Stereotypical Behavior Classification

Jercog Team, Instituto Cajal, CSIC

Gonzalo Ortega

Lab meeting - March 8th 2024

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- Malfunctional abnormal behavior.

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- Malfunctional abnormal behavior.
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Stereotypy

- Malfunctional abnormal behavior.
- Consequence of an abnormal animal in an abnormal environment.
- Unvarying in form, performed almost identically on each repetition.
- Functionless and possible strength development over time.

Contents

NeuroResource

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Mapping Sub-Second Structure in Mouse Behavior

Highlights

- Computational modeling reveals structure in mouse behavior without observer bias
- Mouse behavior appears to be composed of stereotyped, sub-second modules
- From this perspective, new behaviors result from altering both modules and transitions
- Unsupervised analysis reveals how genes and neural activity impact behavior

Authors

Alexander B. Wiltschko, Matthew J. Johnson, Giuliano Iurilli, ..., Victoria E. Abraira, Ryan P. Adams, Sandeep Robert Datta

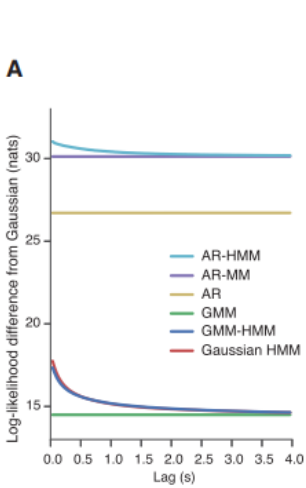
Correspondence

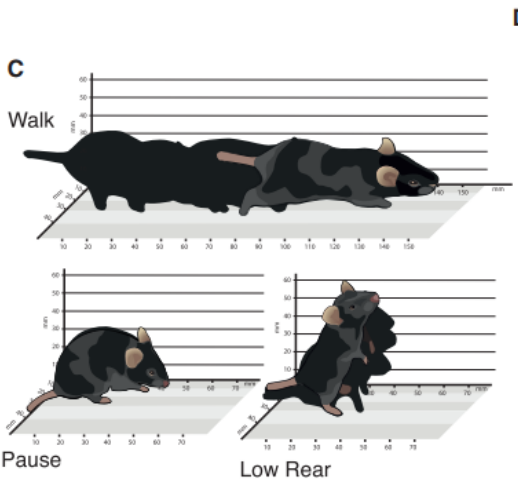
srdatta@hms.harvard.edu

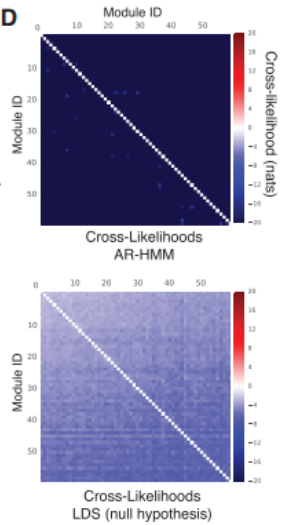
In Brief

Mouse behavior appears inherently divided into brief modules of 3D motion. This sub-second structure reveals the influence of the environment, genes and neural activity on action.

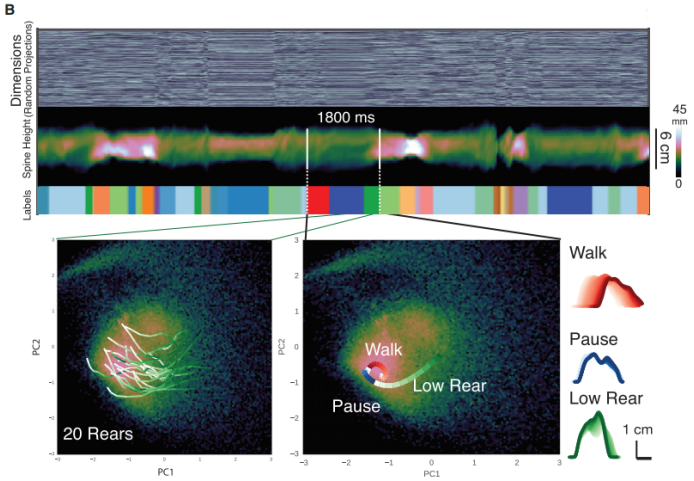
Previous work - Mapping Sub-Second Structre in Mouse Behaviour







