embeddings for each agent in the enclosure which are then concatenated for the group embedding (Figure 10). We train the model using three main tasks: 1) Masked modeling, 2) hand-crafted feature predictions similar to that of [67], and 3) contrastive learning. This model is only applied to the mouse dataset.

We sample a window of 80 frames, encoding the keypoints with a linear projection layer. The sequence of keypoints for each agent is separated by a special learned embedding, similar to a [SEP] token [17]. We use three different kinds of features: 1) Individual-agent features, which are agent specific. 2) Inter-agent, which are features between each pair of agents. Note that these pairings can be directional. 3) Group features which apply to the entire group. Each feature type is encoded and their embeddings are added. In the case of inter-agent features, we encode and add each pair.

Masked Modeling. We mask 70% of the input keypoints and features. Because of the high sampling frequency of the dataset, masked modelling may be trivial through interpolation of nearby frames. We therefore mask spans of the input, following the same masking scheme as SpanBERT [33]. We set the minimum and maximum span length to 3 and 20 respectively and sample lengths according to \( l \sim \text{Geo}(p = 0.2) \). The input subsequence is encoded with a stack of 12 transformer self-attention blocks with hidden size 912, followed by a projection onto a 42 dimensional space for the output embeddings. We apply dropout to these and predict the normalized masked keypoints.

Feature Predictions. We predict individual-agent features directly from each output embedding. Inter-agent features are predicted by taking the output embeddings for the agents in the pair and subtracting them, then regressing the features from this pair embedding. We obtain the final representation for the group by concatenating the embeddings for each agent. We use the group embedding to predict group features and for the final submission. Group embeddings are pooled across frames using a weighted average to get a single embedding for the entire input sequence. This pooled embedding is then used for the contrastive task.

Contrastive Task. We perform a contrastive learning task by taking two randomly subsequences from the same 1 minute clip as the positive pair. Negative pairs are created by pairing with other sequences within the batch. We encode the pooled sequence representation using a 2 layer MLP onto a 42 dimensional space. We take the NT-Xent loss [13] with \( \tau = 0.1 \).

Learning Objectives. The task losses are weighted:

\[
L = L_m + 0.8L_x + 0.8L_y + 0.4L_z + 0.05L_c + 0.1L_{cl}
\]

(9)

Where \( m \) is masked modelling, \( x \) is the individual agent feature prediction task, \( y \) is the inter-agent feature prediction task, \( z \) is the group feature prediction task, \( c \) is the chases task (public task on mouse

Figure 10: T-BERT Model Overview. The trajectory of each agent is concatenated and encoded using BERT [17], trained on masked modeling, predicting hand-crafted features, contrastive loss, and predicting publicly available train tasks.
and $cl$ is the contrastive task. 53 individual agent features were computed for each agent, with 13 inter-agent features for pairs, and 1 group feature for all three mice. Features concerning distances, velocities and accelerations are normalised by mouse length. Angles are encoded ($\sin(\theta)$, $\cos(\theta)$). We apply rotation, reflection and adding gaussian noise to the keypoints [67], each are applied with probability $p = 0.5$. To create frame-level embeddings for a 1 minute sequence, we encode overlapping 80 frame windows of the input using a stride of 40 frames.

An exhaustive hyperparameter search was not possible due to computational constraints, so most parameters were not tuned. We tested input lengths of 60, 80 and 100 frames and found that 80 was optimal. We split the dataset into training and validation splits, with 95% and 5% respectively. We train the model for 160 epochs with a batch size of 16. We used AdamW [44] with a learning rate of 0.00003 and a linear schedule. The model with the lowest validation loss is chosen.

H Reproducibility Checklist

Here we provide additional details based on the ML Reproducibility Checklist.

H.1 Baselines: PCA and TVAE

- **Source code link:**
  - PCA for mouse: https://www.aicrowd.com/showcase/getting-started-mabe-2022-mouse-triplets-round-1
  - PCA for fly: https://www.aicrowd.com/showcase/getting-started-mabe-challenge-2022-fruit-flies-v-0-2-2kb
  - TVAE: https://github.com/AndrewUlmer/MABe_2022_TVAE

- **Data used for training:** Train split of the corresponding dataset, with trajectory data only (no hidden labels).
- **Pre-processing:** The pre-processing for the TVAE is based on [67]. The trajectory data is normalized by image size, then each agent is centered and axis-aligned to compute SVD components with 7 dim per mouse and 10 dim per fly. The agent position, orientation, and pose SVD is then used as input to the TVAE. The PCA baseline does not use SVD as a pre-processing step.
- **How samples were allocated for train/val/test:** MABe2022 provides train and test splits.
- **Hyperparameter considerations:** The hyperparameters used were based on [67] and was not further tuned on MABe2022.
- **Number of evaluation runs:** 5
- **How experiments were ran:** See Section
- **Evaluation metrics:** F1 and MSE.
- **Results:** See Sections
- **Computing infrastructure used:** All baseline experiments were ran on one of three machines: NVIDIA Quadro RTX 6000 GPU, Intel i9-10940X CPU; NVIDIA Quadro RTX 4000 GPU, Intel i7-10700 CPU; NVIDIA Tesla A100 GPU, Intel Xeon Gold 6230R CPU.

