Mobile Robotics for Computer Architects

Vijay Janapa Reddi, Ph. D. Associate Professor

John A. Paulson School of Engineering and Applied Sciences Domain Specific System Architecture (DoSSA) Workshop













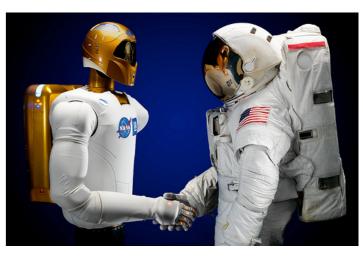


















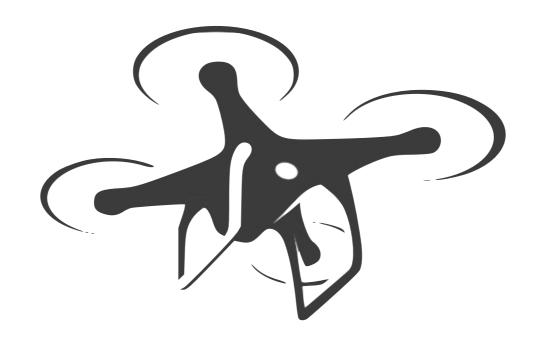


















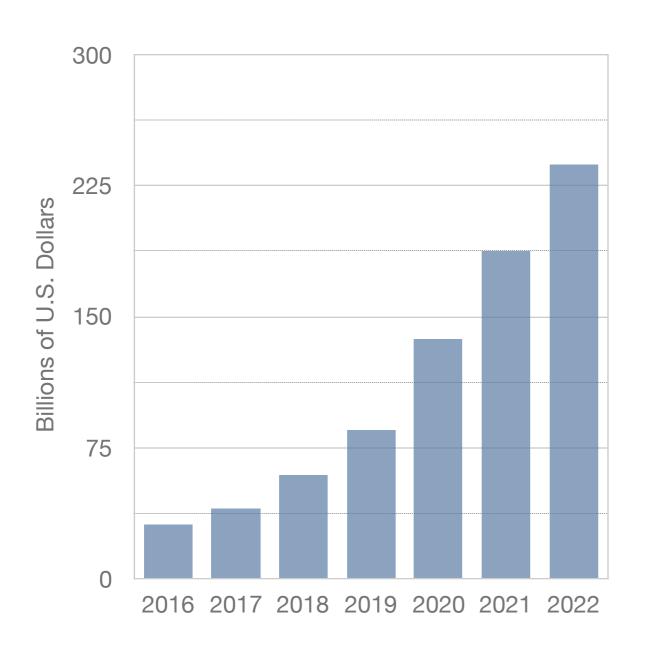








Global Market Size for Robotics

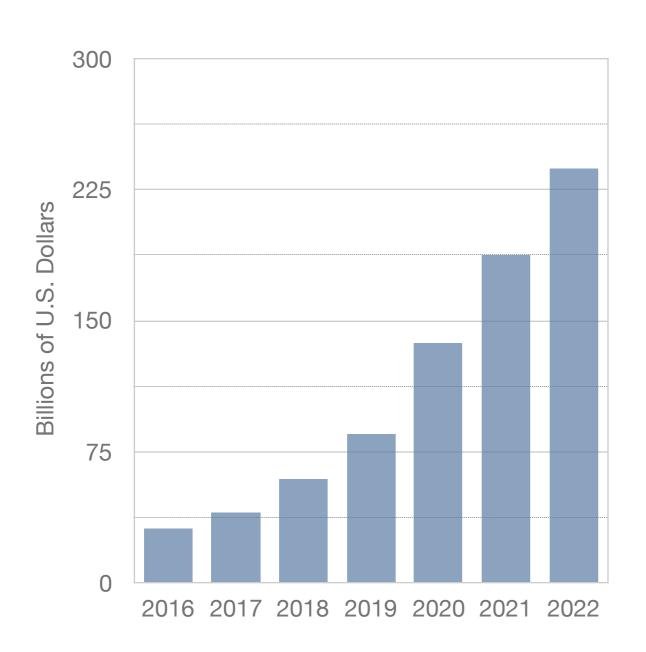


"... revenue generated from the robotics market globally, both industrial and non-industrial, from 2016 to 2022. In 2017, the robotics market is estimated to be worth 40 billion U.S. dollars globally. The industrial robotics market, which has traditionally represented the robotics industry ... is giving way to non-industrial robots, such as personal assistant robots, customer service robots, autonomous vehicles, and unmanned aerial vehicles (UAVs)."

Source: [Statista 2018]



Global Market Size for Robotics



"... revenue generated from the robotics market globally, both industrial and non-industrial, from 2016 to 2022. In 2017, the robotics market is estimated to be worth 40 billion U.S. dollars globally. The industrial robotics market, which has traditionally represented the robotics industry ... is giving way to non-industrial robots, such as personal assistant robots, customer service robots, autonomous vehicles, and unmanned aerial vehicles (UAVs)."

Source: [Statista 2018]



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What are the **challenges** facing aerial robots?



Performance





Performance (Real-time) Reliability **Power** (Endurance) (Safety)



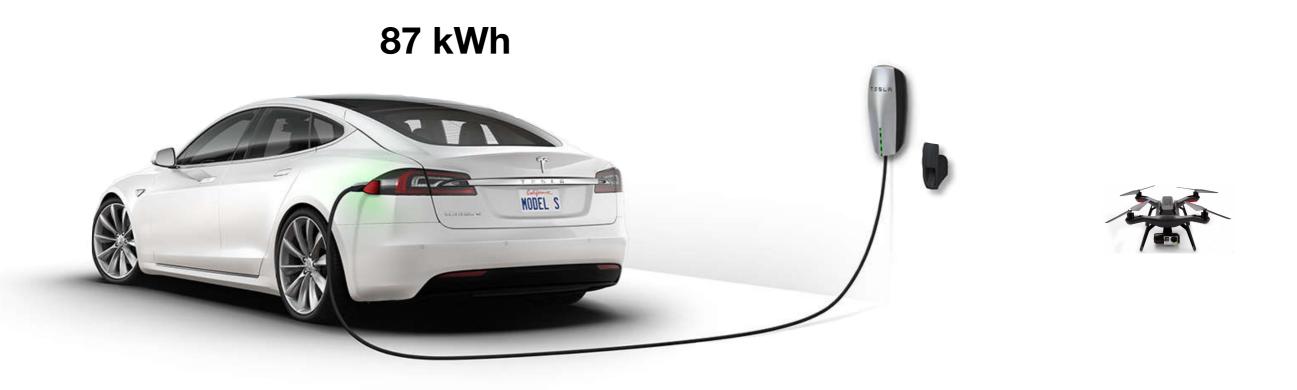




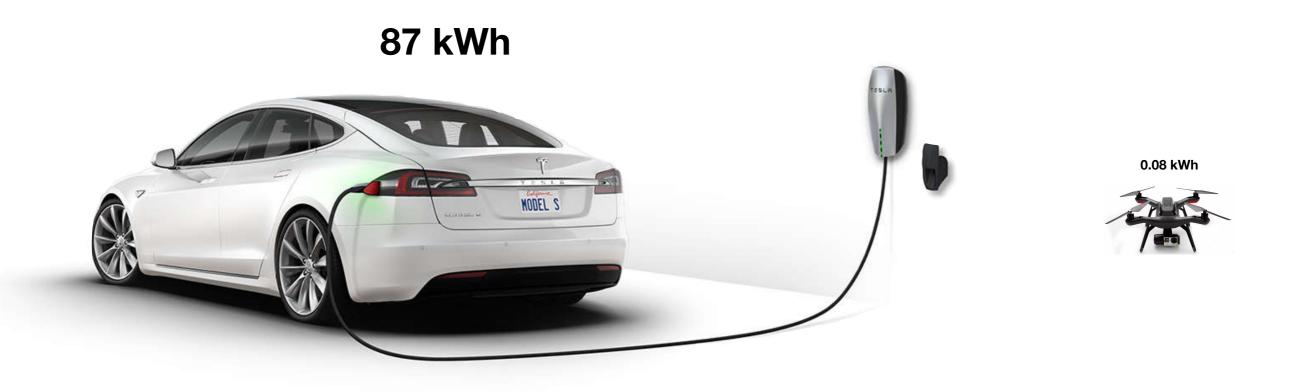




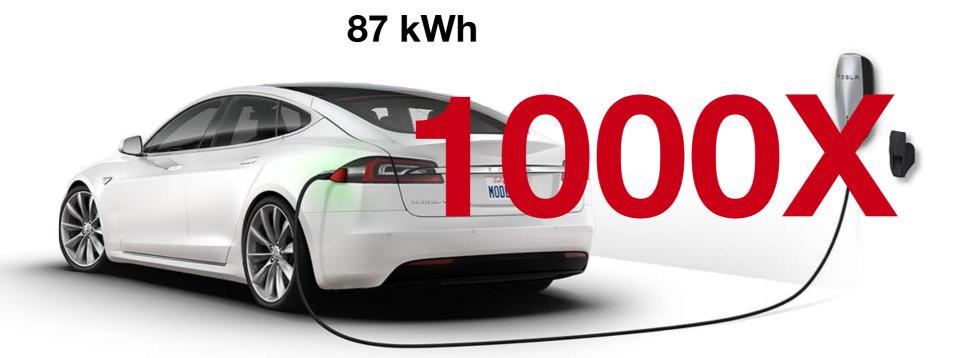






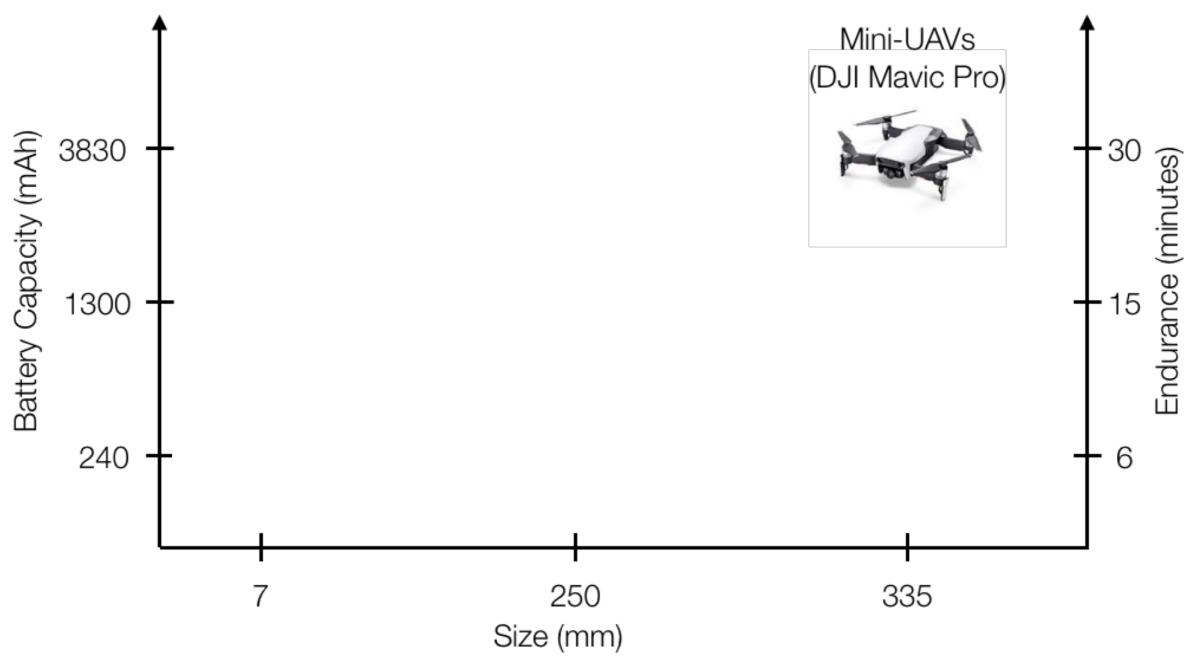




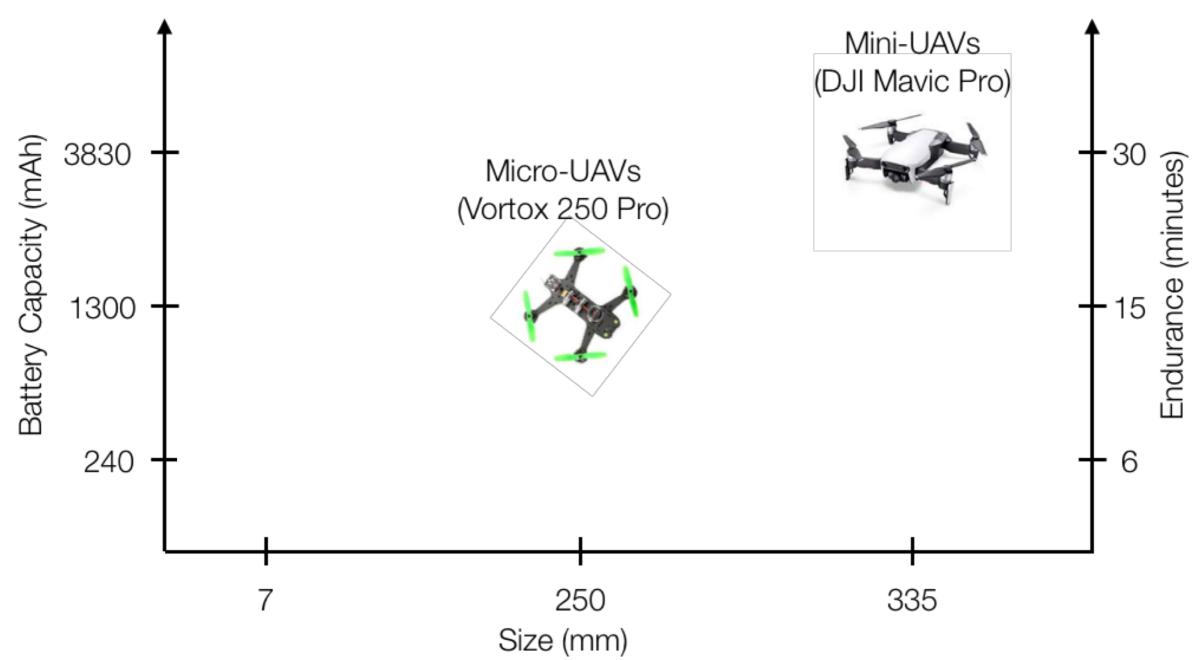




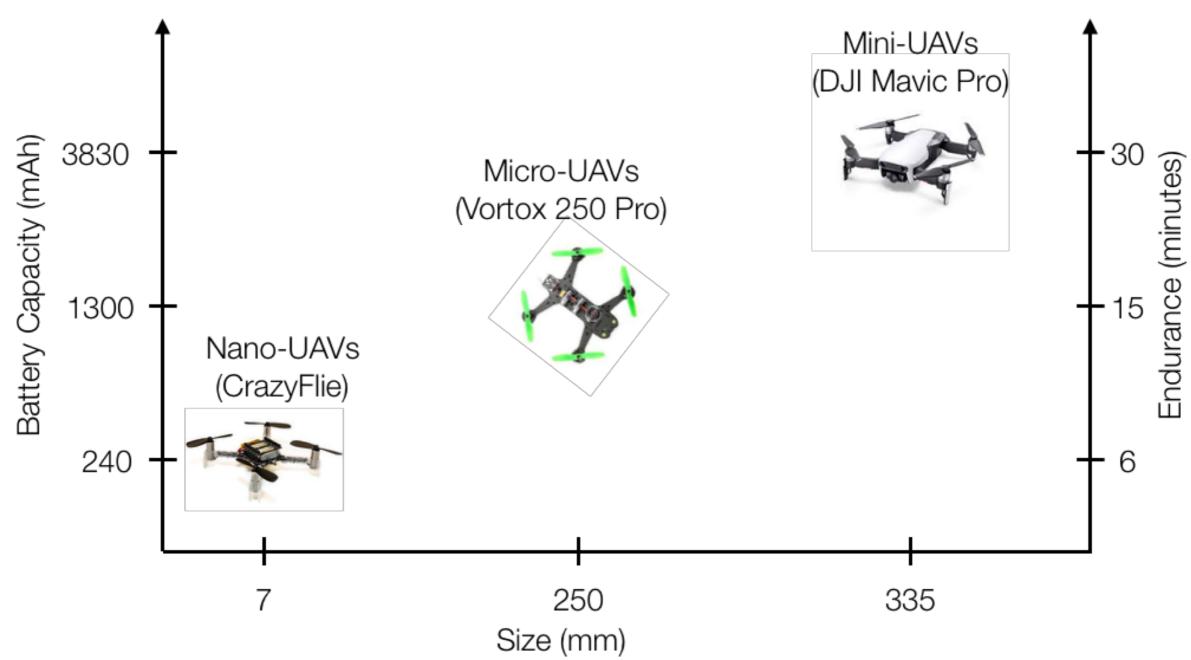






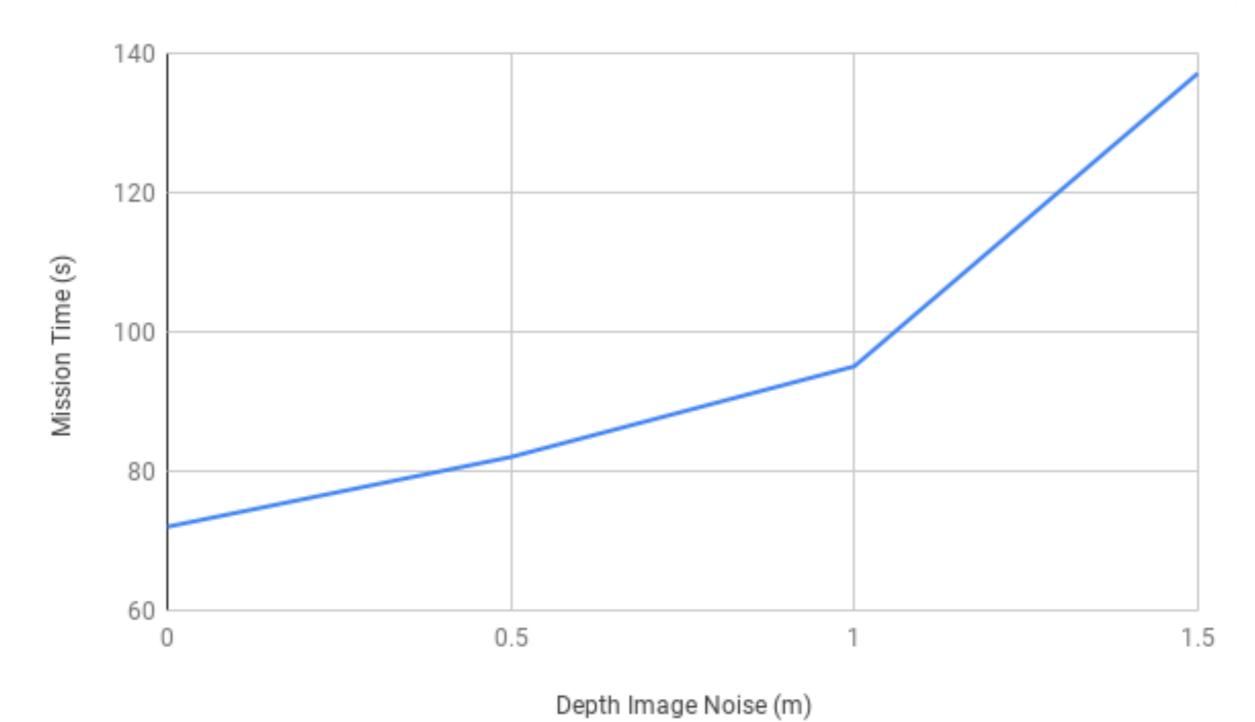








Safety Depends on Robustly Accounting for Failures





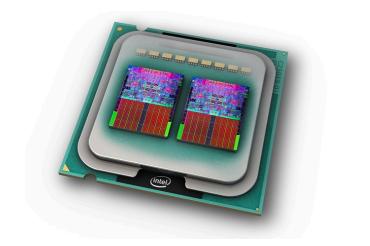
Performance (Real-time) Reliability **Power** (Endurance) (Safety)



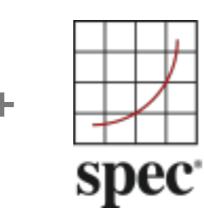
What architectural tools are needed to enable research on aerial robots?



Traditional Computer Architecture Toolkit



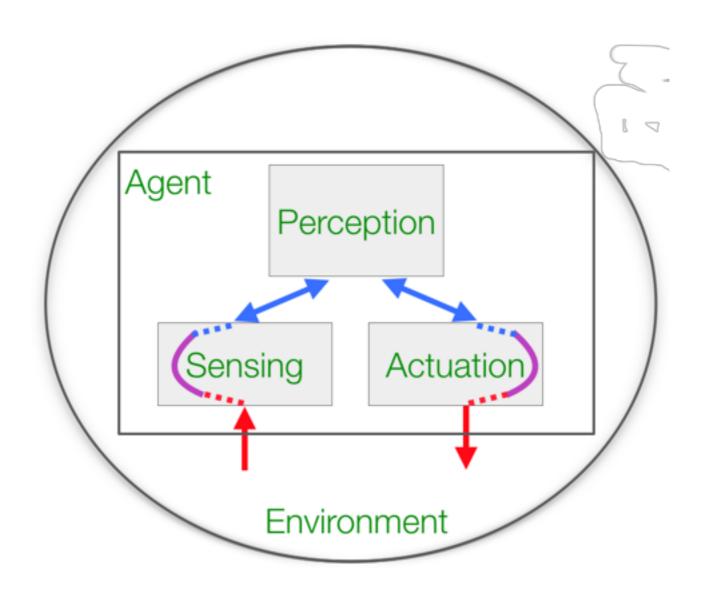






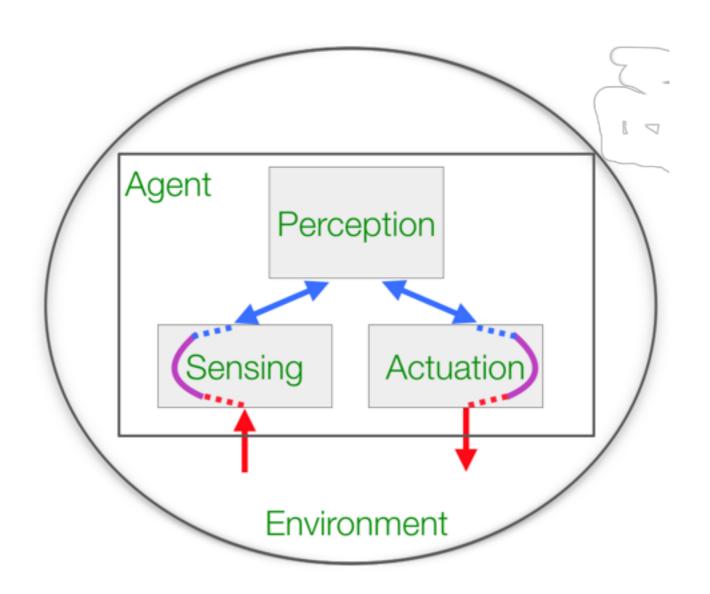


Challenge with the Traditional Toolkit for Robotics



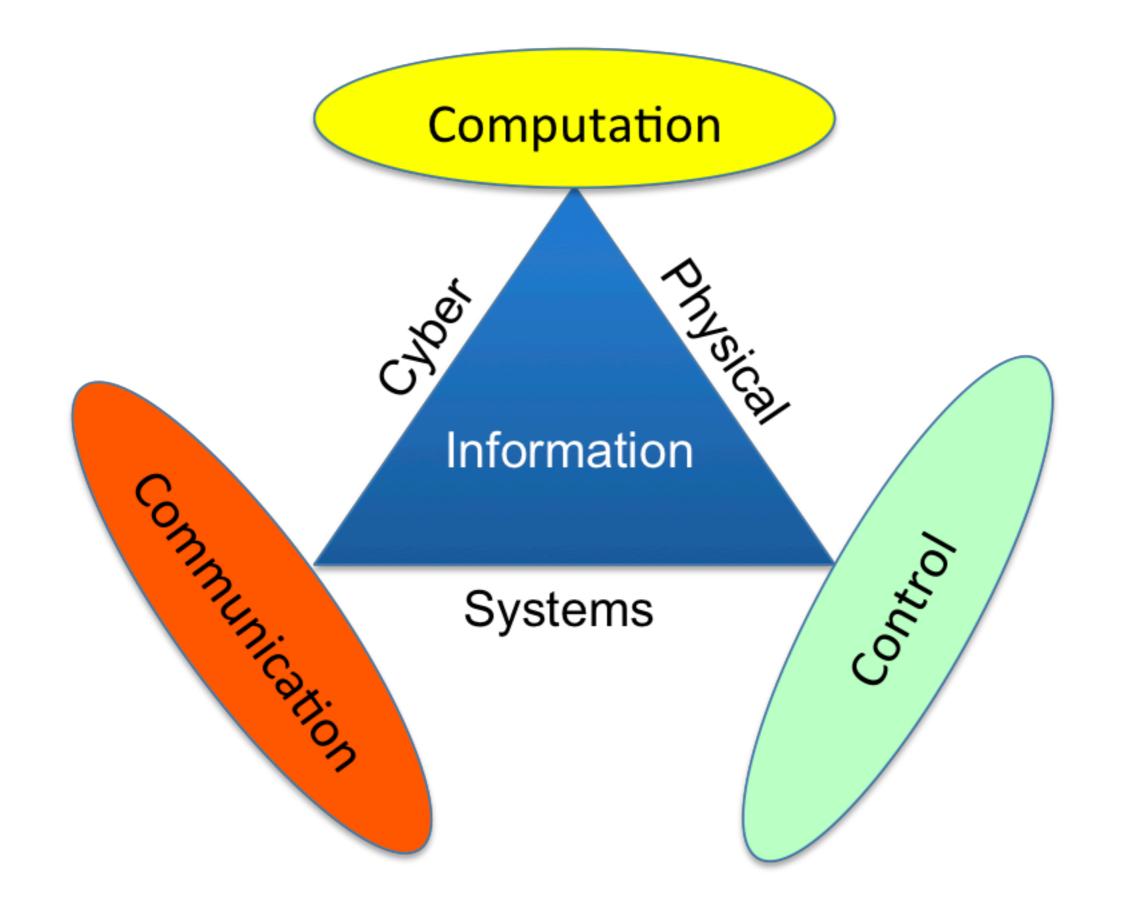


Challenge with the Traditional Toolkit for Robotics



There is a continuous feedback loop.