Previous work - Mapping Sub-Second Structre in Mouse Behaviour



Previous work - 2015

Journal of Animal Ecology

British Ecological Society

Journal of Animal Ecology 2016, **85**, 69–84 doi: 10.1111/1365-2656.12379

SPECIAL FEATURE: STUCK IN MOTION? RECONNECTING QUESTIONS AND TOOLS IN MOVEMENT ECOLOGY

What is the animal doing? Tools for exploring behavioural structure in animal movements

Eliezer Gurarie[1,2]*, Chloe Bracis[3], Maria Delgado[4,5], Trevor D. Meckley[6], Ilpo Kojola[7] and C. Michael Wagner[6]

[1]Department of Biology, University of Maryland, College Park, MD 20742, USA; [2]School of Environmental and Forest Sciences, University of Washington, Seattle, WA 98195, USA; [3]Quantitative Ecology and Resource Management, University of Washington, Seattle, WA 98195, USA; [4]Department of Biosciences, University of Helsinki, 00014 Helsinki, Finland; [5]Research Unit of Biodiversity (UMIB, UO-CSIC-PA), Oviedo University – Campus Mieres, 33600 Mieres, Spain; [6]Department of Fisheries and Wildlife, Michigan State University, East Lansing, MI 48824, USA; and [7]Natural Resources Institute, Box 16, FI-96301 Rovaniemi, Finland

Previous work - Tools for exploring behavioral structure in animal movements

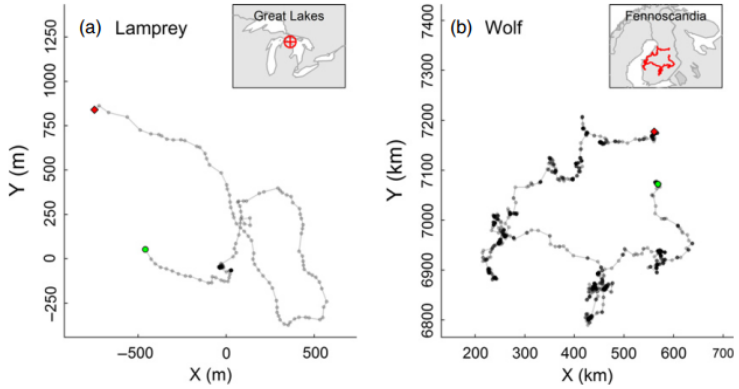


Fig. 2. Tracks analysed for the paper: (a) lamprey in the Lake Huron (see inset) and (b) wolf in Finland (see inset). Green circles and red diamonds indicate the beginning and end of each track.

Previous work - Tools for exploring behavioral structure in animal movements

Table 1. Summary table of four broad categories of behavioural movement analysis methods. The four methods implemented in this paper and the most directly relevant references are bold faced. All of the entries in the last category can be considered multistate random walks, hidden Markov models or state space models

