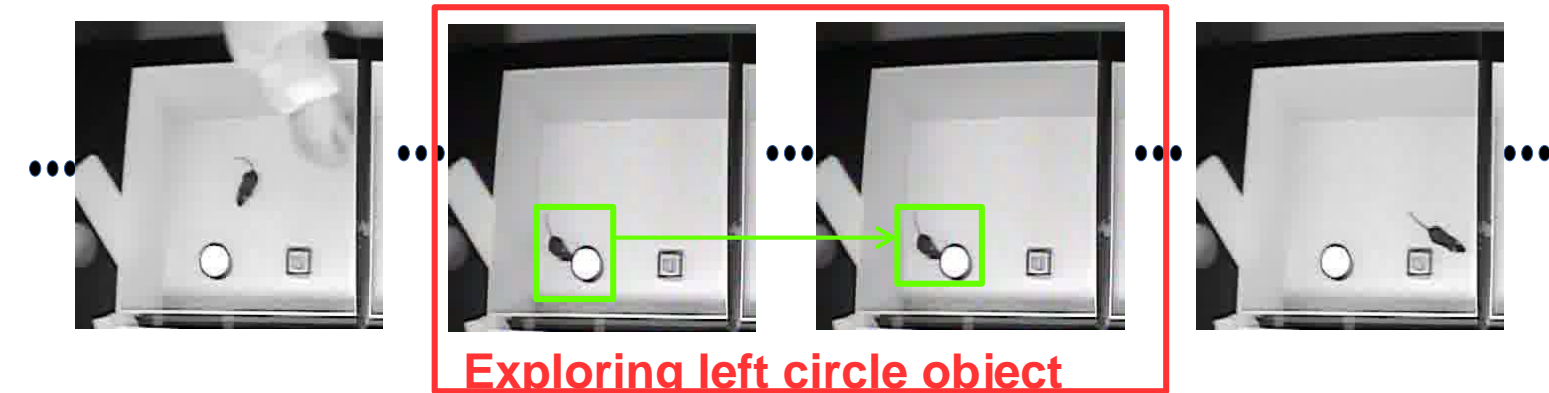


Problem

In neuroscience, understanding animal behaviors is key to studying their memory patterns.

