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ROBOTICS & PERCEPTION GROUP

Learning Vision-based Agile Flight

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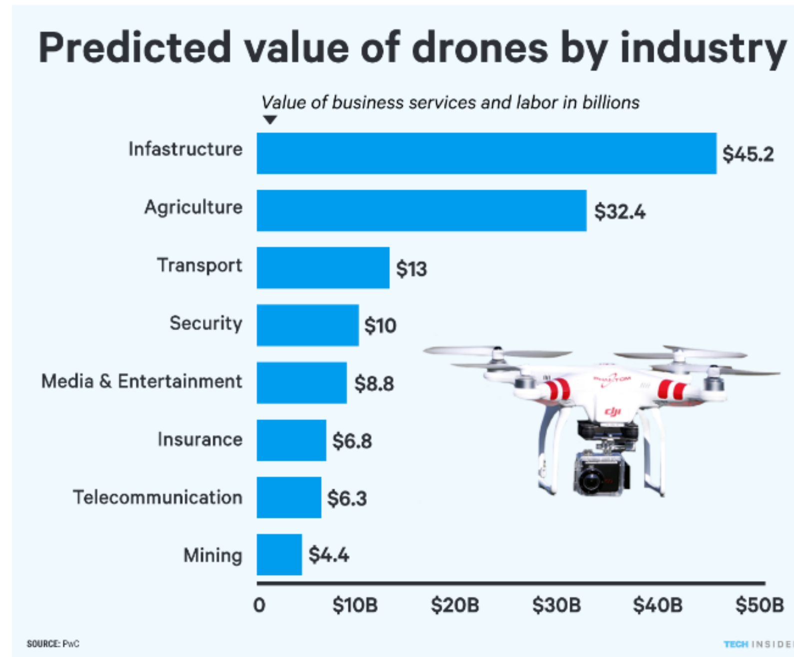
The drone market is valued $130 billions today

Inspection

Agriculture

Transport

Search and Rescue



https://www.pwc.pl/pl/pdf/clarity-from-above-pwc.pdf

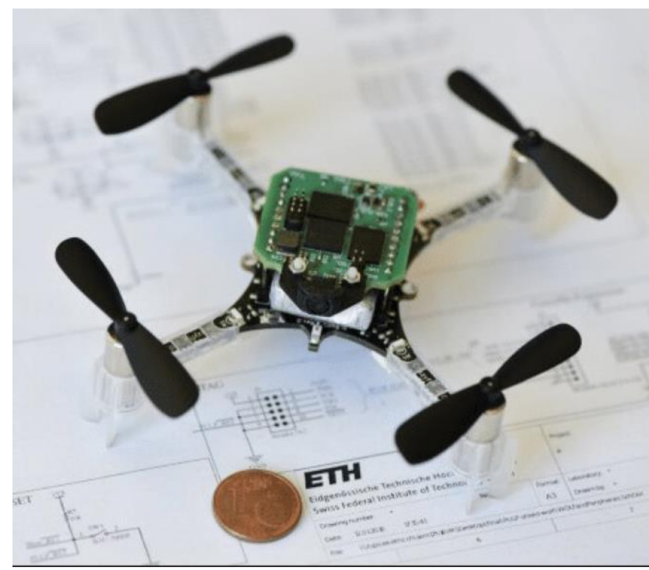
My Motivation: Embodied Intelligence

Embodied intelligence:
Capacity of understanding the world arising from having a body.

Everything that we consider *intelligent* moves and interacts with his surrounding.
What is the role of having body and limited computation for learning?

Internet Intelligence

Embodied Intelligence



How are current commercial drones controlled?

➢ By a human pilot

- requires **line of sight** or **video link**
- requires a **lot of training**

➢ By the autopilot: autonomous navigation

- **GPS**: doesn’t work in GPS denied or degraded environments
- **Lidar** (e.g., Exyn): expensive, heavy, power hungry
- **Cameras** (e.g., Parrot, DJI, Skydio): cheap, lightweight, passive (i.e., low power)

Last 10-years Progress on Autonomous Vision-based Flight

2010
EU SFLY Project (2009-2012)

[Bloesch, ICRA 2010]