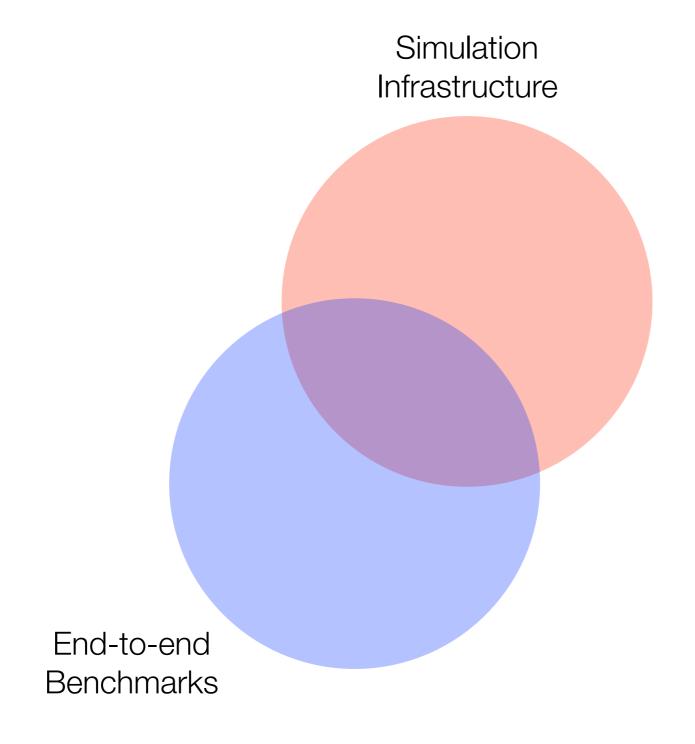




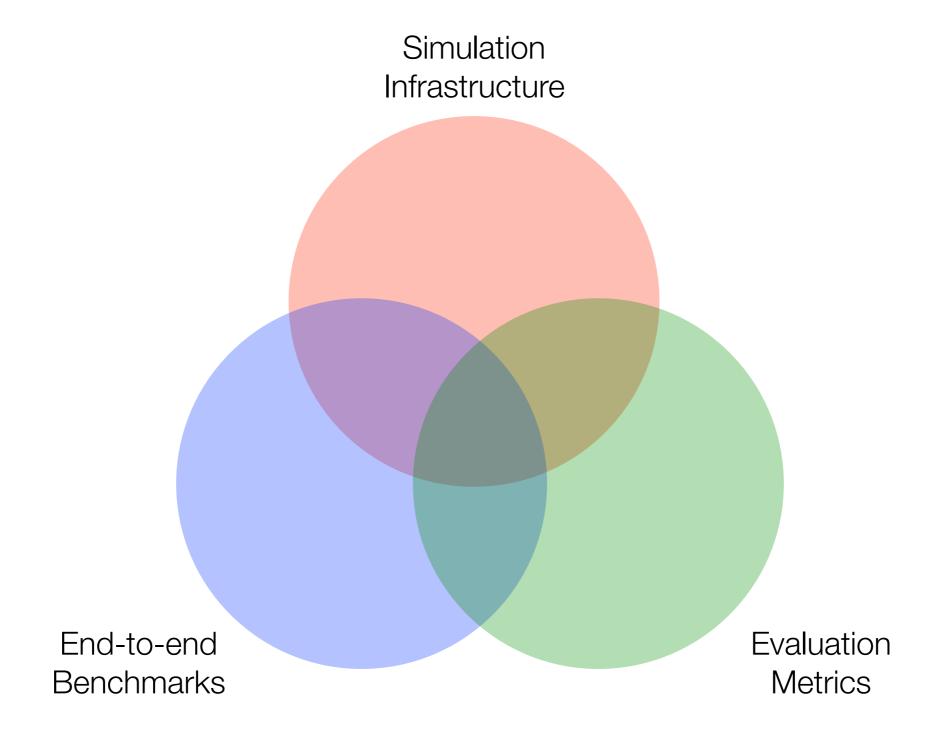


Simulation Infrastructure

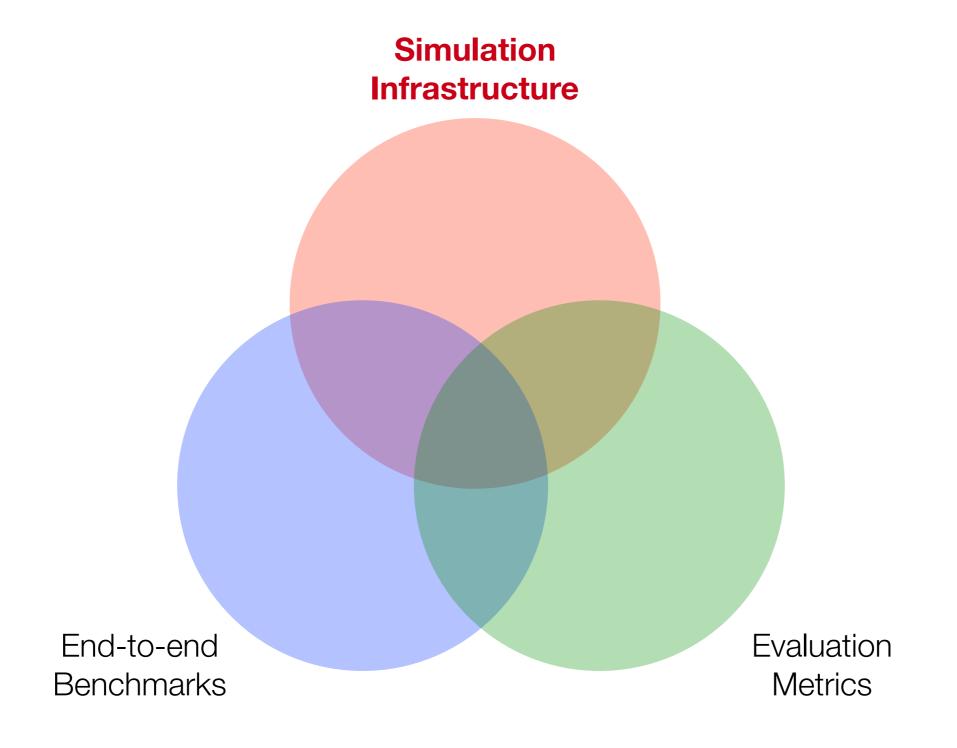






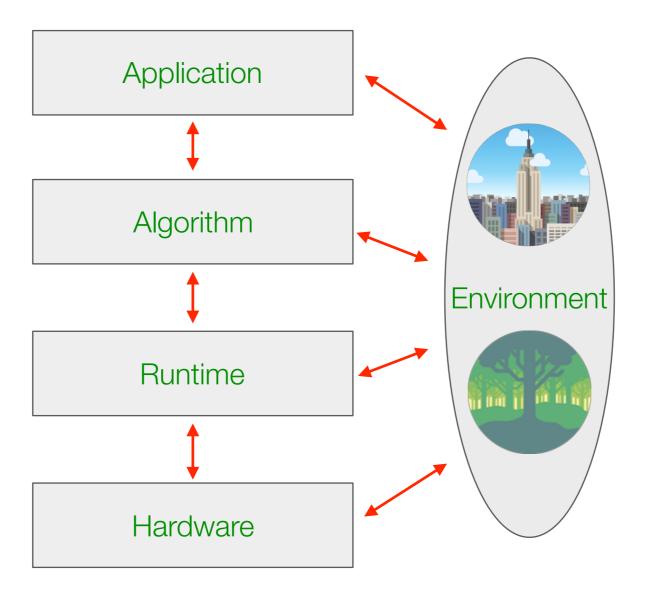






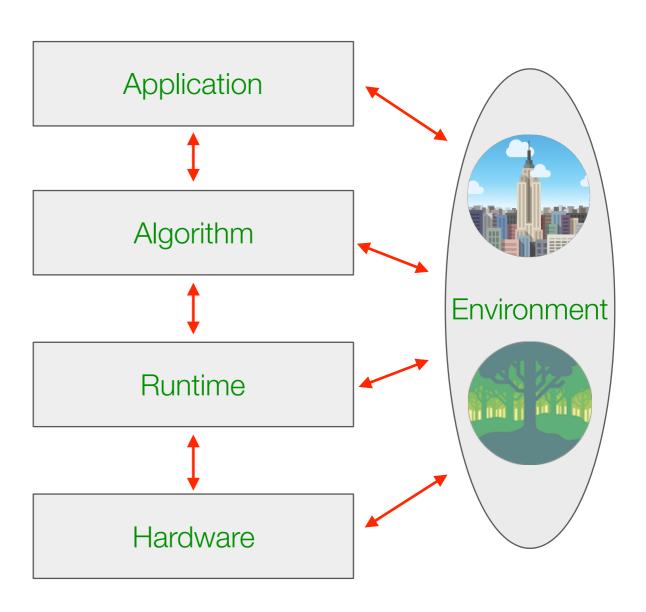


The "World" of an Aerial Agent





Understanding and Capturing the Interactions



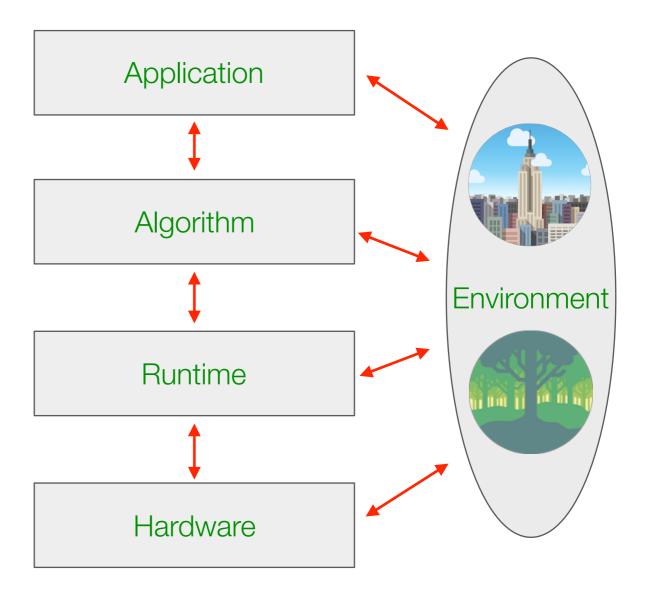


Understanding and Capturing the Interactions

Ideally, each level should be readily explorable...

▶ Independently

In relation to one another





Understanding and Capturing the Interactions

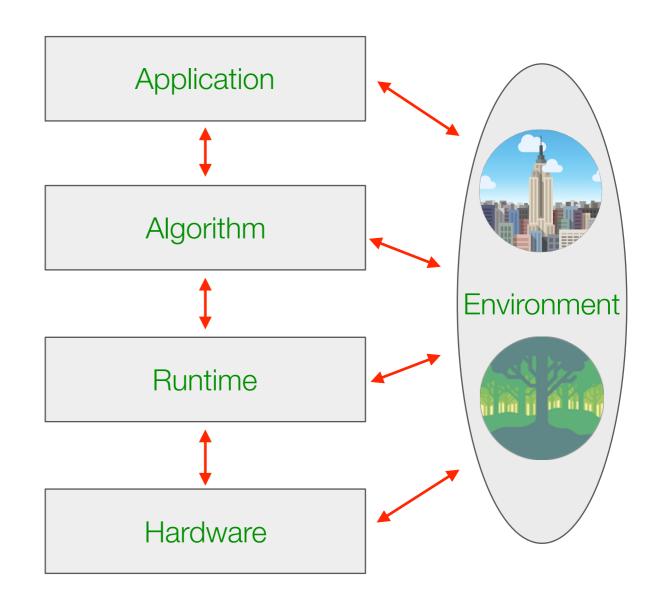
Ideally, each level should be readily explorable...

▶ Independently

In relation to one another

Need development platforms

- ▶ Enable design, prototyping, development and evaluation
- ▶ Fast, accurate, reproducible, ...











AirSim





AirSim

Unreal Engine





AirSim

Unreal Engine

Sensory Data (RGBD, GPS)





AirSim

Unreal Engine



Workload





AirSim

Unreal Engine

Sensory Data (RGBD, GPS)

Workload

Robot Operating System





AirSim

Unreal Engine

Sensory Data (RGBD, GPS)

Workload

Robot Operating System

Companion Computer





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AirSim

Unreal Engine

Sensory Data (RGBD, GPS)

Workload

Robot Operating System

Companion Computer

Flight Commands







AirSim

Unreal Engine



Workload

Robot Operating System

Companion Computer

Flight Commands

Flight Stack







AirSim

Unreal Engine



Workload

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Flight Commands

Flight Stack







AirSim

Unreal Engine



Workload

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AirSim

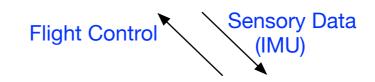
Unreal Engine

Sensory Data (RGBD, GPS)

Workload

Robot Operating System

Companion Computer



Flight Commands

Flight Stack









AirSim

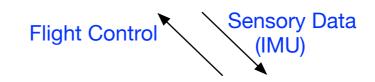
Unreal Engine

Sensory Data (RGBD, GPS)

Workload

Robot Operating System

Companion Computer



Flight Commands

Flight Stack









Drones, batteries, ...

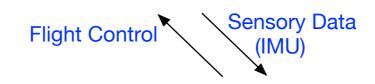
Unreal Engine

Sensory Data (RGBD, GPS)

Workload

Robot Operating System

Companion Computer



Flight Commands

Flight Stack









Environments (forest, urban, ...)

Sensory Data (RGBD, GPS)

Sensory Data Flight Control (IMU)

Workload

Robot Operating System

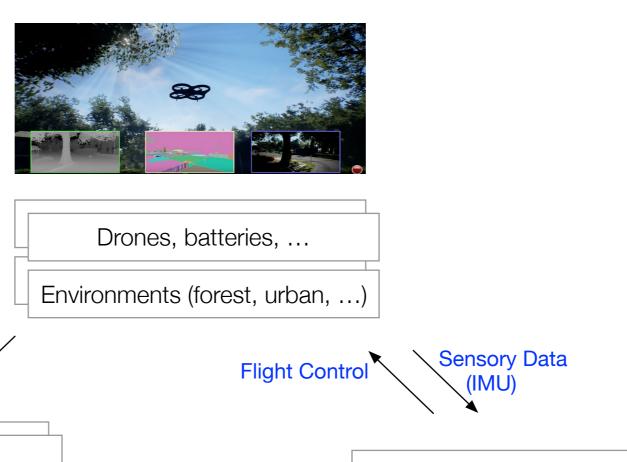
Companion Computer

Flight Commands Flight Stack









Applications, kernels, ...

Sensory Data

(RGBD, GPS)

Robot Operating System

Companion Computer



Flight Stack









Sensory Data (RGBD, GPS)

Flight Control Sensory Data (IMU)

Applications, kernels, ...

Scheduling, mapping, ...

Companion Computer

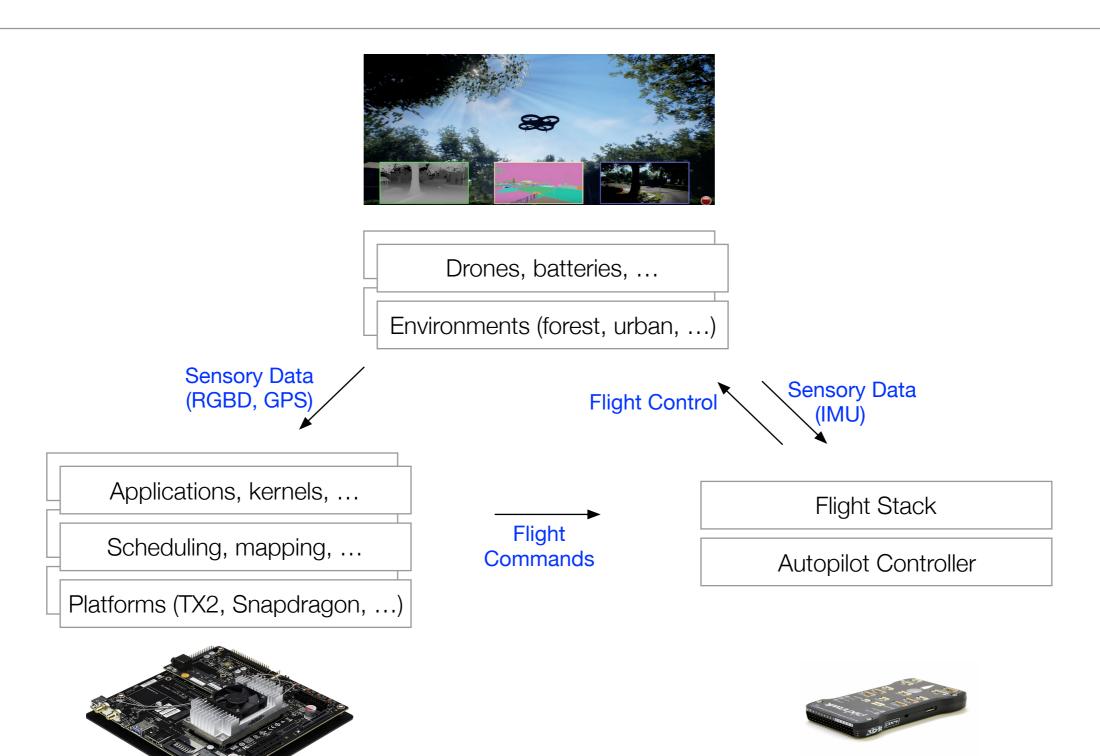
Flight Commands

Flight Stack

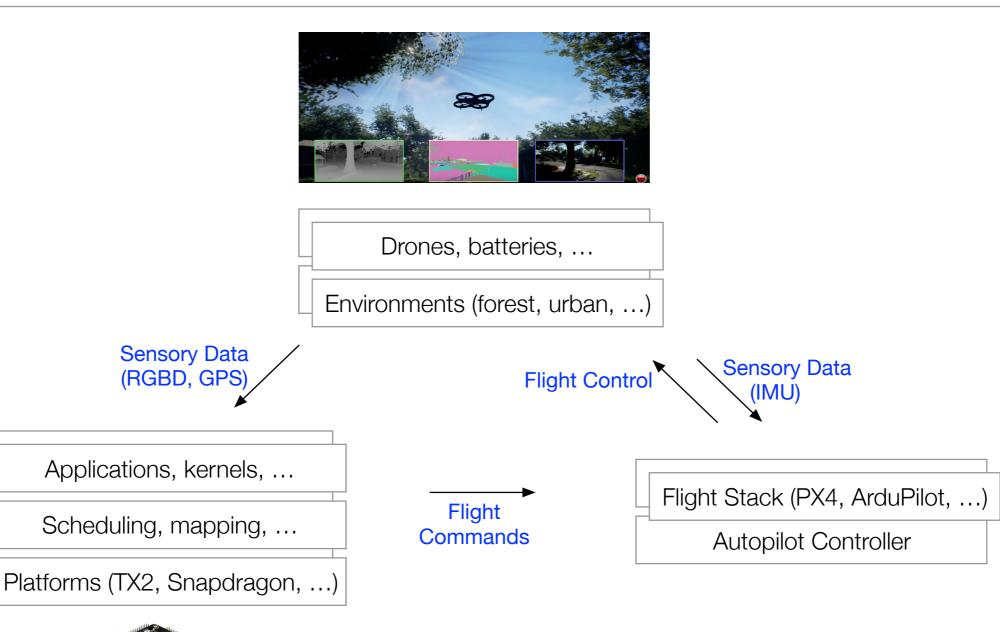












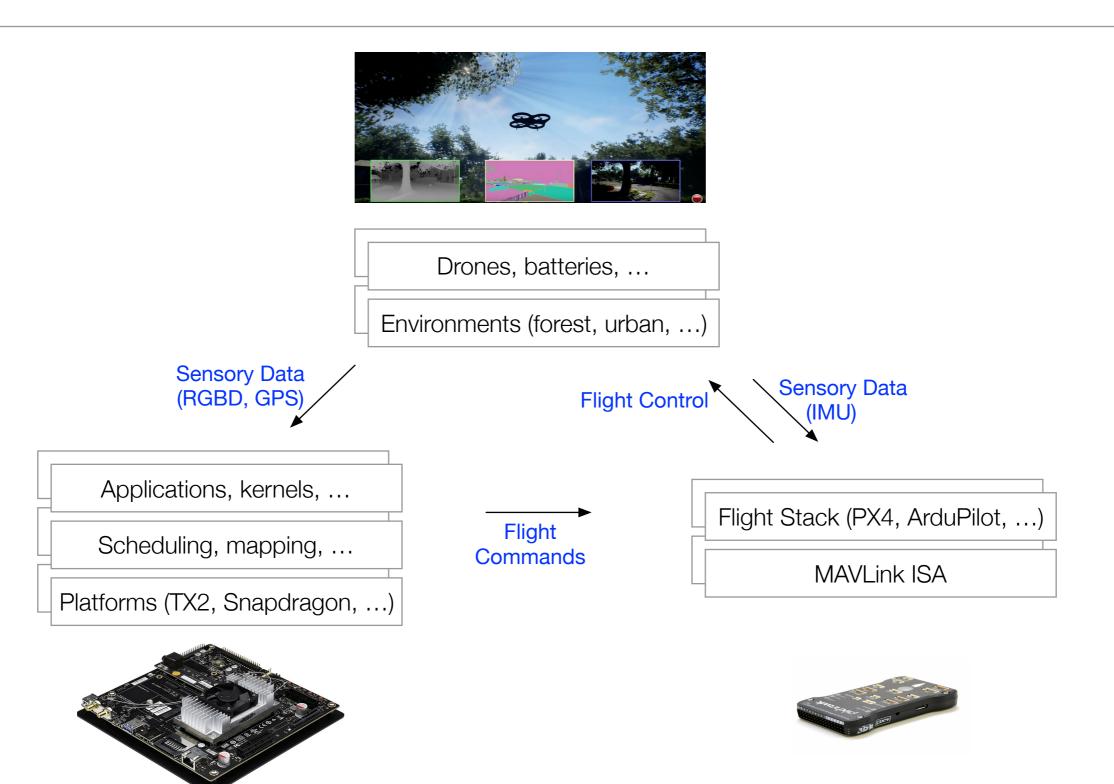


Sensory Data

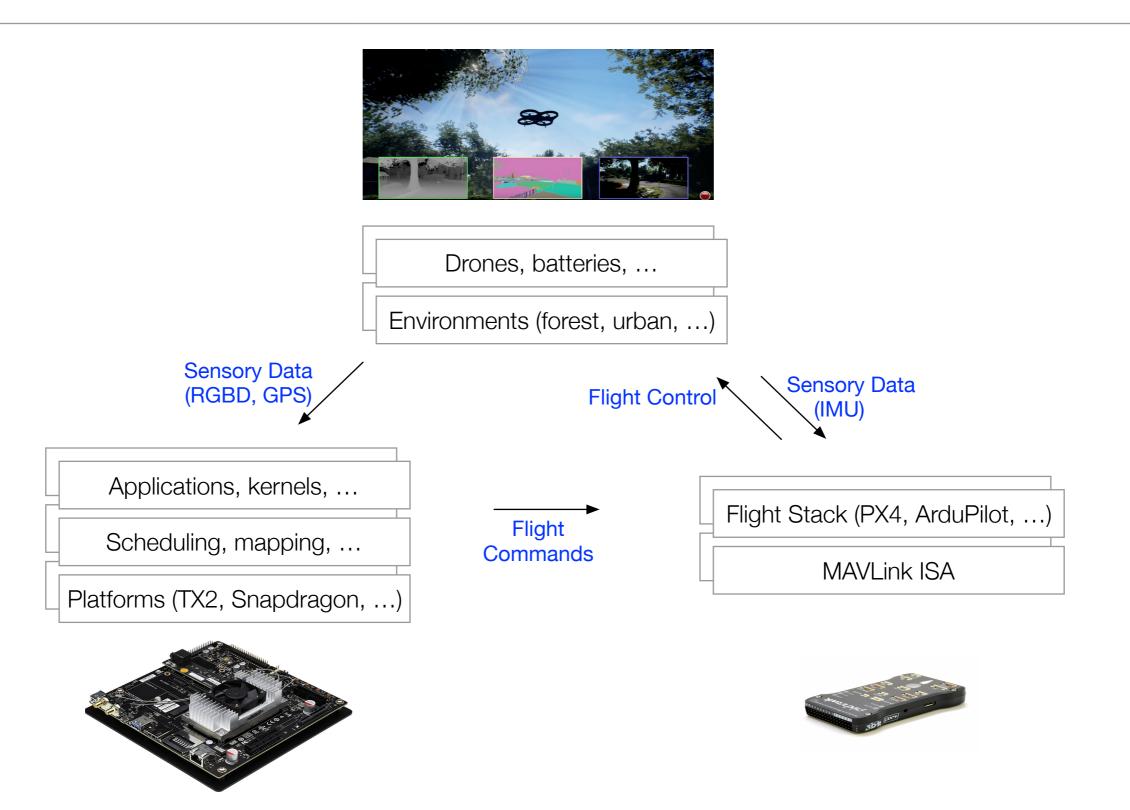
(RGBD, GPS)