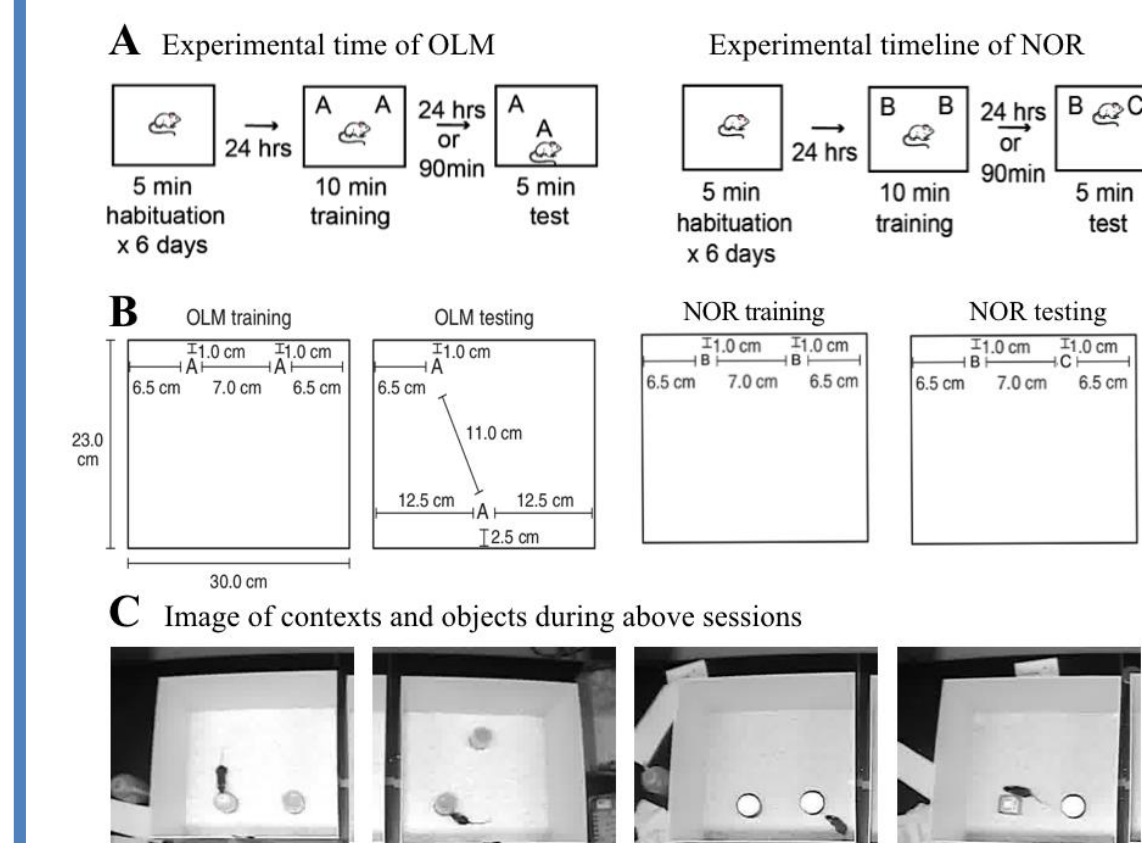


Motivation and Goal

Neuroscience researchers hand-label videos because existing automated systems are unreliable.

- Previous work [Noldus et al. 2001, Burgos-Artizzu et al. 2012, Giancard et al. 2013, Lorbach et al. 2015, ...] or commercial software [2] mainly rely on object tracking and are prone to drifting.
- We instead treat this as a per-frame action classification problem.
- We also want to release a better annotation and visualization UI for neuroscience community.

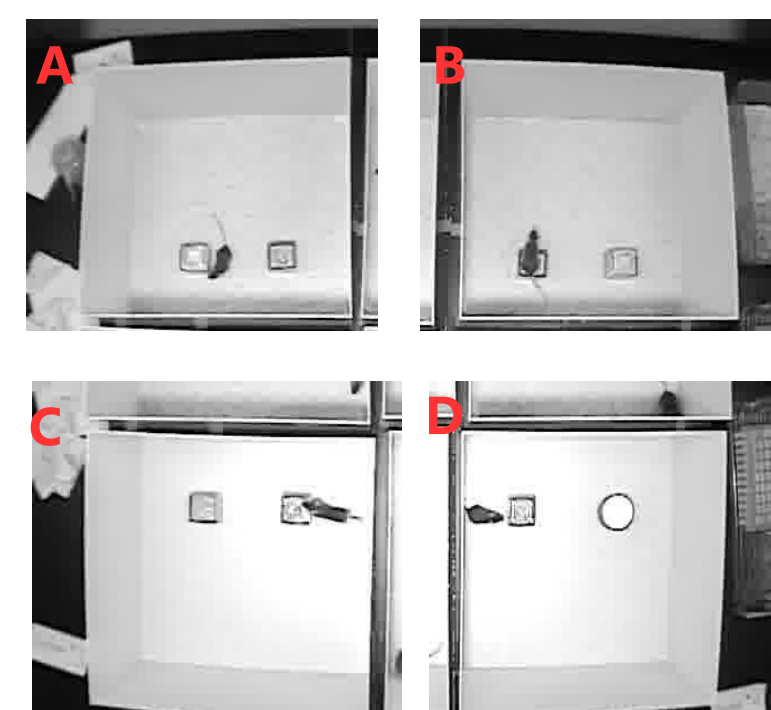
Experimental setup



- We study rodent memory by conducting Object Location Memory (OLM) and Novel Object Recognition memory (NOR) tasks.
- We need to count the exploration time for each object to find the rodent's preference patterns.

Challenges

Strict criteria to judge whether an action is exploration or not based on neuroscience knowledge.