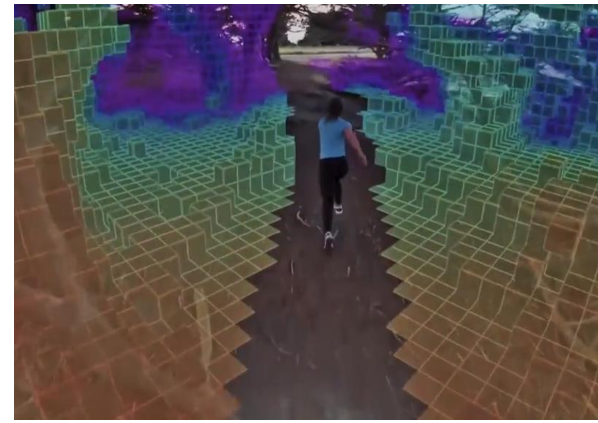
1st onboard goal-oriented vision-based flight

(previous research focused on reactive navigation)

2015
DARPA FLA Program (2015-2018)

[Mohta, JFR 2018]

1st high-speed flight in the wild
(up to 10 m/s)



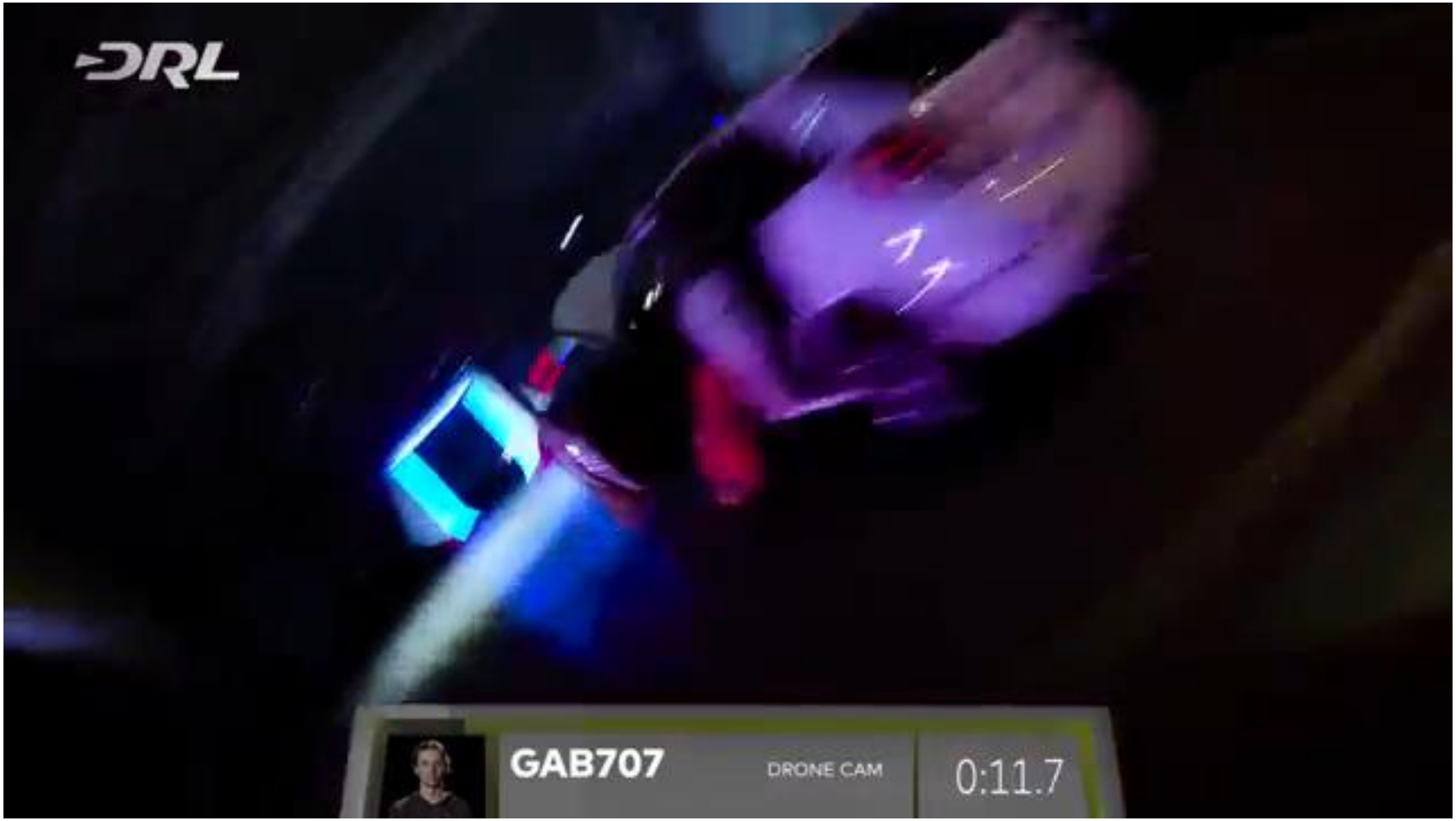
2020

- **Skydio** (2018-2020),
- **DJI** (2018-2020),
- **NASA Mars Helicopter** (2020)

1st products in the market or sent to another planet ☺

What's Next?

