Trade-offs in Limbed Mobility

NSF Workshop on Locomotion and Manipulation
April 2, 2015

Katie Byl

UC SANTA BARBARA
Robotics Lab

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Katie Byl ^ Bill

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Why Locomotion is Hard…

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Why Locomotion is Hard…

Stochastic Environments

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Why Locomotion is Hard...

Stochastic Environments

variability

[variability doesn't necessarily mean <u>uncertainty</u>...]

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Locomotion Goals

Robustness

Agility

Energetics

Robustness

unknown variability

Agility

Energetics

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Robustness

<u>un</u>known variability

Agility

known variability

Energetics

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Robustness

<u>un</u>known variability

Agility

known variability

Energetics

as efficient as practical

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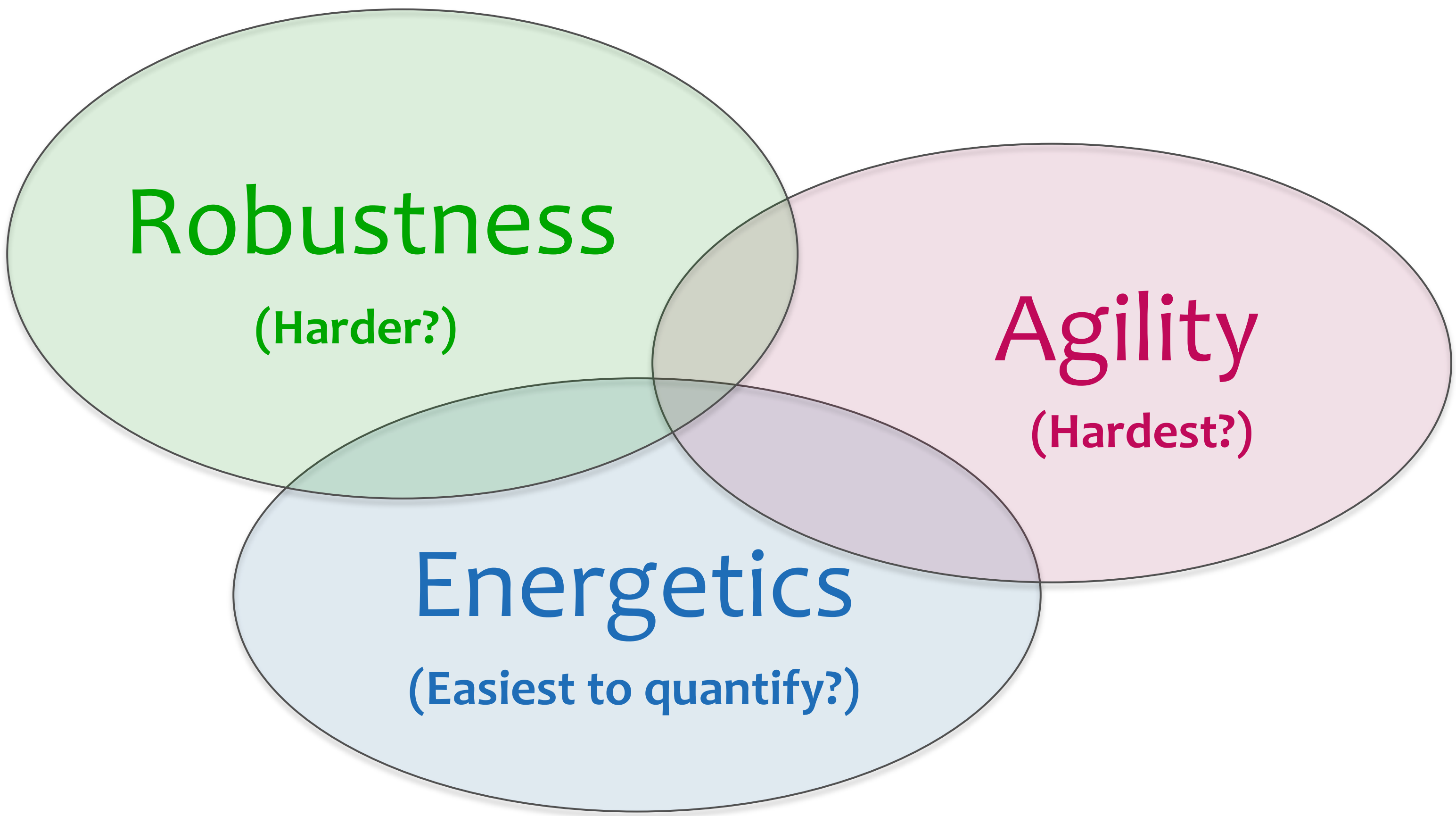
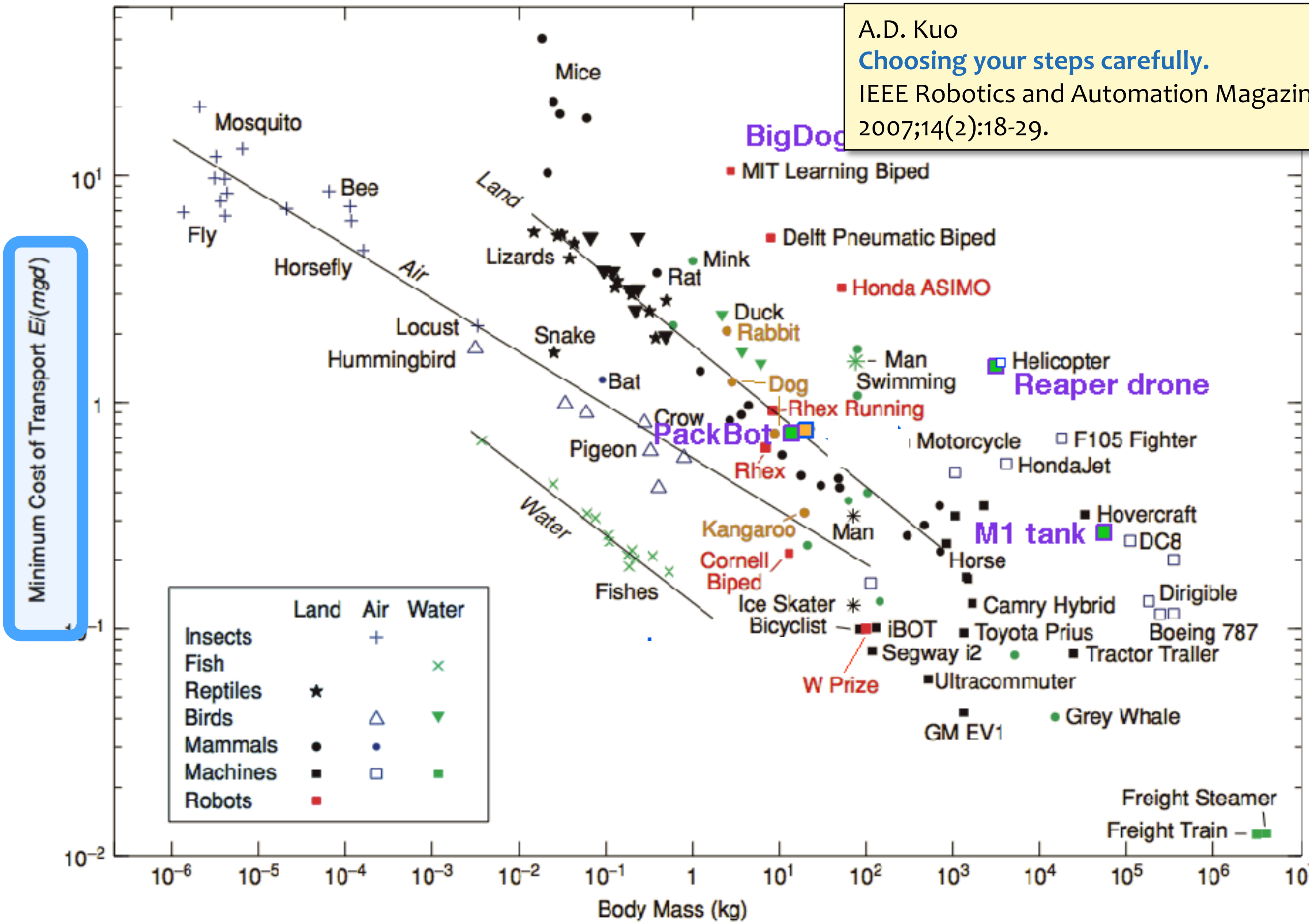
Locomotion metrics?

