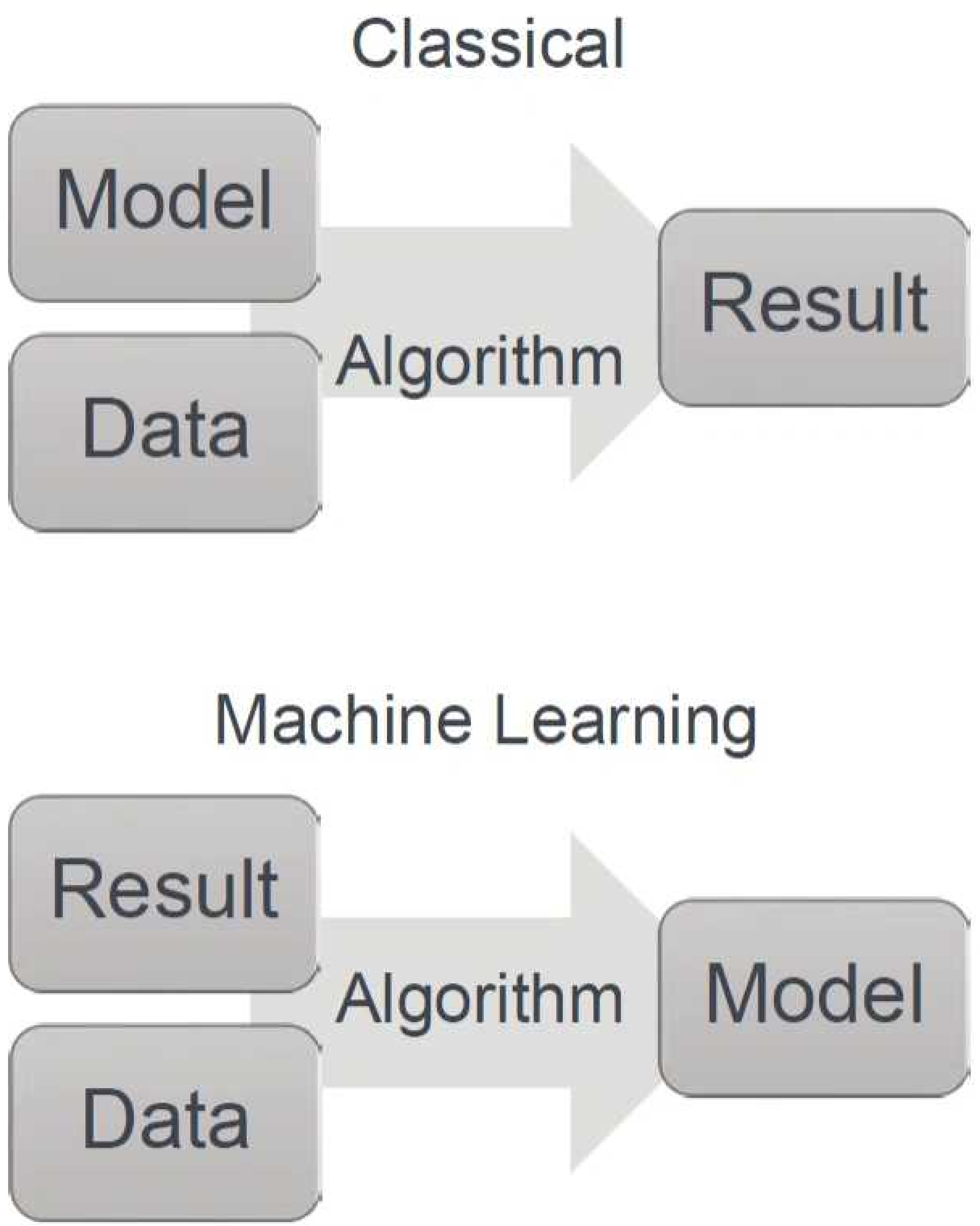
# Why Machine Learning?

- Model may be unavailable
- Knowledge-based appoach may be slow
- Find patterns hidden in data
- Model order reduction
- Tackle even huge, high-dimensional problems
- Get unexpected solutions



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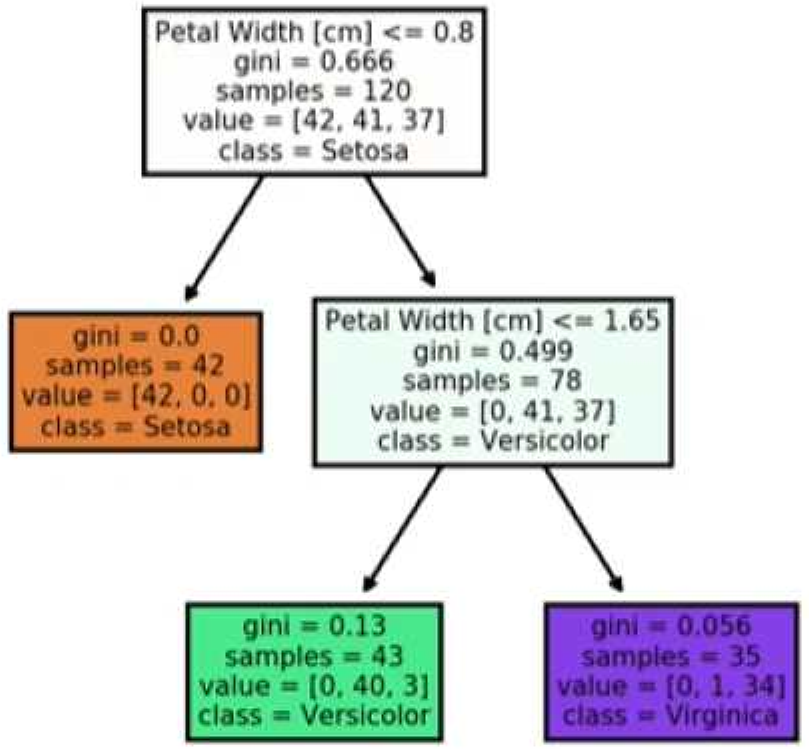
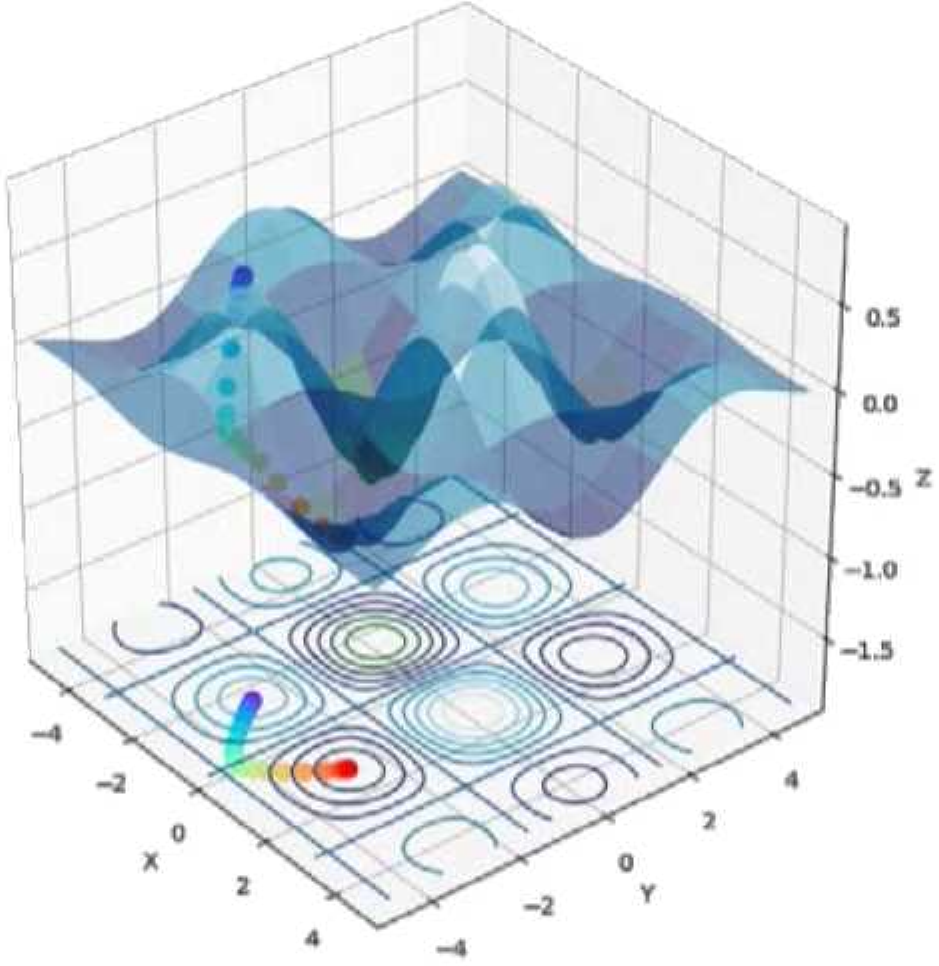
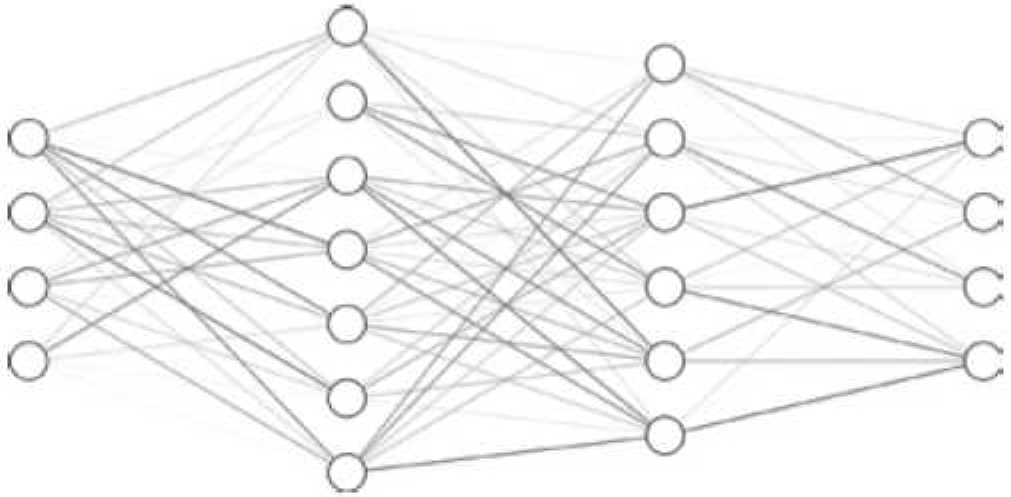
# Outline

- Python Introduction
- Foundation (Linear Algebra and Statistics)
- Regression and Classification
- Optimization
- Dimensionality Reduction
- Trees and Forests
- Artificial Neural Networks
- …



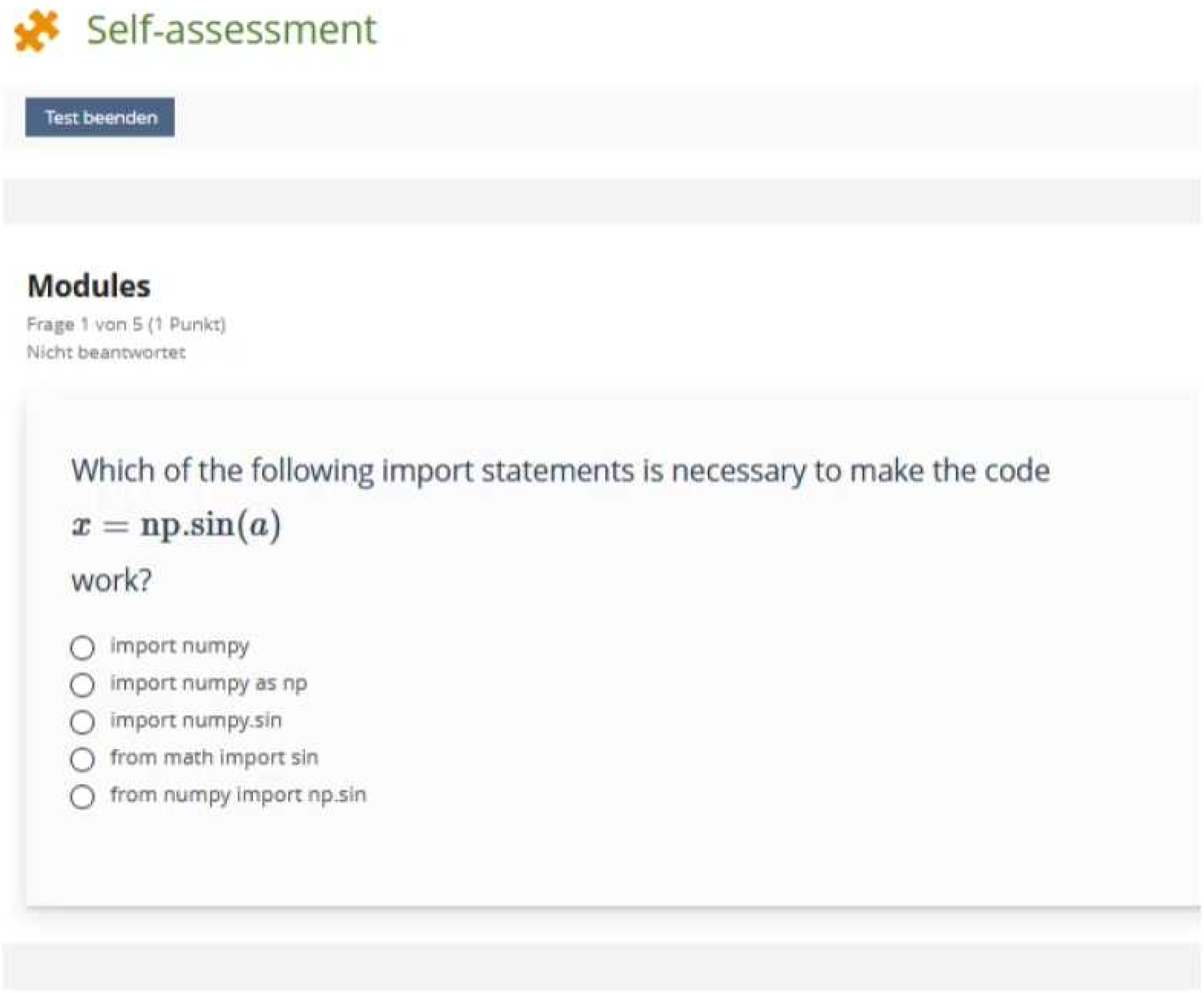



# Course Structure

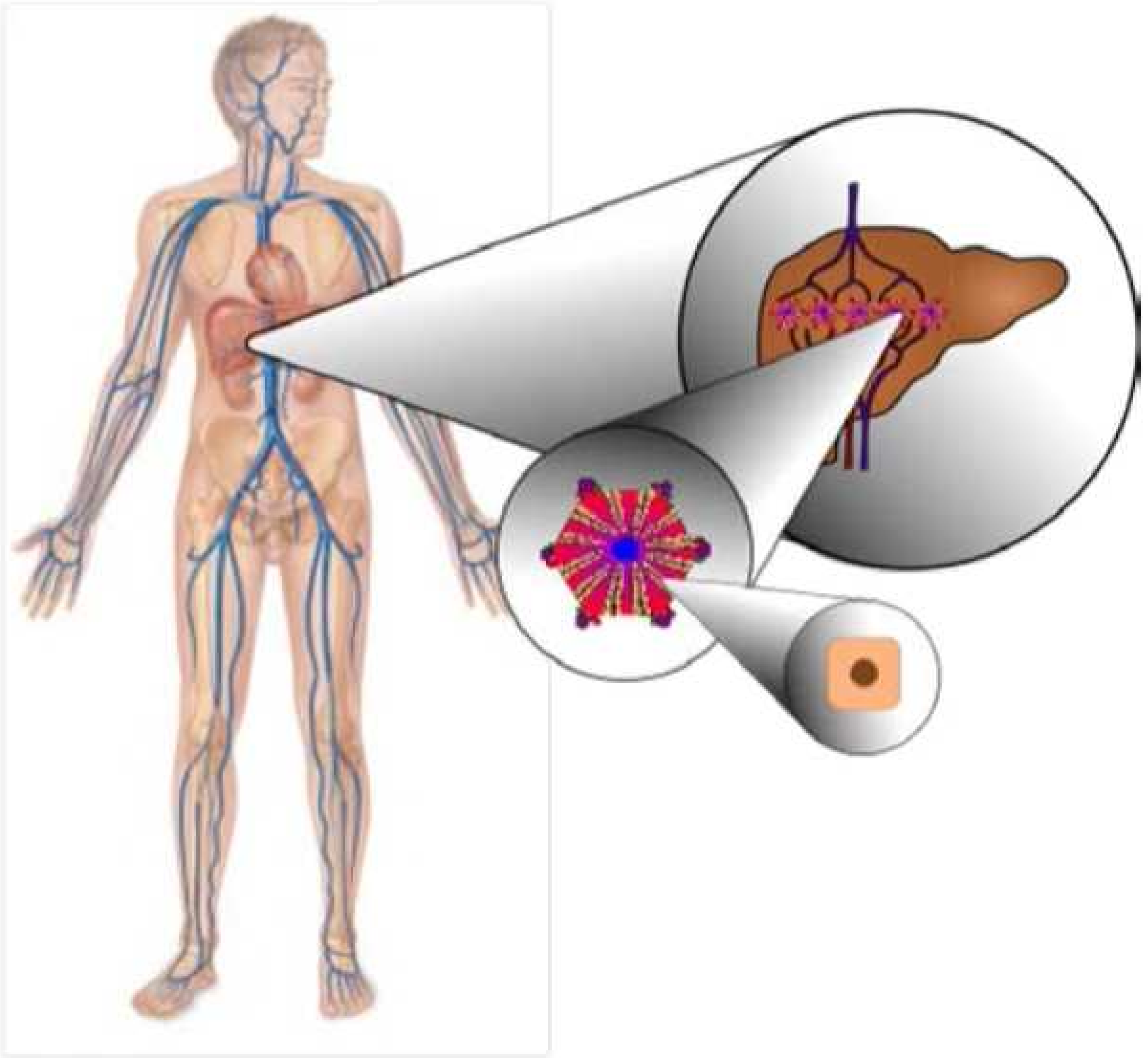
- Weekly lectures on Wednesdays as videos
- Weekly exercises (partly Jupyter, partly other forms)
- Exercises are *optional*, but highly recommended!
- Solutions are published two weeks later
- Grade determined by oral exam of 20 minutes
- Date, location etc. later
- Questions? Forums in Ilias or email