What does it take to fly as **good as or better** than human pilots?



WARNING! This drone is NOT autonomous; it is operated by a human pilot.
Human pilots take years to acquire the skills shown in this video.

Why Agile Flight?

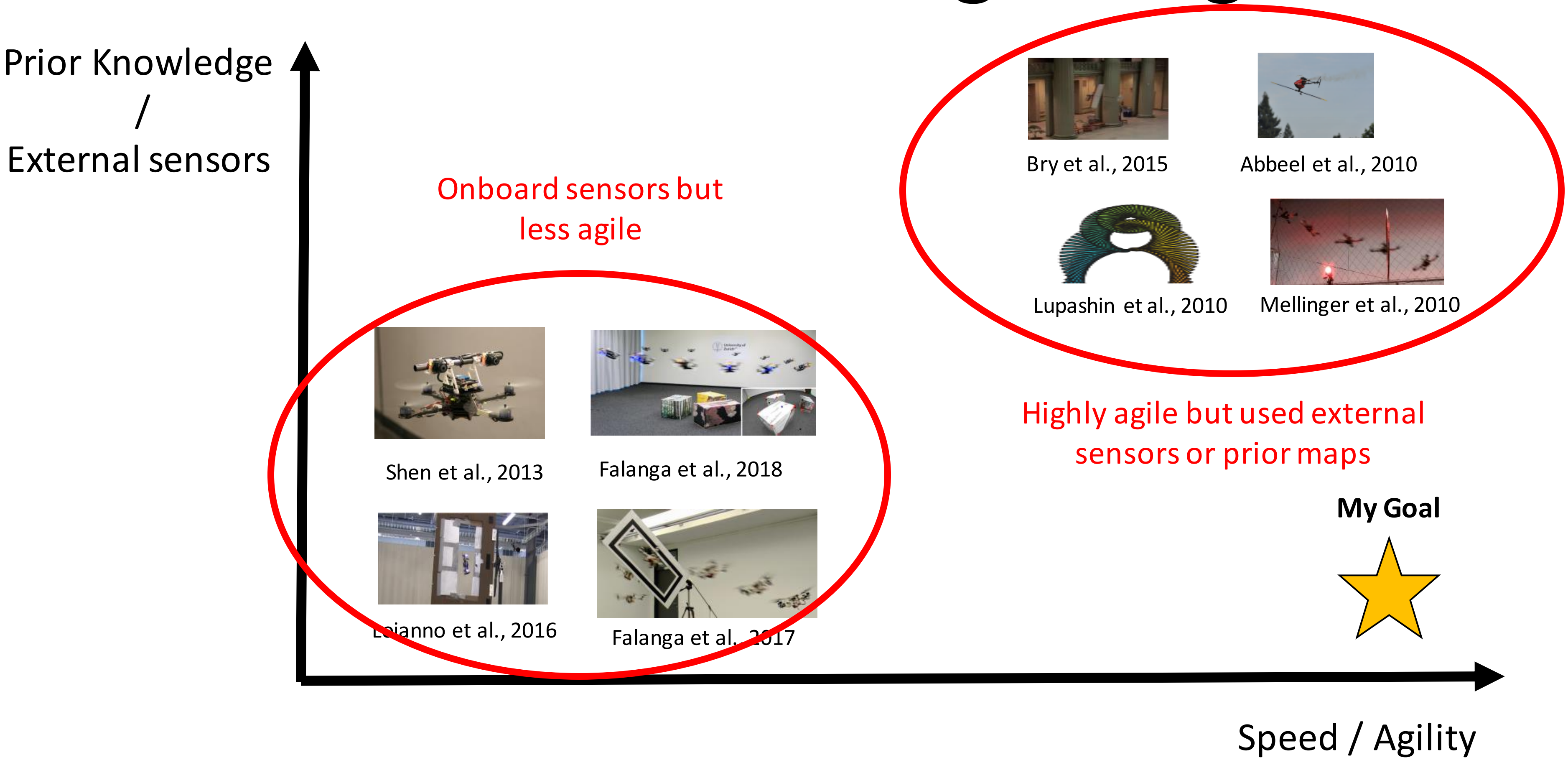
- **Making drones faster increases their range** (limited by battery life)
- **Applications**: search & rescue, inspection, delivery
- **Raises fundamental challenges for robotic research**: perception, planning, control
- **Pushes the limits** of vision-based navigation