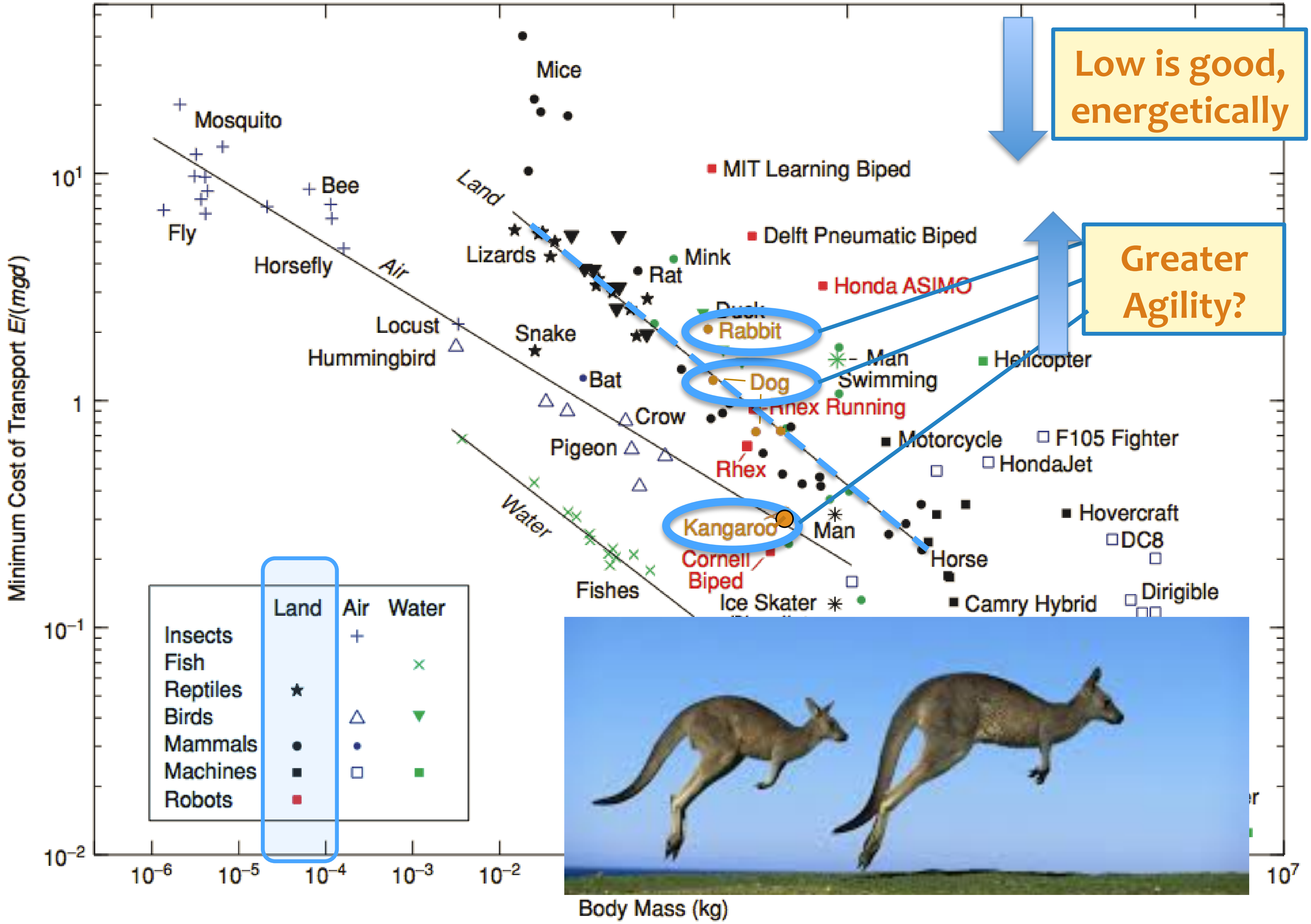


Energetics: Cost of Transport

A.D. Kuo
Choosing your steps carefully.
IEEE Robotics and Automation Magazine.
2007;14(2):18-29.