H.2 T-Perceiver

- **Source code link:** [https://colab.research.google.com/drive/13_M6yzF1VQ4STuJsO1at-GWK2_TDGTNV?usp=sharing](https://colab.research.google.com/drive/13_M6yzF1VQ4STuJsO1at-GWK2_TDGTNV?usp=sharing)

- **Data used for training:** 75% of the clips in the train split of the corresponding dataset, with trajectory data and publicly available labels, in addition to all trajectories in the test split.
- **Pre-processing:** None, besides computing higher-dimensional hand-crafted features.
- **How samples were allocated for train/val/test:** MABe2022 provides train and test splits. Val split was created from a random 25% of the train split.
• **Hyperparameter considerations:** The hyperparameters were not systematically tuned on MABe2022.

• **Number of evaluation runs:** 5

• **How experiments where ran:** See Section G

• **Evaluation metrics:** F1 and MSE.

• **Results:** See Sections 4

• **Computing infrastructure used:** All experiments were ran on Google Colab with Tesla P100.

### H.3 T-GPT

- **Source code link:** Pending public release.

- **Data used for training:** All available data of the corresponding dataset (both train and test splits), with trajectory data only (no hidden labels).

- **Pre-processing:** The trajectory data is normalized, using the mean and standard deviation of the keypoint coordinates on the training set.

- **How samples were allocated for train/val/test:** MABe2022 provides train and test splits.

- **Hyperparameter considerations:** Hyperparameters are not tuned systematically, except for learning rate \( \{10^{-4}, 10^{-5}, 10^{-6}\}\).

• **Number of evaluation runs:** 5

• **How experiments where ran:** See Section G

• **Evaluation metrics:** F1 and MSE.

• **Results:** See Sections 4

• **Computing infrastructure used:** All experiments were ran on one Nvidia Tesla V100 GPU.

### H.4 T-PointNet

- **Source code link:** [https://github.com/Param-Uttarwar/mabe_2022](https://github.com/Param-Uttarwar/mabe_2022)

- **Data used for training:** Train split of the corresponding dataset, with trajectory data only (no hidden labels).

- **Pre-processing:** The trajectory data is normalized, using the mean and standard deviation of the keypoint coordinates on the training set.

- **How samples were allocated for train/val/test:** MABe2022 provides train and test splits.

- **Hyperparameter considerations:** The hyperparameters considered were learning rate \( \{10^{-3}, 3 \times 10^{-4}, 10^{-4}\}\), dropout rate \( \{0.0, 0.2, 0.5\}\), weight decay on or off, cosine similarity or normalized L2 loss.

• **Number of evaluation runs:** 5

• **How experiments where ran:** See Section G

• **Evaluation metrics:** F1 and MSE.

• **Results:** See Sections 4

• **Computing infrastructure used:** All experiments were ran on one NVIDIA GeForce RTX 3090 GPU with Intel Xeon Gold 6258R CPU.
H.5 T-BERT

- **Source code link**: [https://github.com/edhayes1/MABe](https://github.com/edhayes1/MABe)
- **Data used for training**: Train split of the corresponding dataset, with trajectory data only and publicly available labels.
- **Pre-processing**: The pre-processing for T-BERT is based on [67], but without the SVD computation. The trajectory data is normalized by image size, then each agent is centered and axis-aligned.
- **How samples were allocated for train/val/test**: MABe2022 provides train and test splits. 5% of the train split was used for validation.
- **Hyperparameter considerations**: The hyperparameters considered were hidden size \( \{576, 768, 912\} \), layers \( \{10, 12, 16\} \), and masking probability \( \{0.4, 0.6, 0.7, 0.8\} \).
- **Number of evaluation runs**: 5
- **How experiments were ran**: See Section 6
- **Evaluation metrics**: F1 and MSE.
- **Results**: See Sections 4
- **Computing infrastructure used**: All experiments were ran on one Nvidia RTX 3090, with Intel i9-10900KF CPU.