search & rescue

delivery

inspection

Related Work on Agile Flight

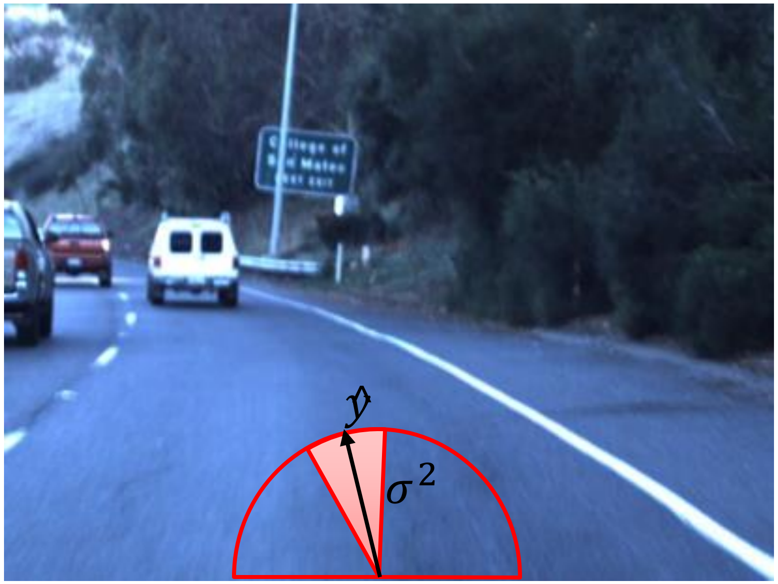


Specific Research Questions

- ***RQ1:*** *Under which conditions can a neural network be successfully integrated in a robotic system?*
- ***RQ2:*** *What are the conditions for a neural network to transfer knowledge between different domains (e.g. simulation to reality)?*
- ***RQ3:*** What does it take to achieve similar spatial awareness to a human with comparable sensing (and computing) in the context of high-speed flight?

Research Question I

Under which conditions can a neural network be used to control a robotic system?



Low Uncertainty

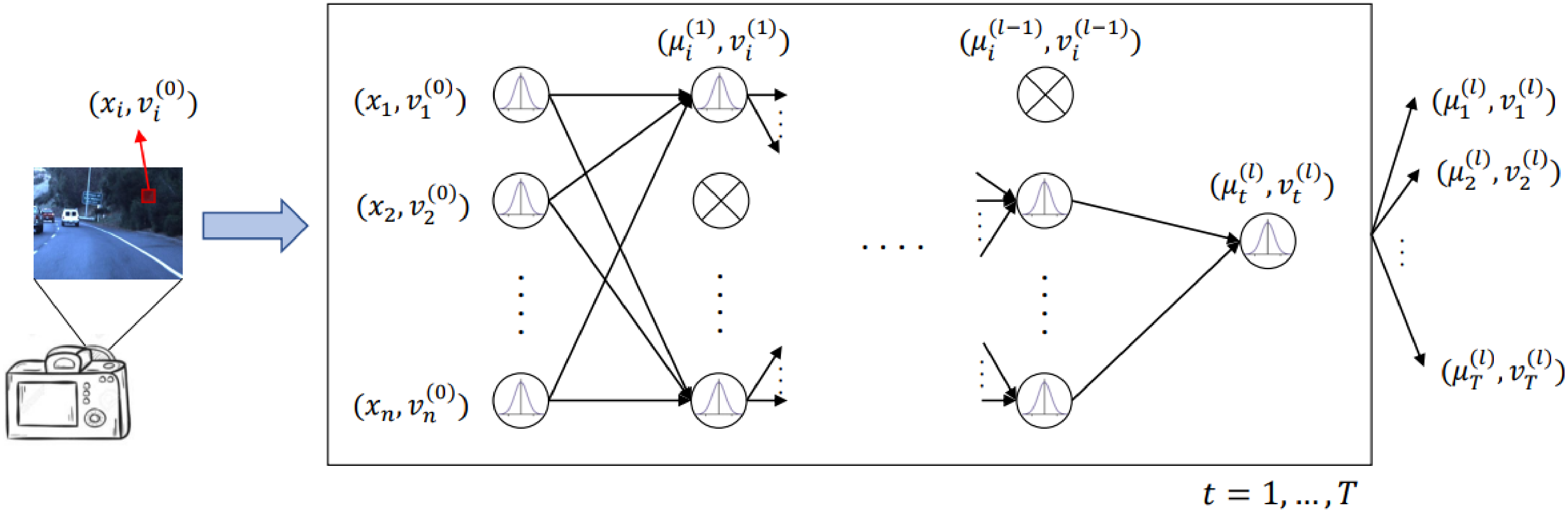
Sensor Failure

High Uncertainty

- A robotic system **cannot blindly trust** neural network predictions:
  - What happens if the **current observation** is very **different** from the **training** ones?
  - What if some **sensors fail**?