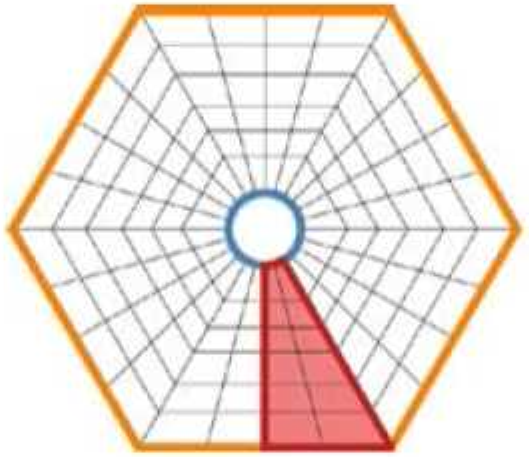
# Tools

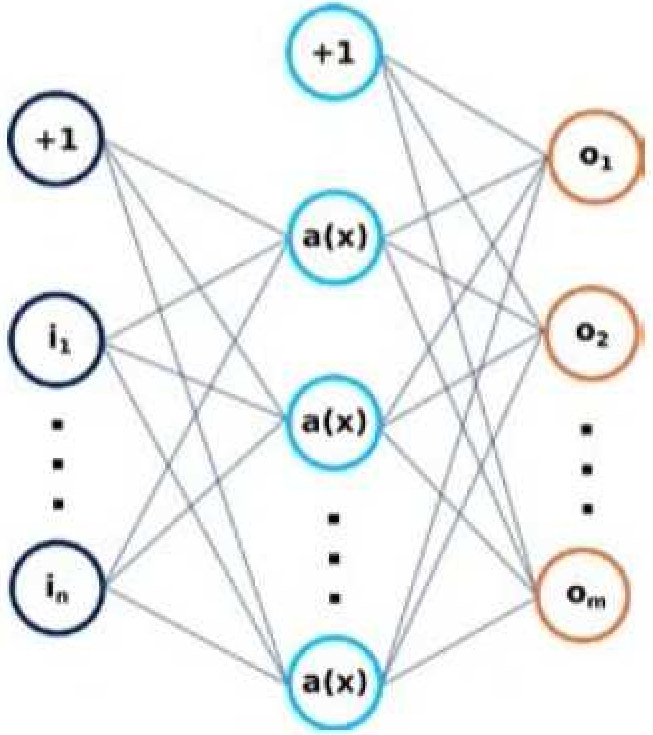
- Lecture videos (Ilias)
- Jupyter (see first lecture)
- Discussion forums (Ilias)
- Self-assessments (ungraded)
- …