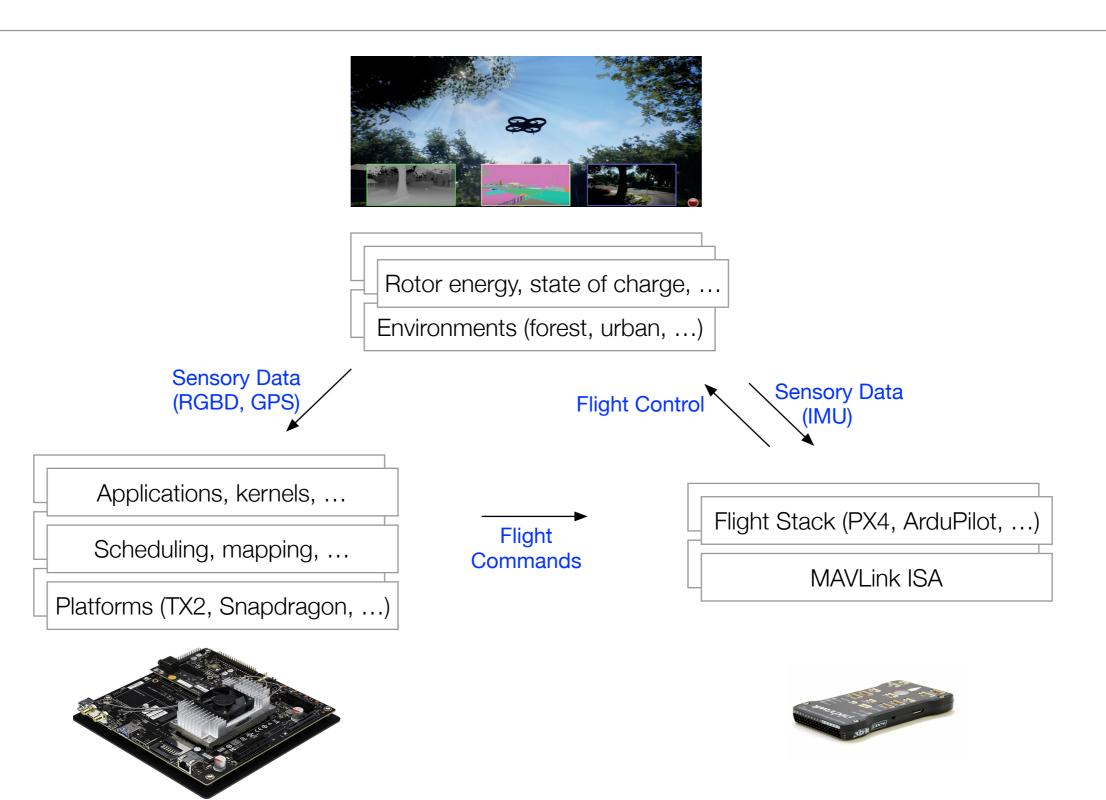




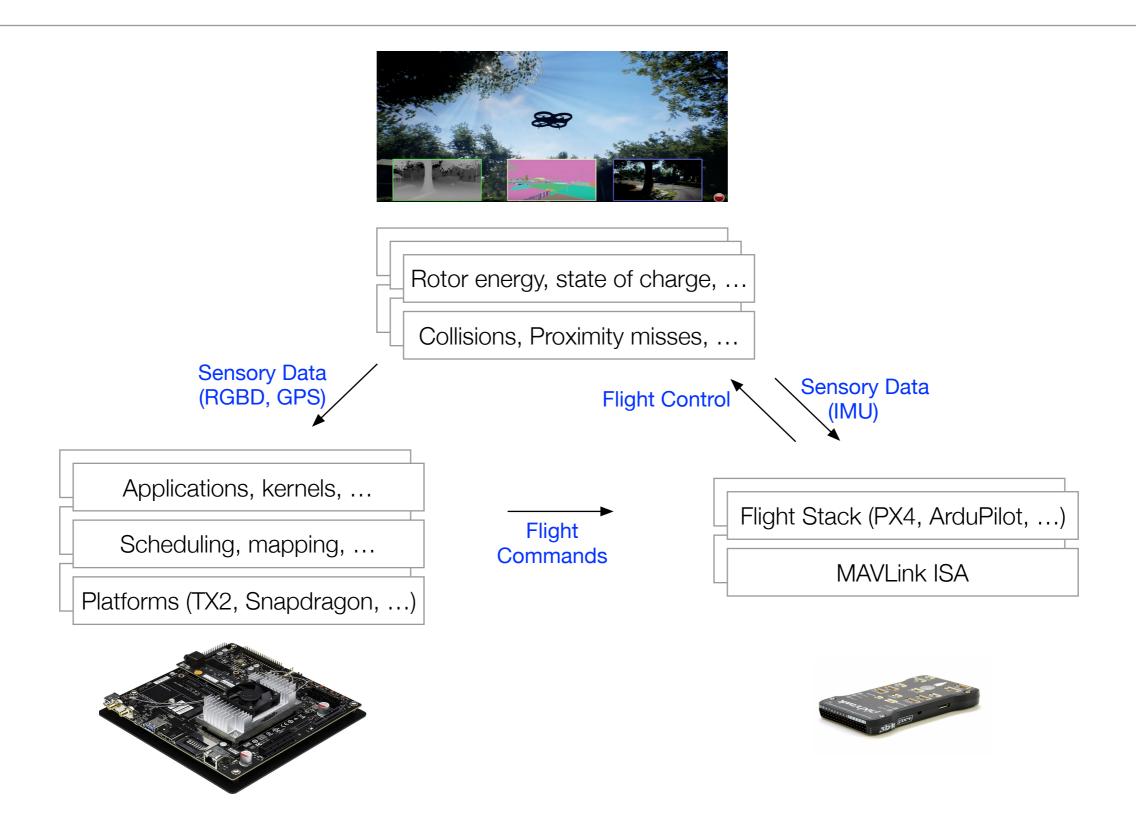




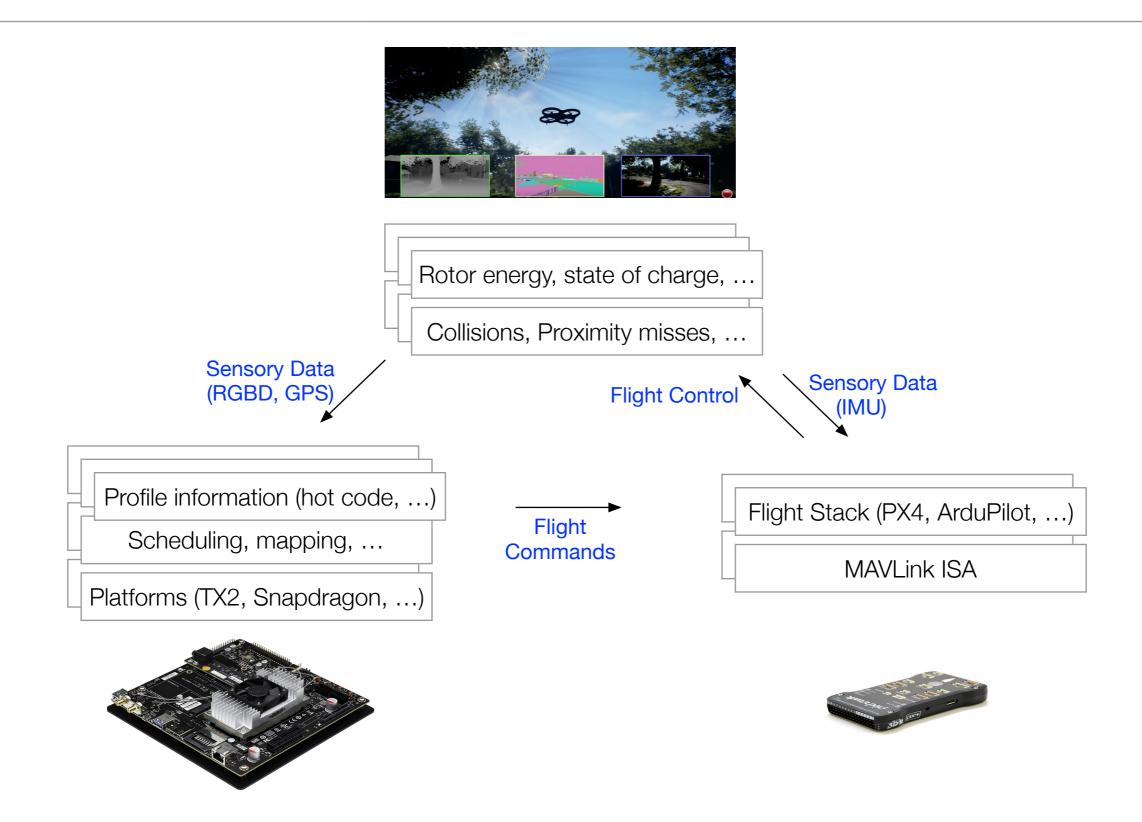




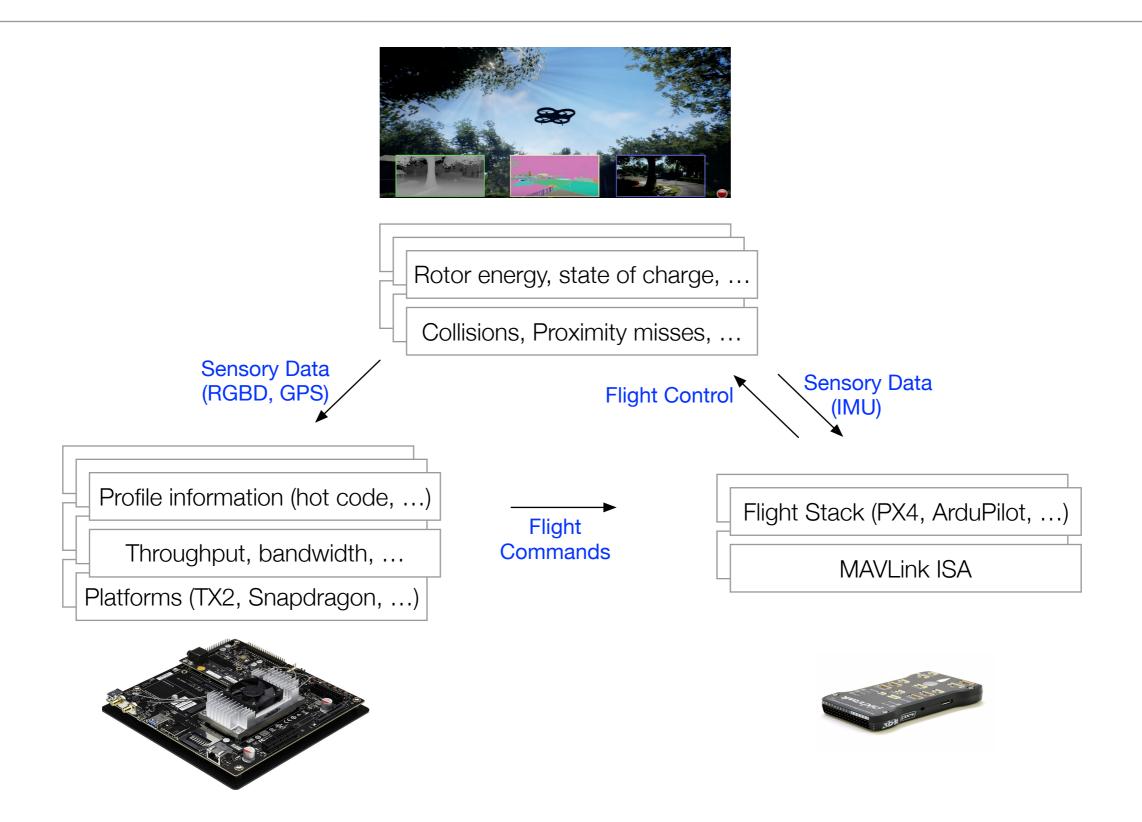




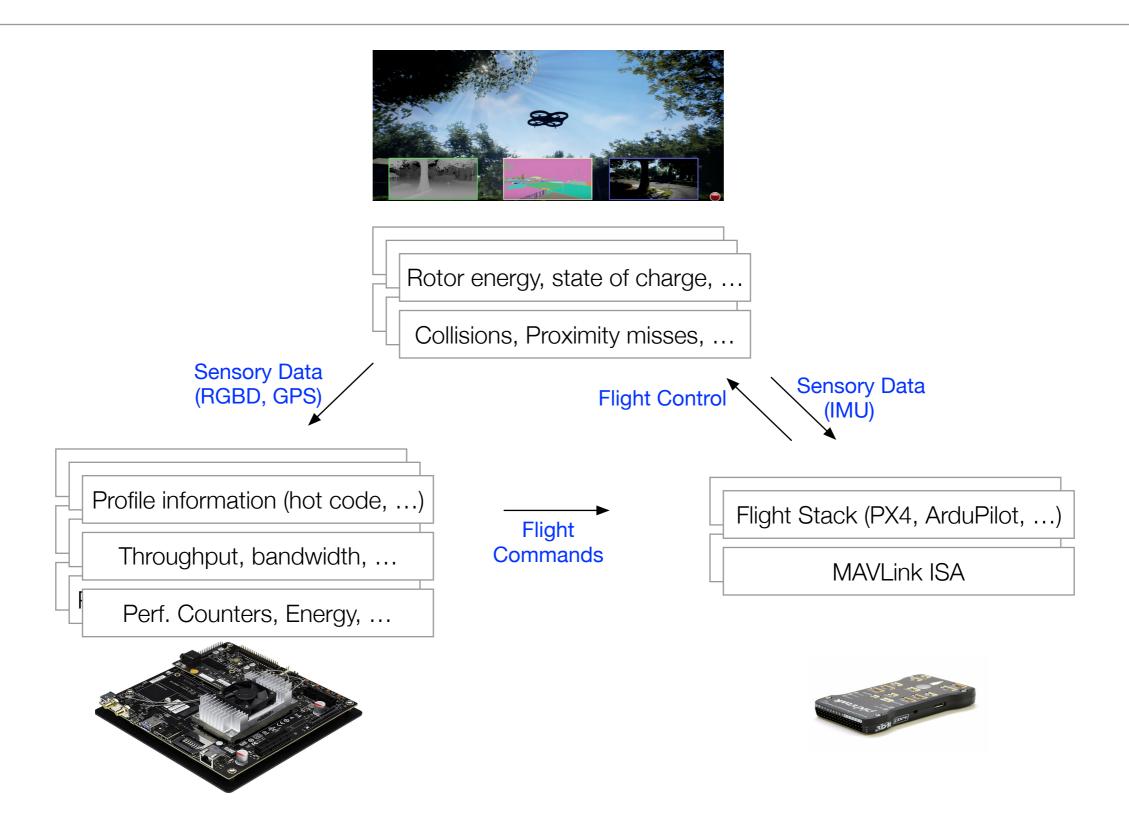






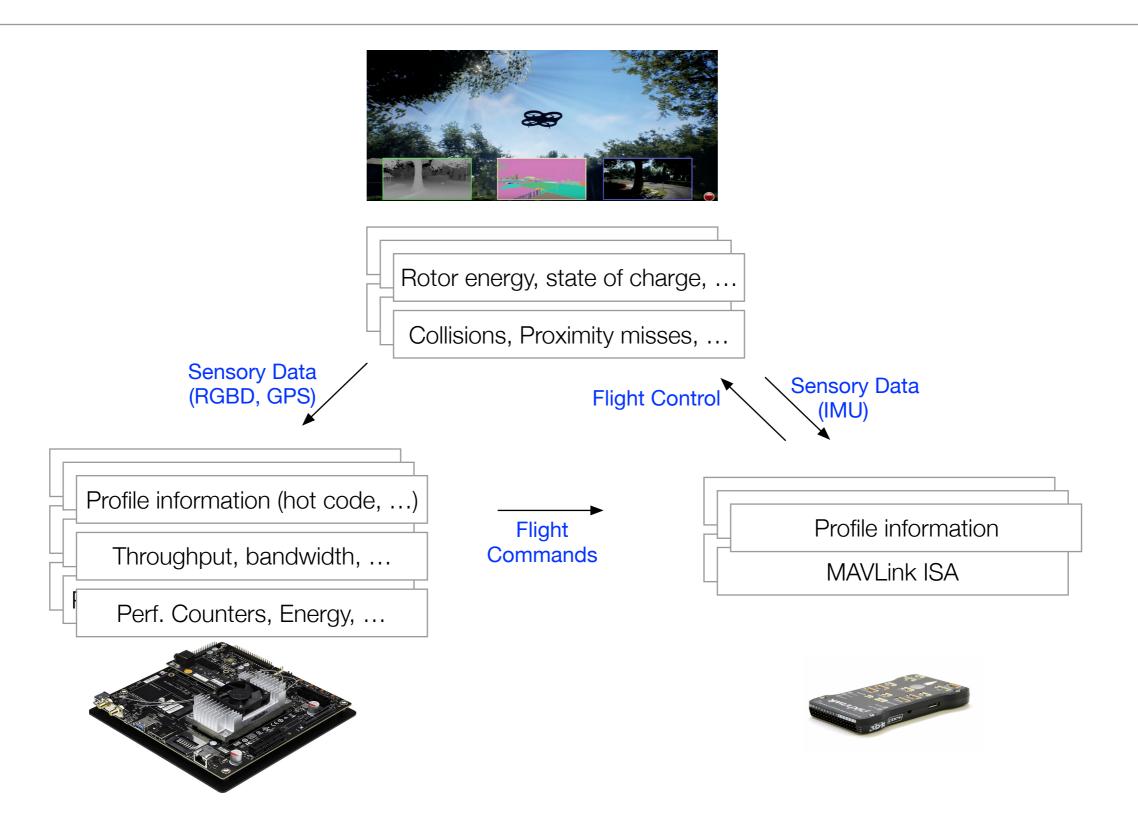






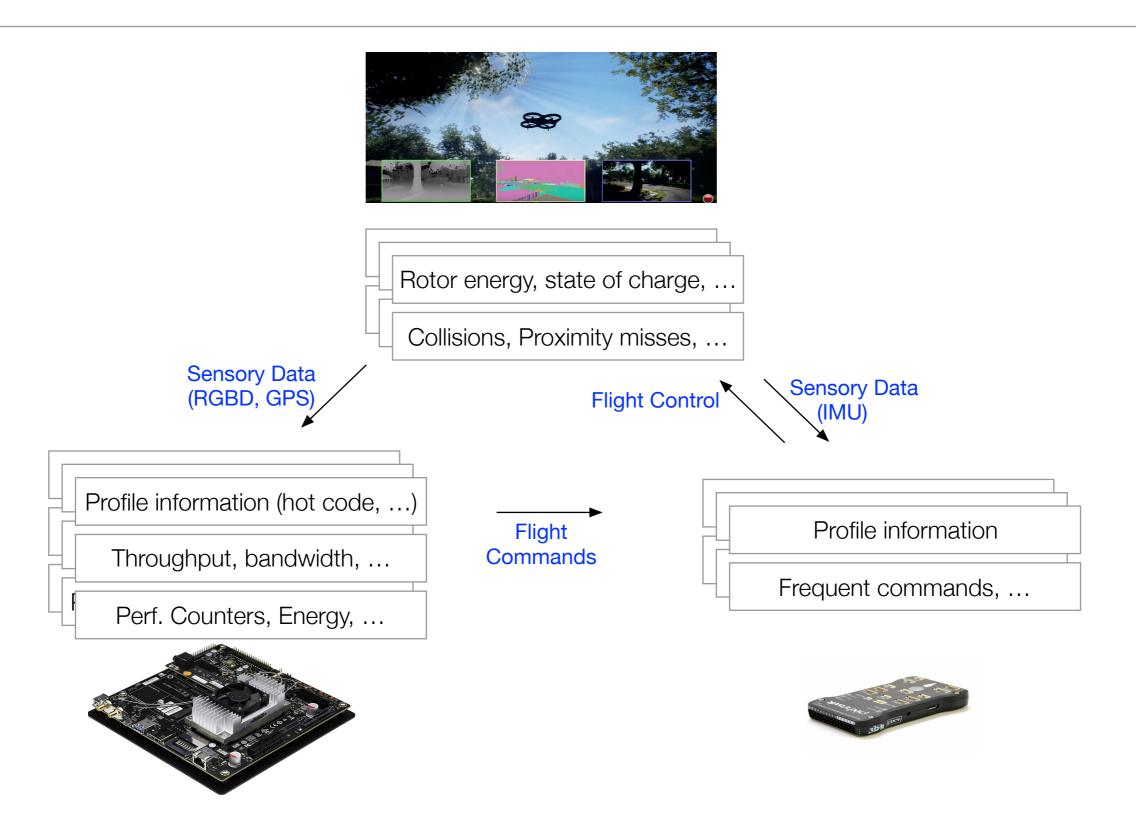


Closed-loop Simulation Profiles

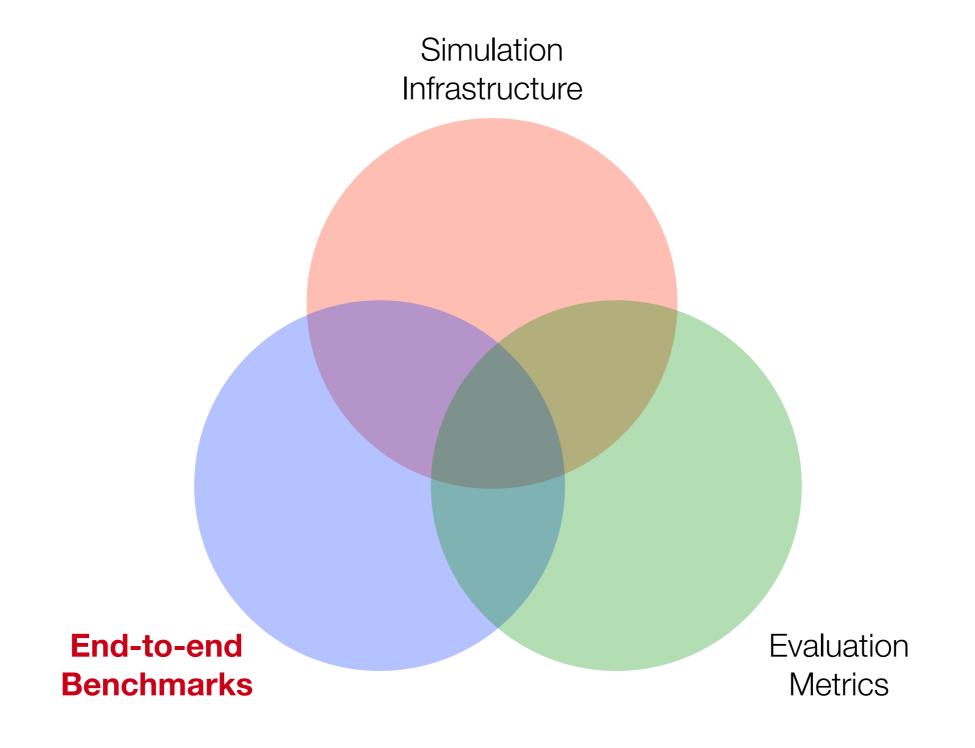




Closed-loop Simulation Profiles



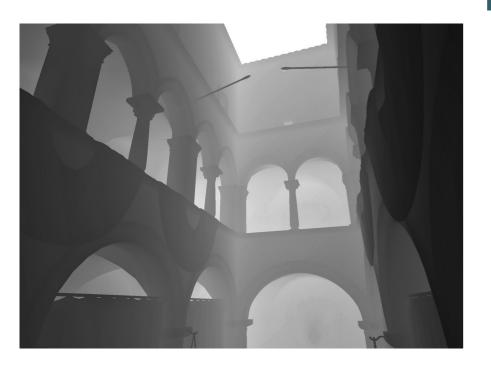




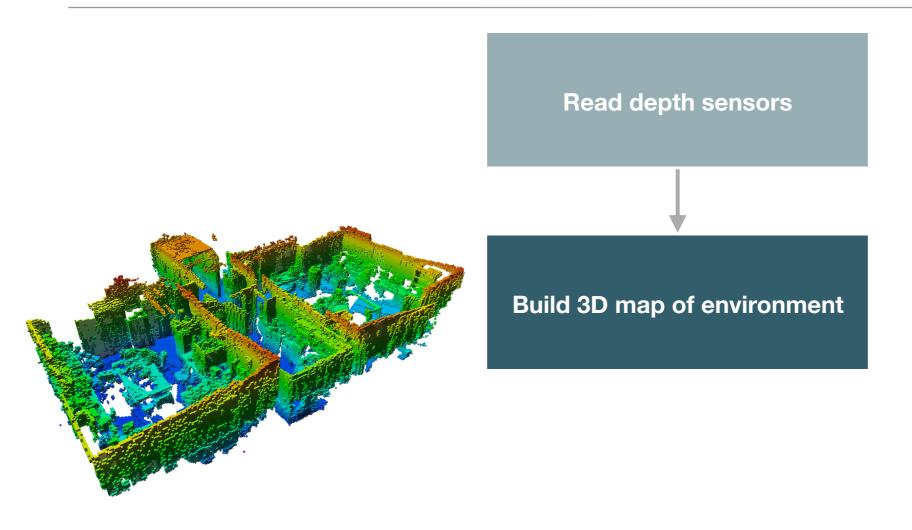




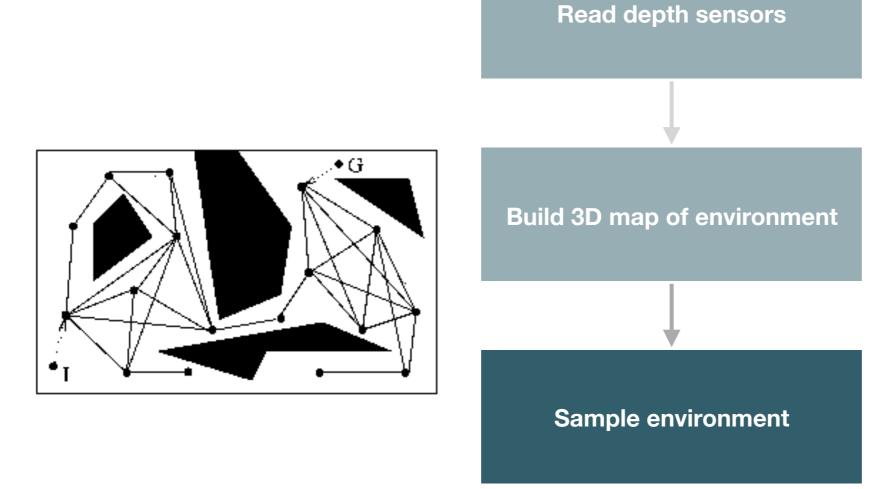
Read depth sensors



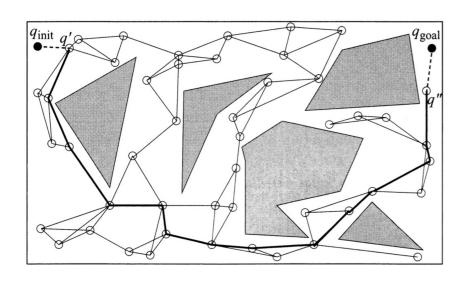


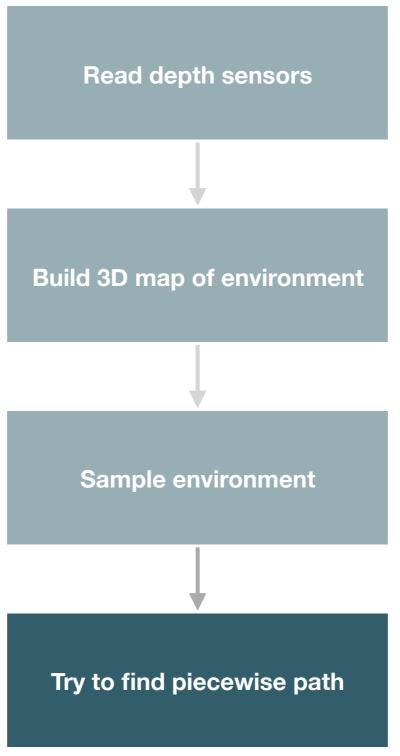




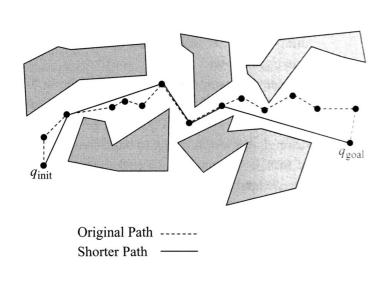


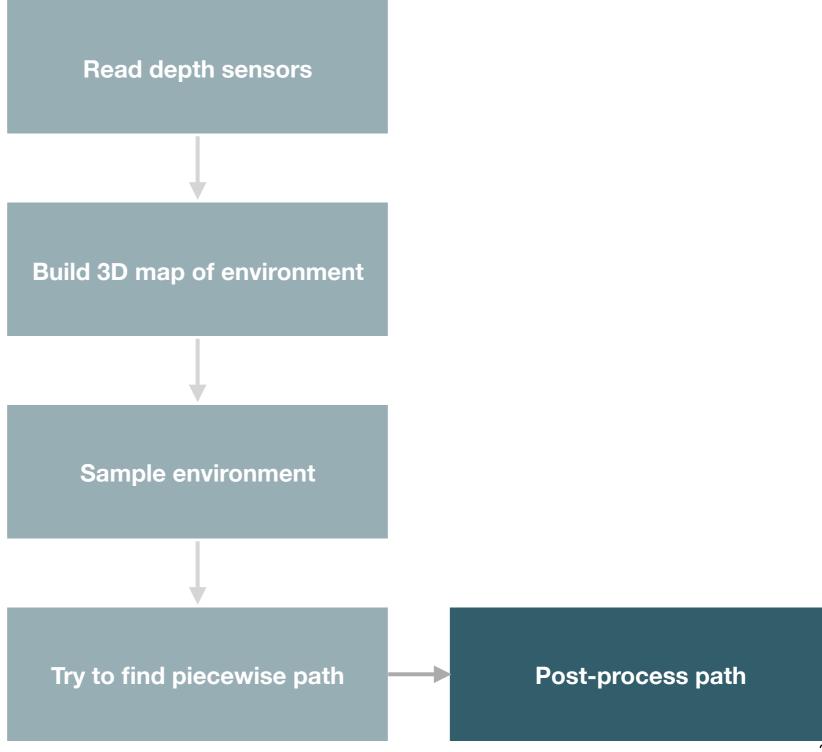




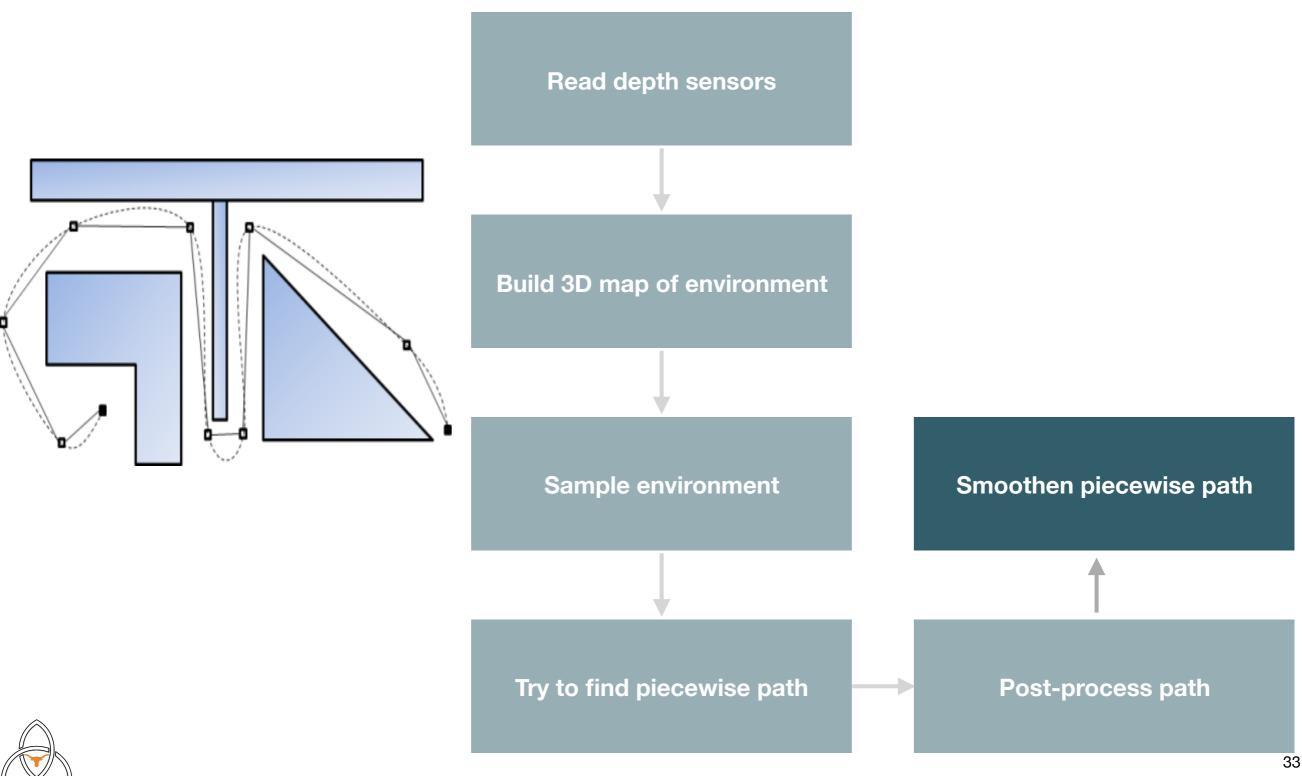




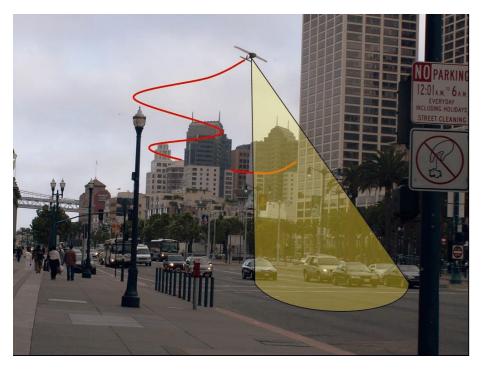


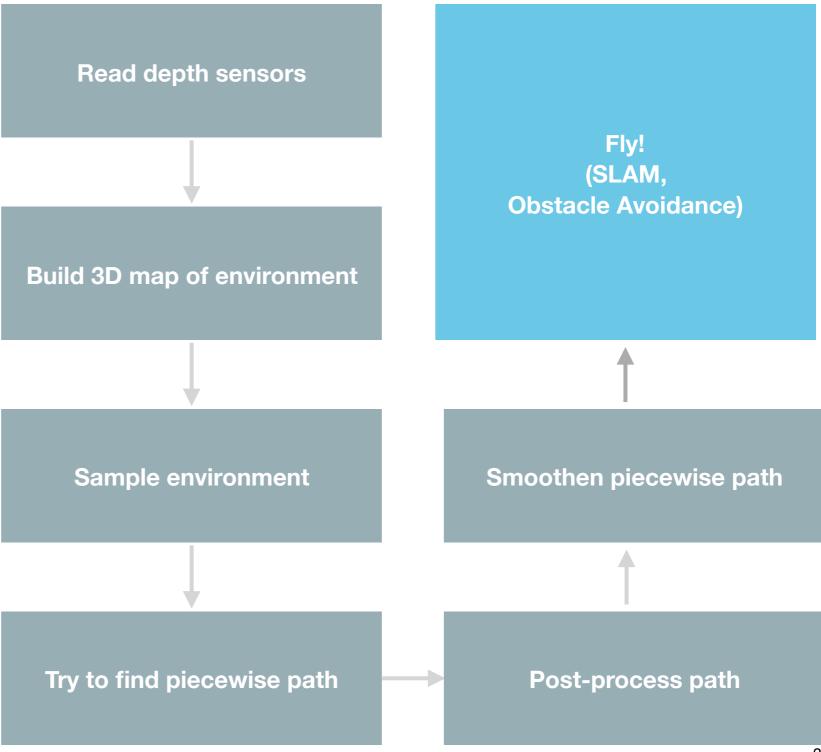




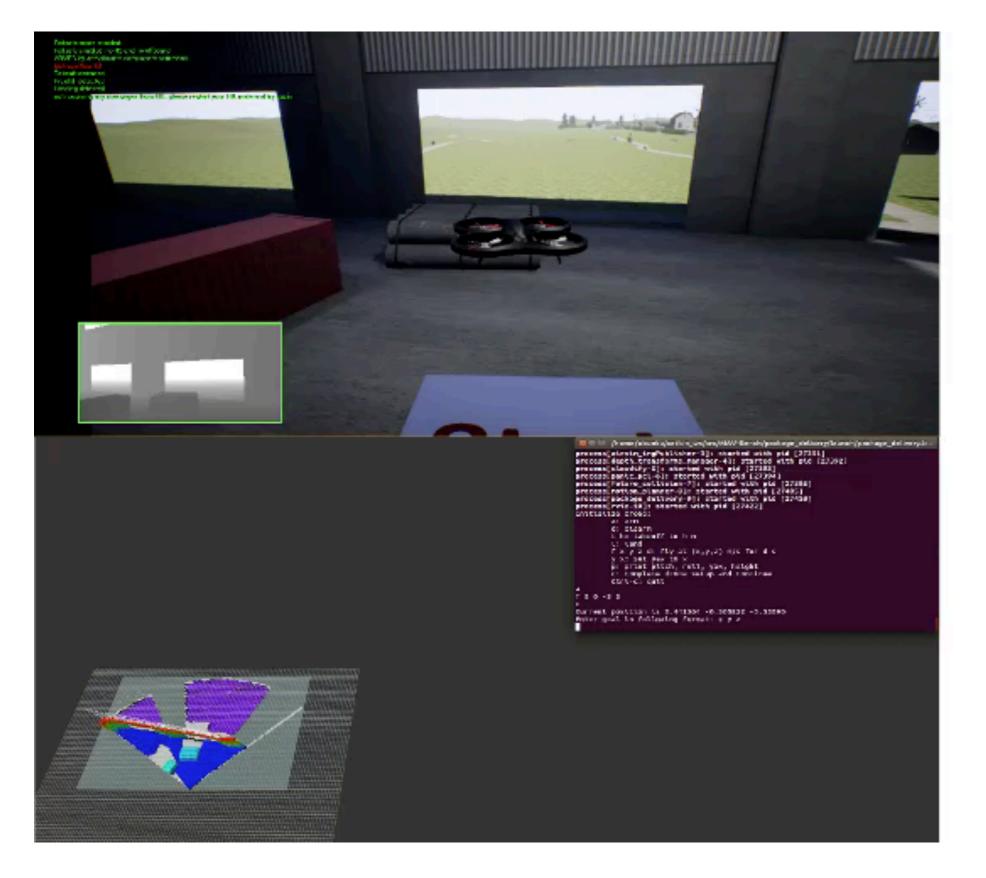