Research Question I

Proposed a General Framework to estimate prediction uncertainty for neural nets.

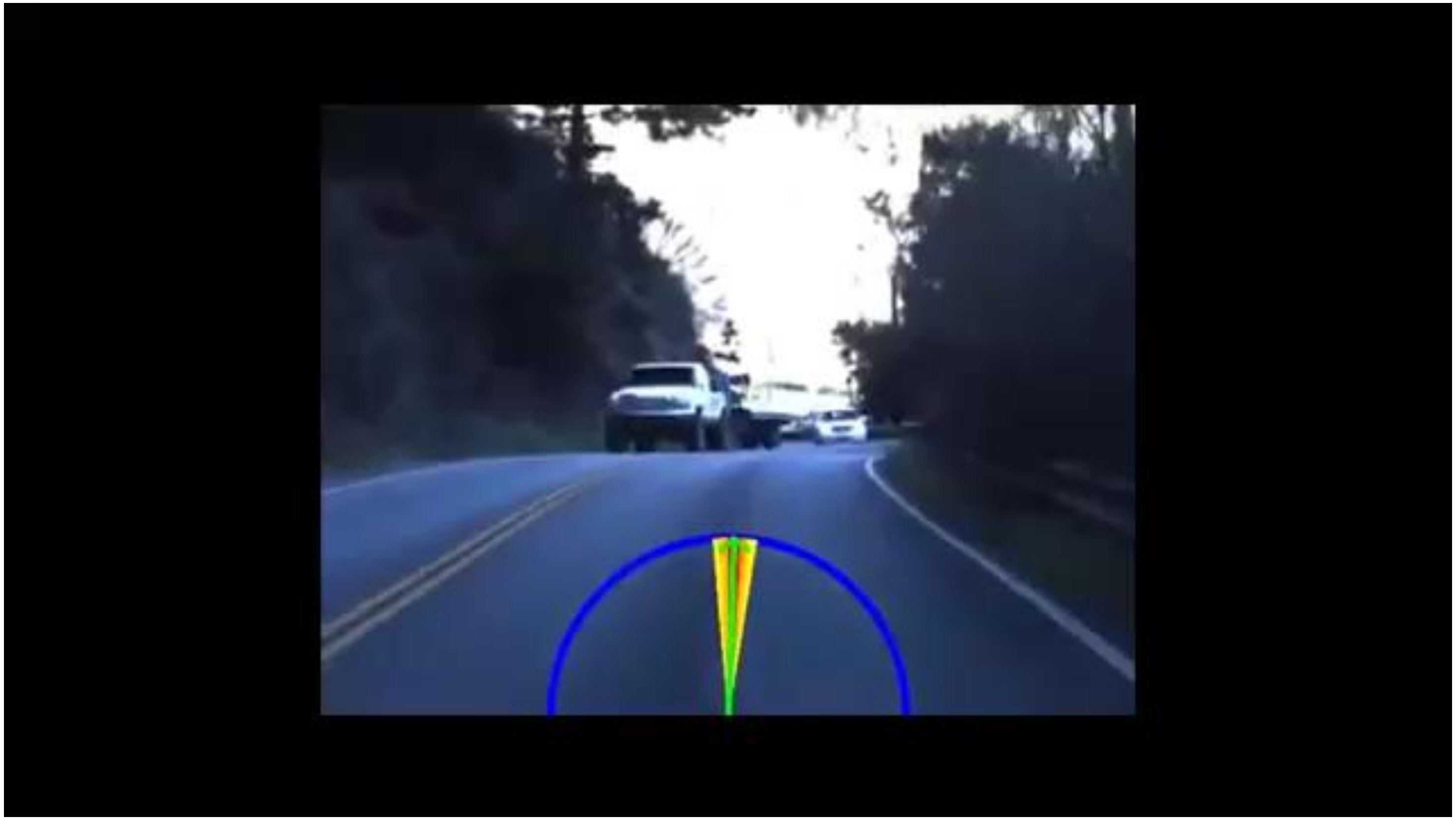


- Use **prior information** about the data (sensor noise) to compute data uncertainty
- Model the **relationship between data and model** uncertainty

Loquercio et al., A General Framework for uncertainty estimation in Deep Learning, Robotics and Automation Letters (RA-L), 2020.