Category	Method	References
Metric-based	Fractal analysis	Fritz, Said & Weimerskirch (2003), Laidre *et al.* (2004) Nams & Bourgeois (2004); Tremblay, Roberts & Costa (2007)
	Tortuosity measures	Bovet & Benhamou (1988); Benhamou (2004)
	First passage time (FPT)	**Fauchald & Tveraa (2003)**
	Residence time (RT)	Barraquand & Benhamou (2008)
Classification and segmentation	Penalized contrasts	Lavielle (2005), Calenge (2006)
	Bayesian partitioning (BPMM)	**Calenge (2006)**
	k-clustering	van Moorter *et al.* (2010)
	RT (segmentation step)	Barraquand & Benhamou (2008)
Phenomenological time-series analysis	Autocorrelation functions	Boyce *et al.* (2010)
	Change point analysis (BCPA)	**Gurarie, Andrews & Laidre (2009), Gurarie (2013)** Kranstauber *et al.* (2012)
	Wavelet	Polansky *et al.* (2010)
Mechanistic movement modelling	**Multistate random walk (MRW)**	**Morales *et al.* (2004)**
	Ignoring location error	Forester *et al.* (2007), Langrock *et al.* (2012) Patterson *et al.* (2008), McClintock *et al.* (2012)
	Accounting for error	Jonsen *et al.* (2013), Breed *et al.* (2012)

nature neuroscience

TECHNICAL REPORT

https://doi.org/10.1038/s41593-018-0209-y

DeepLabCut: markerless pose estimation of user-defined body parts with deep learning

Alexander Mathis[1,2], Pranav Mamidanna[1], Kevin M. Cury[3], Taiga Abe[3], Venkatesh N. Murthy[2], Mackenzie Weygandt Mathis[1,4,8*] and Matthias Bethge[1,5,6,7,8]

Previous work - 2022

frontiers | Frontiers in Veterinary Science

ORIGINAL RESEARCH
published: 23 June 2022
doi: 10.3389/fvets.2022.884437

Check for updates

Clustering for Automated Exploratory Pattern Discovery in Animal Behavioral Data

*Tom Menaker[1], Joke Monteny[2], Lin Op de Beeck[2] and Anna Zamansky[1]**

[1] Information Systems Department, University of Haifa, Haifa, Israel, [2] Department of Biotechnology, Vives University College, Ghent, Belgium

Previous work - Clustering for Automated Exploratory Pattern Discovery

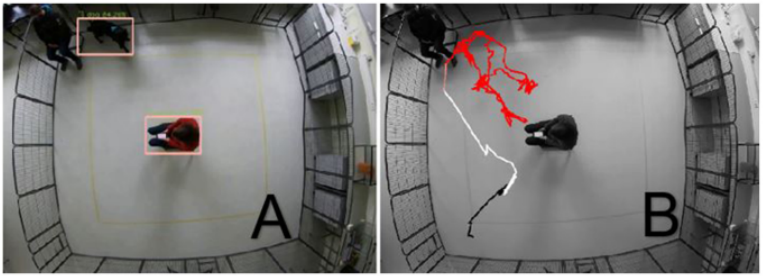


FIGURE 2 | (A) Detection; **(B)** trajectory extraction.

Previous work - Clustering for Automated Exploratory Pattern Discovery

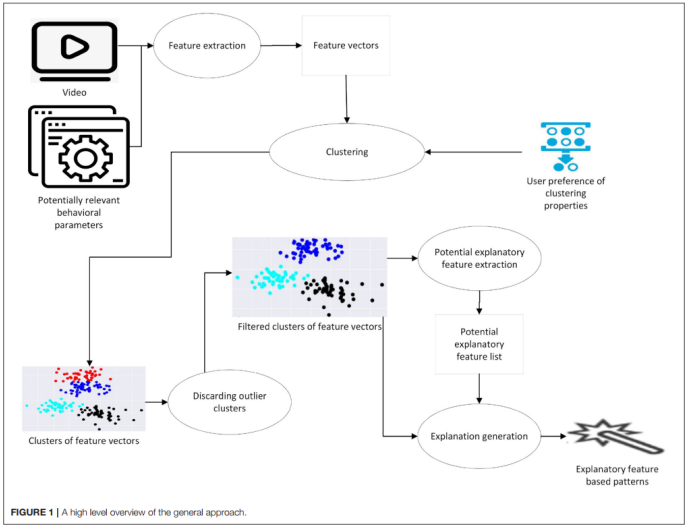


FIGURE 1 | A high level overview of the general approach.