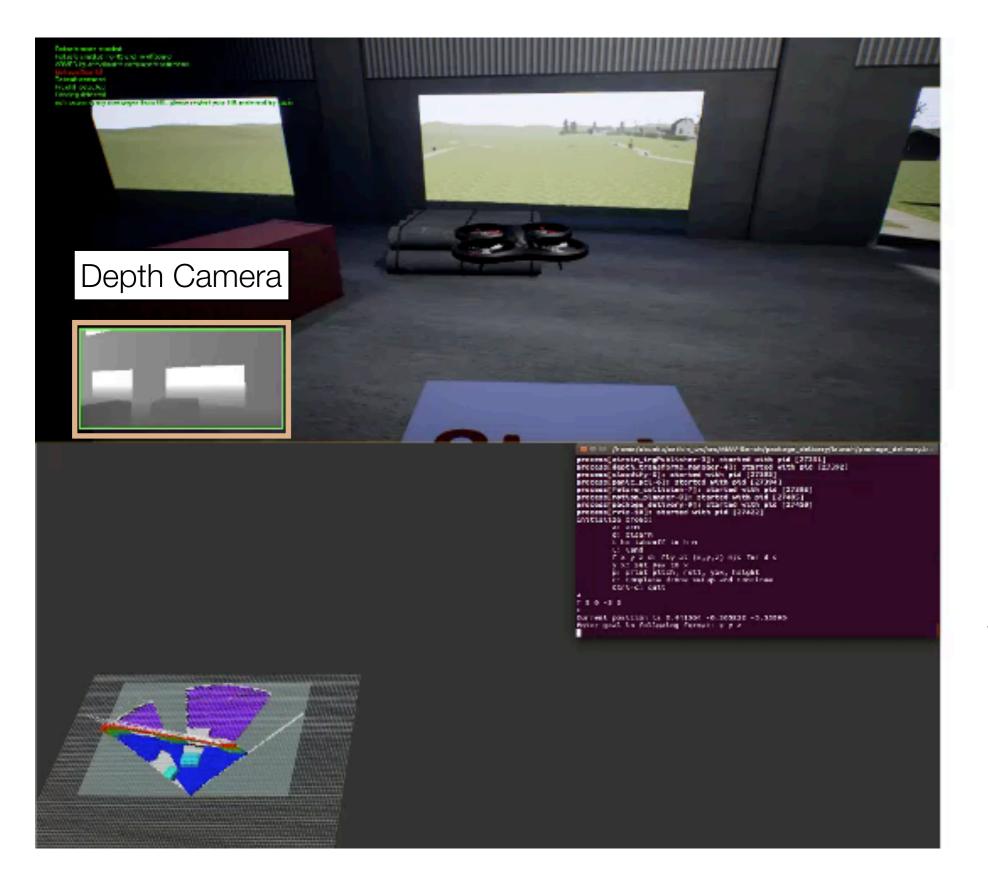




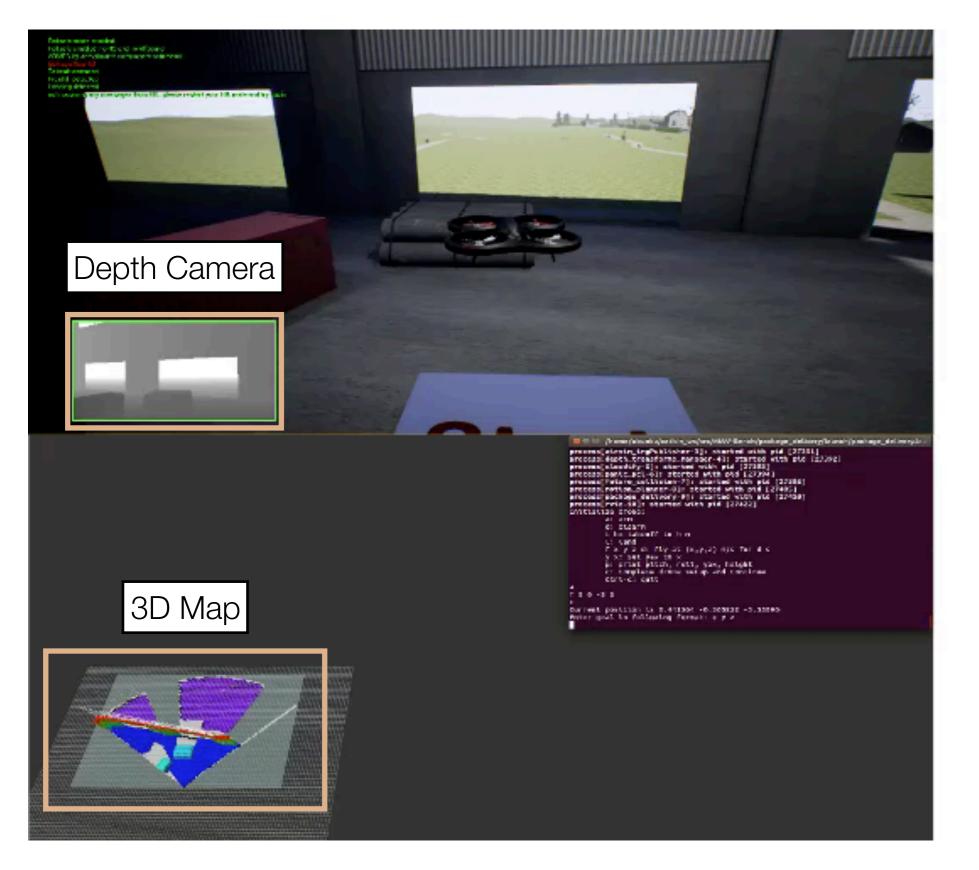




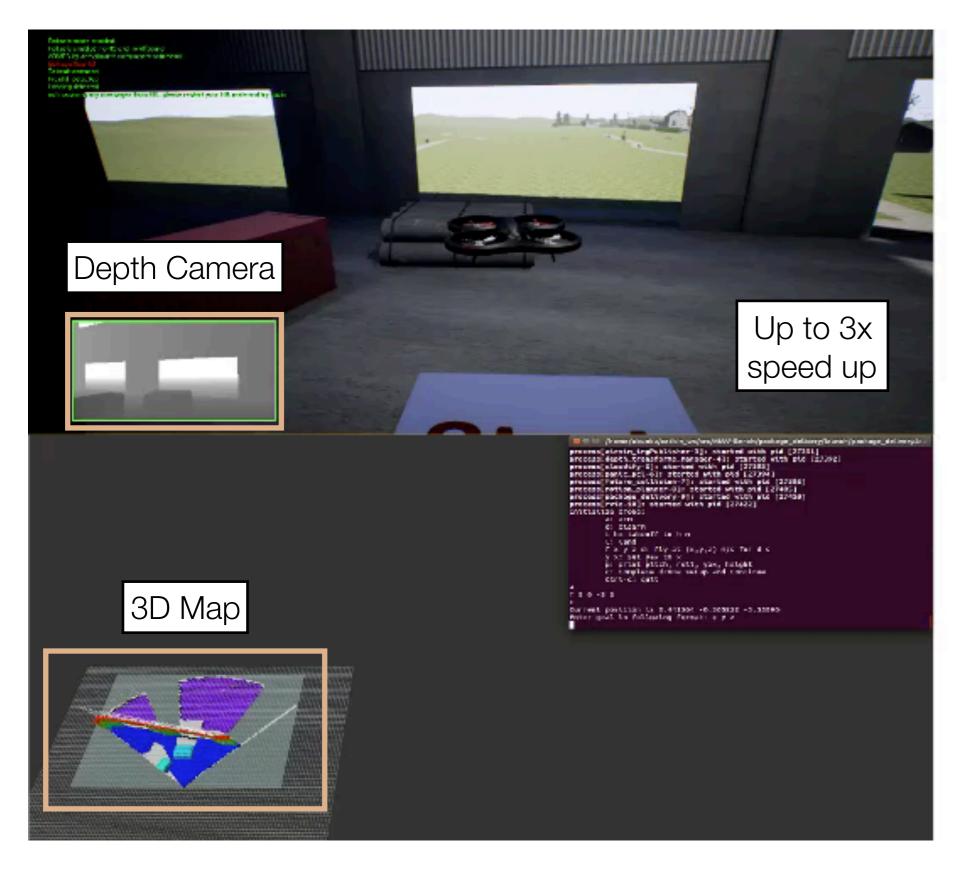




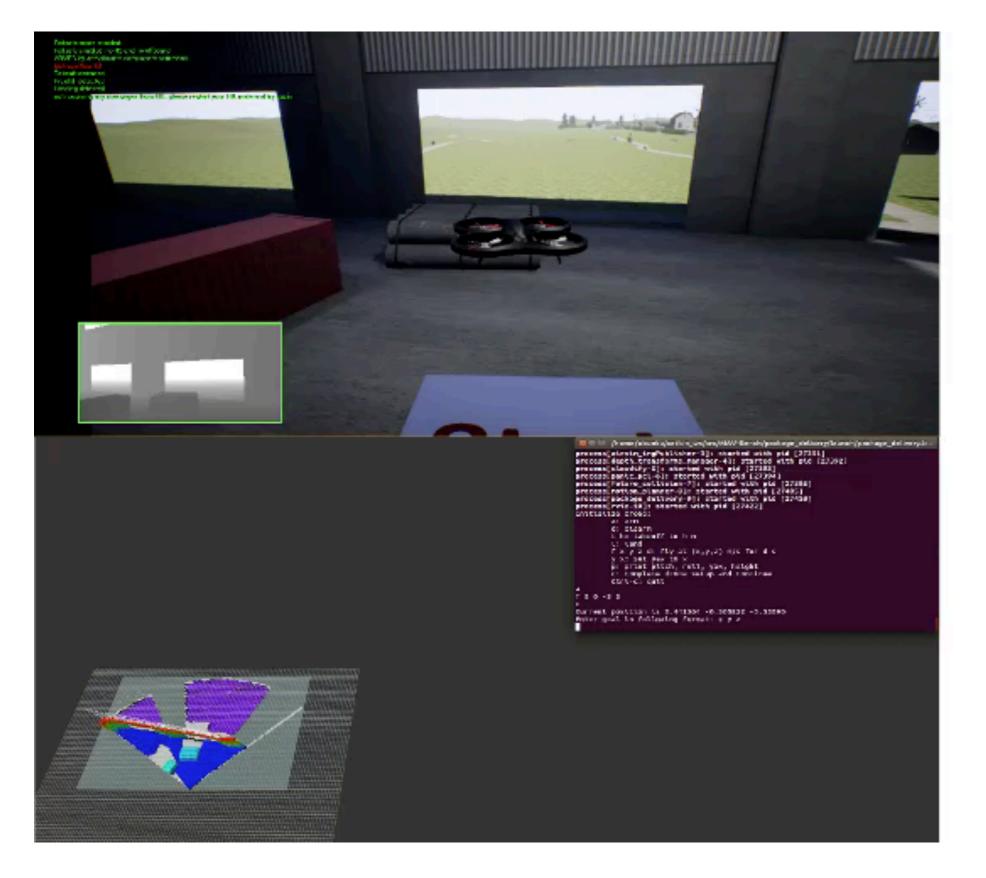




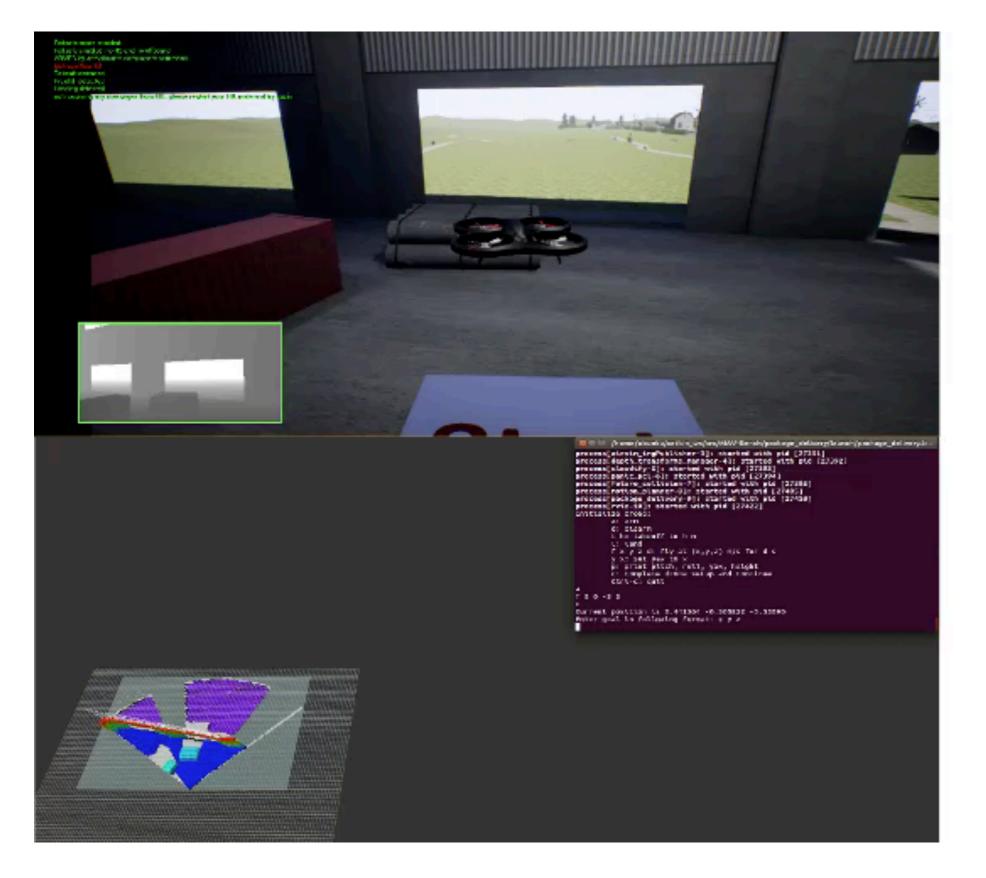










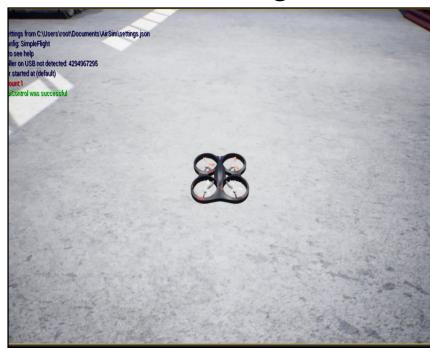


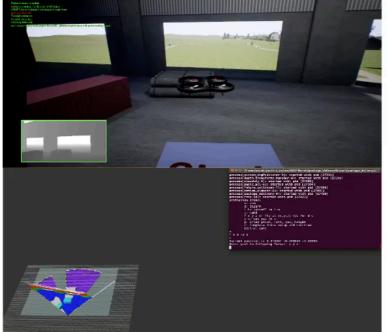


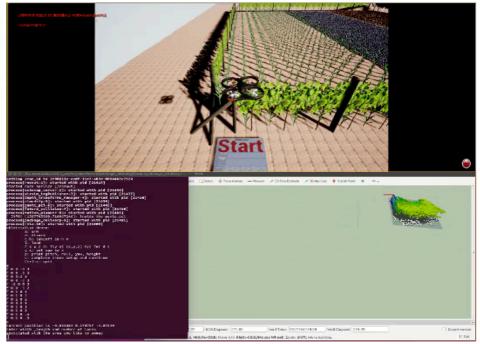
Indoor Navigation

Package Delivery

Surveying



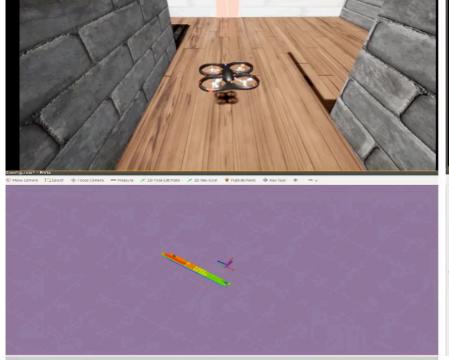




3D Mapping

Search and Rescue

Aerial Photography





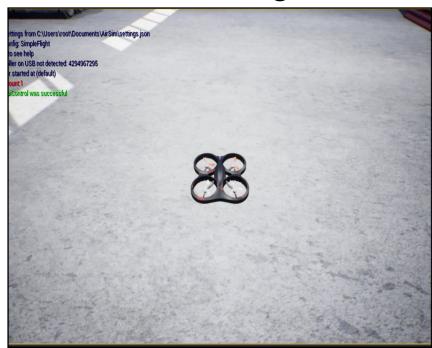


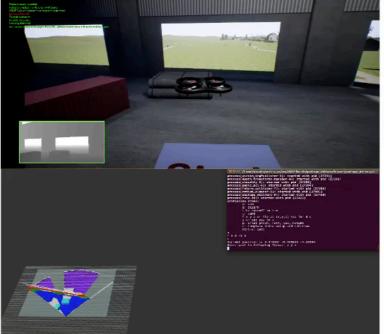


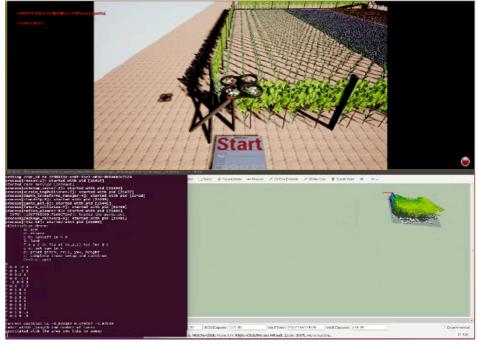
Indoor Navigation

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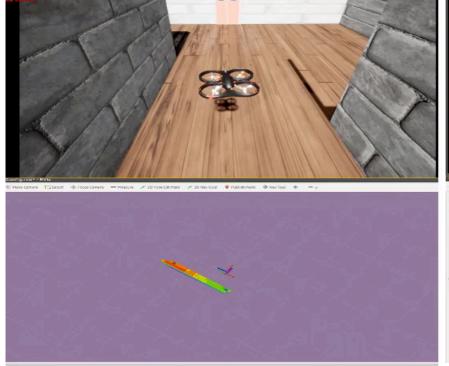




3D Mapping

Search and Rescue

Aerial Photography









MAVBench: Kernel Decomposition



MAVBench: Kernel Decomposition

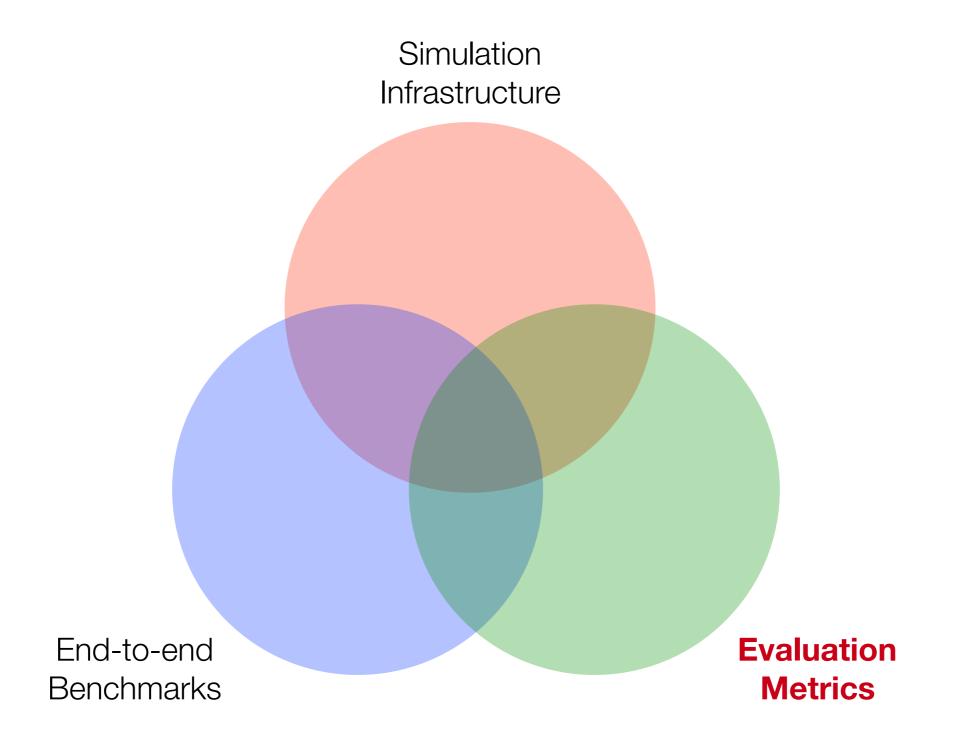