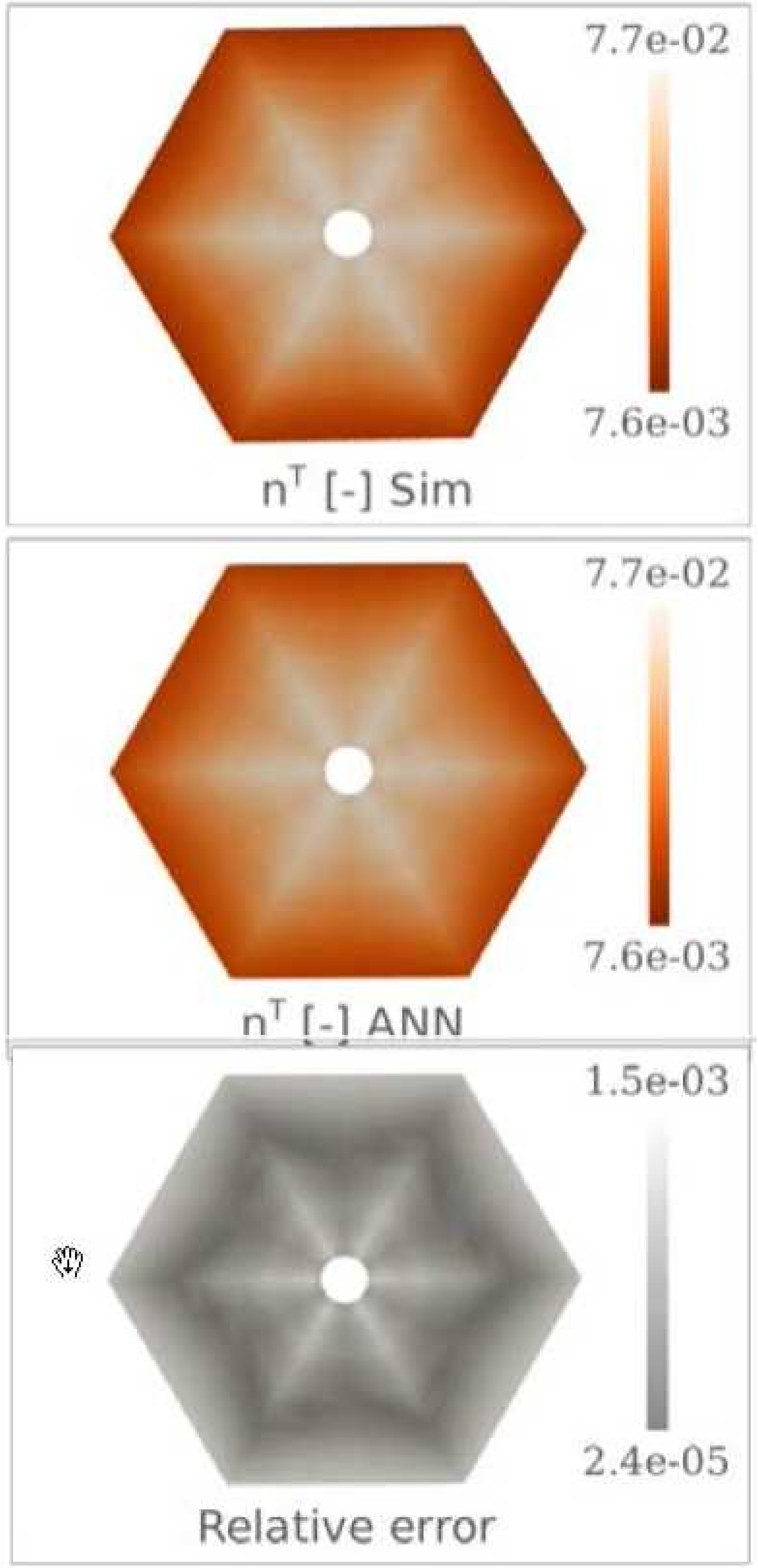
# Surrogate Modeling

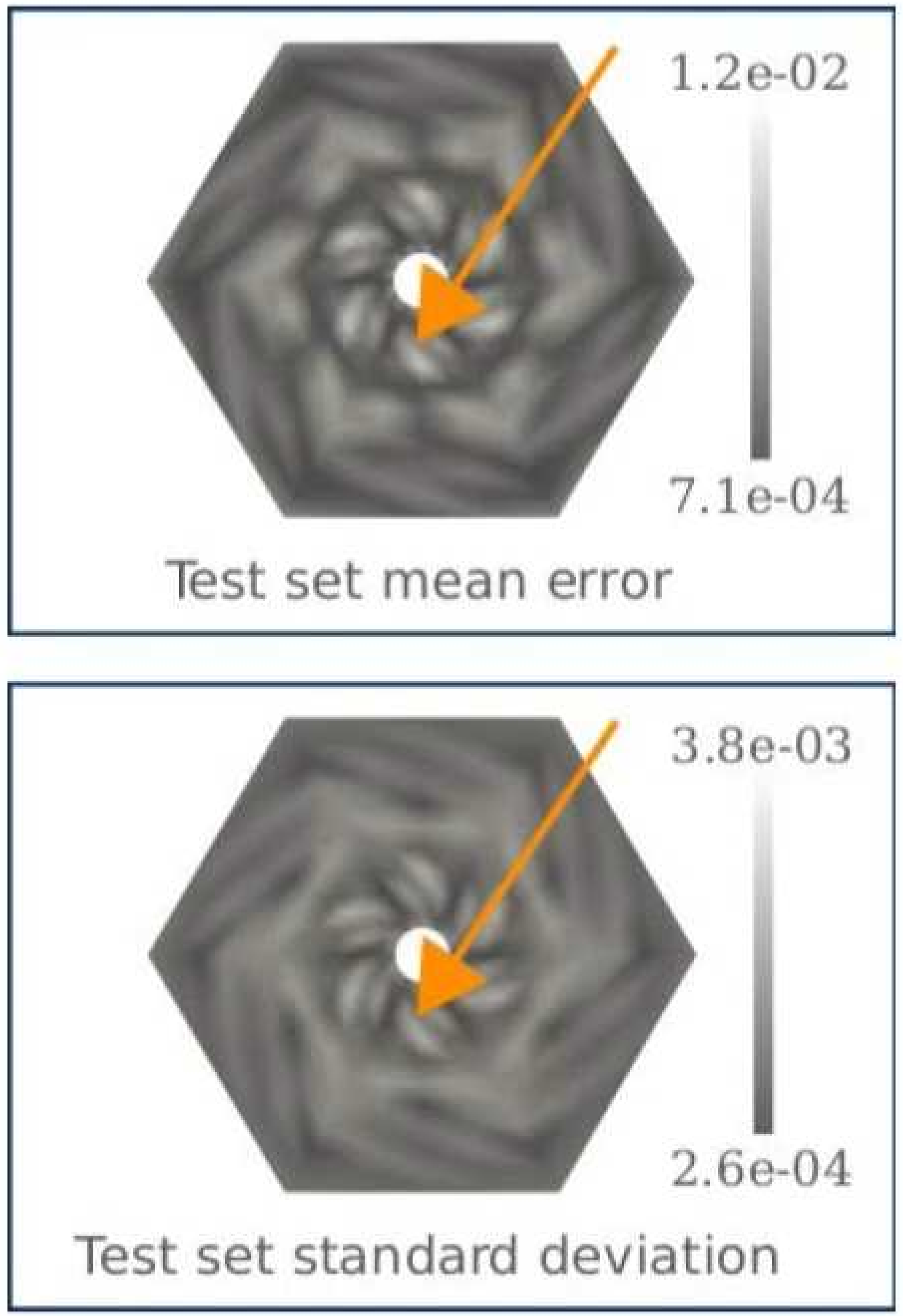


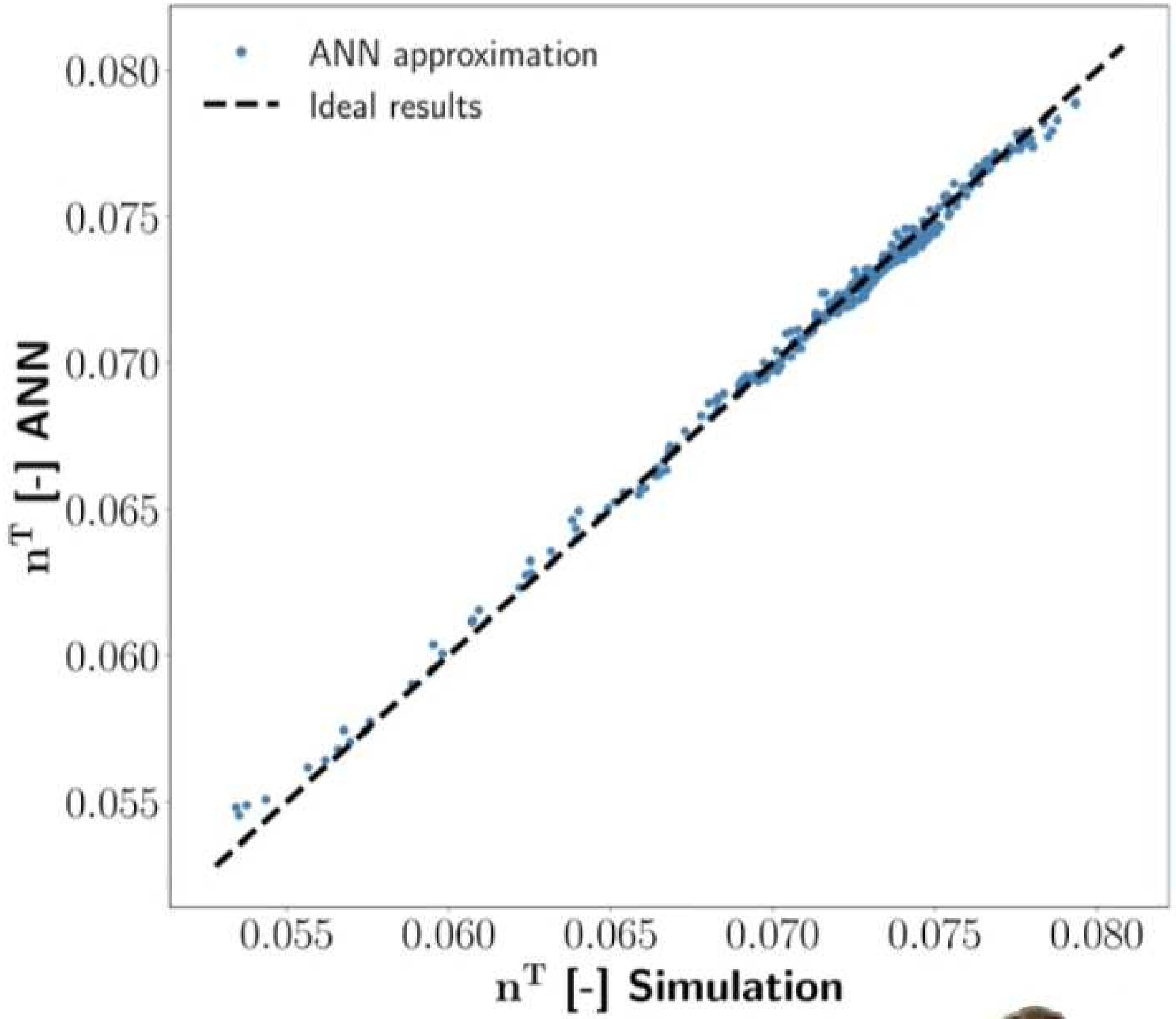


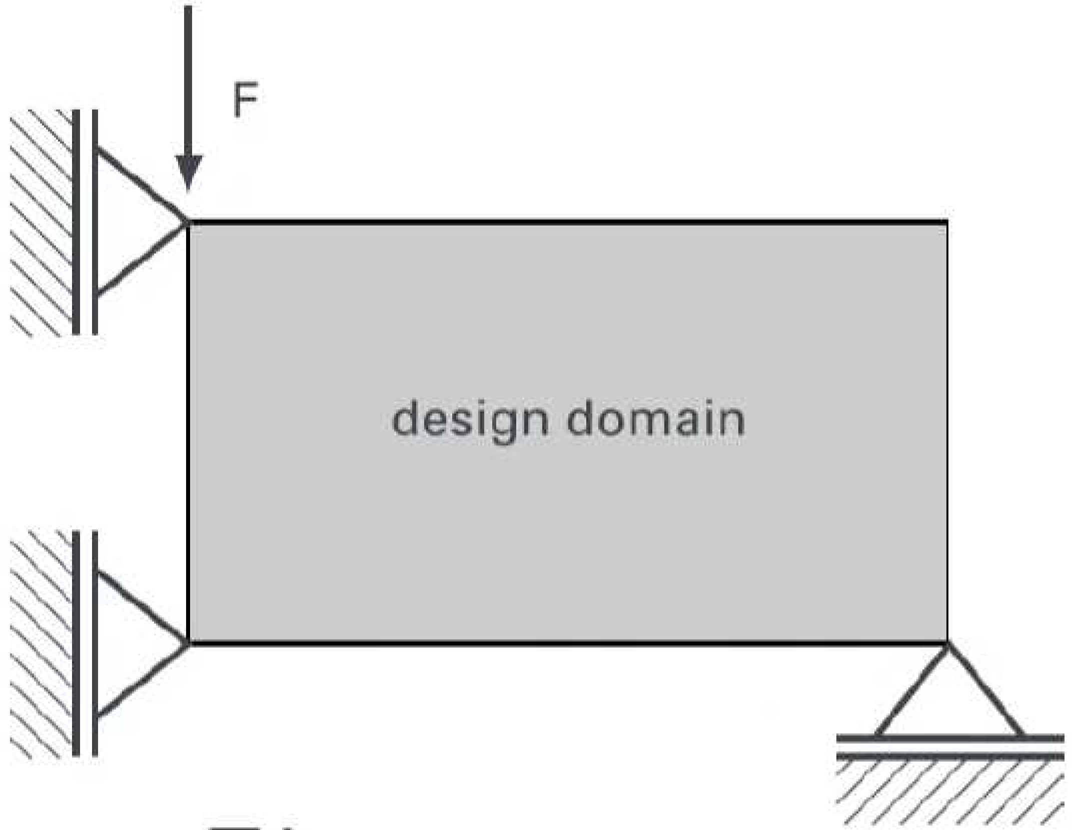
# Surrogate Modeling

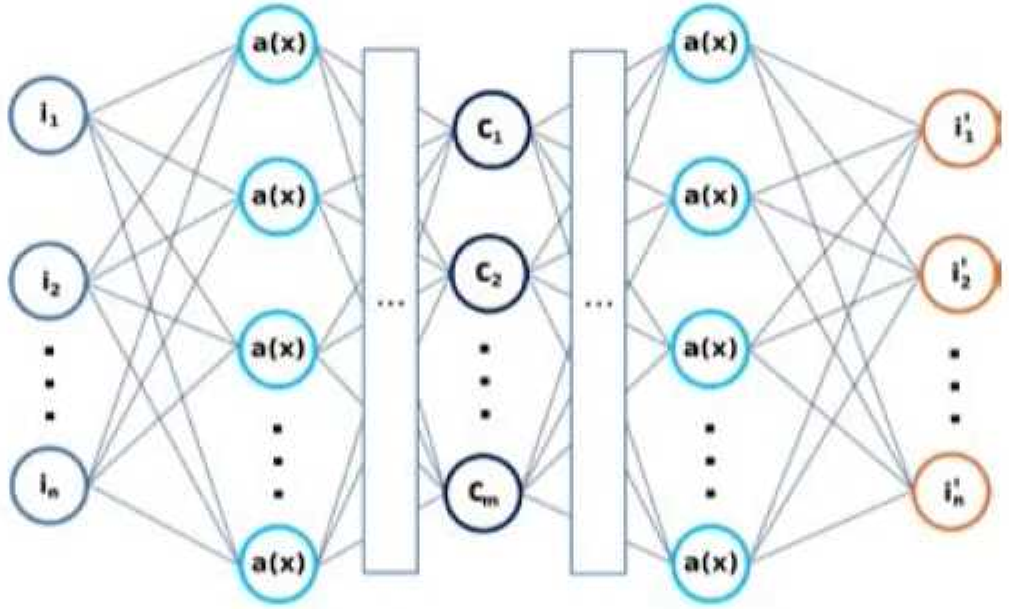


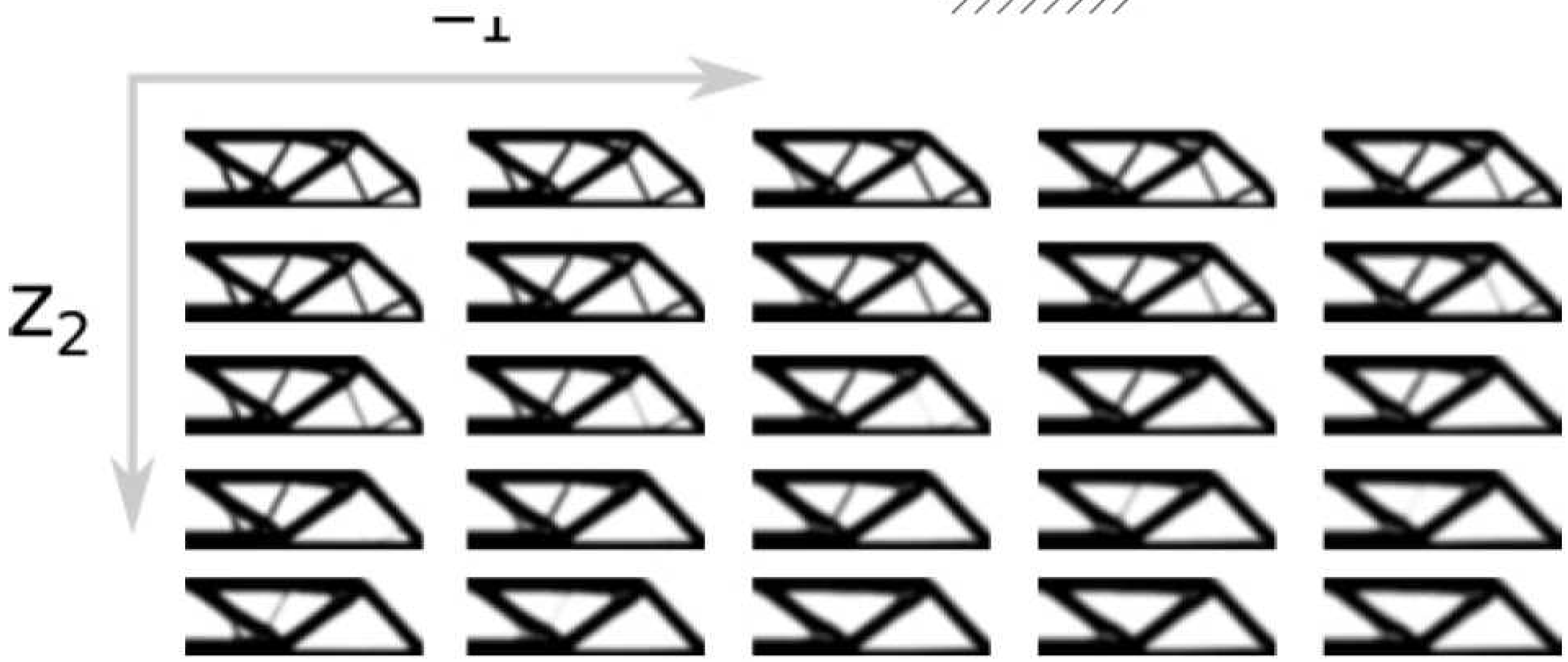



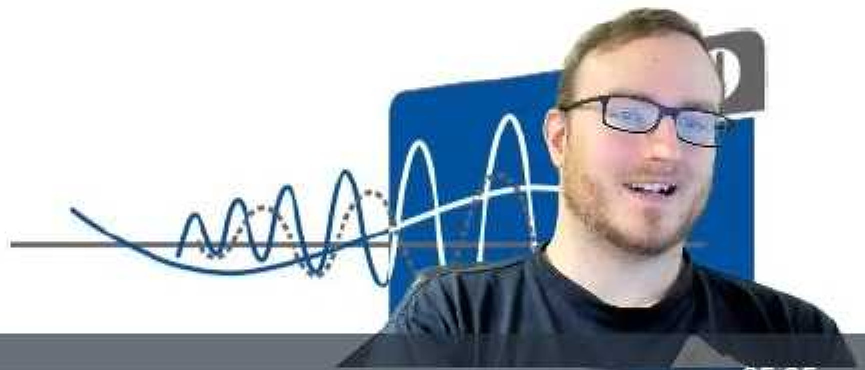



# Conditional Latent Space Exploration





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# Why Machine Learning?

- Restricted regions
- Multiple gliders

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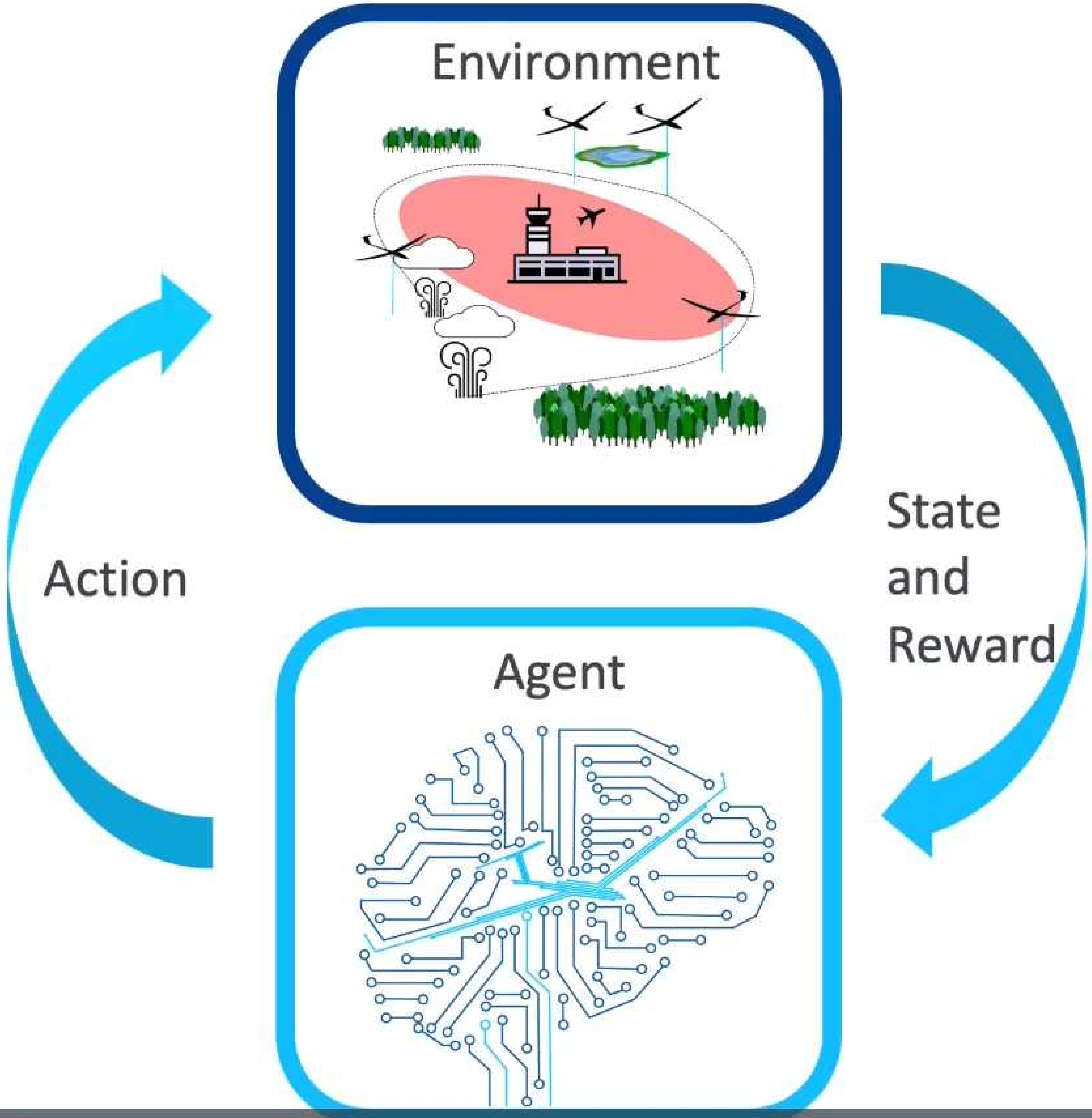
# Reinforcement Learning



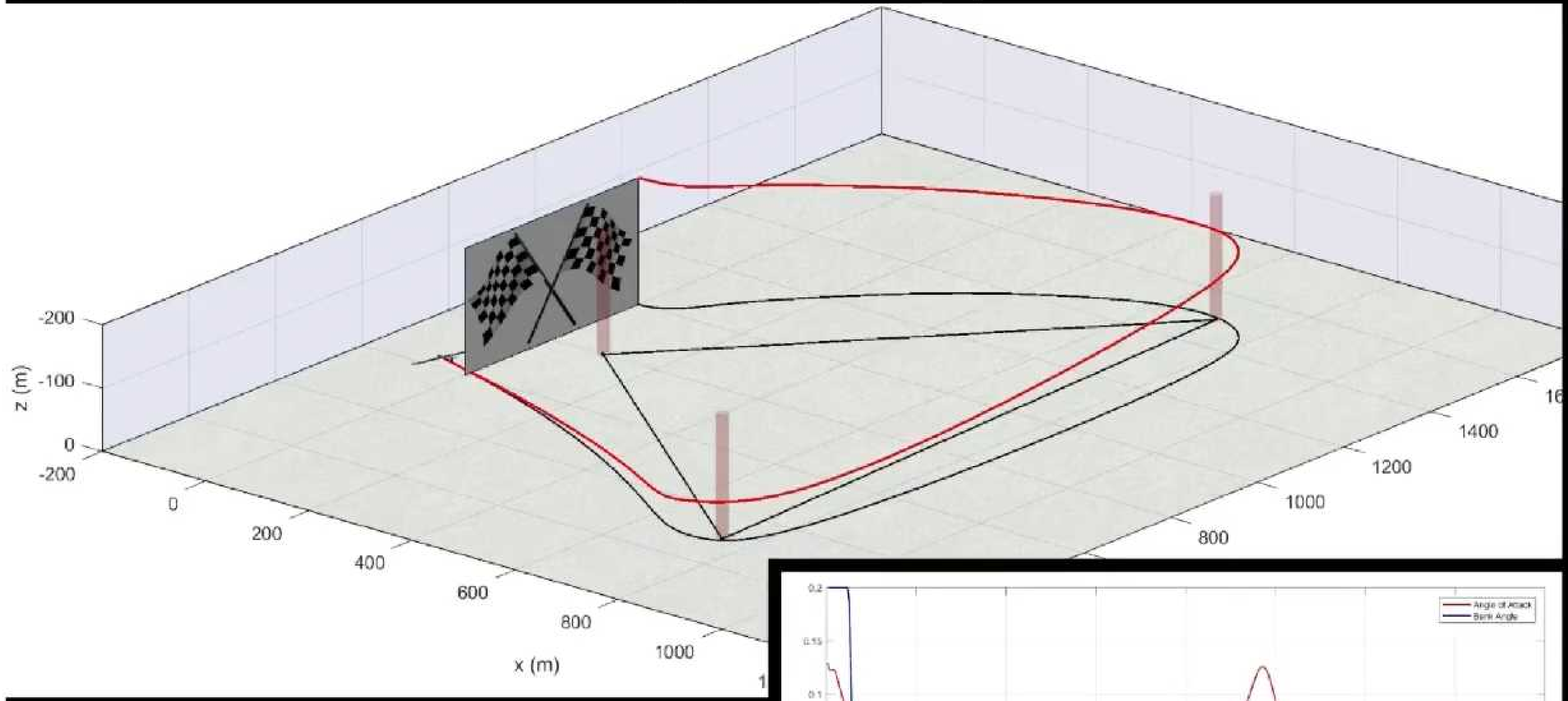

Key ideas:

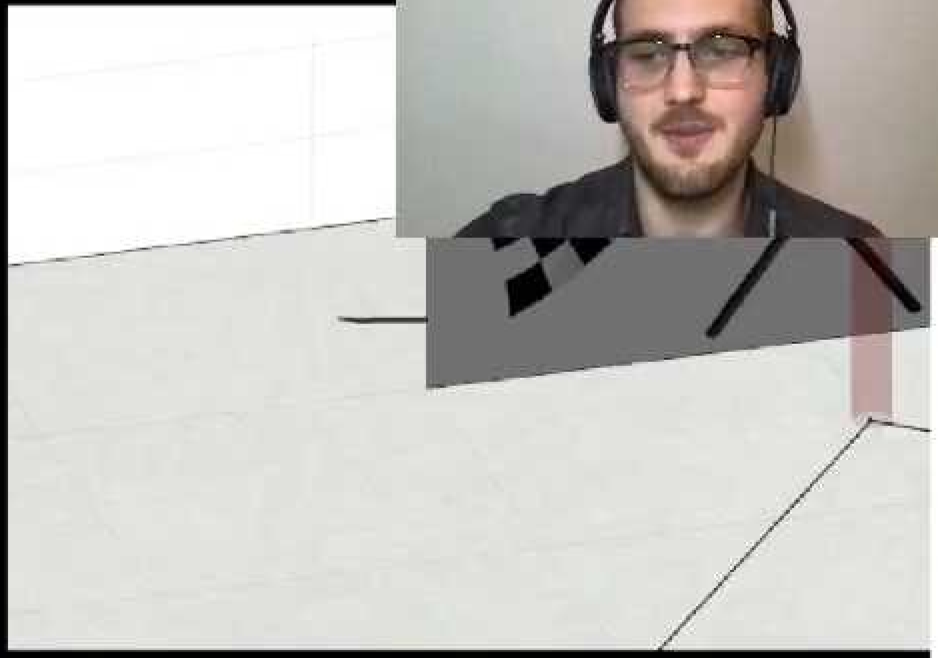
- Agent basically means control law:
  It maps a state to an action to take

# Example:

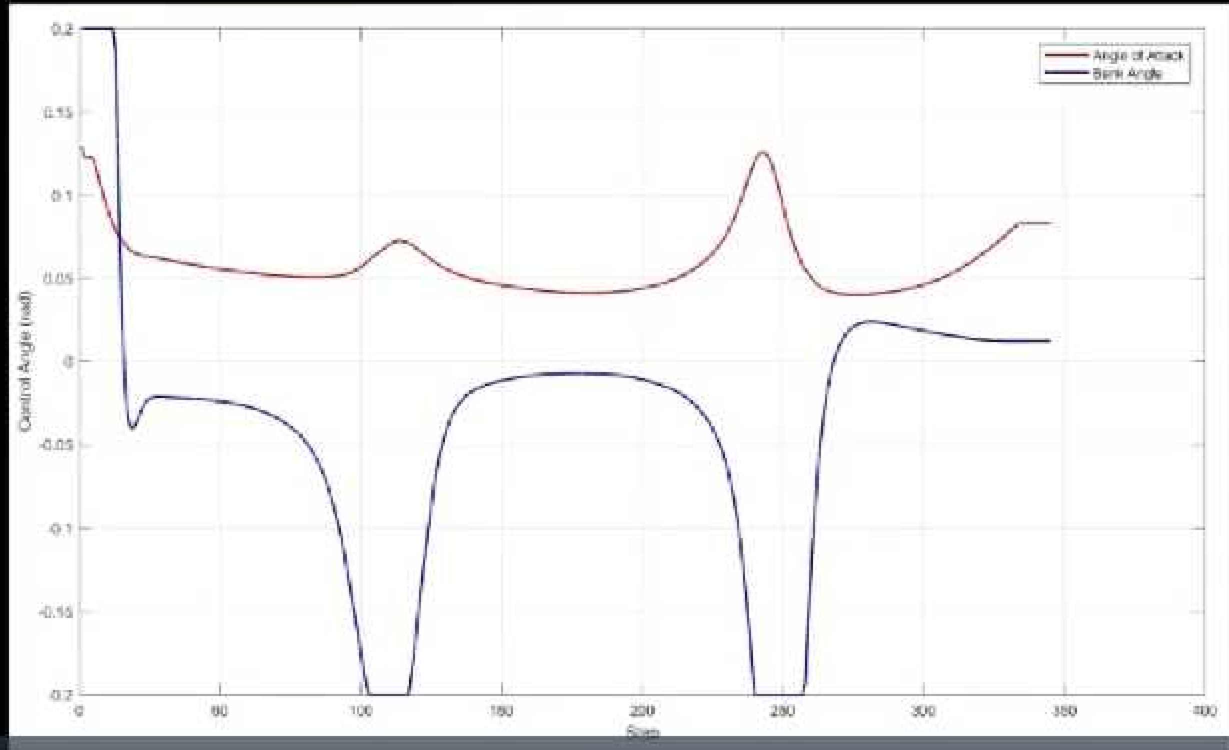
After 800 Iterations: Final Mission

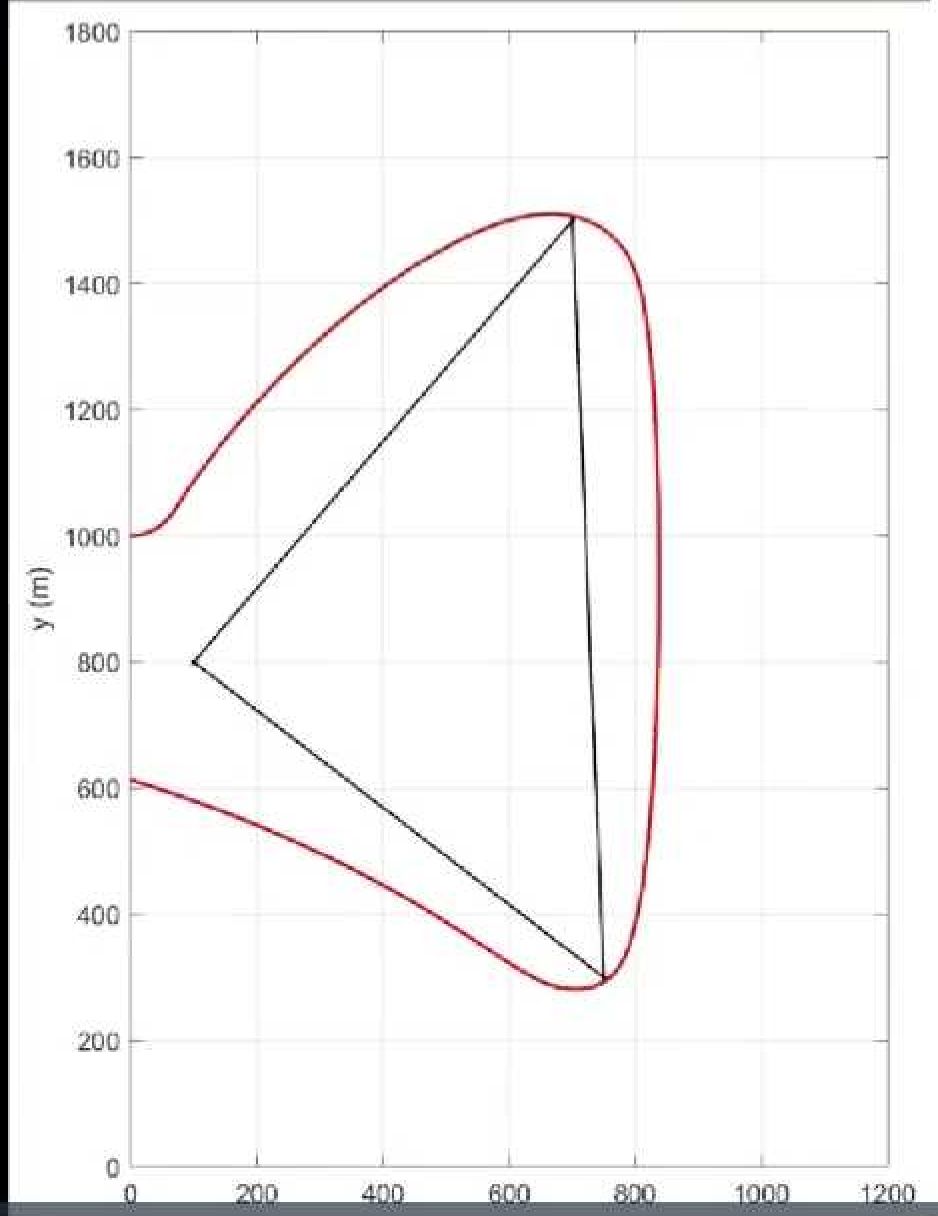
**Time: 167 s**



| Iteration | Time |
|---|---|
| 20 | Target missed |
| 200 | 244 s |
| 500 | 183 s |
| 800 | 167 s |



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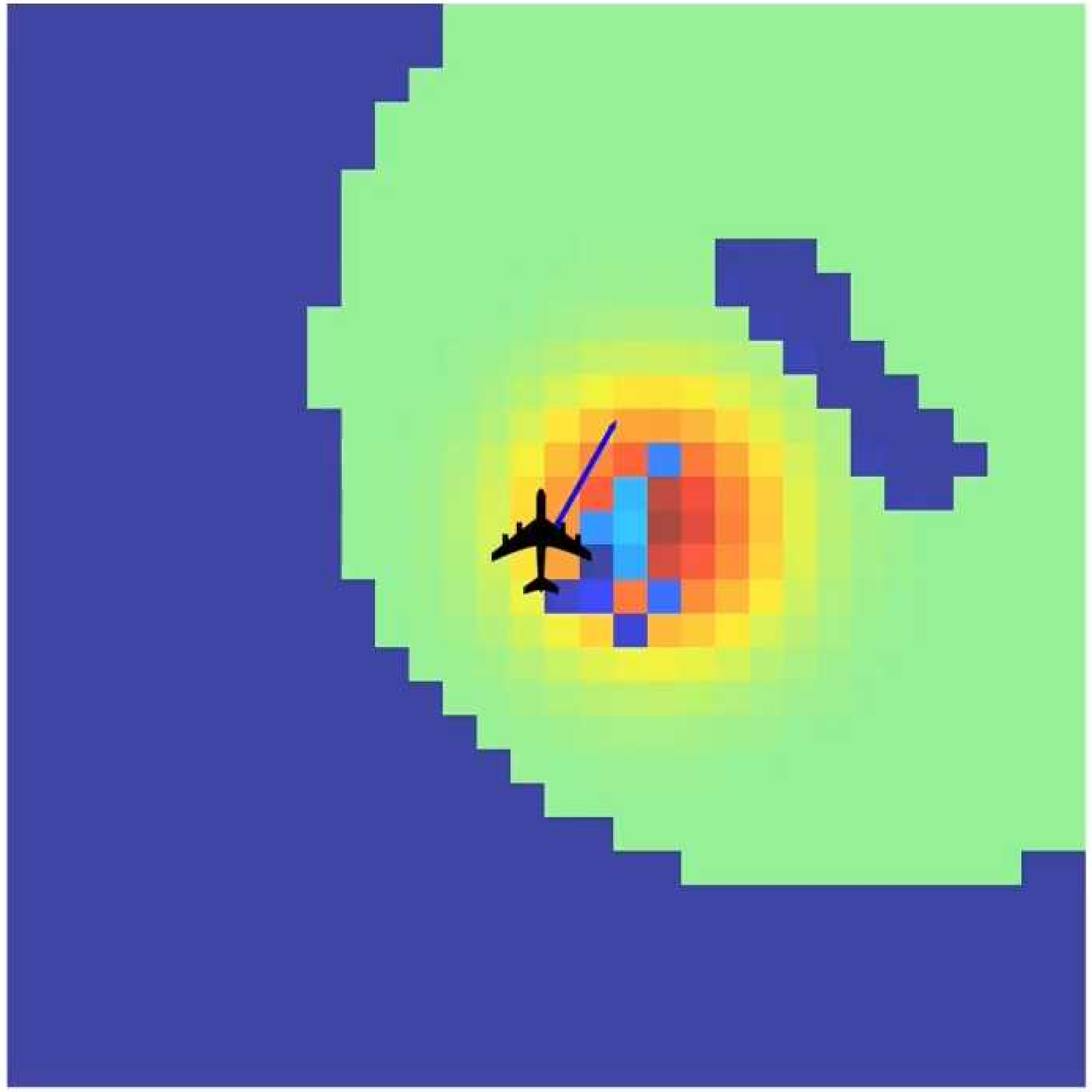
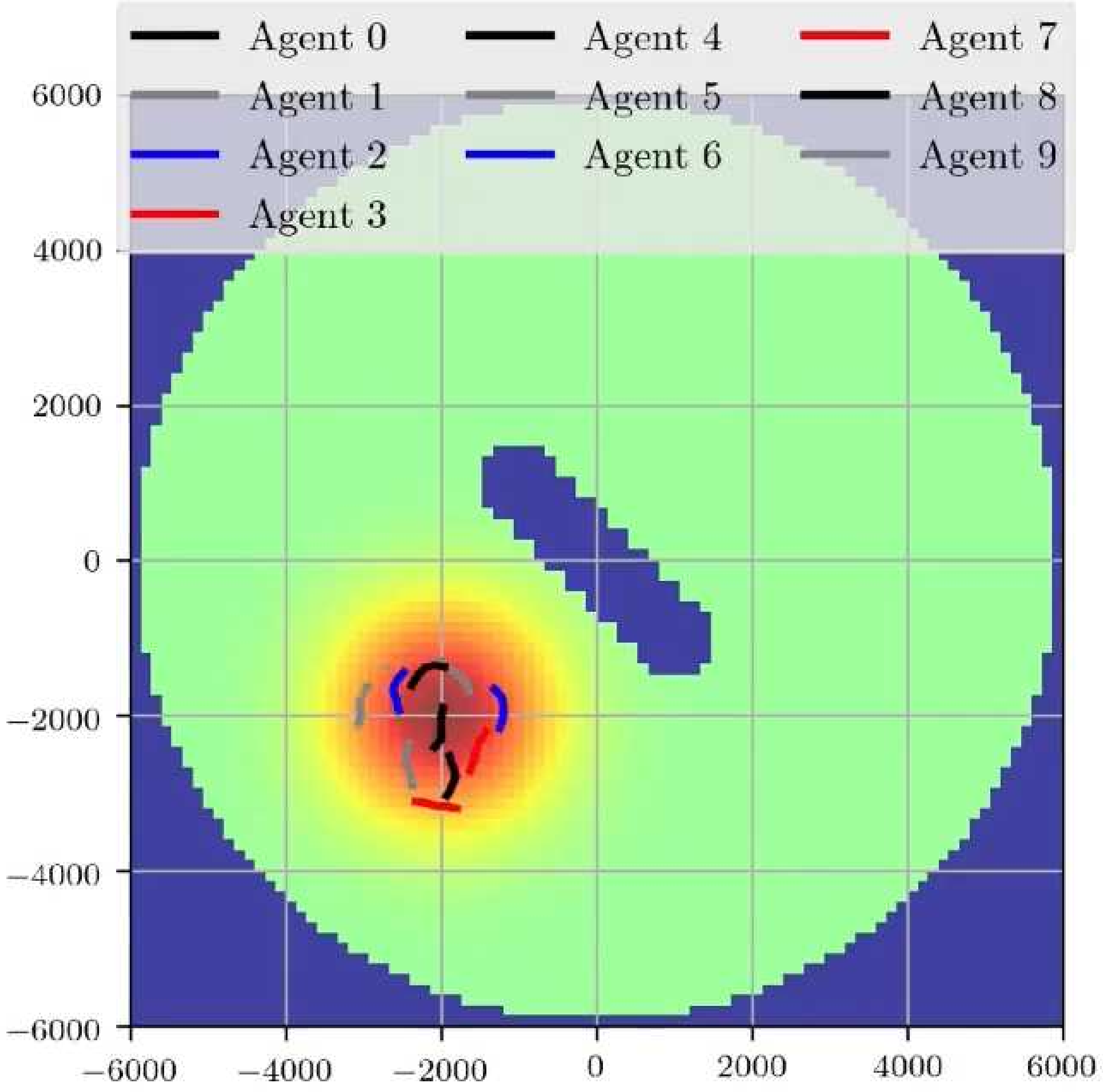
# Thermalling of Multiple Agents

How each agent perceives their environment:



How this works out for 10 agents




"Multi-Agent Reinforcement Learning for Thermalling in Updrafts"

