# Imitation learning to understand behaviour

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# Motivation

#### fly behaviour are diverse and complex





To gain insight into the structure and rules governing fly behaviour.

To identify the important components for deciding fly actions.

### **Predicting behaviour**



Pedestrian prediction for self-driving cars



Stock market forecast



Sports Analytics

#### **Our Approach (Outline)**

- 1. Simulate an artificial fly that behaves like a fly.
  - Using machine learning (ML), we build a black box model that produce fly behaviours without explicit rules, instead by pattern recognition and inference from the data
- 2. Interpret and understand the behaviour of artificial fly
  - Do controlled experiments: psychophysics studies and look into how black box model functions

### **Quantifying behaviour**







Approximate ...







what fly is doing

what fly is seeing

its relative position to the chamber

### Predicting the next movement

Output t+1



#### State t-1 : Learned representation of past

### Predicting the next movement

#### Position t+1



#### **Predicts 8 motion features:**

- Forward velocity
- Side velocity
- angular velocity
- Left & right wing length
- Left & right wing angle
- Body length

### **Model Architectures**

Xt - Output Xt - Input Ut, Lt - Intermediate layers

### **Model Architectures**

LINEAR RNN **CNN** Yt Yt  $\mathbf{Y}_{t}$ Ut Ut X~t Lt Lt X~t X~t

> Model with memory: Recurrent neural network

Simple model: Linear Regression

Convolutional neural network

Feedforward model:

### Artificial fly is an agent



Virtual fly bowl

### Artificial male & female fly





### Social interaction system



The behaviours that we consider to differentiate between real versus simulated flies:

- Movement patterns
- Avoiding obstacles
- Exploring the edge of the arena
- Social interactions

### Simulations

RNN

#### **Simulations**

Videos

**Real Data** 

CNN

LINEAR

### **Artificial Fly Evaluation**

Goal: Simulated fly to use mechanisms that real fly is using. How to measure how true this is?

### **Artificial Fly Evaluation**

#### Self-driving car



Performance Metrics: Is it hitting the pedestrians? Fruit fly



What metric is meaningful for predicting behaviour?

### **Artificial Fly Evaluation**

#### What type of difference matters more?



**Ground Truth** 



Output 1

Output 2

### **Evaluation : Distribution Distance**

Velocity 0.03 Welocity 0.03 0.02 0.02 0.01 0.01 0.00 0 5 10 15 mm/s

#### **Closest distance between flies**



### **Evaluation : Distribution Distance**

#### Velocity



#### **Closest distance between flies**



### **Evaluation : Distribution Distance**



#### **Closest distance between flies**



### **Evaluation : Real / Fake Discrimination**



Discriminative Network Distinguish whether the trajectories are real or fake

Simulated Trajectory

### **Evaluation : Real / Fake Discrimination**



Male



Female

#### **Our Approach (Outline)**

- 1. Simulate an artificial fly that behaves like a fly.
- 2. Interpret and understand the behaviour of artificial fly



**Predicted trajectories of next 3 seconds** 

![](_page_26_Picture_2.jpeg)

Is position

1 to 2s position

2 to 3s position

Histogram over fly trajectories of next 3 seconds

![](_page_27_Picture_2.jpeg)

Fly simulation movie

ls position

![](_page_28_Picture_3.jpeg)

![](_page_28_Picture_4.jpeg)

#### Last 50 frames of forward velocity data

![](_page_29_Picture_2.jpeg)

**Contributed forward motions among last 50 motions data** 

![](_page_30_Picture_2.jpeg)

#### Movie of fly simulation with contributed forward motions

![](_page_31_Picture_2.jpeg)

77.91ppm

![](_page_31_Picture_5.jpeg)

#### Movie of fly simulation with contributed forward motions

![](_page_32_Picture_2.jpeg)

### **Behaviour Analysis: Searching for hypothesis**

Apply the analysis to different situations
 Look for interesting scenarios
 Narrow down the set of hypothesis

![](_page_33_Picture_2.jpeg)

![](_page_34_Picture_0.jpeg)

- Observed that simulated flies behave like real flies
- Learned that RNN produces behaviours that are closer to real flies based on our metrics
- Introduced visualization tools that help analyze artificial fly predictions

### Future work

- Analyze internal representations of artificial fly to understand the key components
- Apply on different genotypes of flies to look for difference in behaviours

### Acknowledgements

![](_page_35_Picture_1.jpeg)

![](_page_35_Picture_2.jpeg)

![](_page_35_Picture_3.jpeg)

![](_page_35_Picture_4.jpeg)

Roian Egnor

![](_page_35_Picture_6.jpeg)

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![](_page_35_Picture_7.jpeg)

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#### **Kristin Branson**

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Allen Lee

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Elizabeth Gillette

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Heejun Choi

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Paola Correa

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Robert Lines

CVML **Scientific Computing** Eyrun Eyjolfdottir **Nakul Verma Rinat Mohar Natalie Falco Monet Weldon** Najla Masoodpanah **Andrew Evans** 

**Predicted trajectories of next 3 seconds** 

![](_page_36_Picture_2.jpeg)

< 1s position</li>
1 to 2s position
2 to 3s position

Ref Tie back to real goals.

Identify prediction change dramatically

listogram over fly trajectories of next 3 seconds

![](_page_37_Picture_4.jpeg)

ls position

1 to 2s position

2 to 3s position

Still frame of lines and then heatmap

Now we show movies of next 3 seconds

# haviour Analysis: Look at edictions into the future

Fly simulation movie

![](_page_38_Picture_4.jpeg)

![](_page_38_Picture_5.jpeg)

![](_page_38_Picture_6.jpeg)

## Behaviour Analysis: input contribution analysis

Vision features - approximation of what fly sees (pink)

![](_page_39_Picture_2.jpeg)

## Behaviour Analysis: input contribution analysis

Last 50 frames of vision features (pink)

![](_page_40_Picture_2.jpeg)

# Behaviour Analysis: input contribution analysis

**Contributed visions** among last 50 vision features

![](_page_41_Picture_2.jpeg)