	Perception									Pla	Control		
	Point Cloud Generation	Occupancy Map Generation	Collision Check	Object Detection	Object Tracking		Localization		PID	Smoothened Shortest Path	Frontier Exploration	Lawn Mowing	Path Tracking/ Command Issue
	Generation	Generation	Check	Detection	Buffered	Real Time	GPS	SLAM		Shortest Latt	Exploration	litowing	
Scanning												X	X
Aerial				X	v	X	X		X				X
Photography				Λ	Λ	Λ	Λ		Λ				Λ
Package	X	X	X				X	X		X			X
Delivery										Λ			Λ
3D	X	X	X				v	X			X		X
Mapping							Λ				Λ		Λ
Search and	X	X	X	X			X	X			X		X
Rescue	1	11					71	1			1		71



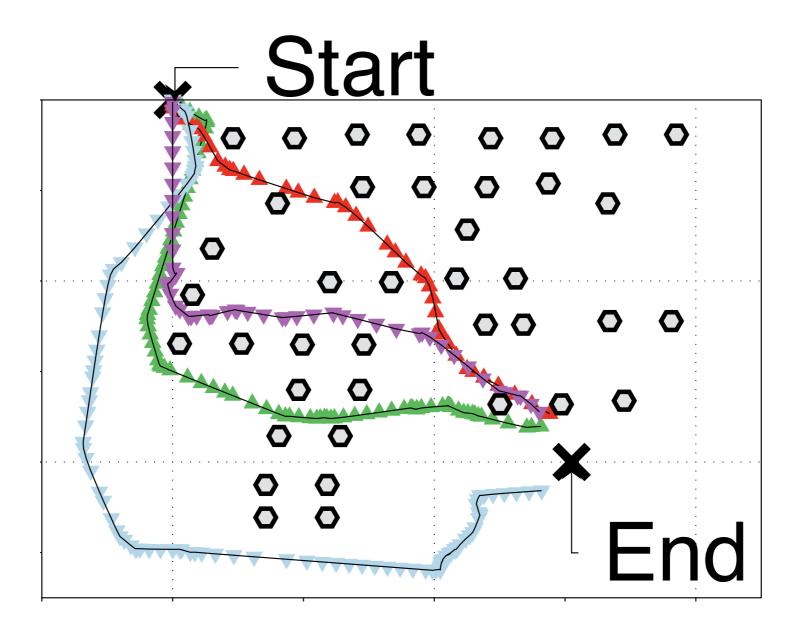
MAVBench: Kernel Decomposition

	Perception									Con			
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Scanning												X	X
Aerial				X	X	X	X		X				X
Photography													
Package Delivery	X	X	X				X	X		X			X
3D													
Mapping	X	X	X				X	X			X		X
Search and Rescue	X	X	X	X			X	X			X		X