Schimpf et al., accepted for presentation at AIAA Scitech 2021

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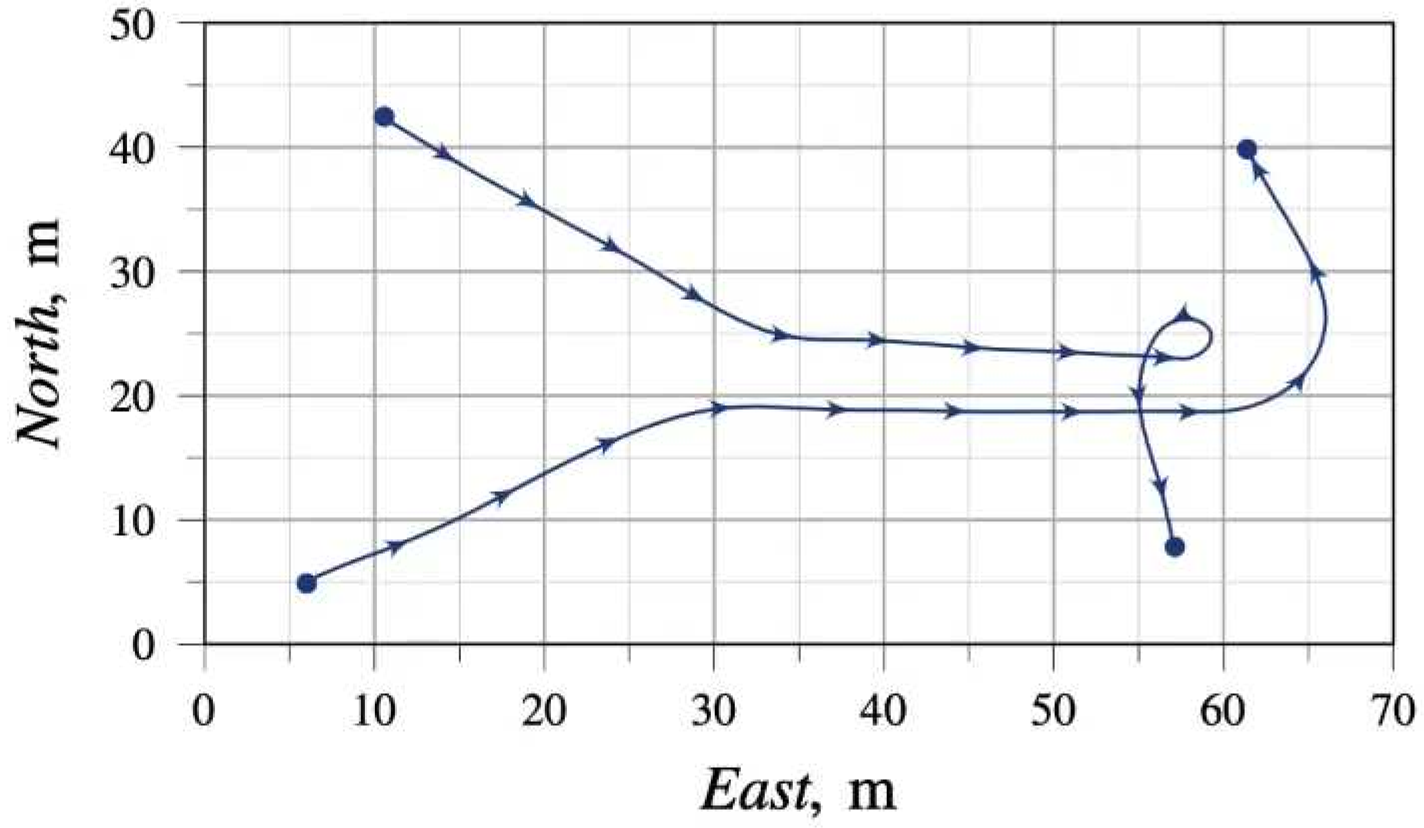
# Collision Avoidance

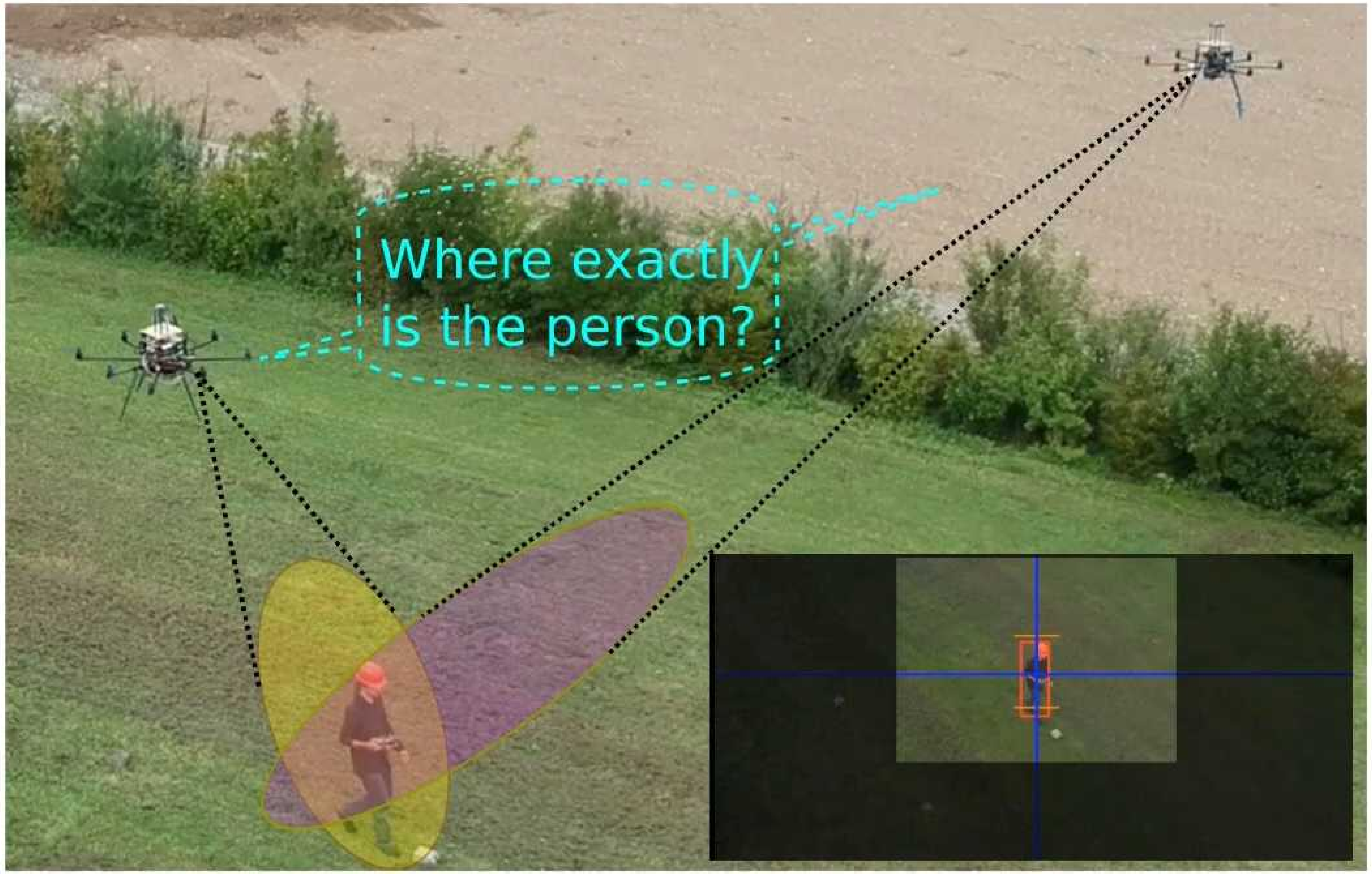



"LSTM-Based Spatial Encoding: Explainable Path Planning for Time-Variant Multi Agent-Systems"
Schlichting et al., accepted for presentation at AIAA Scitech 2021

# Other questions that we are working on

- How can we choose the best strategy for a given situation?
- How can we predict the probability of updrafts occuring in a given area?
- How can we use updrafts to cover distances as quickly as possible?
- Energy compensated estimation of climbrates from noisy sensors
- Applications of ML for autonomous landing
- ...

# Cooperative Perception using Multiple Aerial Vehicles

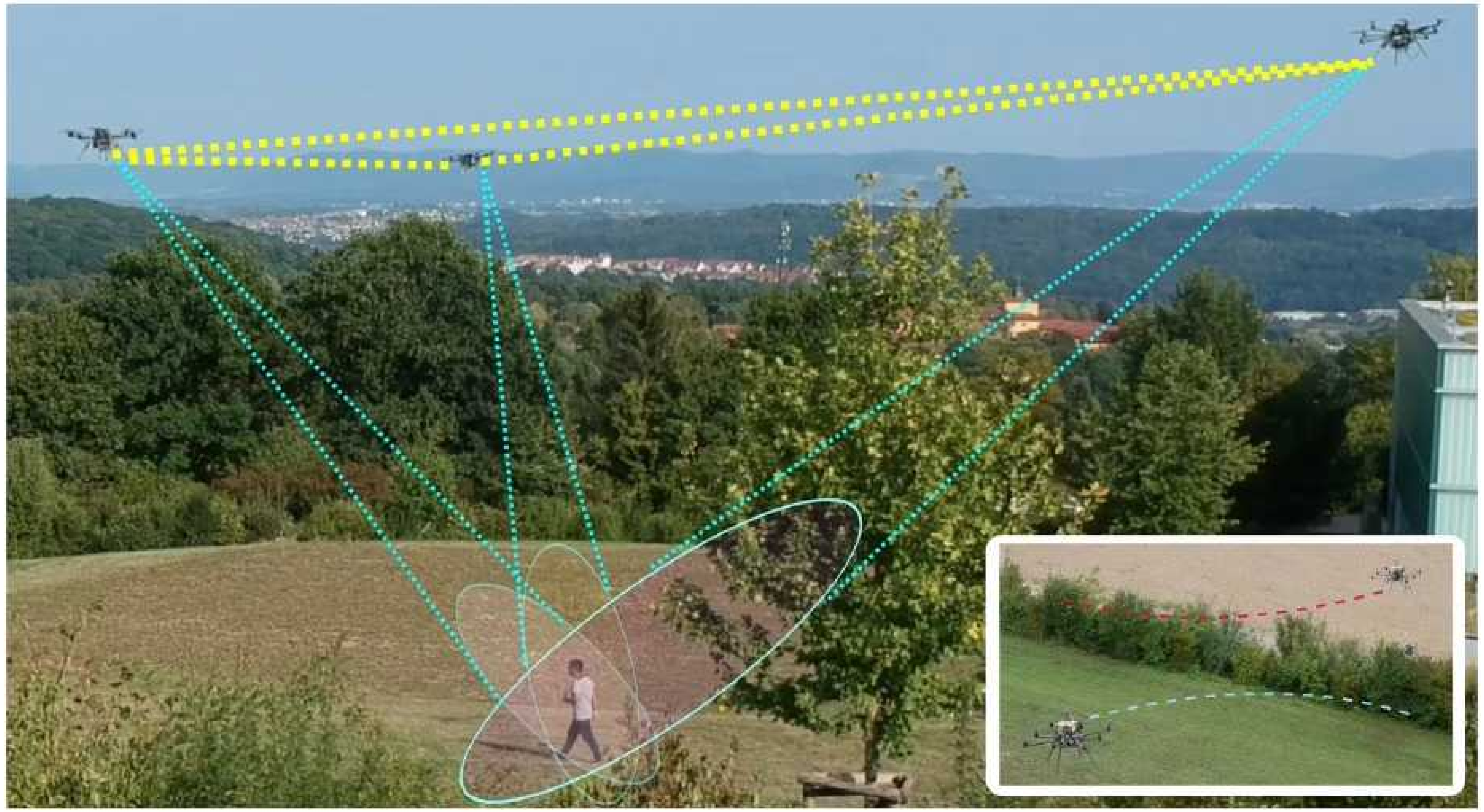



Offline pose, shape and scene estimates for Post-Analysis Applications

Online and On-board pose estimates for Real-time Applications

[1] E. Price et al., "Deep Neural Network-Based Cooperative Visual Tracking Through Multiple Micro Aerial Vehicles," in IEEE Robotics and Automation Letters (and IROS). 2018.

# Perception-driven Formation Control of MAVs

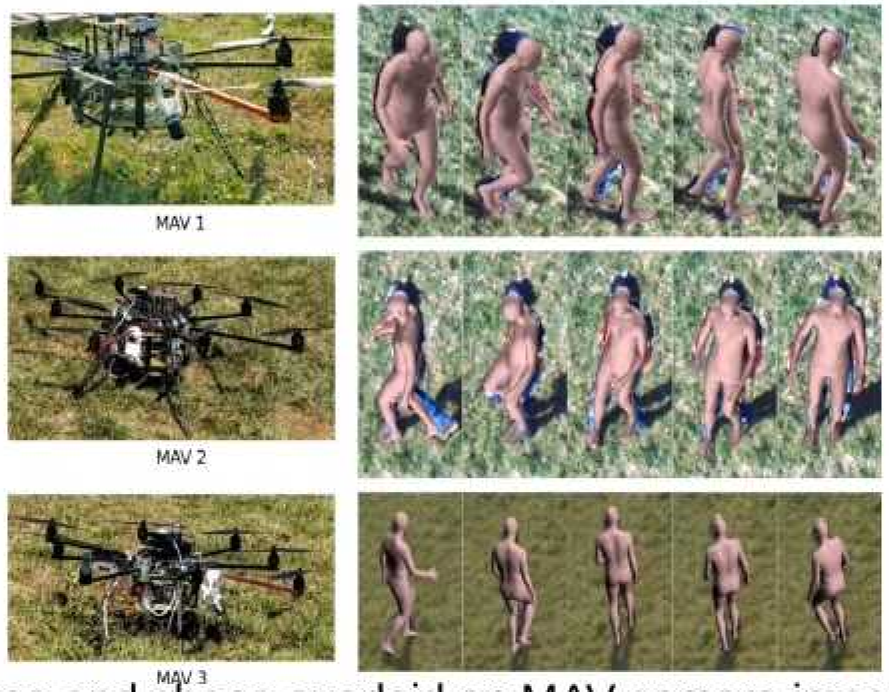


- Autonomous cooperative detection, tracking and following.
- Active perception-based formation of MAVs:
  - Minimizes uncertainty in the fused person position estimate.
  - On-board processing, no markers on the human, no pre-specified formation geometry.

[1] R. Tallamraju et al., "Active Perception based Formation Control for Multiple Aerial Vehicles," in IEEE Robotics and Automation Letters. 2019.