For example, below cases do not count as exploration:

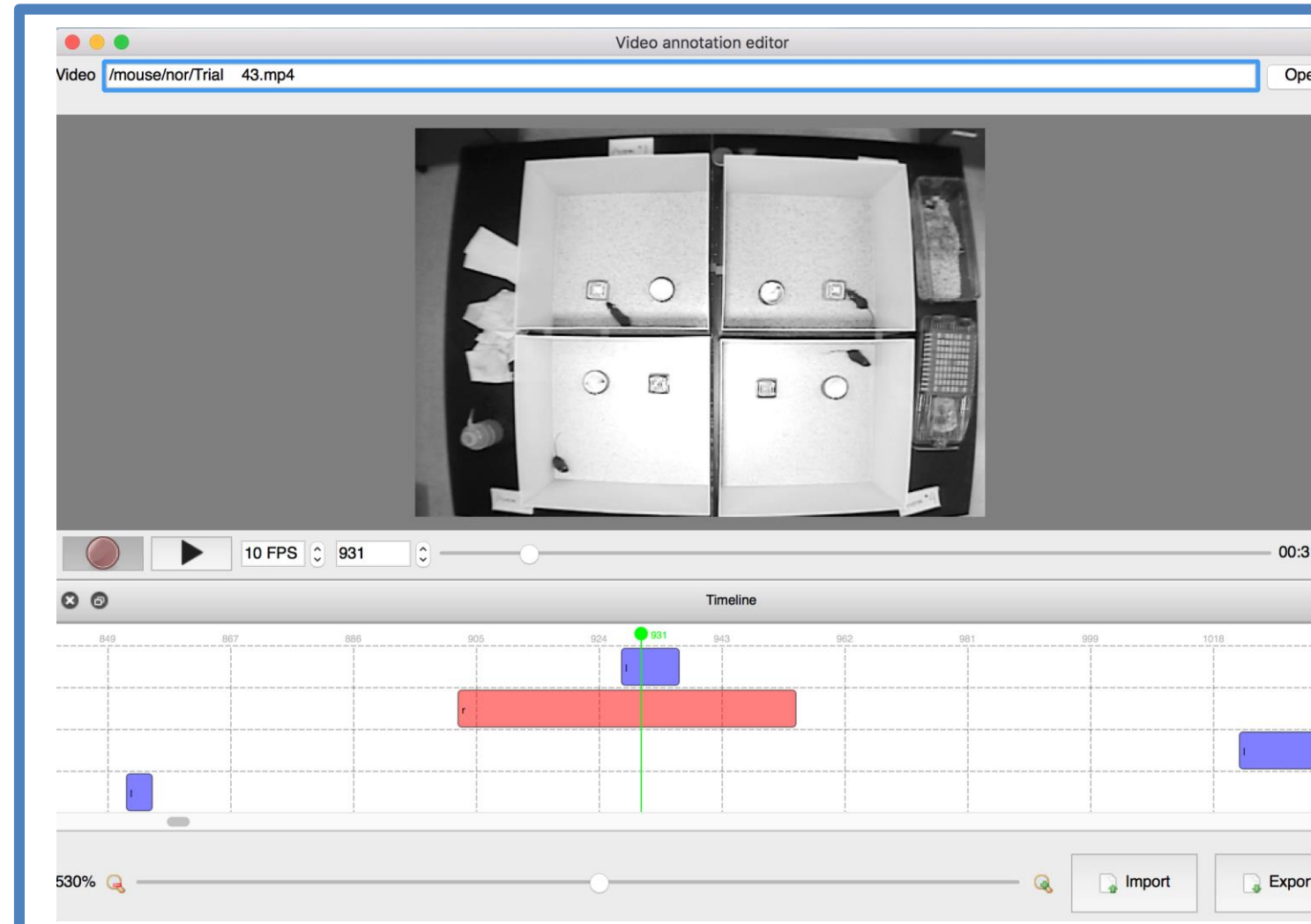
- Not approaching the object (e.g., if the rodent re-orientates itself and the nose accidentally comes close to the object)
- On top of the object
- Looking over the object
- Repetitive behavior like digging close or biting the object