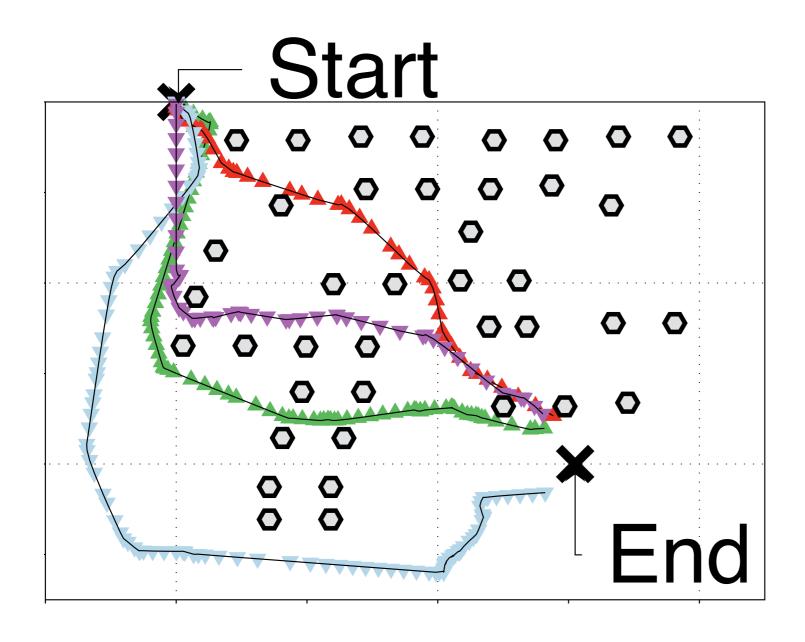




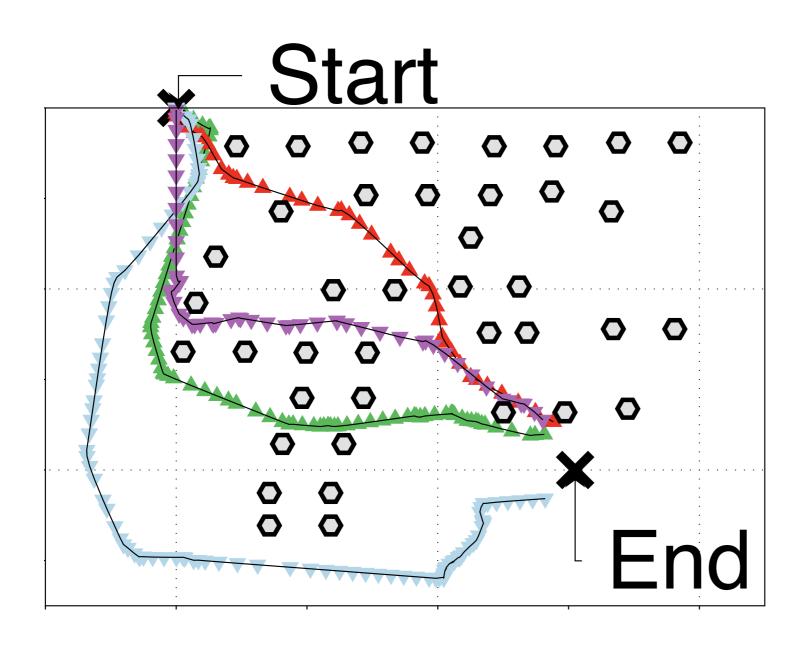






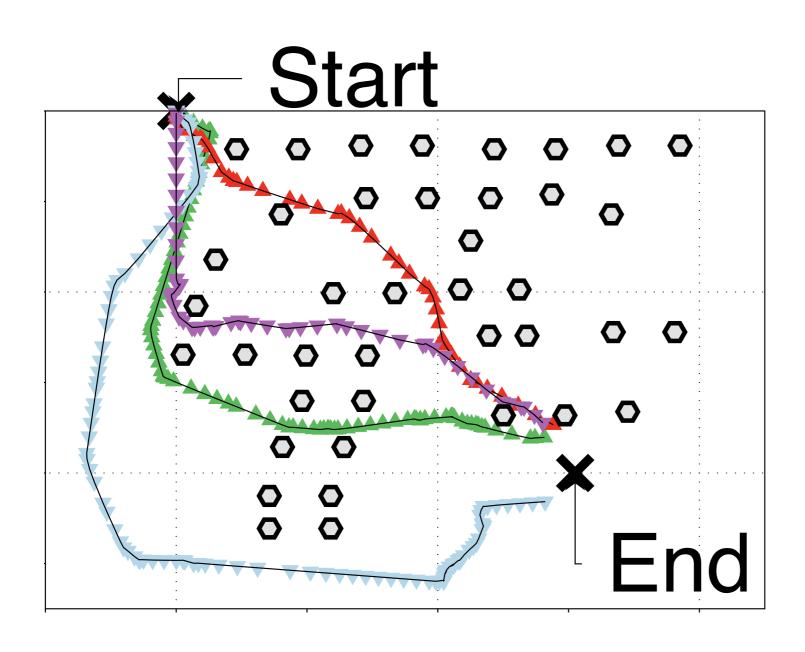






Trajectory

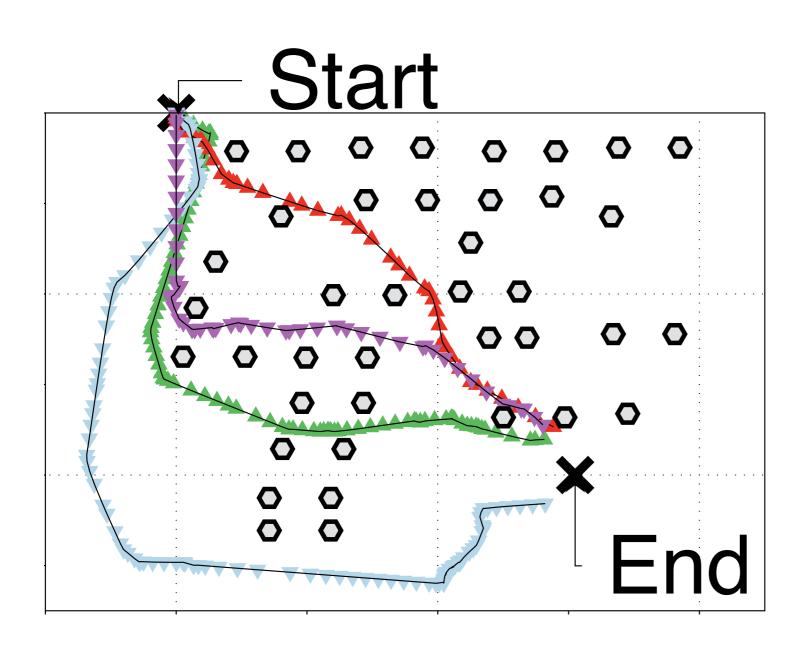




Trajectory

Energy



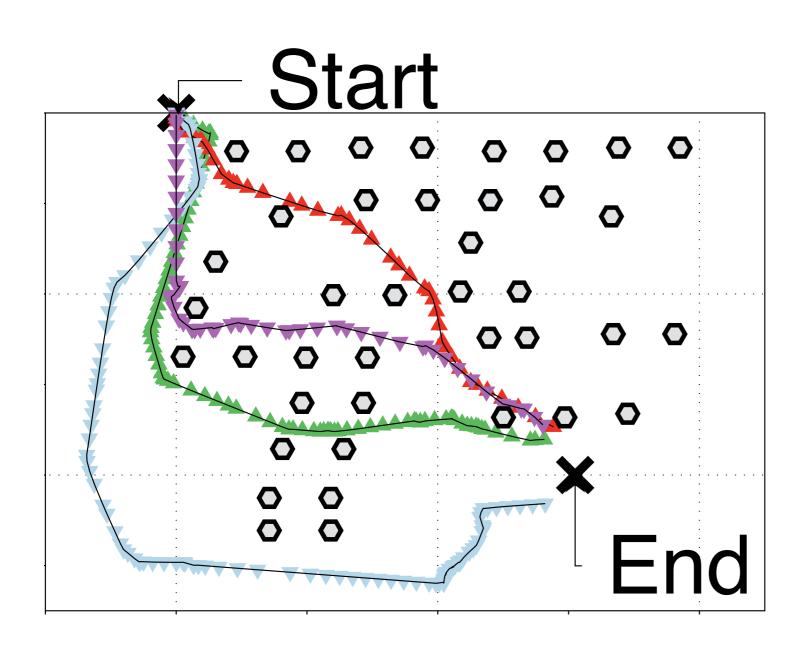


Trajectory

Energy

Mission time





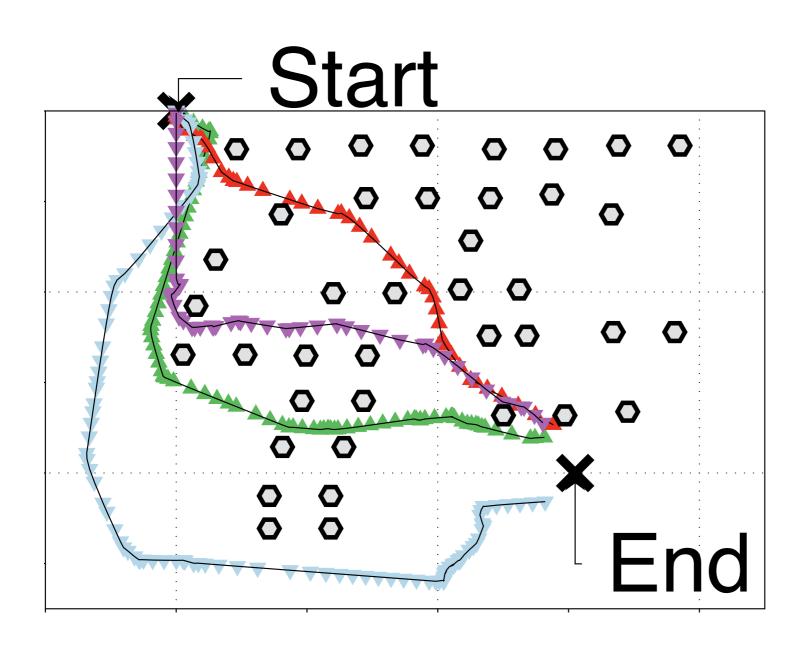
Trajectory

Energy

Mission time

Velocity





Trajectory

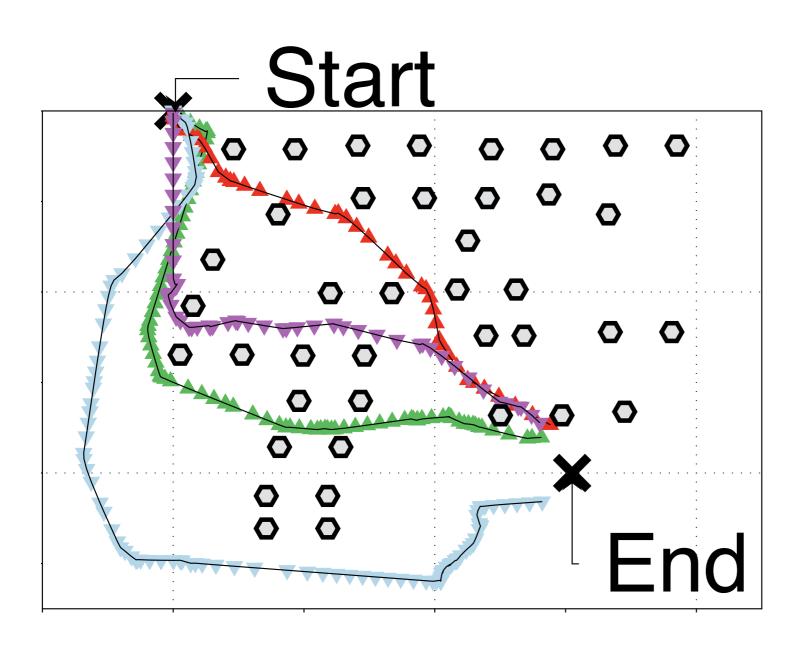
Energy

Mission time

Velocity

Jerk





Trajectory

Energy

Mission time

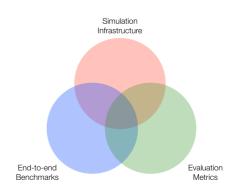
Velocity

Jerk

. . .





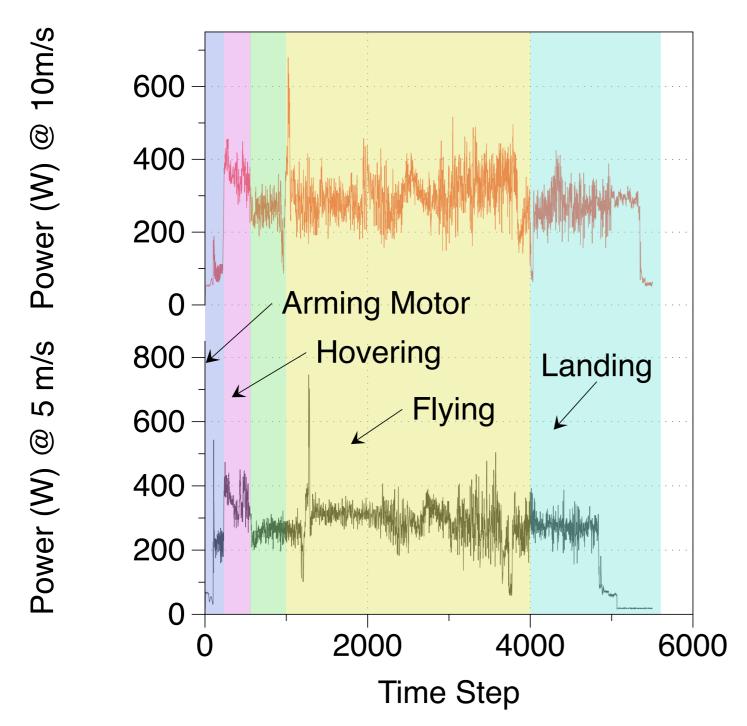


Performance



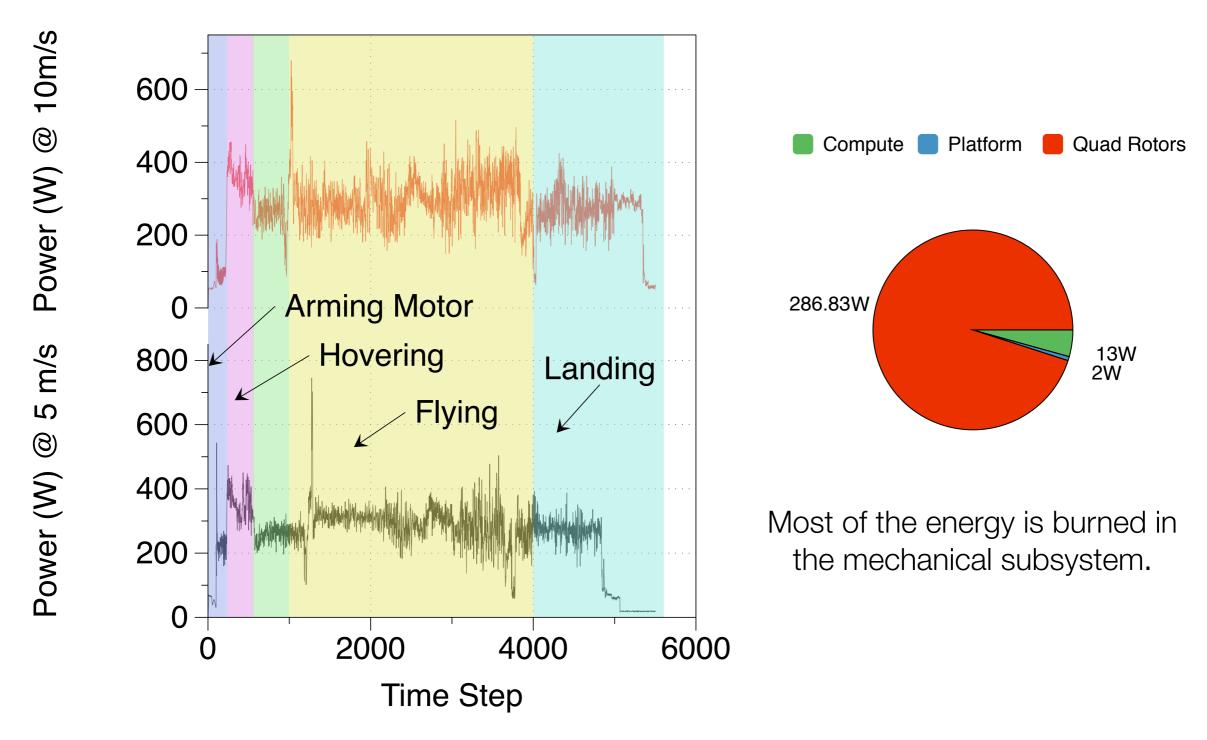


Where have my Joules gone?



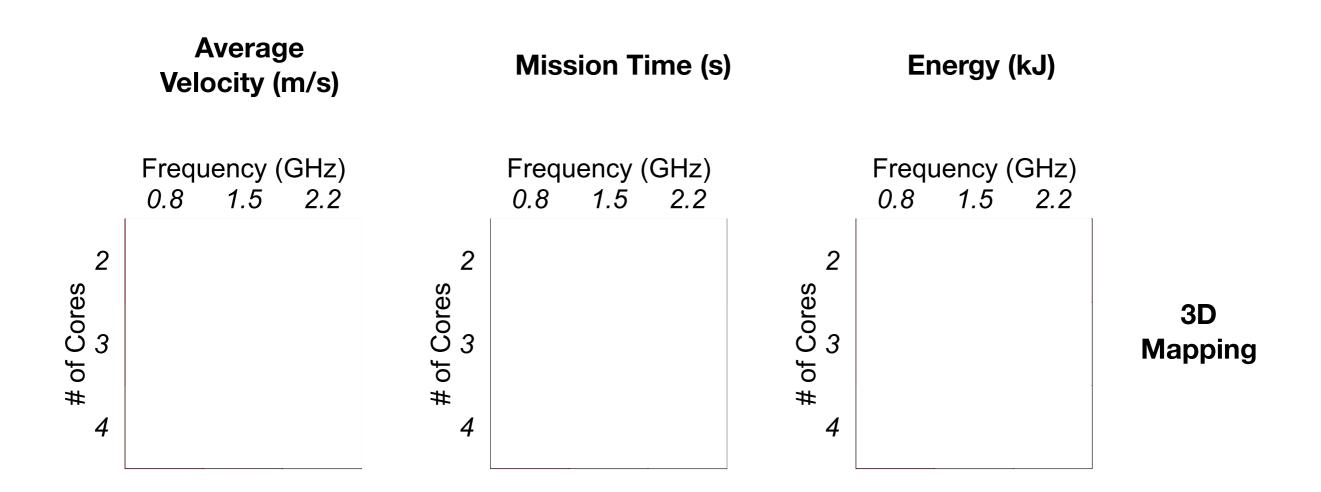


Where have my Joules gone?