# Human Motion Capture from a MAV Formation

3D pose and shape overlaid on an external camera view



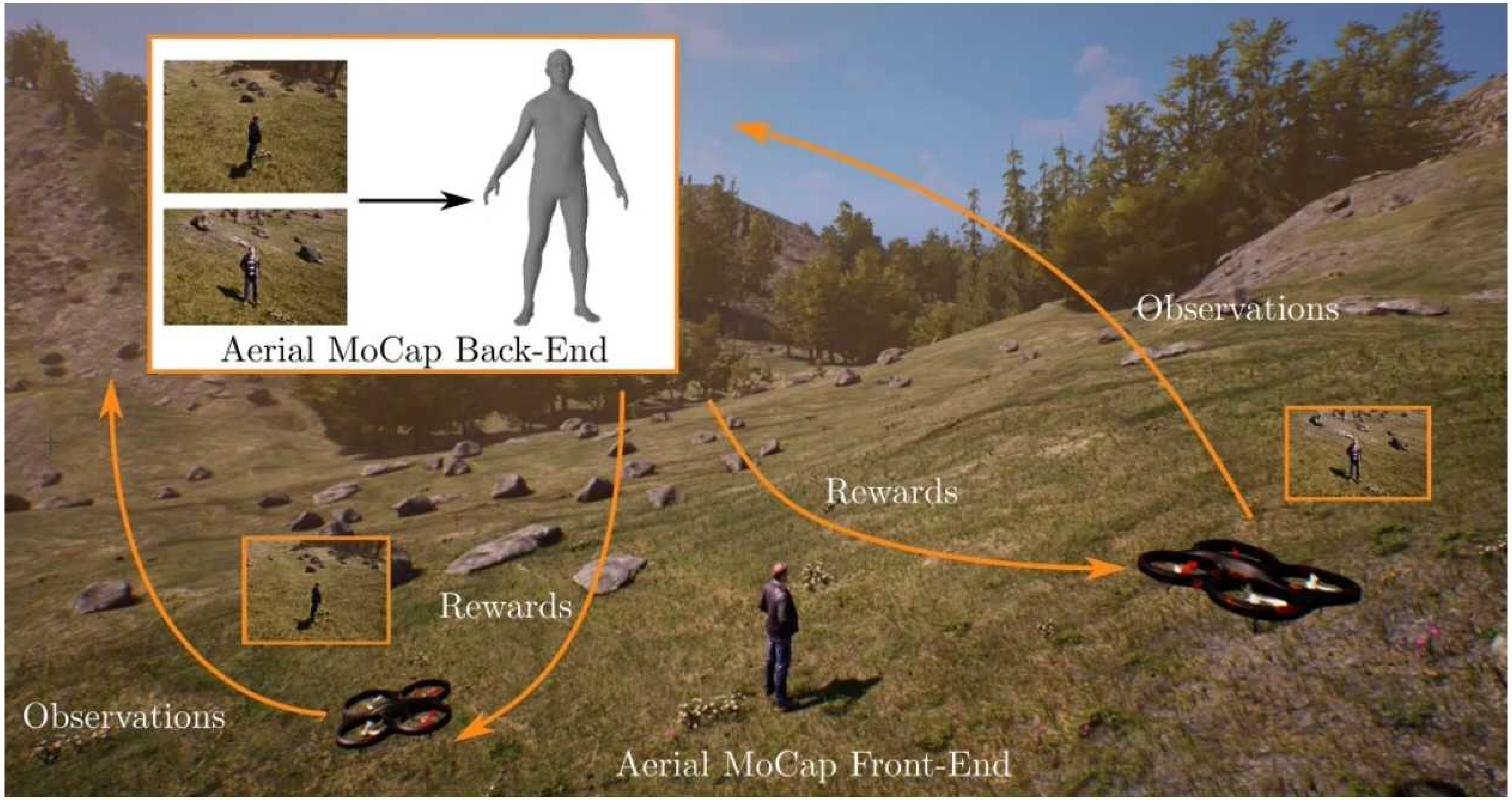

3D pose and shape overlaid on MAV camera images

walking sequence

exercise sequence

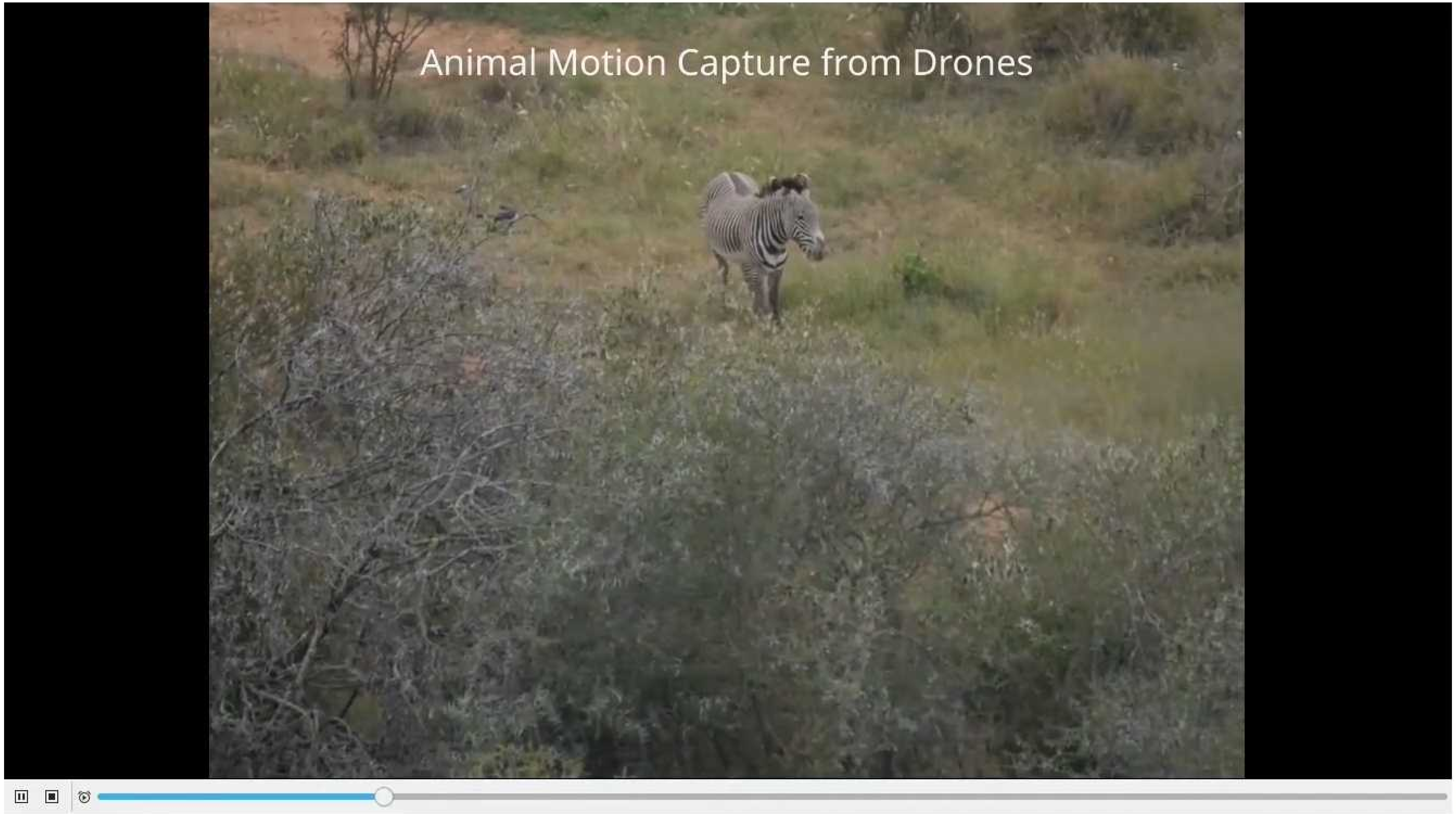
[3] N. Saini et al., "Markerless Outdoor Human Motion Capture Using Multiple Autonomous Micro Aerial Vehicles," in International Conference on Computer Vision (ICCV), 2019.

# End-to-end Human Motion Capture from a MAV Formation




[3] R. Tallamraju et al., " AirCapRL: Autonomous Aerial Human Motion Capture Using Deep Reinforcement Learning," in IEEE Robotics and Automation Letters, 5(4):6678 - 6685, IEEE, October 2020, Also accepted and presented in the 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS).

# Animal Motion Capture from Micro Aerial Vehicles




# Topics that I will teach

- Probability and Statistics
    - Basic concepts of probability
    - Probability calculus
    - Distributions
- Estimation
    - Deterministic vs probabilistic

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Germany

# Thank you!

**Jun.-Prof. Dr.-Ing. Aamir Ahmad**

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Fax +49 (0) 711 685- 66670

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Institute for Flight Mechanics and Controls
Pfaffenwaldring 27, 70569 Stuttgart