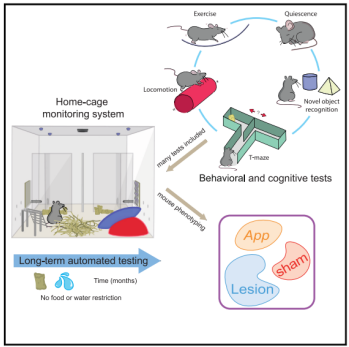
Previous work - 2023

Cell Reports
Methods

Article

A fully automated home cage for long-term continuous phenotyping of mouse cognition and behavior

Graphical abstract



Authors

Hinze Ho, Nejc Kejzar, Hiroki Sasaguri, ...,
Bart De Strooper, Marius Bauza,
Julija Krupic

Correspondence

m.bauza@ucl.ac.uk (M.B.),
jk727@cam.ac.uk (J.K.)

In brief

Ho et al. develop a home-cage system for mice with a fully automated T-maze, novel object recognition, and object-in-place tasks, as well as monitoring of locomotion. The system shows accuracy comparable to analogous standard tests and can be used for large-scale behavioral screening for genes and neural circuits underlying learning and memory.

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Methods - DeepLabCut

DeepLabCut is a toolbox for state-of-the-art markerless pose estimation of animals performing various behaviors.

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DeepLabCut is a toolbox for state-of-the-art markerless pose estimation of animals performing various behaviors.

- Extract frames and label data.

Methods - DeepLabCut

DeepLabCut:
a software package for
animal pose estimation

DeepLabCut is a toolbox for state-of-the-art markerless pose estimation of animals performing various behaviors.

- Extract frames and label data.
- Select and train our deep neural network.

Methods - DeepLabCut

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- Evaluate network performance.

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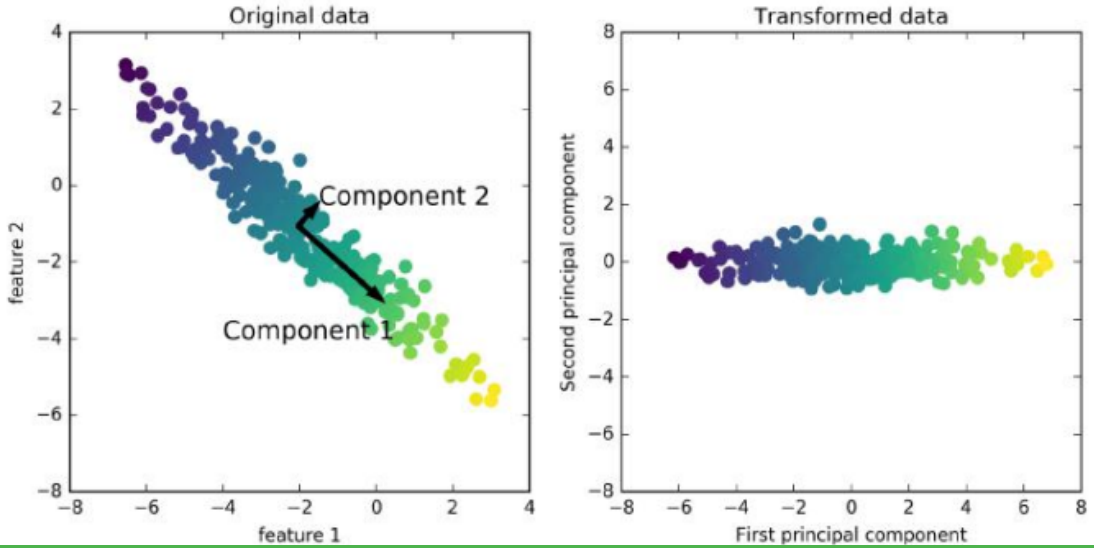
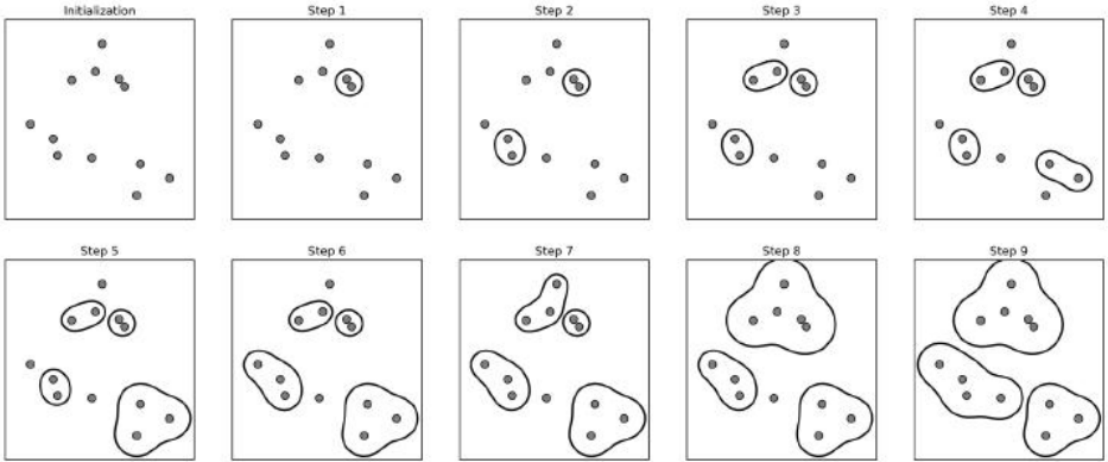
DeepLabCut is a toolbox for state-of-the-art markerless pose estimation of animals performing various behaviors.