Research Question I

The proposed framework was tested on several computer vision and control tasks.



- End-to-End Steering Angle Prediction
- Object Future Motion Prediction
- Object Recognition
- Closed Loop Control of a Quadrotor

Loquercio et al., A General Framework for uncertainty estimation in Deep Learning, Robotics and Automation Letters (RA-L), 2020.

Research Question II

What are the conditions for a neural network to transfer knowledge between domains?

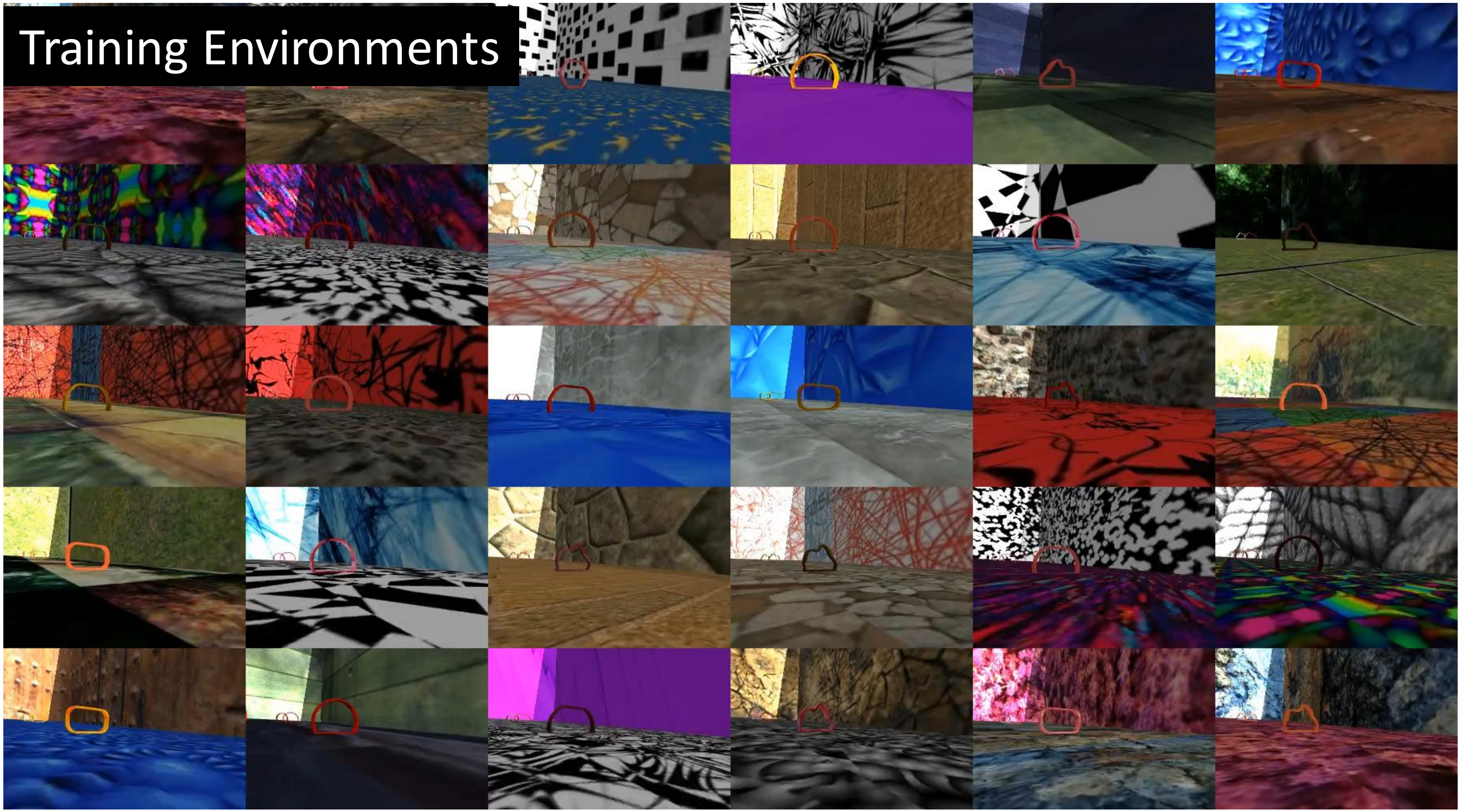
Train

Test

- Cannot harm drones at train time.
- Cheap to collect data.
- Can train on ***ANY*** trajectory, even the one difficult for drone pilots.