-7:34

University of Stuttgart
Institute of Aerodynamics and Gas Dynamics

OTTO VON GUER
UNIVERSIT
MAGDEBURG



Andrea Beck

# Introduction & ML in Fluid Mechanics

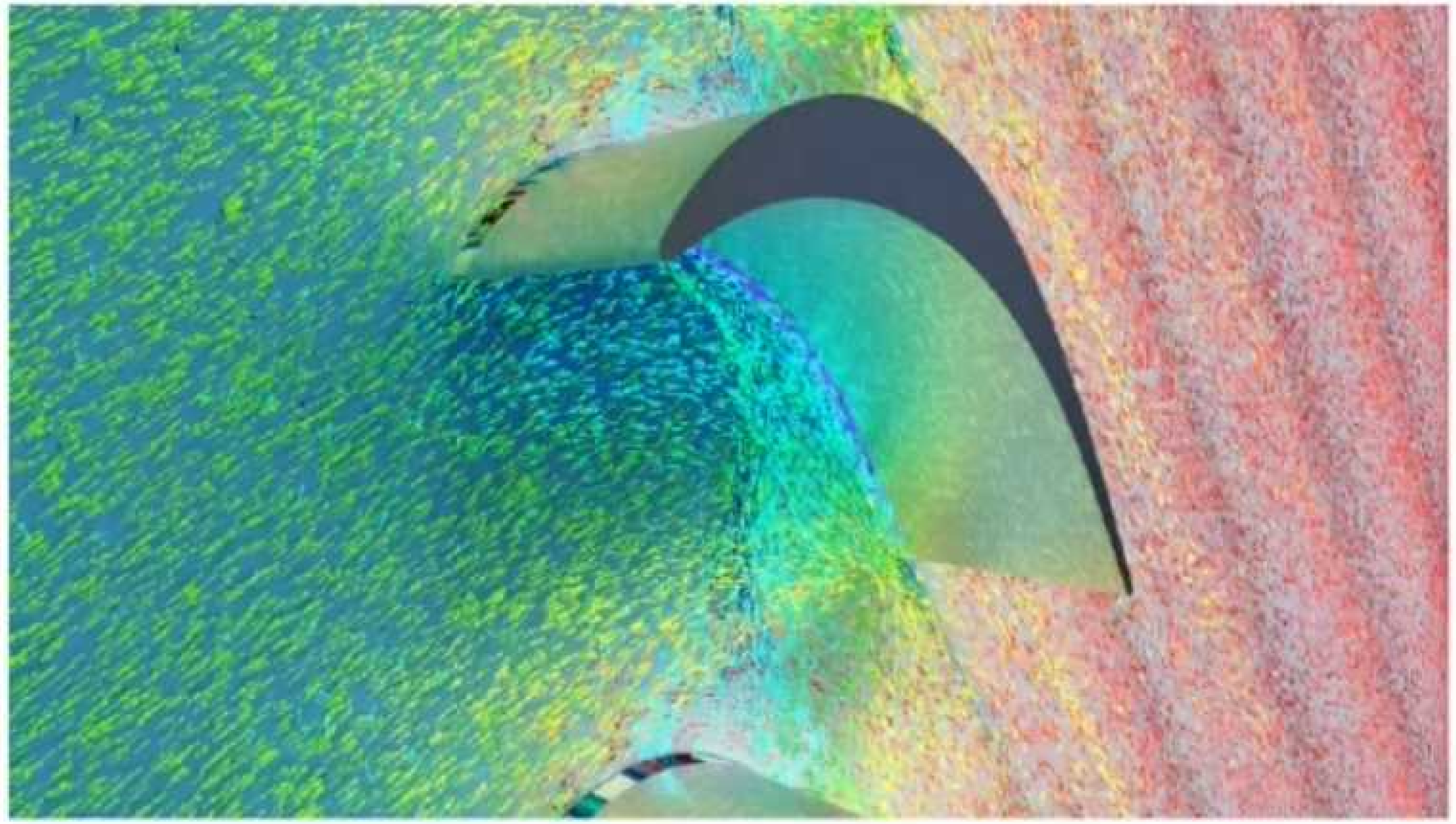
## AMLE 2020

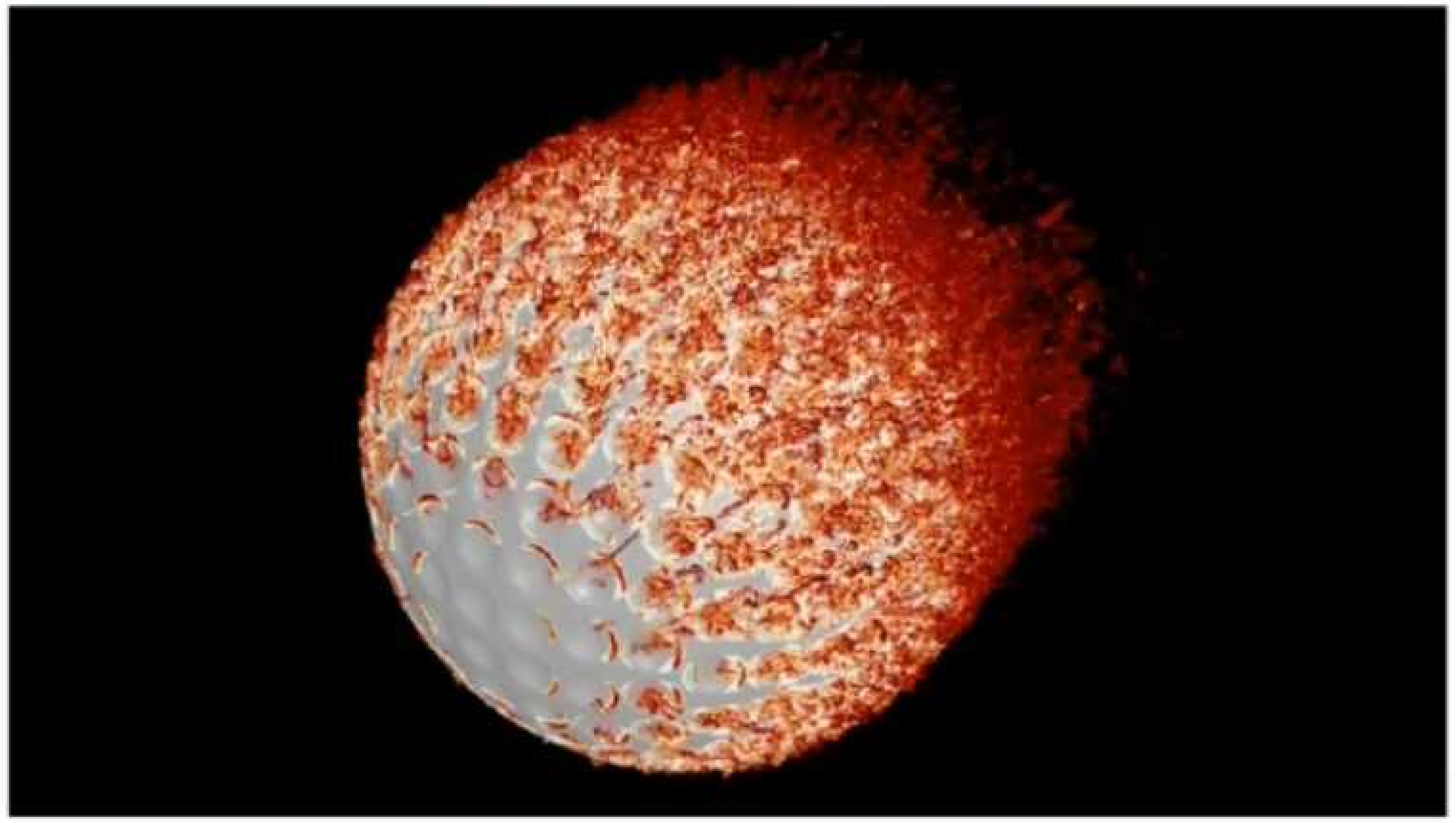
# Introduction

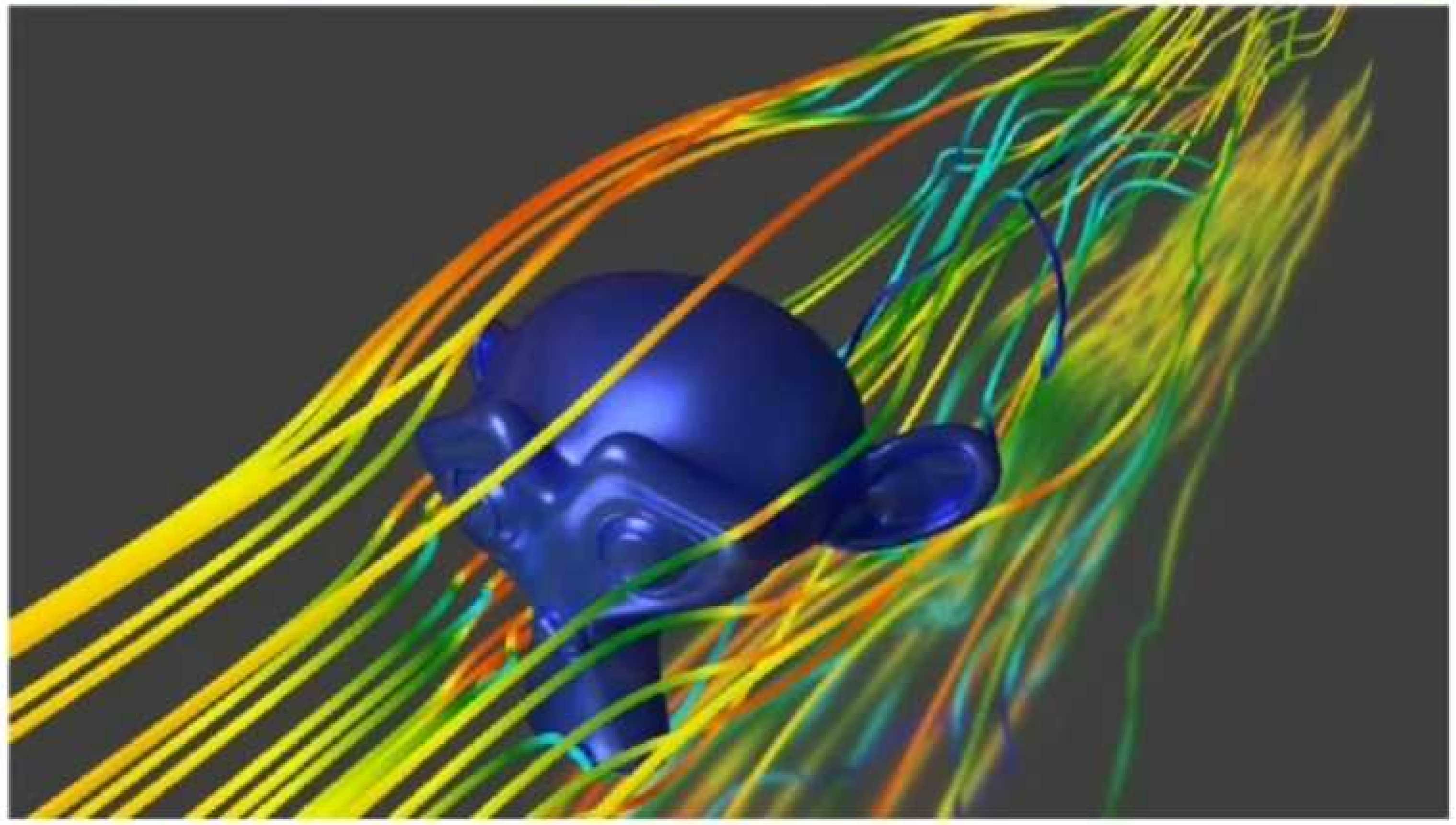
- Aerospace Engineer by training, ML researcher by choice!
- Associate Professor at Otto-von-Guericke-Universität Magdeburg
- Group Leader at Institute of Aerodynamics and Gasdynamics (IAG), Universität Stuttgart: Numerics Research Group
- You may know me from
  - SimTech CoE Data-Integrated Simulation Science
  - M.Sc. module Discontinuous Galerkin methods (go sign up!)
  - Open Source CFD code FLEXI for the compressible Navier-Stokes equations
- I'm interested in combining ML with (numerical) fluid mechanics to find new solutions to rather old problems
- Best way of contact: beck@iag.uni-stuttgart.de

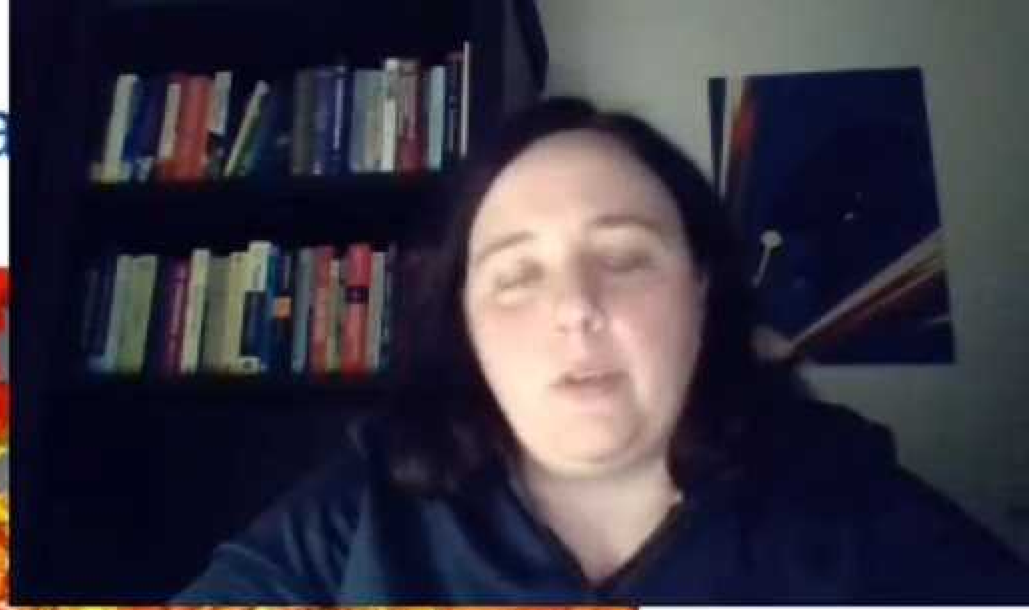
www.flexi-project.org

# DG: LES, moving meshes, acoustics, multiphase, UQ, particle-la



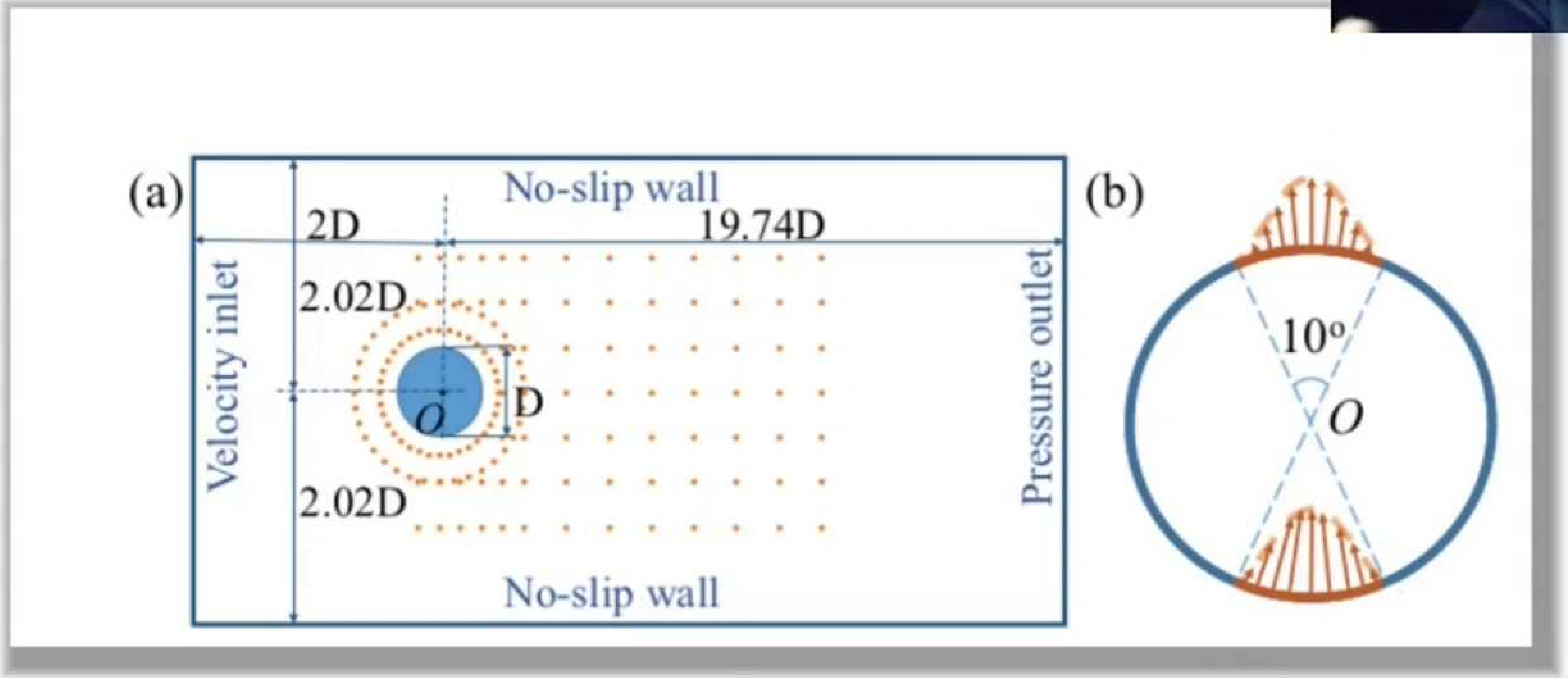






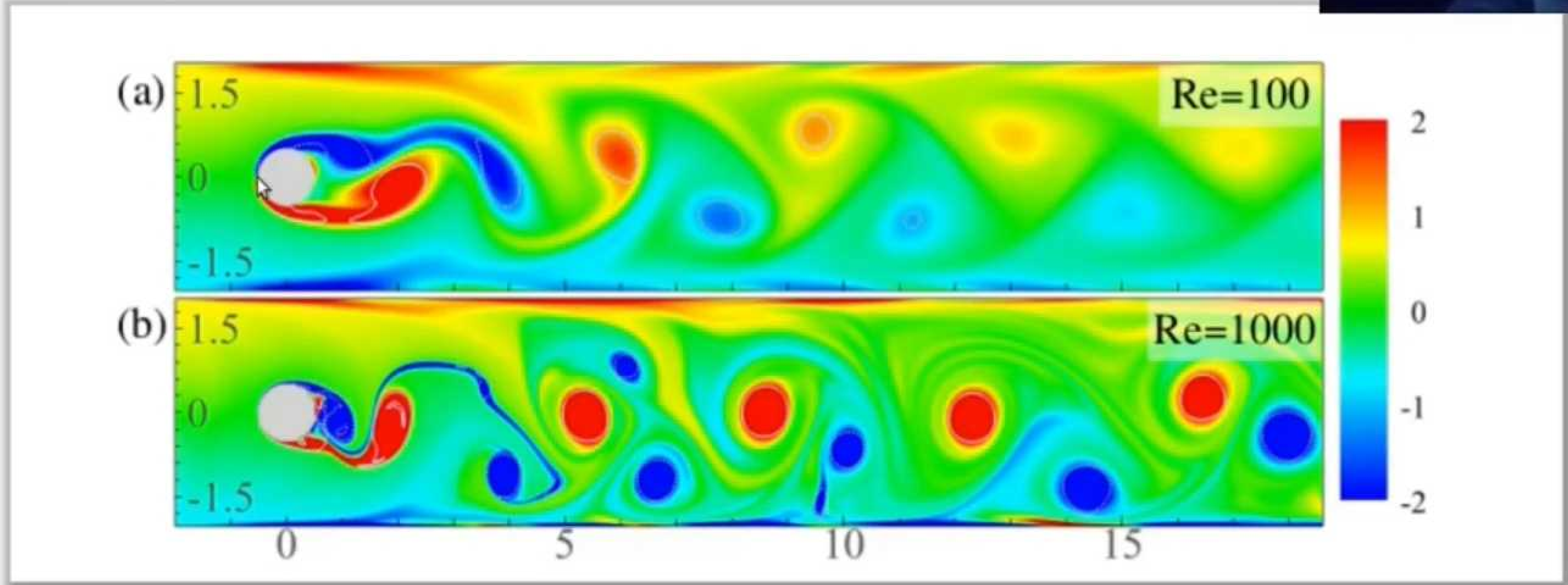
# ML and Fluids, Example I

- Problem: Drag Reduction through Active Flow Control
- Setup: Cylinder with controllable jets at the top and bottom