- Extract frames and label data.
- Select and train our deep neural network.
- Evaluate network performance.
- Run inference on new videos and create labeled videos.

Methods - Principal Component Analysis



Methods - Agglomerative Clustering



Contents

Stereotypes - Circling, twirling

A circling mouse repetitively traces a loosely circular path.

Stereotypes - Circling, twirling

A circling mouse repetitively traces a loosely circular path.

- Changing location (**position**).
- Changing direction angle in the same orientation (**triangulation**, **angle speed**, **speed**).
- Returning to original position at some point (**position**).

Stereotypes - Scratching, self-grooming

A mouse is cleaning its own body and fur by means of grooming-related behaviors such as licking and scratching.

Stereotypes - Scratching, self-grooming

A mouse is cleaning its own body and fur by means of grooming-related behaviors such as licking and scratching.

- Steady location (**position**).
- Possible altitude change (**height**).
- Fast head movements (**head speed**).
- Body torsion (**body triangulation**, **angles**).

Stereotypes - Pica behavior, scratch bedding

The mouse will dig the bedding with its front limbs or with its snout.

Stereotypes - Pica behavior, scratch bedding

The mouse will dig the bedding with its front limbs or with its snout.

- Steady location (**position**).
- Snout or front limbs' movement (**head speed**, **front limbs speed**).
- Back hunched posture (**body triangulation**, **angles**).

Stereotypes - Rearing

The mouse will put its weight on its hind legs, raise, its forelimbs from the ground, and extend it's head upwards.

Stereotypes - Rearing

The mouse will put its weight on its hind legs, raise, its forelimbs from the ground, and extend it's head upwards.