Research Question II

What are the conditions for a neural network to transfer knowledge between domains?



Loquercio, et al., *Deep Drone Racing with Domain Randomization*, IEEE T-RO, 2019. [PDF](). [Video]().
Best System Paper Award at Conference for Robotics Learning (CORL), 2018.

Research Question II

Domain Randomization allows a network to learn domain invariant representations.

But it is very sample inefficient!

The amount of required training data scales exponentially with the task complexity.

Loquercio, et al., *Deep Drone Racing with Domain Randomization*, IEEE T-RO, 2019. PDF. Video.

Best System Paper Award at Conference for Robotics Learning (CORL), 2018.

Research Question II

What are the conditions for a neural network to transfer knowledge between domains?

Find input representations that are domain invariant.

- *Mathematically shown that abstract **sensor representations** strictly **decrease** the simulation to reality **gap.***
- ***Input representations** can either be **learned** (e.g., via domain randomization) or **designed** with domain knowledge.*

Lemma 1: For a Lipschitz continuous policy π the simulation to reality gap $J(\pi_r) - J(\pi_s)$ is upper-bounded by

$$J(\pi_r) - J(\pi_s) \leq C_{\pi_s} K \mathbb{E}_{\rho(\pi_r)}\big[DW(M, L)\big], \tag{10}$$

where K denotes the Lipschitz constant.

Lemma 2: A policy acting on an abstract representation of the observation $\pi_f \colon f(\mathbb{O}) \rightarrow \mathbb{U}$ reduces the simulation to reality gap with respect to another policy $\pi_o \colon \mathbb{O} \rightarrow \mathbb{U}$ acting on raw observations.

Kaufmann*, Loquercio*, Ranftl, Mueller, Koltun, Scaramuzza, ***Deep Drone Acrobatics*, RSS 2020**
Best Paper Award Finalist

Research Question II

Use **domain expertise** to **design** domain invariant **input representations**.

Kaufmann*, Loquercio*, Ranftl, Mueller, Koltun, Scaramuzza, ***Deep Drone Acrobatics*, RSS 2020**

Best Paper Award Finalist

Research Question II

This also applies to domain/robot **invariant output representations!**

Loquercio, et al., *DroNet: Learning to Fly by Driving*, Robotics and Automation Letters (RA-L), 2018

Research Question III

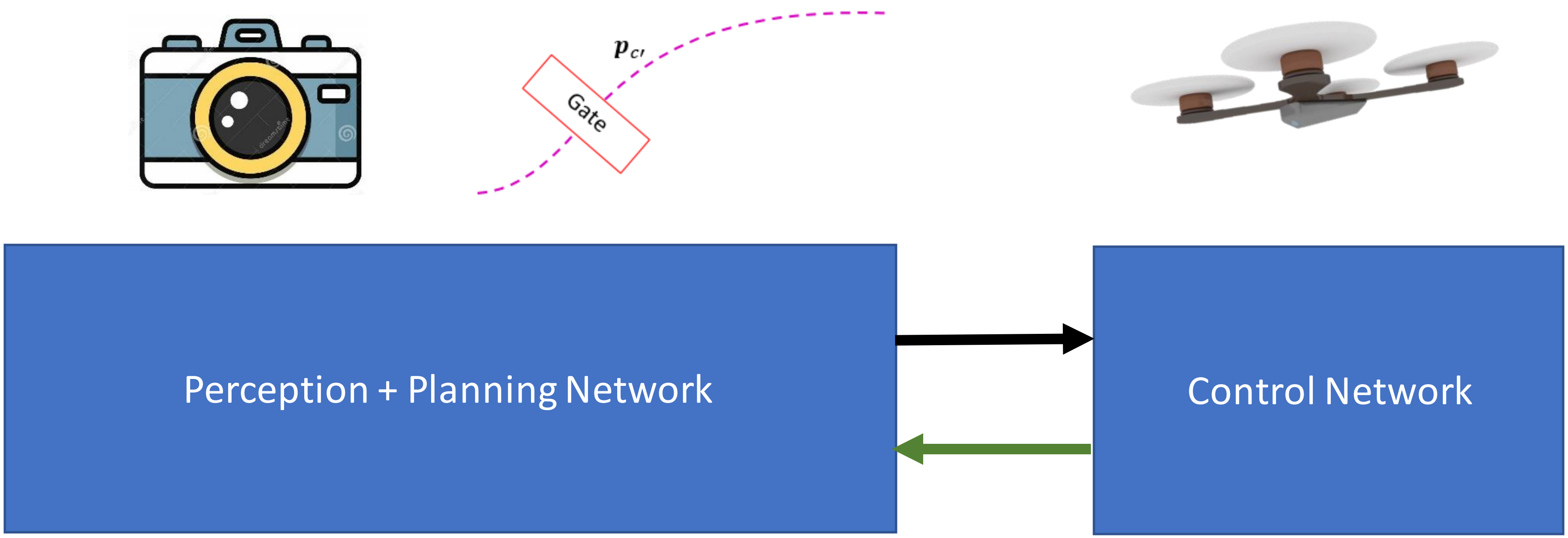
What does it take to achieve similar **spatial awareness** to a human **with comparable sensing (and computing)** in the context of **high-speed flight**?