Dataset

We collected and annotated a new Rodent Memory (RM) video dataset containing more than 80 videos with frame-level action labels using our UI. (See “Experiments” for C0-C4 definitions.)

| | #videos | #Frames | C0 | C1 | C2 | C3 | C4 |
|-----------|---------|---------|--------|------|------|------|------|
| NOR train | 36 | 450720 | 429916 | 7314 | 3815 | 5139 | 4536 |
| NOR test | 12 | 152776 | 144707 | 2148 | 1750 | 2382 | 1789 |
| OLM train | 24 | 227716 | 220039 | 1829 | 1557 | 1645 | 2646 |
| OLM test | 8 | 77108 | 73516 | 777 | 491 | 1025 | 1299 |

UI

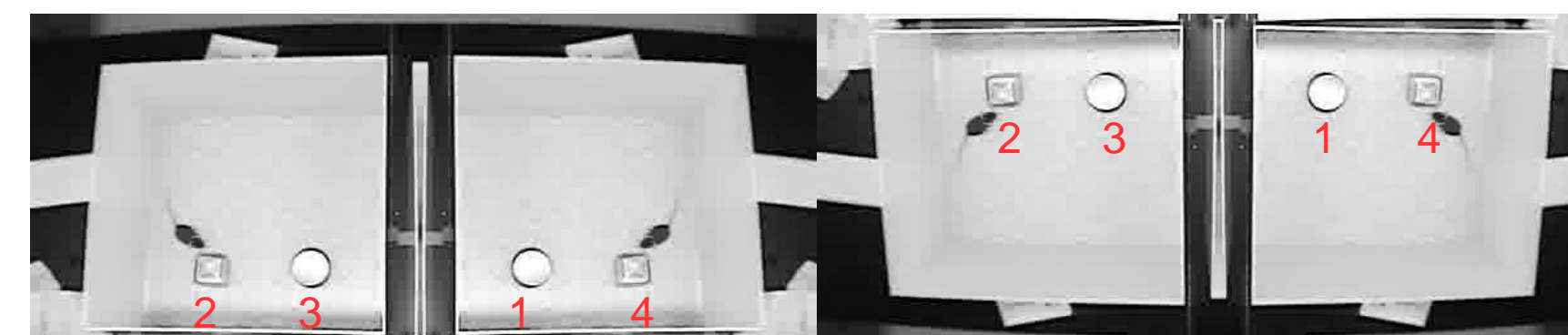


| | GT avg. length | Avg. len [1] | Accuracy |
|-----|----------------|--------------|----------|
| NOR | 13.5 | 4.2 | 68.7% |
| OLM | 17.3 | 4.3 | 63.6% |

Compared to a previous timer-based annotation approach [1], our UI helps to get more accurate ground-truth, while being easier to use.

Approaches

- We leverage off-the-shelf convolutional neural networks (CNN) for behavior classification.
 - AlexNet: takes one frame as input, filters move within single image
 - C3D: takes sequence of frames as input, filters also move along the temporal axis
- Pre-trained weights used to initialize models
 - AlexNet: pre-trained on ImageNet
 - C3D: pre-trained on Sports-1M
- Data augmentation is used to enlarge training set; Post-processing is used to smooth the final prediction.



Experiments

We compare against a widely-used commercial software Any-Maze [2], which tracks rodent body key-points.