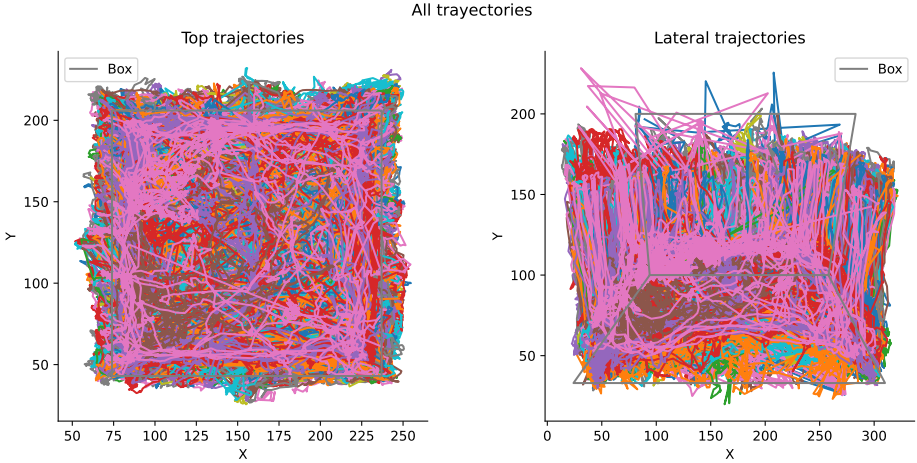
- Steady location (**position**).
- Altitude change (**height**).
- Head stretching (**head triangulation**, **angles**).

Stereotypes - Other

- Jumping
- Looping
- Walking on tiptoes
- Route tracing
- Wiping
- Chewing
- Moon-walk

Contents

Results - Trayectories



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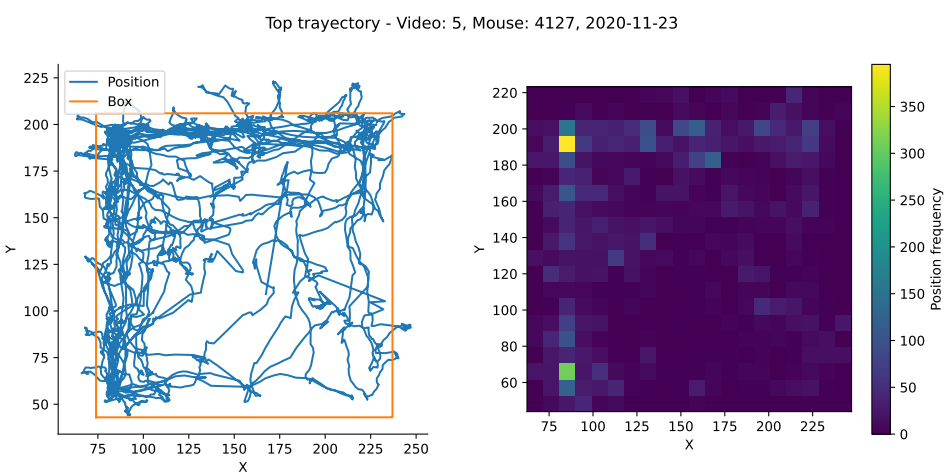
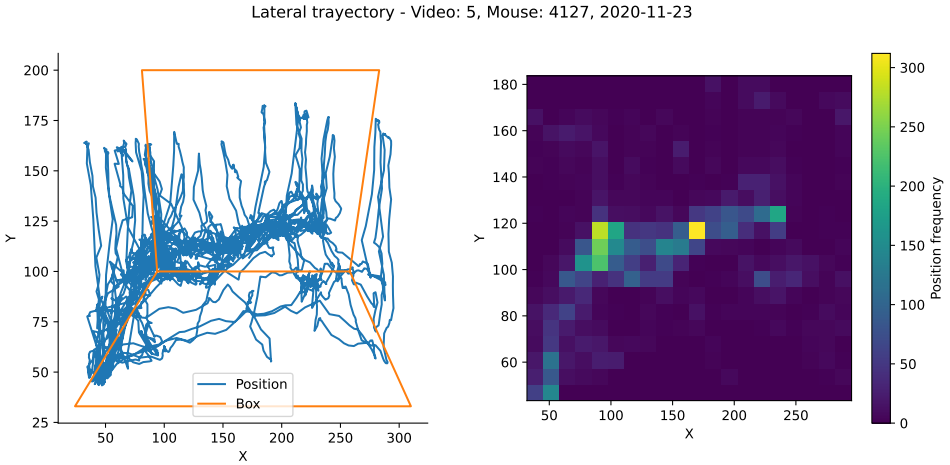
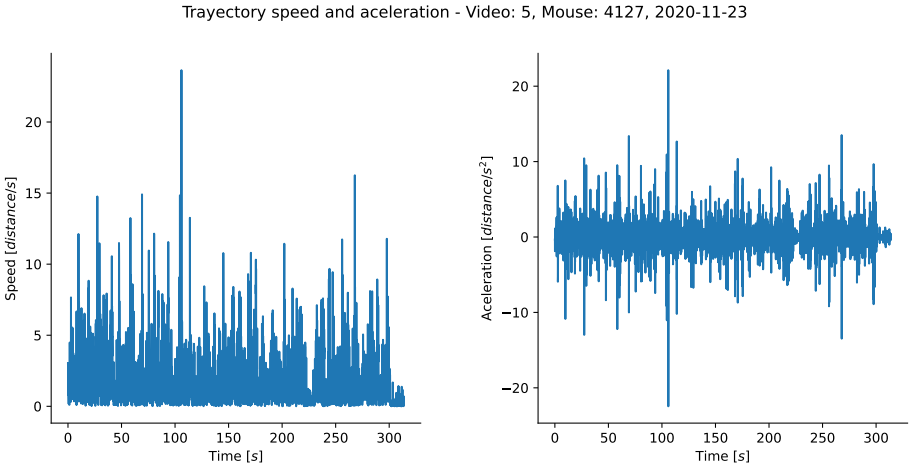