Loquercio, et al., *Deep Planning Networks, In Preparation*

Research Question III

What we need:
- Very fast perception.
- Data-Efficient and generalizable neural networks.

Key idea: interpretable and differentiable representations
(e.g. the drone’s path).



Results Real World: Tree Avoidance

Conclusions & Takeaways

- Autonomous **vision-based agile flight** as a new research topic (at least 10 years to solve it)
  - Raises **fundamental problems** for robotics **research**
  - **Pushes the limit of existing algorithms** in extreme situations

- **Combining model based and ML** methods can greatly **boost the performance,** but the important **question is what** should be **learned** and what should be **modeled**

Code, **datasets**, **videos**, and **publications**, **slides**: https://antonilo.github.io/

I am on the academic job market!

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List of publications

Loquercio A.*, E. Kaufmann*, R. Raft, A. Dosovitskiy, M. Mueller, V. Koltun, D. Scaramuzza "Deep Drone Acrobatics." *RSS (2020).*

Loquercio A., Dosovitskiy A., Scaramuzza D. "Learning Depth via Interaction." *Robotics and Automation Letters (RA-L), 2020.*

Messikomer n., Gehrig D., **Loquercio A.**, Scaramuzza D. "Event-Based Asyncronous Sparse Convolutional Neural Networks." ECCV*, 2020.*

Loquercio A., Segu M., Scaramuzza D. "A General Framework for Uncertainty Estimation in Deep Learning." *Robotics and Automation Letters (RA-L), 2020.*

Gehrig D., **Loquercio A.**, Derpanis KG, Scaramuzza D. "End-to-End Learning of Representations for Asynchronous Event-Based Data." *IEEE International Conference on Computer Vision (ICCV), 2019.*

Loquercio A.*, E. Kaufmann*, R. Raft, A. Dosovitskiy, V. Koltun, D. Scaramuzza "Deep Drone Racing: From Simulation to Reality with Domain Randomization." *IEEE Transaction on Robotics (T-RO) 2019*

Yang Y.*, **Loquercio A.***, Scaramuzza D., Soatto S., "Unsupervised Moving Object Detection via Contextual Information Separation." *IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2019.*

D. Palossi, **Loquercio A.**, F. Conti, E. Flamand, D. Scaramuzza, L. Benini "A 64mW DNN-based Visual Navigation Engine for Autonomous Nano-Drones." *IEEE Internet of Things Journal, 2019*.

E. Kaufmann*, **Loquercio A.***, R. Raft, A. Dosovitskiy, V. Koltun, D. Scaramuzza "Deep Drone Racing: Learning Agile Flight in Dynamic Environments." *Conference on Robotic Learning (CoRL) 2018*

Maqueda I. A., **Loquercio A.**, Gallego G., Garcia N., Scaramuzza D. "Event-based Vision meets Deep Learning on Steering Prediction for Self-driving Cars." *IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2018*.

Loquercio A., Maqueda I. A., Del Blanco C. R., Scaramuzza D. "DroNet: Learning to Fly by Driving." *Robotics and Automation Letters (RA-L) 2018*.

Ye Y., Cieslewski T., **Loquercio A.**, Scaramuzza D. "Place Recognition in Semi-Dense Maps: Geometric and Learning-Based Approaches." *BMVC 2017*.

Loquercio A., Dymczyk M., Zeisl B., Lynen S., Gilitschenski I., Siegwart R. "Efficient Descriptor Learning for Large Scale Localization." *ICRA 2017*.