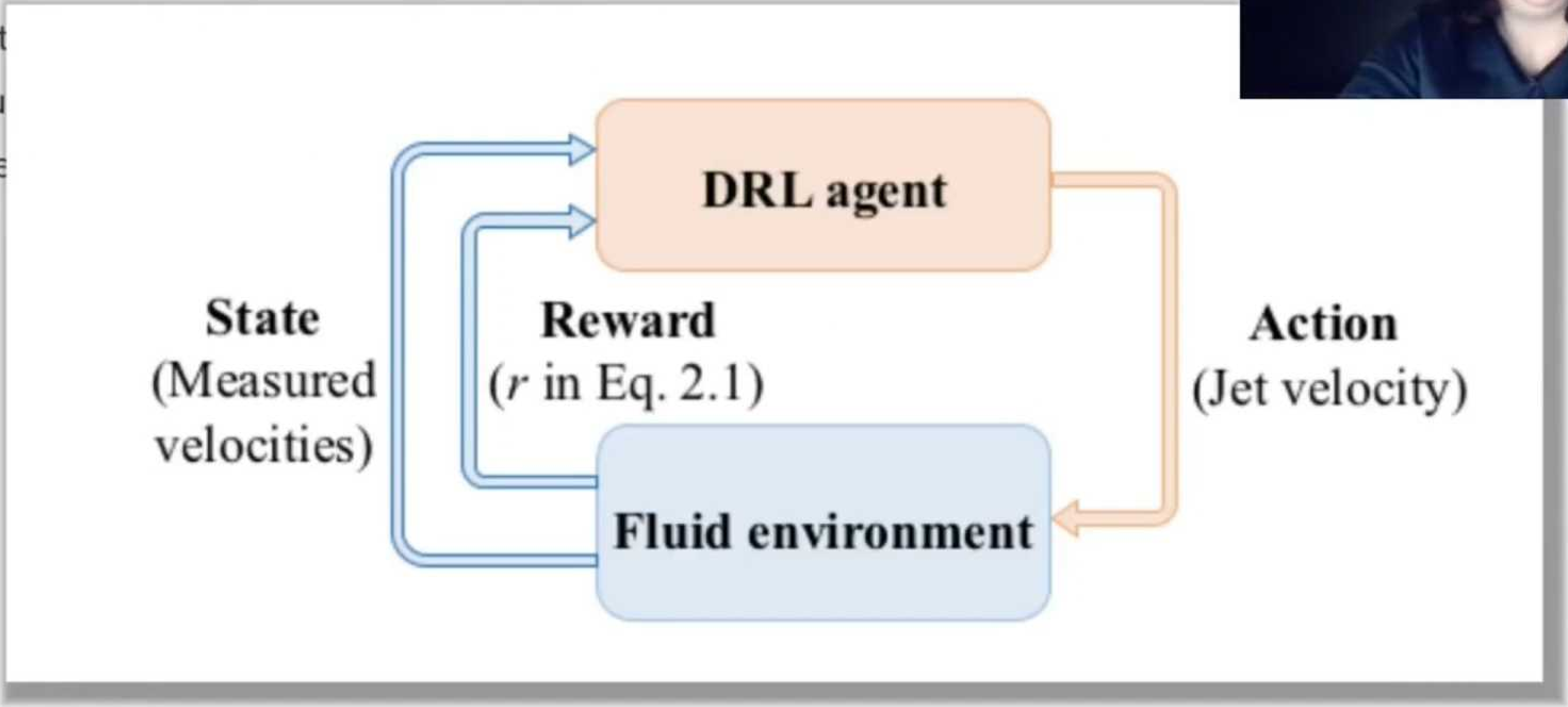

# ML and Fluids, Example I

- Problem: Drag Reduction through Active Flow Control



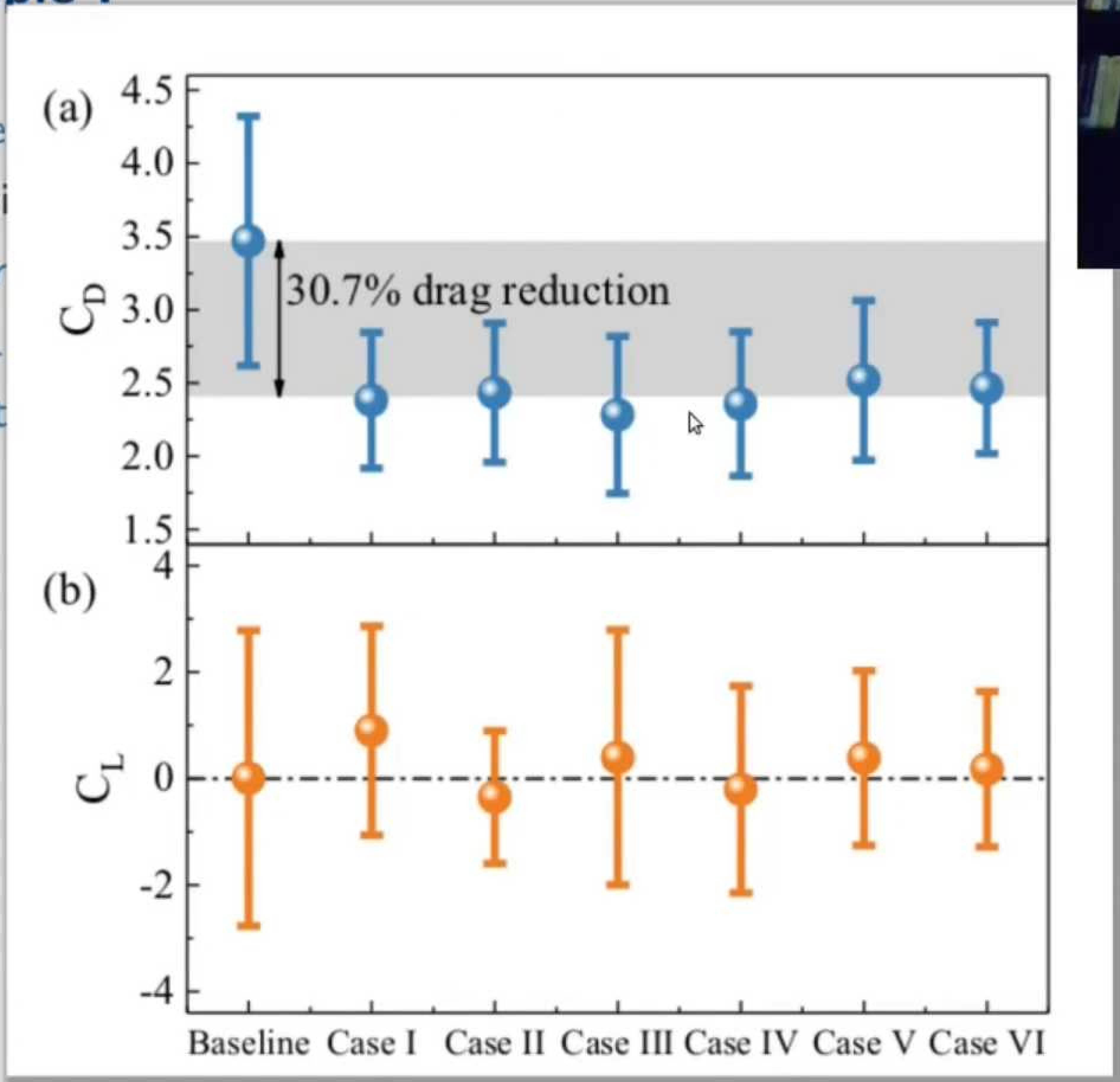

# ML and Fluids, Example I

- Problem: Drag Reduction through Active Flow Control
- Set
- Qu
- Me



# ML and Fluids, Example I

- Problem: Drag Re
- Setup: Cylinder wi
- Question: How str
- Method: Deep RL
- Result: Significant

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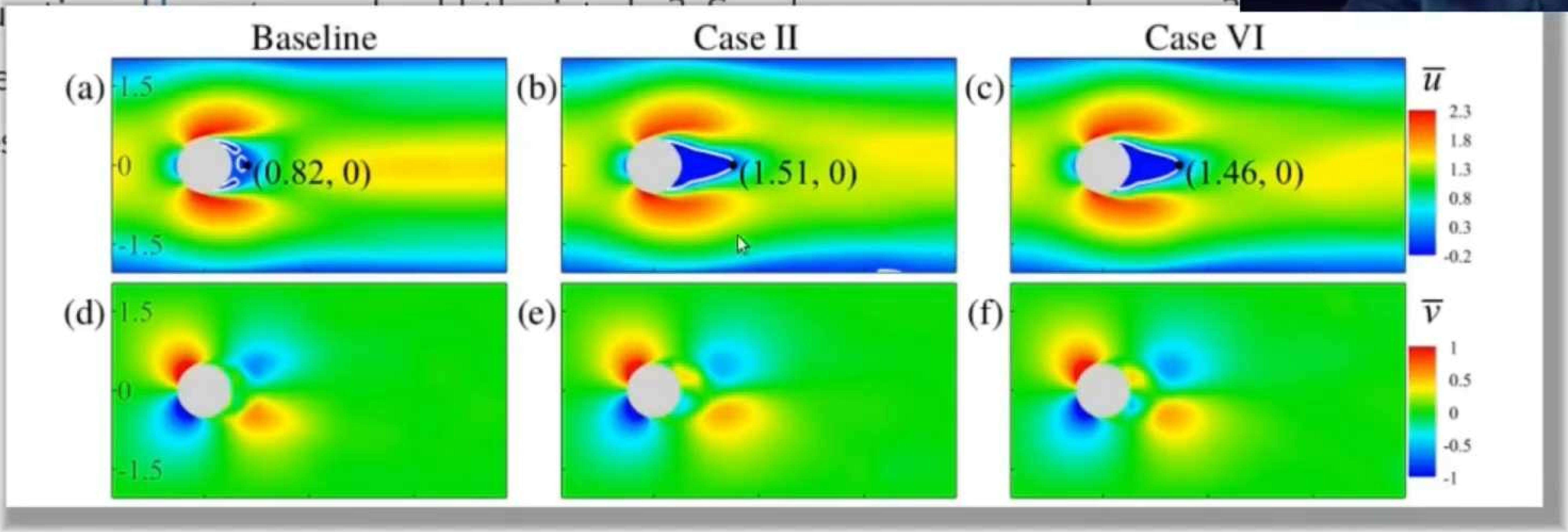
# ML and Fluids, Example I

- Problem: Drag Reduction through Active Flow Control
- Setup: Cylinder with controllable jets at the top and bottom
- Qu
- Me
- Res

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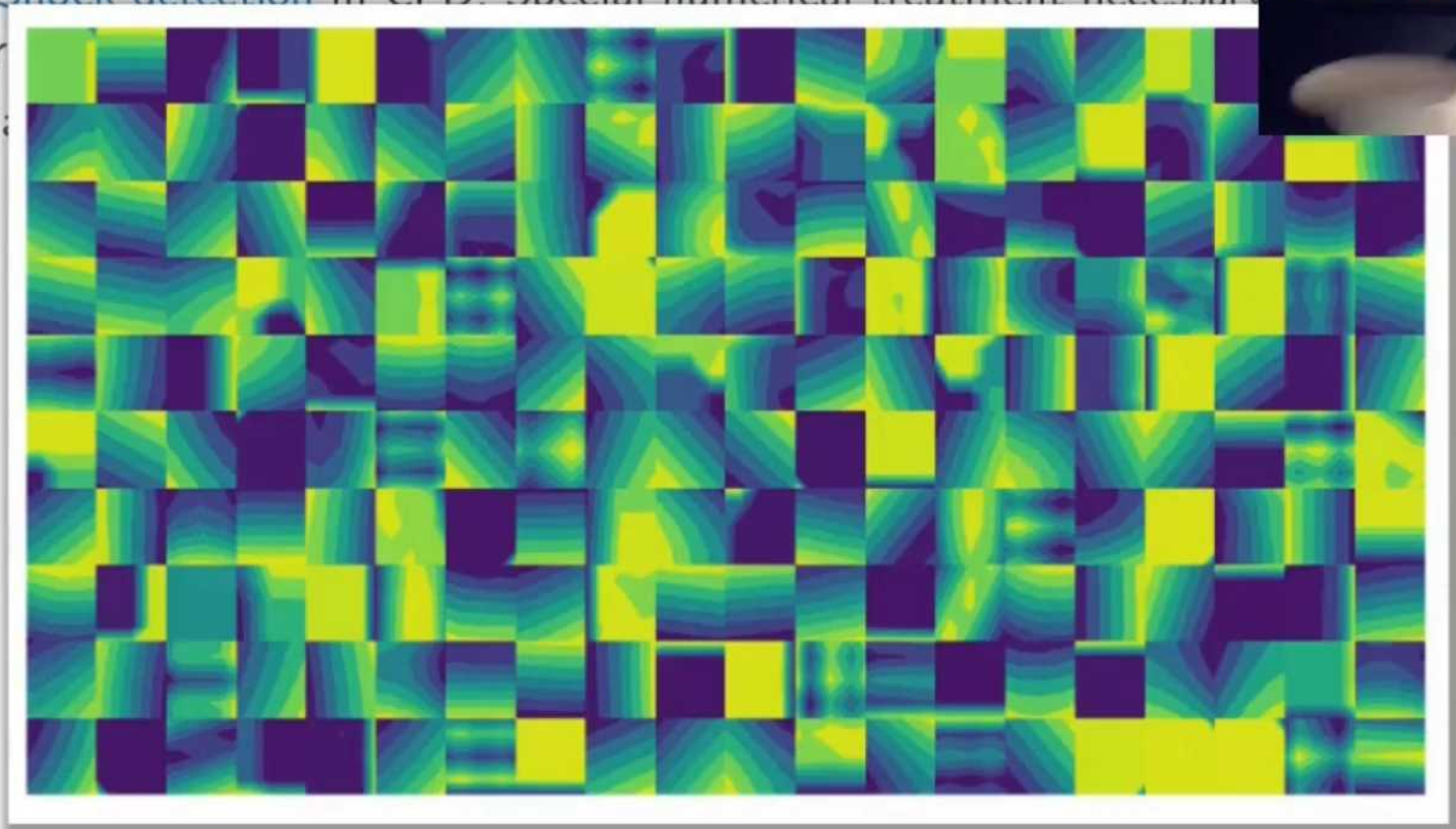
# ML and Fluids, Example I

- Problem: Drag Reduction through Active Flow Control
- Setup: Cylinder with controllable jets at the top and bottom
- Question: How strong should the jets be? Synchronous or asynchronous?
- Method: Deep RL with actor/critique architecture
- Result: Significant drag reduction of over 30%!
- Especially important in a dynamic field such as ML: Give credit!
- All figures and results are from: "Applying Deep Reinforcement Learning to active flow control in turbulent conditions", Ren, Rabault, Tang, 2020: https://arxiv.org/abs/2006.10683

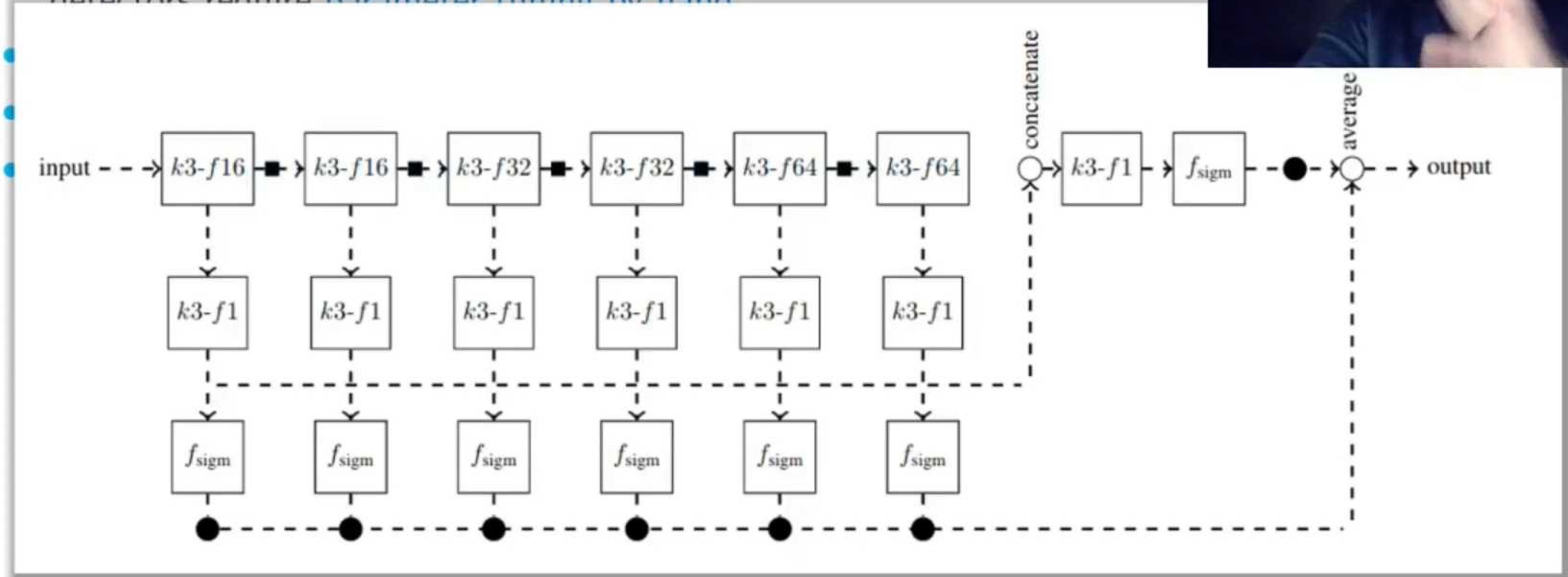
# ML and Fluids, Example II

- Problem: Shock detection in CFD: Special numerical treatment necessary
  detectors r
- Setup: An
- Question:



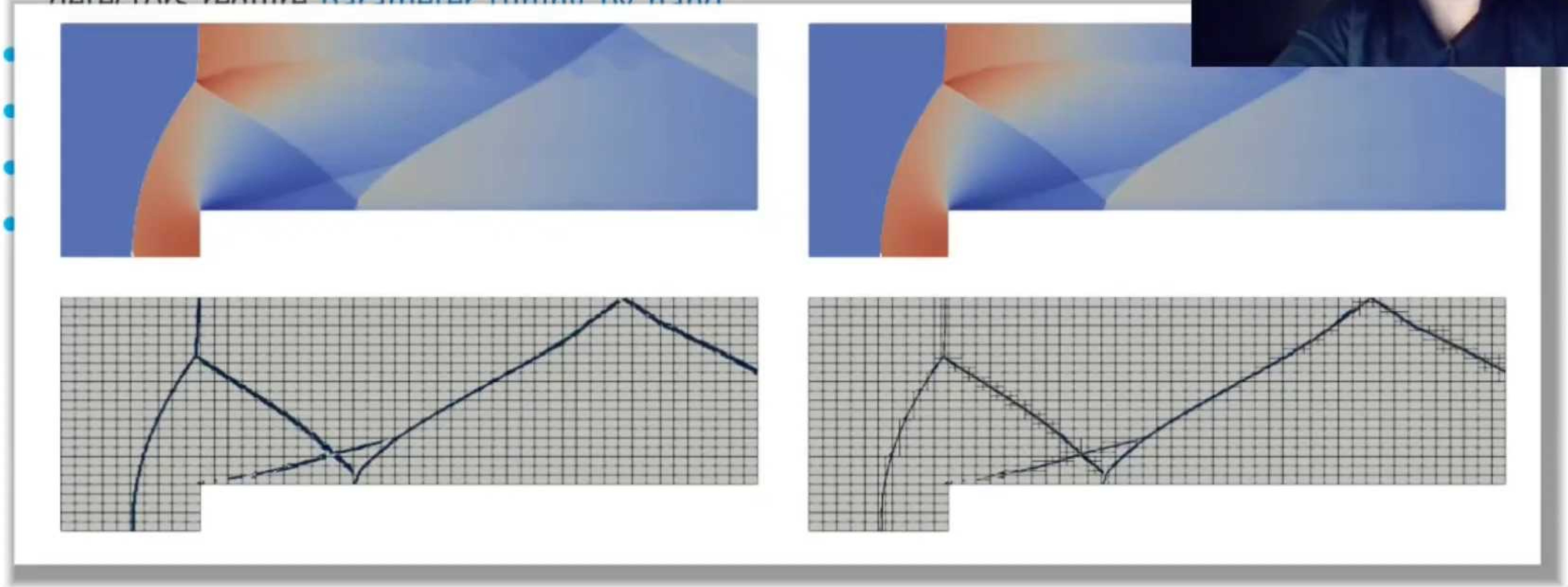
# ML and Fluids, Example II

- Problem: Shock detection in CFD: Special numerical treatment necessary
  detectors require parameter tuning by hand




# ML and Fluids, Example II

- Problem: Shock detection in CFD: Special numerical treatment necessary
  detectors require parameter tuning by hand



# ML and Fluids, Example II

- Problem: Shock detection in CFD: Special numerical treatment necessary detectors require parameter tuning by hand
- Setup: Analytical shock / non-shock fluid solutions
- Question: Is it a shock? Where is the shock
- Method: Supervised learning with Holistic Edge Detection
- Result: Parameter-free shock detection and localization
- All figures and results are from: "A Neural Network based Shock Detection and Localization Approach for Discontinuous Galerkin Methods", Beck, Zeifang, Schwarz, Flad, 2020: Journal of Computational Physics



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