Results - Trayectories

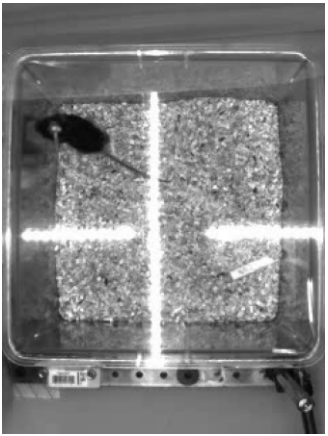


Results - Speed and acceleration



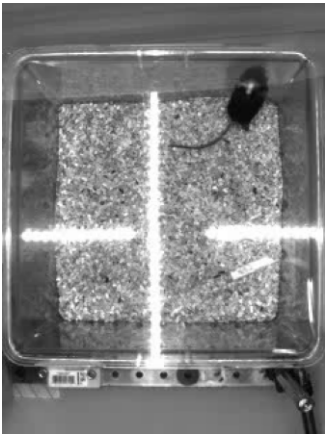
Results - Rearing

Frame 0:07.72s



Results - Rearing

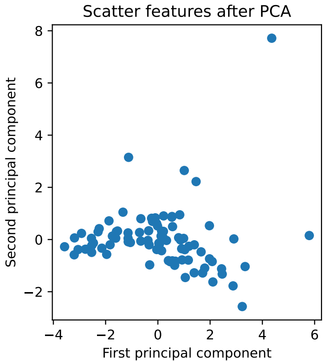
Frame 1:06.25s

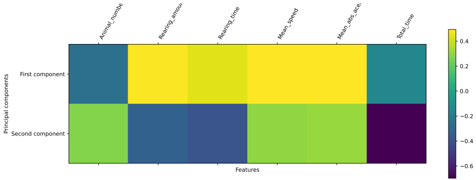


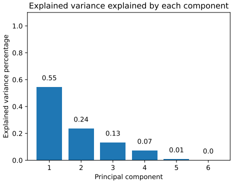
Results - Features from the first 10 videos

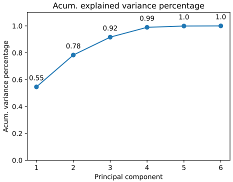
	Animal_number	Rearing_amount	Rearing_time	Mean_speed	Mean_abs_aceleration	Total_time
0	4128	14	9.20	2.579577	1.377203	312.30
1	4128	8	7.90	2.357050	1.341135	313.05
2	4128	19	16.90	2.454795	1.319198	309.10
3	4128	4	1.55	2.103530	1.167052	309.95
4	4128	7	6.85	1.519415	0.872352	314.35
5	4127	15	15.20	1.765167	1.010548	313.75
6	4127	12	13.25	1.472821	0.862514	313.90
7	4127	6	5.85	0.685737	0.421801	313.30
8	4127	0	0.00	0.671228	0.460215	314.00
9	4127	15	8.55	2.041685	1.105965	315.00