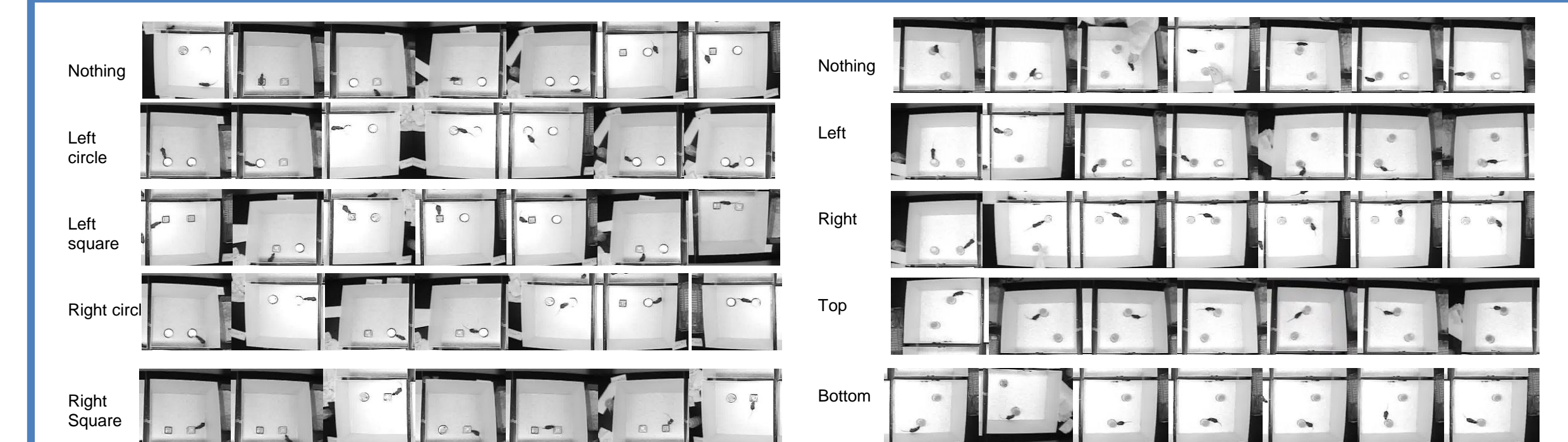
| Per-frame Classification Accuracy (%) | | | | | |
|---------------------------------------|--------------|----------|----------|----------|----------|
| | Any-maze [2] | Alex-net | C3D(d=3) | C3D(d=5) | C3D(d=9) |
| NOR | 78.34 | 93.17 | 89.30 | 87.54 | 77.74 |
| OLM | 74.25 | 95.24 | 91.98 | 83.03 | 73.39 |

| NOR prediction | | | | | |
|------------------|-------|-------|-------|-------|-------|
| C0: Nothing | 87.74 | 3.84 | 2.60 | 3.49 | 2.33 |
| C1: Left circle | 0.23 | 99.44 | 0 | 0.19 | 0.14 |
| C2: Left square | 1.26 | 0 | 95.94 | 0.06 | 2.74 |
| C3: Right circle | 3.74 | 0 | 0.04 | 96.22 | 0 |
| C4: Right square | 5.76 | 0.11 | 0 | 0 | 94.13 |

| OLM prediction | | | | | |
|------------------|-------|-------|-------|-------|-------|
| C0: Nothing | 87.85 | 2.66 | 1.51 | 4.70 | 3.27 |
| C1: Left circle | 7.34 | 92.66 | 0 | 0 | 0 |
| C2: Right circle | 0.81 | 0 | 99.19 | 0 | 0 |
| C3: Top | 0.68 | 0 | 0 | 99.32 | 0 |
| C4: Bottom | 0.38 | 0 | 0 | 0 | 99.62 |

Our approaches significantly outperforms the commercial AnyMaze tracking baseline.

Qualitative Results



Our model detects the various rodent explorations across a wide range of videos.

Neuroscience Experiments

| Correlation coefficient with GT | | | |
|---------------------------------|------|-------|-------|
| Annotator | T1 | T2 | DI |
| Any-maze | 0.67 | 0.659 | 0.599 |
| Ours | 0.79 | 0.952 | 0.845 |

- T1, T2: exploration time of two objects
- Discrimination Index:

$$DI = (T1 - T2) / (T1 + T2)$$

Our model is reliable enough to replace human annotations in neuroscience experiments.

References

1. A. V. Ciernia and M. A. Wood. Examining object location and object recognition memory in mice. In Current Protocols in Neuroscience, 2014.
2. Any-maze behavioral tracking software. <http://www.anymaze.co.uk/index.htm>.