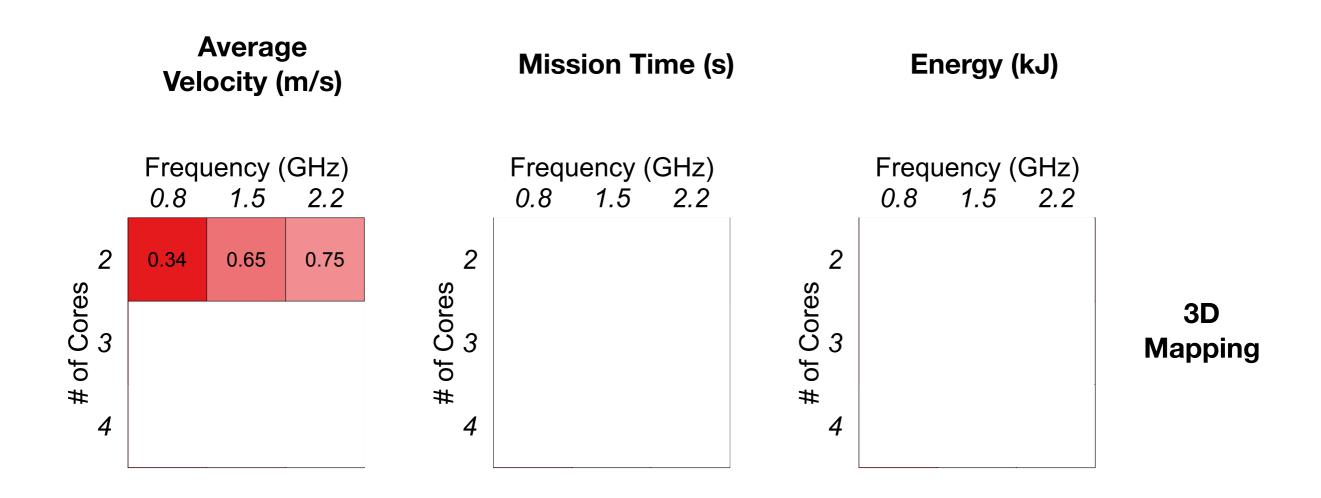


Core/Frequency Sensitivity Analysis

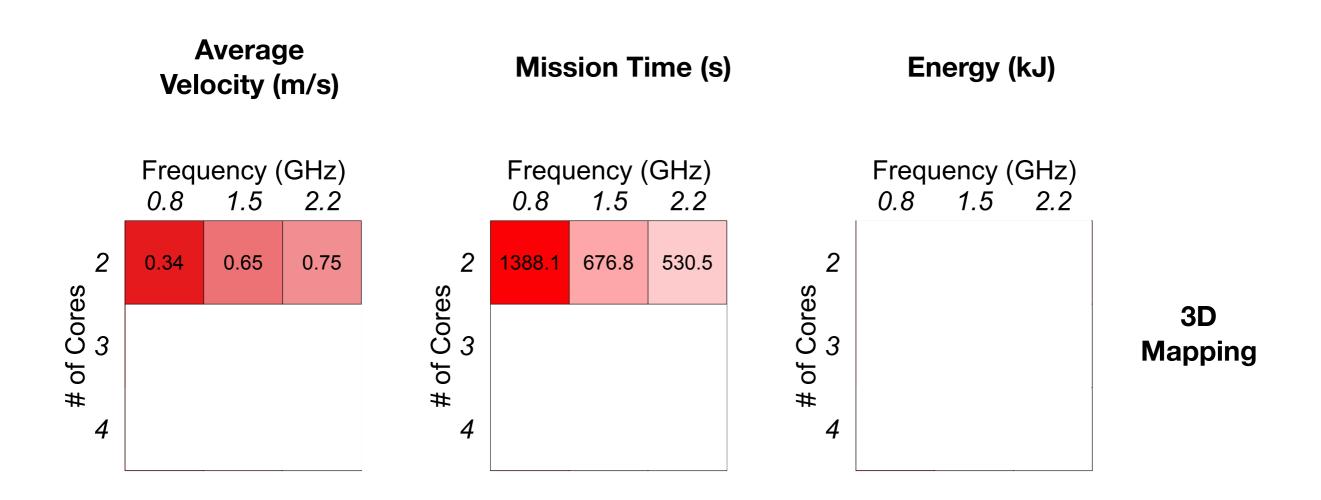




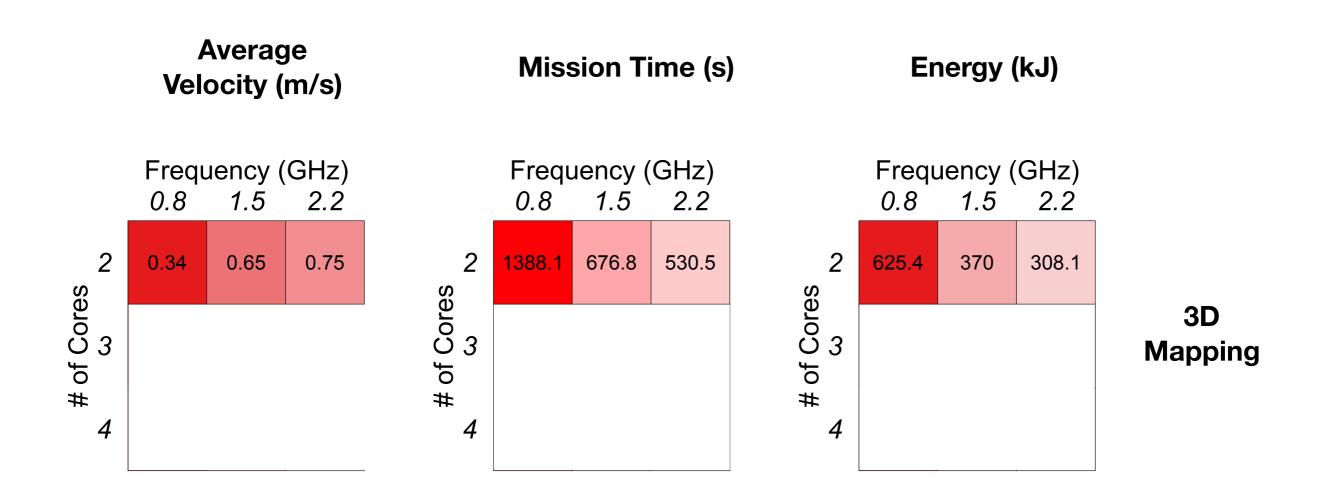
Core/Frequency Sensitivity Analysis



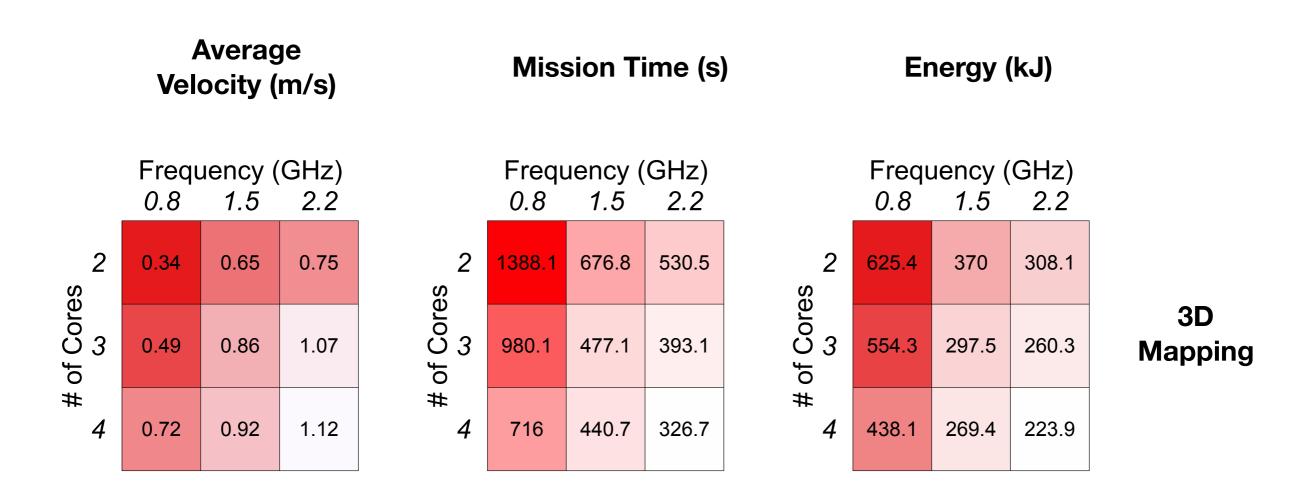




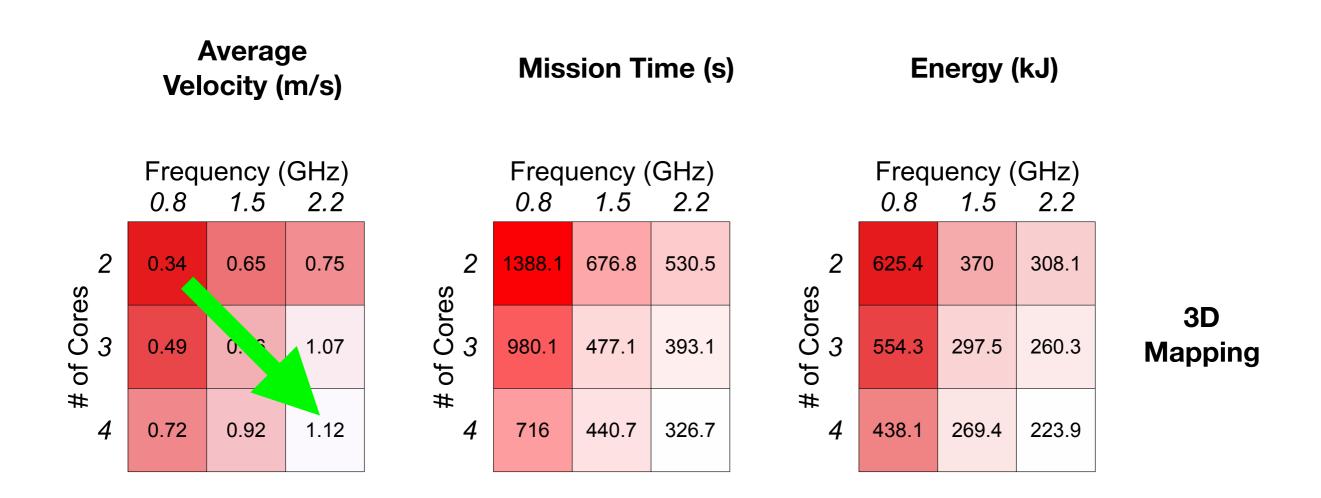




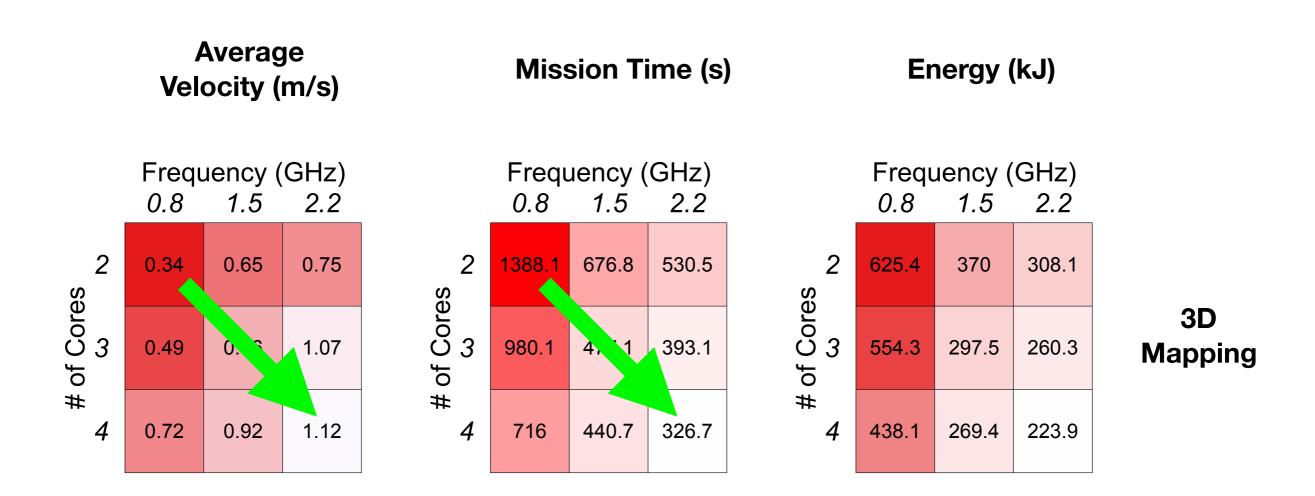




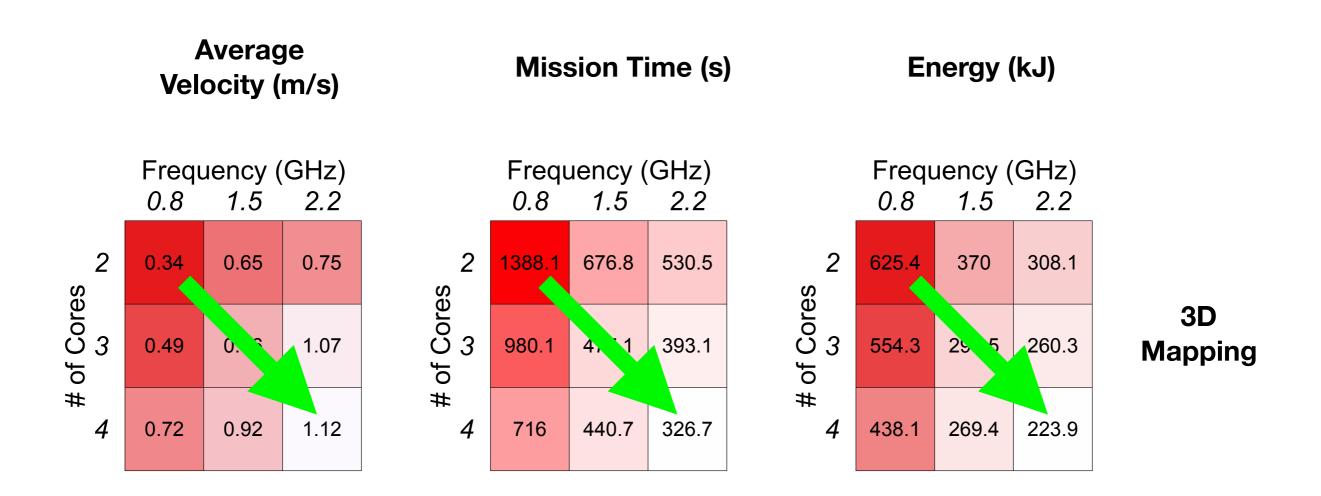




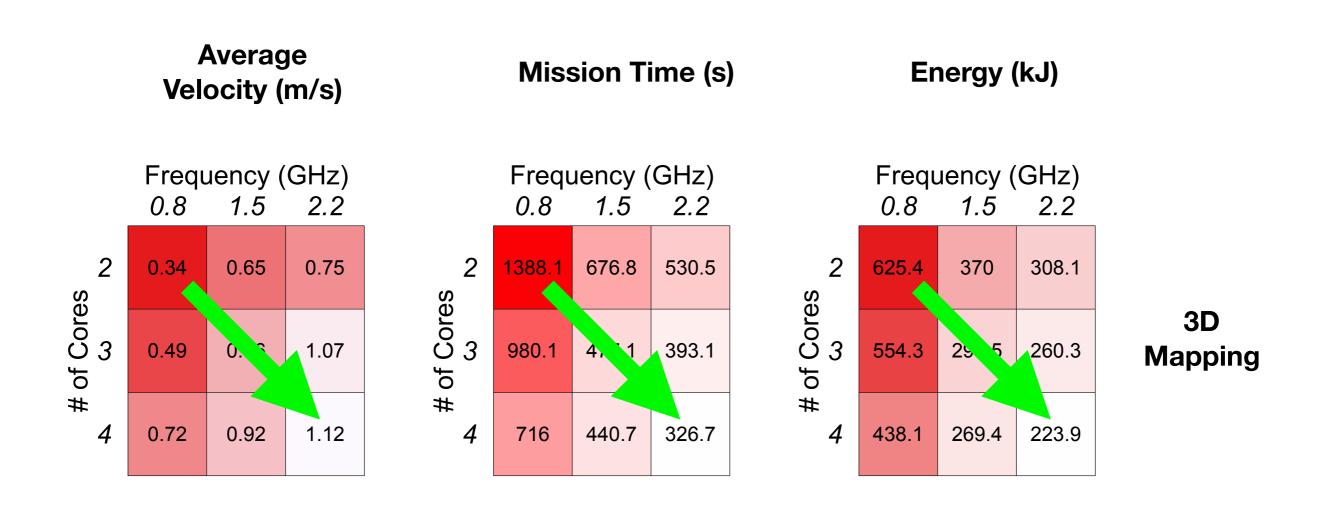








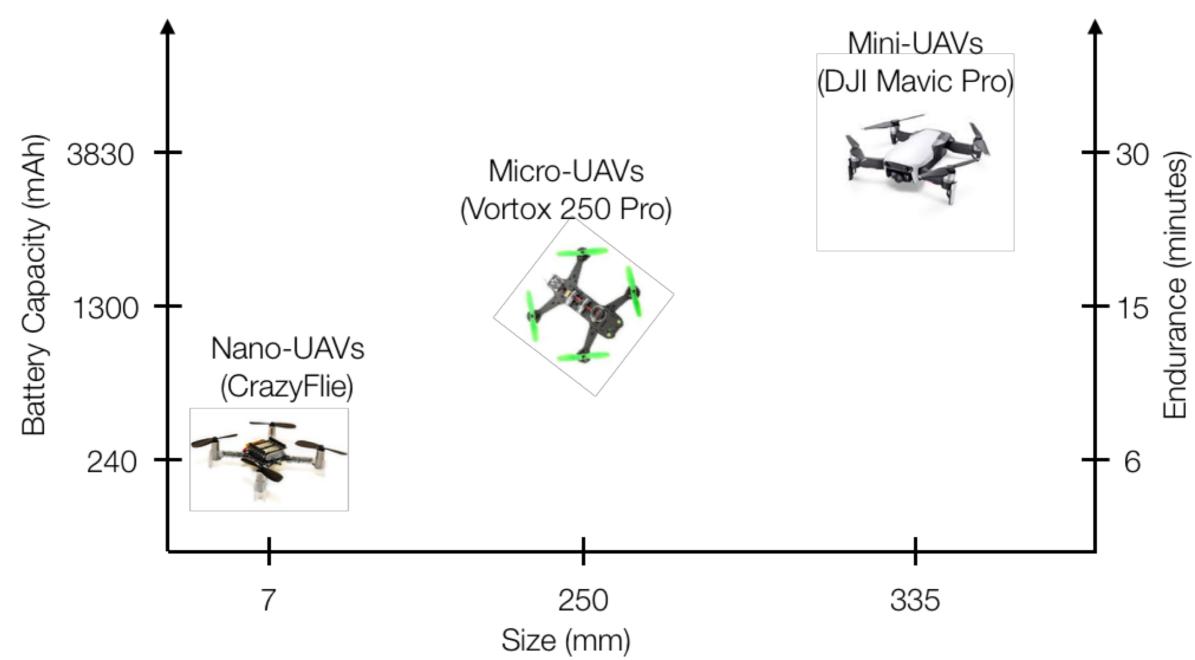




3X improvement in speed, flight time and energy as compute capability increases



Recall: Power Depends on Physical Form Factor





MAVBench: Micro Aerial Vehicle Benchmarking

Behzad Boroujerdian*[†] Hasan Genc*[†] Srivatsan Krishnan[†] Wenzhi Cui[†] Aleksandra Faust[∓] Vijay Janapa Reddi^{†‡§}

https://github.com/MAVBench

†The University of Texas at Austin

‡Harvard University

∓Google Brain

§Google

Abstract—Unmanned Aerial Vehicles (UAVs) are getting closer to becoming ubiquitous in everyday life. Among them, Micro Aerial Vehicles (MAVs) have seen an outburst of attention recently, specifically in the area with a demand for autonomy. A key challenge standing in the way of making MAVs autonomous is that researchers lack the comprehensive understanding of how performance, power, and computational bottlenecks affect MAV applications. MAVs must operate under a stringent power budget, which severely limits their flight endurance time. As such, there is a need for new tools, benchmarks, and methodologies to foster the systematic development of autonomous MAVs. In this paper, we introduce the "MAVBench" framework which consists of a closed-loop simulator and an end-to-end application benchmark suite. A closed-loop simulation platform is needed to probe and understand the intra-system (application data flow) and inter-system (system and environment) interactions in MAV applications to pinpoint bottlenecks and identify opportunities for hardware and software co-design and optimization. In addition to the simulator, MAVBench provides a benchmark suite, the first of its kind, consisting of a variety of MAV applications designed to enable computer architects to perform characterization and develop future aerial computing systems. Using our open source, end-to-end experimental platform, we uncover a hidden, and thus far unexpected compute to total system energy relationship in MAVs. Furthermore, we explore the role of compute by presenting three case studies targeting performance, energy and reliability. These studies confirm that an efficient system design can improve MAV's battery consumption by up to 1.8X.

I. INTRODUCTION

Unmanned aerial vehicles (a.k.a drones) are becoming an important part of our technological society. With myriad use cases, such as in sports photography [1], surveillance [2], disaster management, search and rescue [3], [4], transportation and package delivery [5]–[7], and more, these unmanned aerial vehicles are on the cusp of demonstrating their full potential.

Hence, drones are rapidly increasing in number. Between 2015, when the U.S. Federal Aviation Administration (FAA) first required every owner to register their drone, and 2017, the number of drones has grown by over 200%. At the time of writing, the FAA indicates that there are over 900,000 drones registered with the FAA drone registry database (Figure 1). By 2021, the FAA expects this number will exceed 4 million units [8]. Such an upward trend can be explained by the new opportunities that unmanned aerial vehicles are enabling.

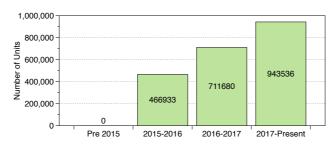


Fig. 1: Rapidly growing interest in UAVs. Data mined from FAA vehicle registration. The number of FAA registrations increased by 2X over the past two years, and it is rapidly growing. The FAA projects that by 2021 the number will exceed 4M units [9].

The growth and significance of this emerging domain of autonomous agents call for architects attention. Challenges such as low endurance (how long the drone can last in the air) and small battery capacities for drones demand hardware and system architects' attention. The limited on-board energy budget manifests itself in the limited endurance and range of drones. This can be seen in various off-the-shelf commercial drones where endurance is typically less than 20 minutes, and flight range is about 15 miles [6]. To practically deploy drones, both their endurance and range must be improved.

In this paper, we investigate and show the role of computing given the endurance and range challenges. For example, we show how a powerful compute subsystem can be deployed to mitigate the problem of limited endurance. The drone's compute subsystem dictates how fast a drone can maneuver, fly, and efficiently finish its mission. Hence, a computing subsystem that takes a long time to do path planning while the drone is hovering in the air, results in the inefficient consumption of energy. Furthermore, a more powerful compute subsystem can lead to more intelligent decision making (e.g., shorter paths to take). It is important to note that enabling intelligence on drones is challenging because of the computational power, size, weight, and cooling limitations.

To enable research and investigation, the foremost challenge to address is the lack of systematic benchmarks and infrastructure for research. To address this shortcoming, we introduce MAVBench, the first of its kind, a platform for the holistic evaluation of aerial agents, involving a closed-loop simulation



https://github.com/MAVBench

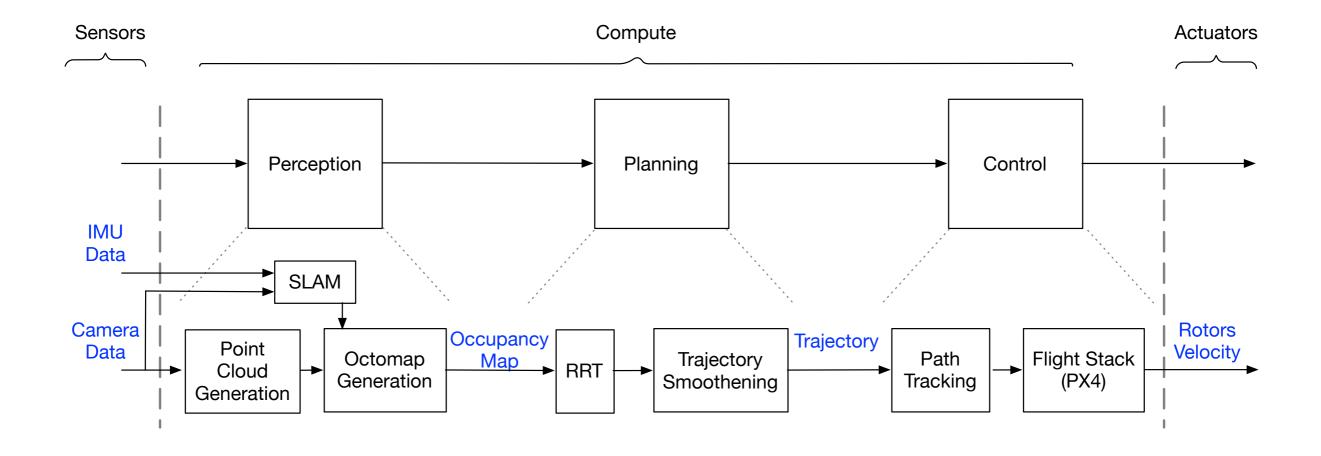


^{*} These two authors contributed equally.

The Al Revolution

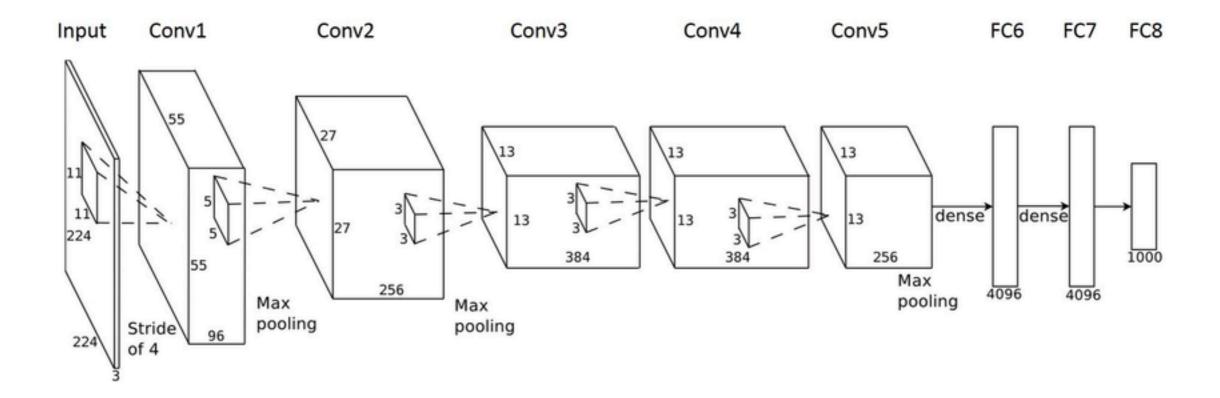


The Traditional "PPC" Pipeline



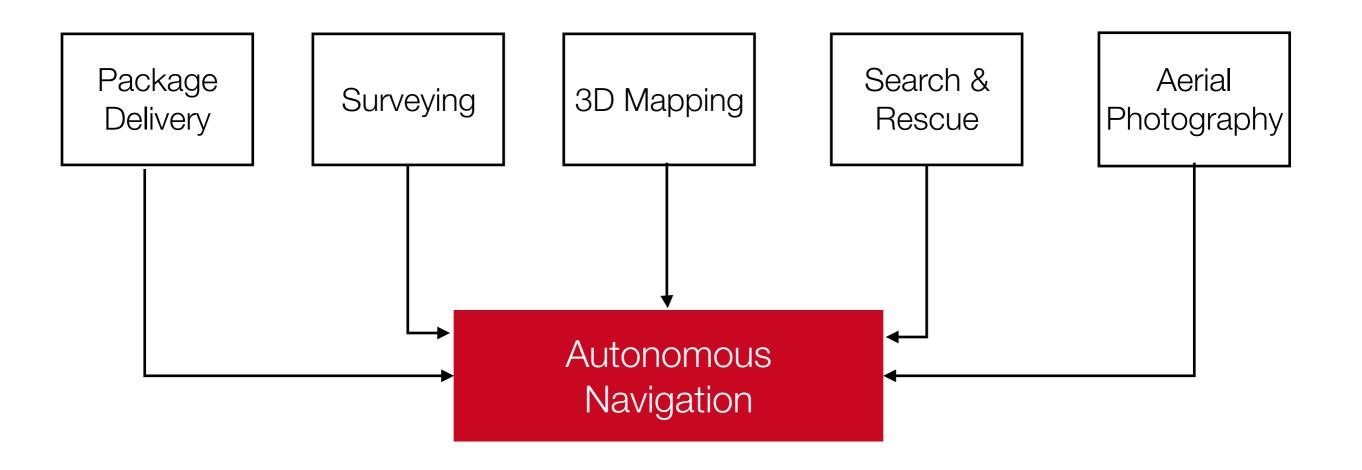


Deep Neural Nets



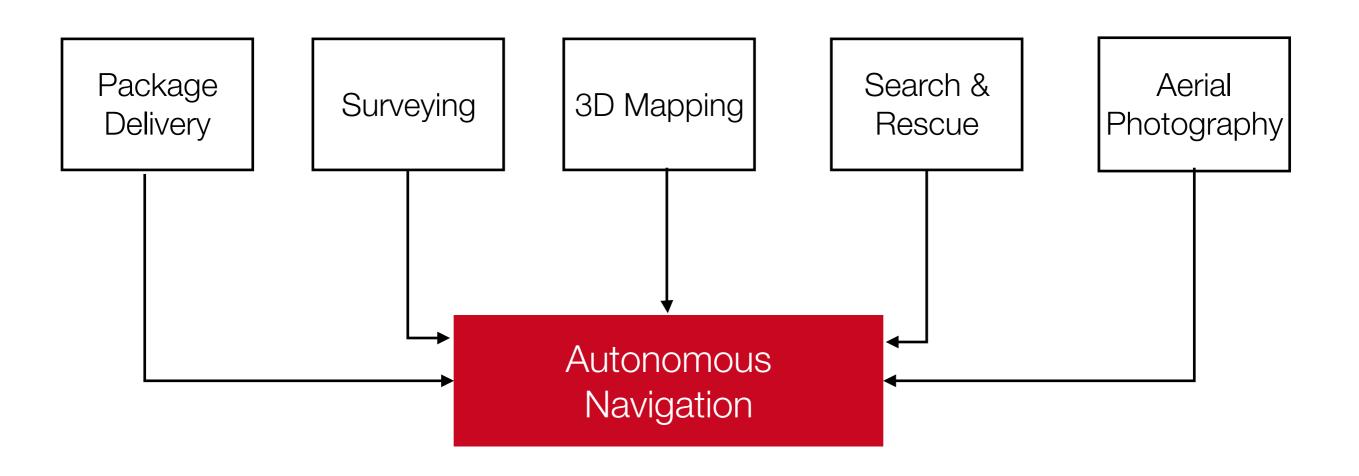


Autonomous Navigation





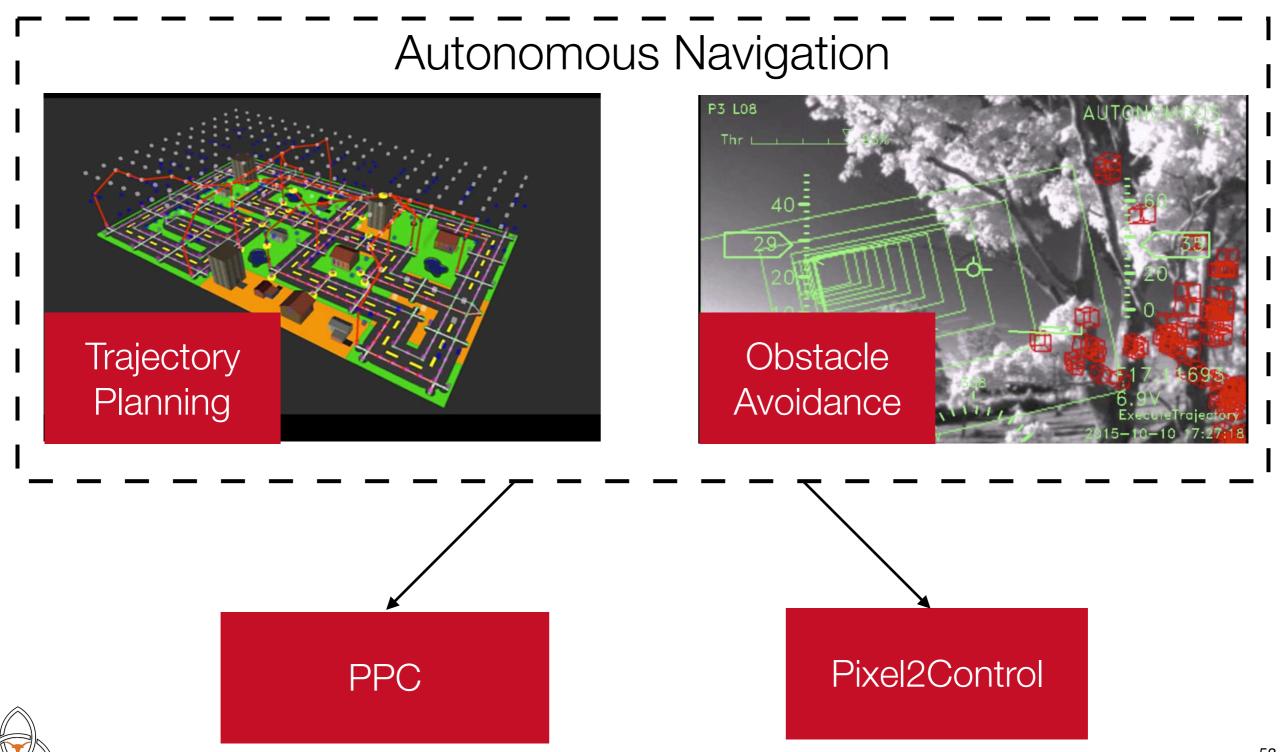
Autonomous Navigation



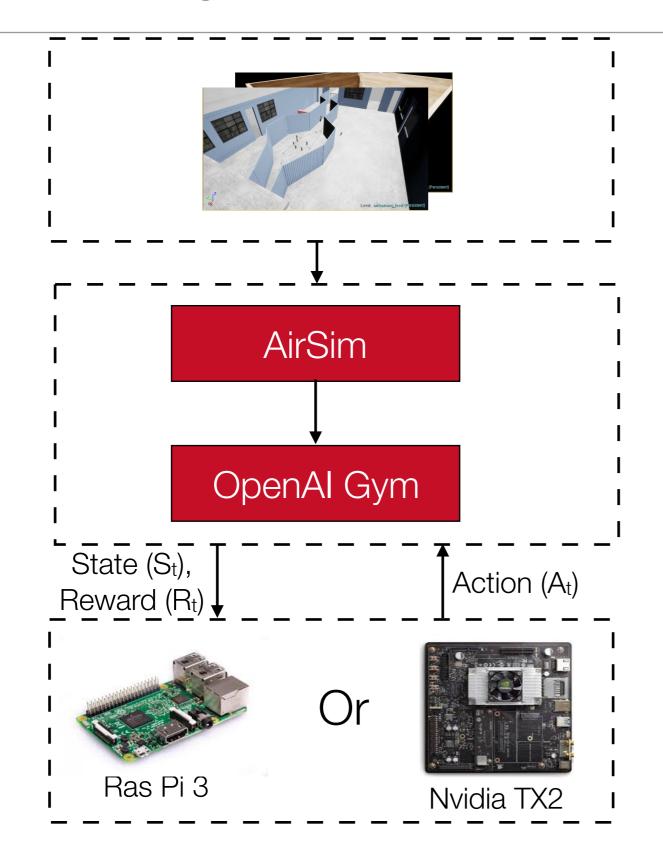
Autonomous navigation is a common kernel across multiple application