Results - PCA

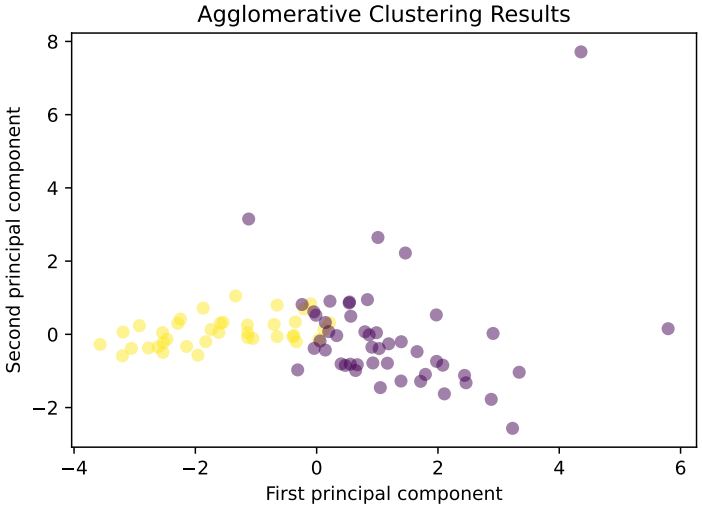

Scatter features after PCA
Second principal component
First principal component
8
6
4
2
0
−2
−4
−2
0
2
4
6


Animal_numbe
Rearing_amou
Rearing_time
Mean_speed
Mean_abs_ace
Total_time
Principal components
First component
Second component
Features
0.4
0.2
0.0
−0.2
−0.4
−0.6


Explained variance explained by each component
Explained variance percentage
Principal component
0.55
0.24
0.13
0.07
0.01
0.0
1.0
0.8
0.6
0.4
0.2
0.0
1
2
3
4
5
6


Acum. explained variance percentage
Acum. variance percentage
Principal component
0.55
0.78
0.92
0.99
1.0
1.0
1.0
0.8
0.6
0.4
0.2
0.0
1
2
3
4
5
6

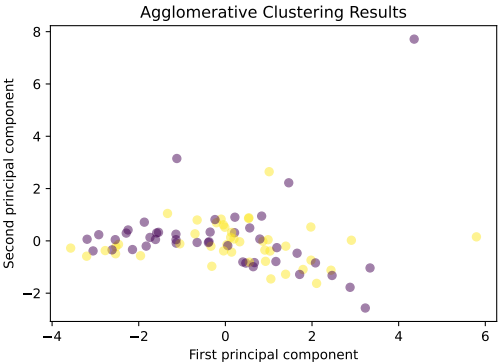
Results - Agglomerative Clustering Results

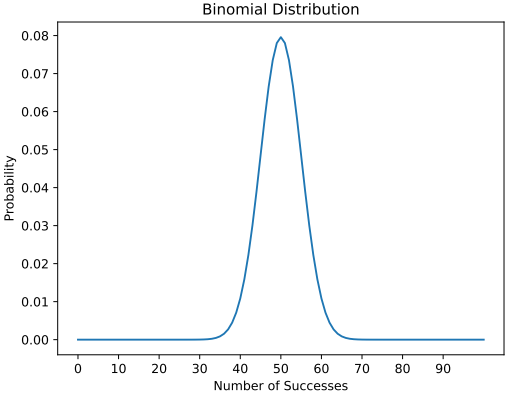


Contents

Results - Random method

$$P(X = k) = \binom{n}{k} p^k (1-p)^{n-k}$$





Results - Random method comparison