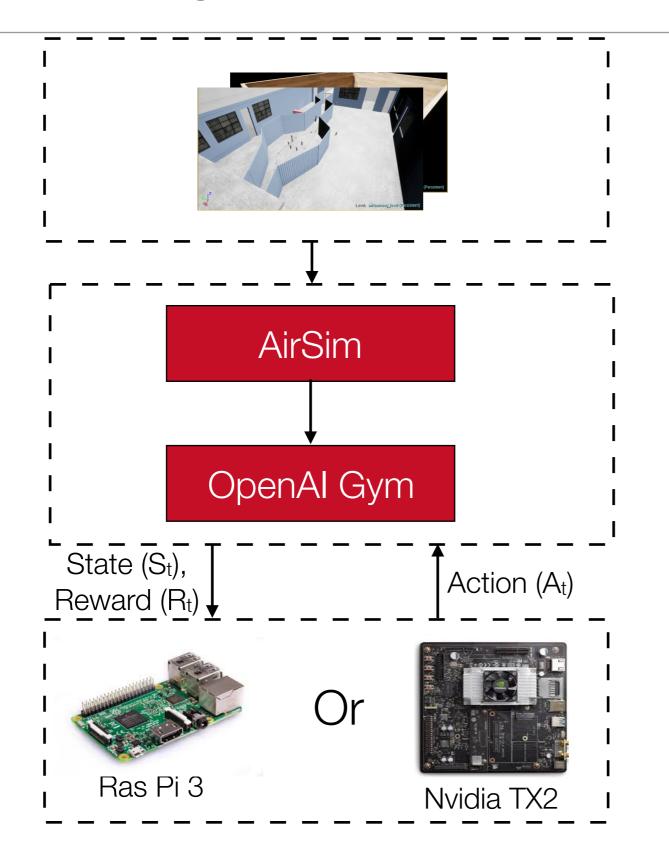
Autonomous Navigation - Two Paradigms









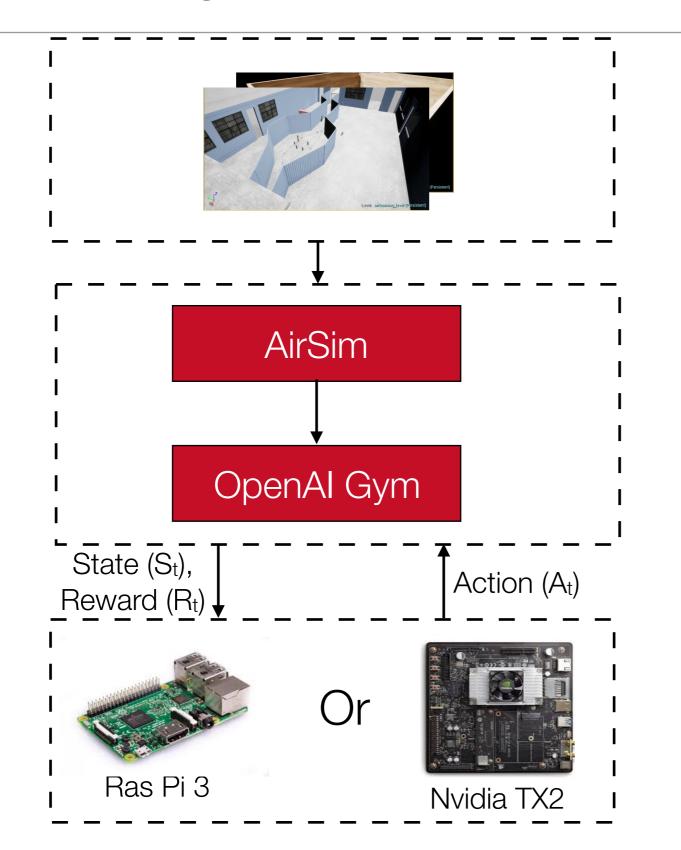


Simulation Environment

DRL Framework

Compute System





Simulation Environment

DRL Framework

Compute System



Simulation Environment



https://youtu.be/DMCj0bwHmds



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https://youtu.be/JRZ1lxHMWnc



https://youtu.be/Oh3Hj0HsG50



Simulation Environment



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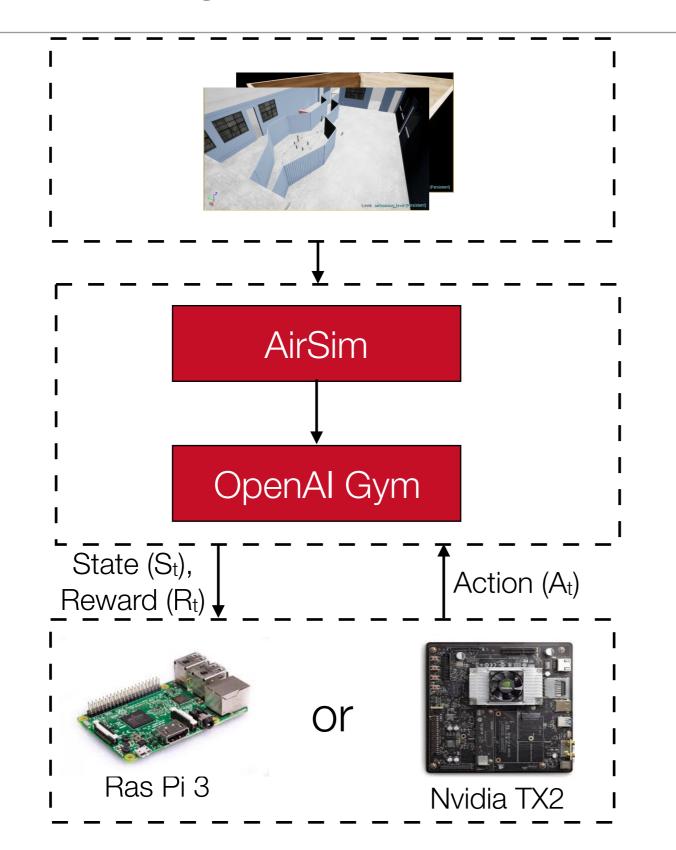


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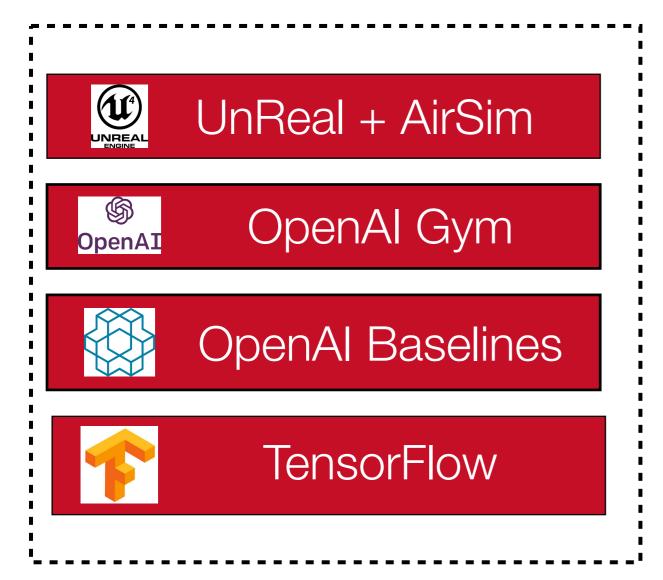
Simulation Environment

DRL Framework

Compute System



Deep RL Framework



Depth Image + RGB + IMU

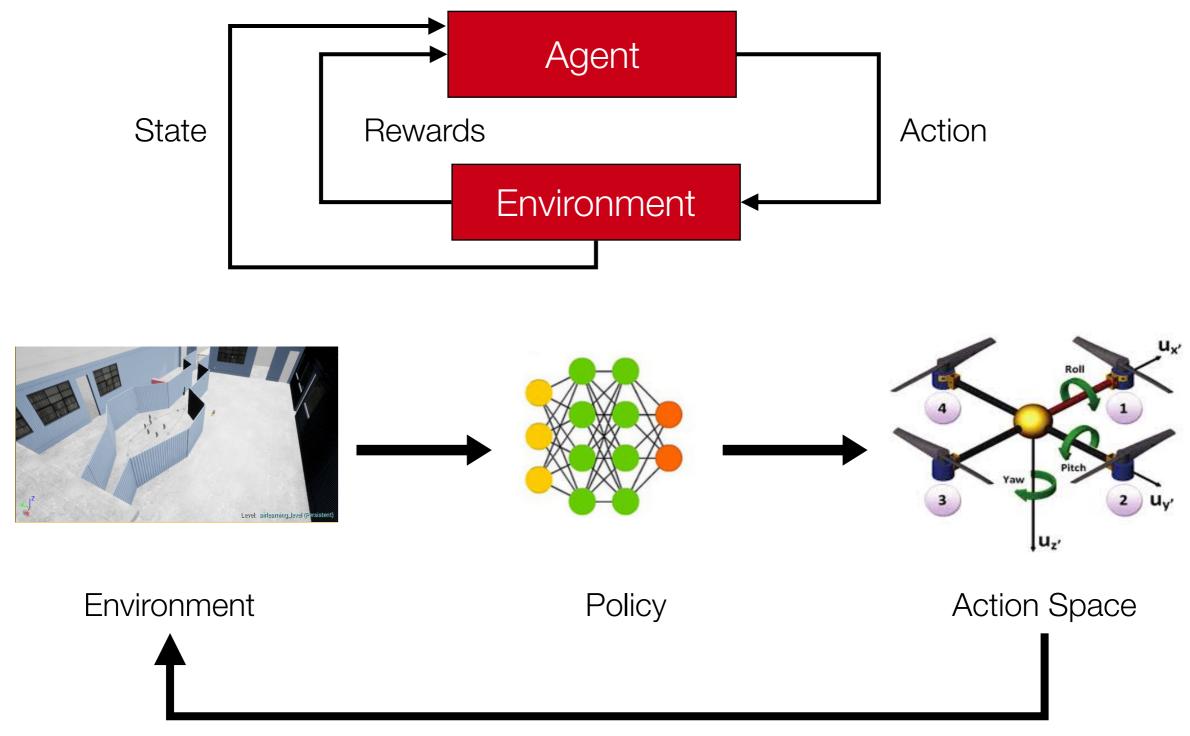
Reinforcement Learning

Algorithms (DQN, DDQN, A3C)

Machine Learning Backend

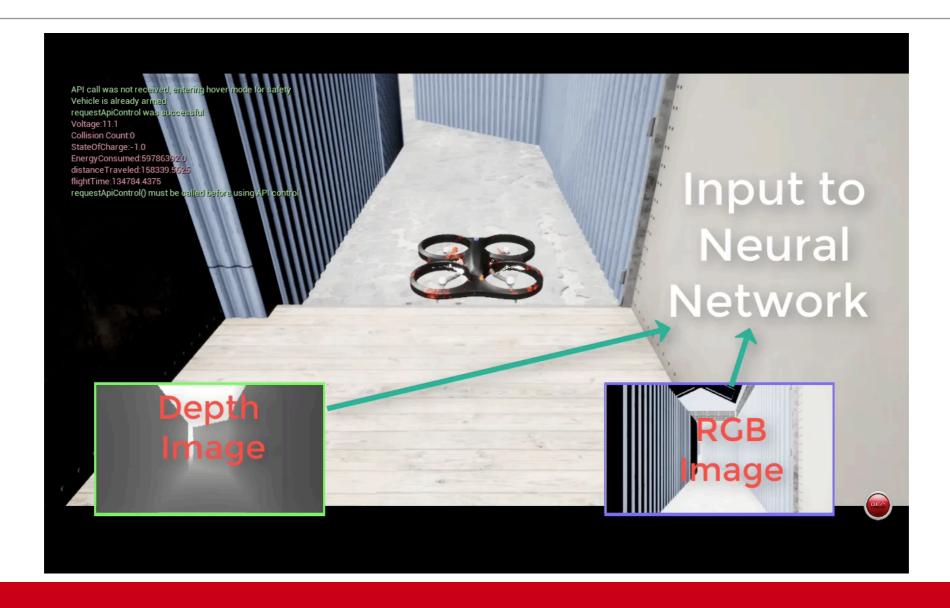


Reinforcement learning based Drone Control





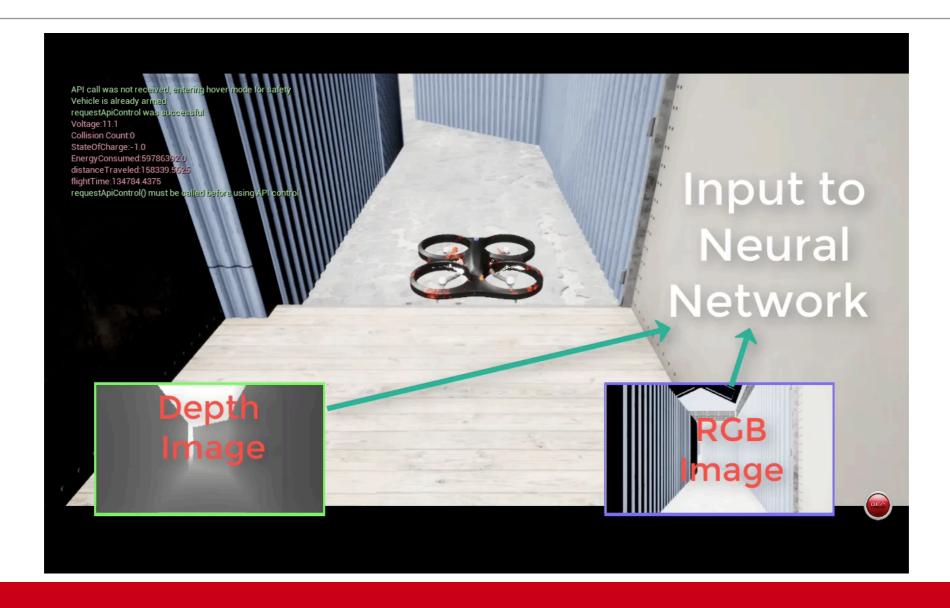
AirLearning Demonstration



Demonstrates that the UAV has learned to navigate in a narrow passageway

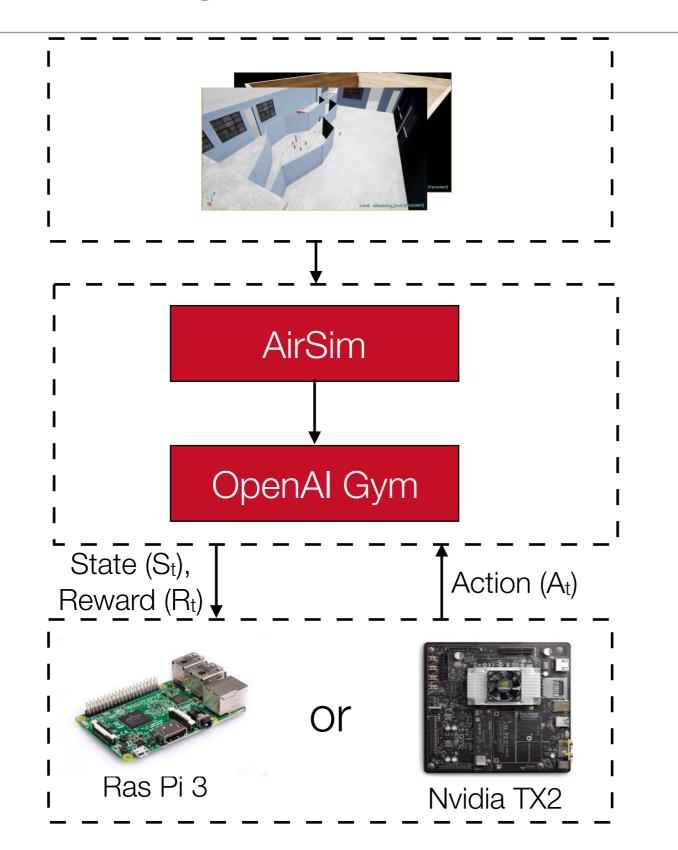


AirLearning Demonstration



Demonstrates that the UAV has learned to navigate in a narrow passageway





Simulation Environment

DRL Framework

Compute System

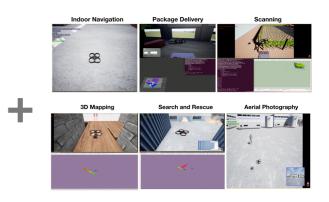












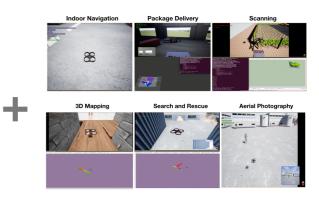












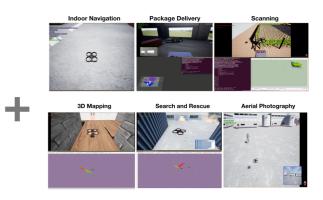






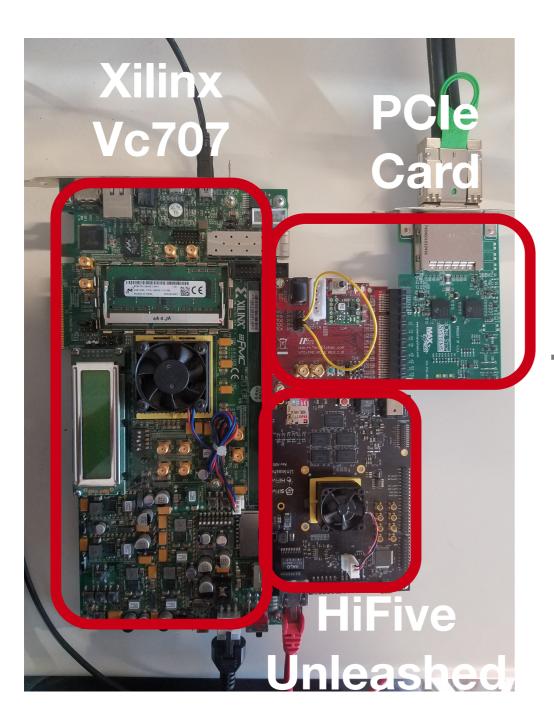






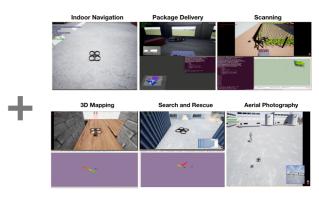












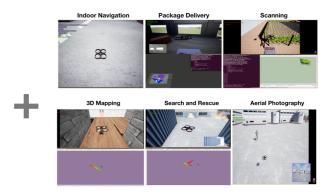






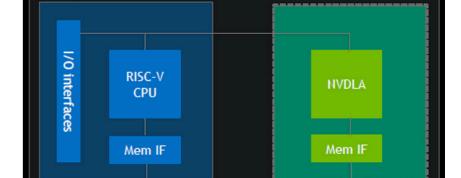






FPGA

DRAM

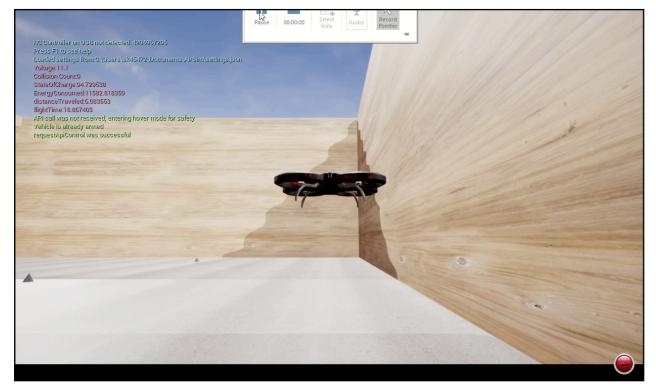


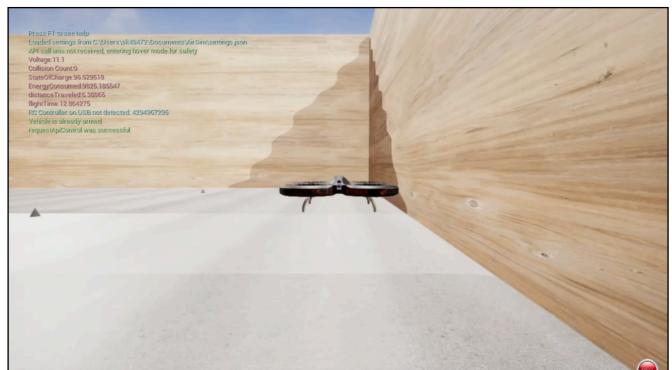
Freedom Unleashed

DRAM



Algorithm Performance: Small vs. Large Policy



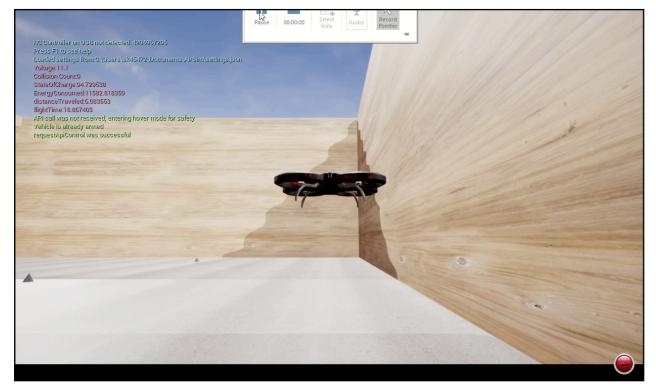


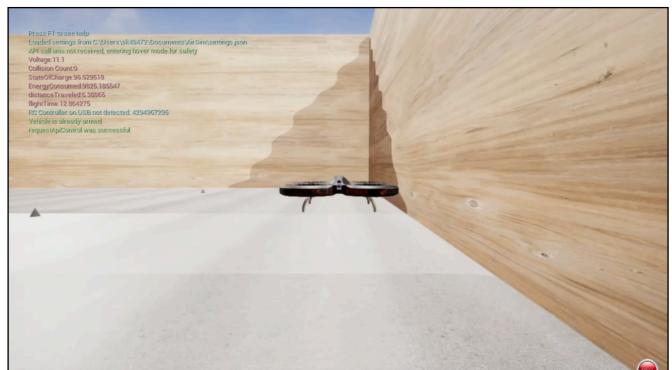
Small Policy

Large Policy



Algorithm Performance: Small vs. Large Policy





Small Policy

Large Policy



			erception		Pla	nning		Control					
	Point Cloud Generation	Occupancy Map Generation	Collision Check	Object Detection	Object Tracking		Localization		PID	Smoothened Shortest Path		Lawn Mowing	Path Tracking/ Command Issue
	Generation	Generation	Check	Detection	Buffered	Real Time	GPS	SLAM		Shortest Lain	Елриотиноп	Mowing	Communa Issue
Scanning												X	X
Aerial				X	v	X	X		v				X
Photography				Λ	Λ	Λ	Λ		Λ				Λ
Package	X	X	X				X	X		X			X
Delivery	Λ	Λ	Λ				Λ	Λ		Λ			Λ
3D	X	V	X				v	X			X		X
Mapping	Λ	Λ	Λ				Λ	Λ			Λ		Λ
Search and Rescue	X	X	X	X			X	X			X		X



			erception	Planning				Control					
	Point Cloud Generation	Occupancy Map Generation	Collision Check	Object Detection	Iracking		Localization		PID	Smoothened Shortest Path	Frontier Exploration	Lawn	Path Tracking/ Command Issue
	Generation	Generation	Check	Detection			GPS	SLAM		Shortest Lain	Ехрючиноп	Mowing	Communa Issue
Scanning												89	1
Aerial				307	80	18	0		0				1
Photography				307	00	10	U		U				1
Package	2	630	1				0	55		182			1
Delivery	2	030	1				0	33		102			1
3D	2	482	1				0	46			2647		1
Mapping	2	402	1				U	40			2047		1
Search and Rescue	2	427	1	271			0	45			2693		1



			P	erception						Pla	Control		
	Point Cloud Generation	Occupancy Map Generation	Collision Check	Object Detection	Object Tracking		Localization		PID	Smoothened Shortest Path	Frontier Exploration	Lawn Mowing	Path Tracking/ Command Issue
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			P	erception						Pla	Control		
	Point Cloud Generation	Occupancy Map Generation	Collision Check	Object Detection	Object Tracking		Localization		PID	Smoothened Shortest Path	Frontier Exploration	Lawn Mowing	Path Tracking/ Command Issue
	Generation	Generation	Check	Detection	Buffered	Real Time	GPS	SLAM			Елриониион	wowing	Communa Issue
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Mapping	2	402	1					40			2047		1
Search and Rescue	2	427	1	271			0	45			2693		1

Identify bottlenecks and accelerate them through domain specific logic.



Summary



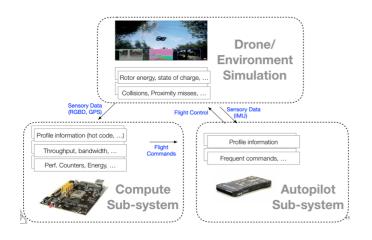






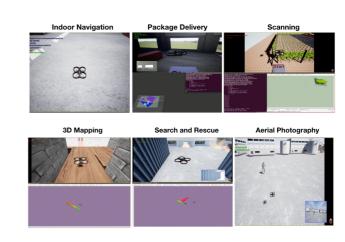






Closed-loop simulation is important for the development of architectural solutions for autonomous machines.

End-to-end applications are needed to do hardware and software co-design to design domain specific accelerators







RISC-V with ROS unlocks the potential of designing custom hardware accelerators that are open source to drive innovation