Agility vs Energetics Trade-off?



Rabbit Agility

Danish Rabbit Hopping Championship, 2010
https://www.youtube.com/watch?v=ptyKSiRyQ4Y

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(Wait: Did she throw the bunny?)

Danish Rabbit Hopping Championship, 2010
https://www.youtube.com/watch?v=ptyKSiRyQ4Y

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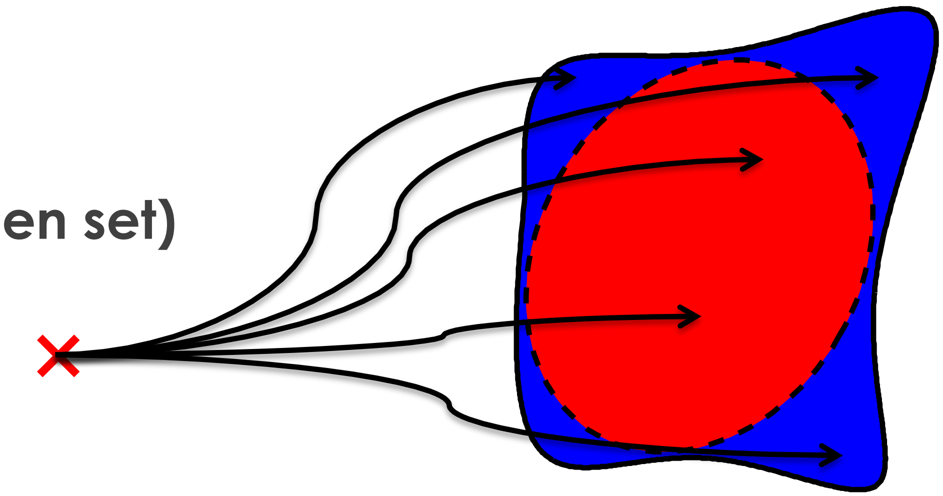
Agility and Robustness, Intuitively

- One to many

(can reach points in some open set)

Agility (?)

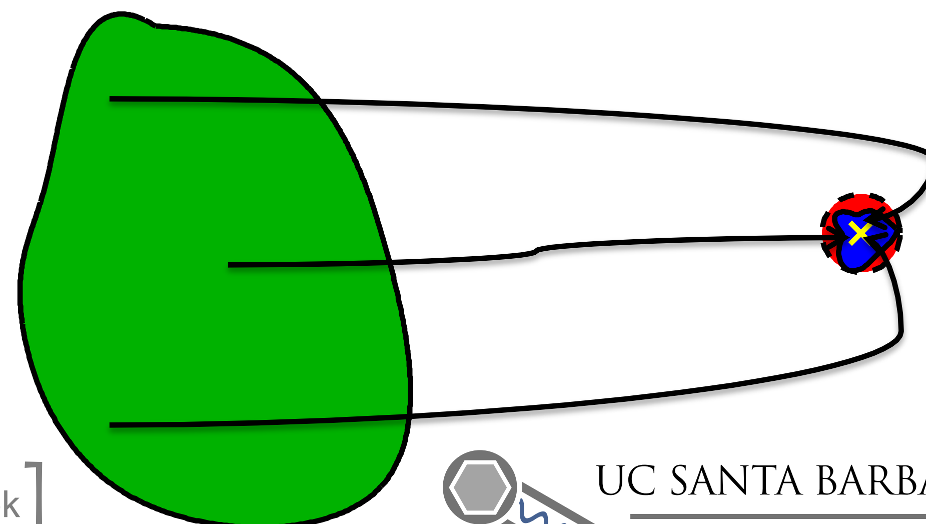


(arriving at/within some Δt)

- Many to one

(recover, to some tolerance)

Robustness (?)



[e.g., "funnels"… Burridge, Rizzi, and Koditschek]

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Quantifying Agility

- Want to: quantify the set of states achievable in a characteristic time,

- Penalized by inaccuracies.

Coping with variable terrain is a challenge – even without uncertainty*. Errors should be quantifiable, in terms of their impact.

[* e.g., DARPA LittleDog program]

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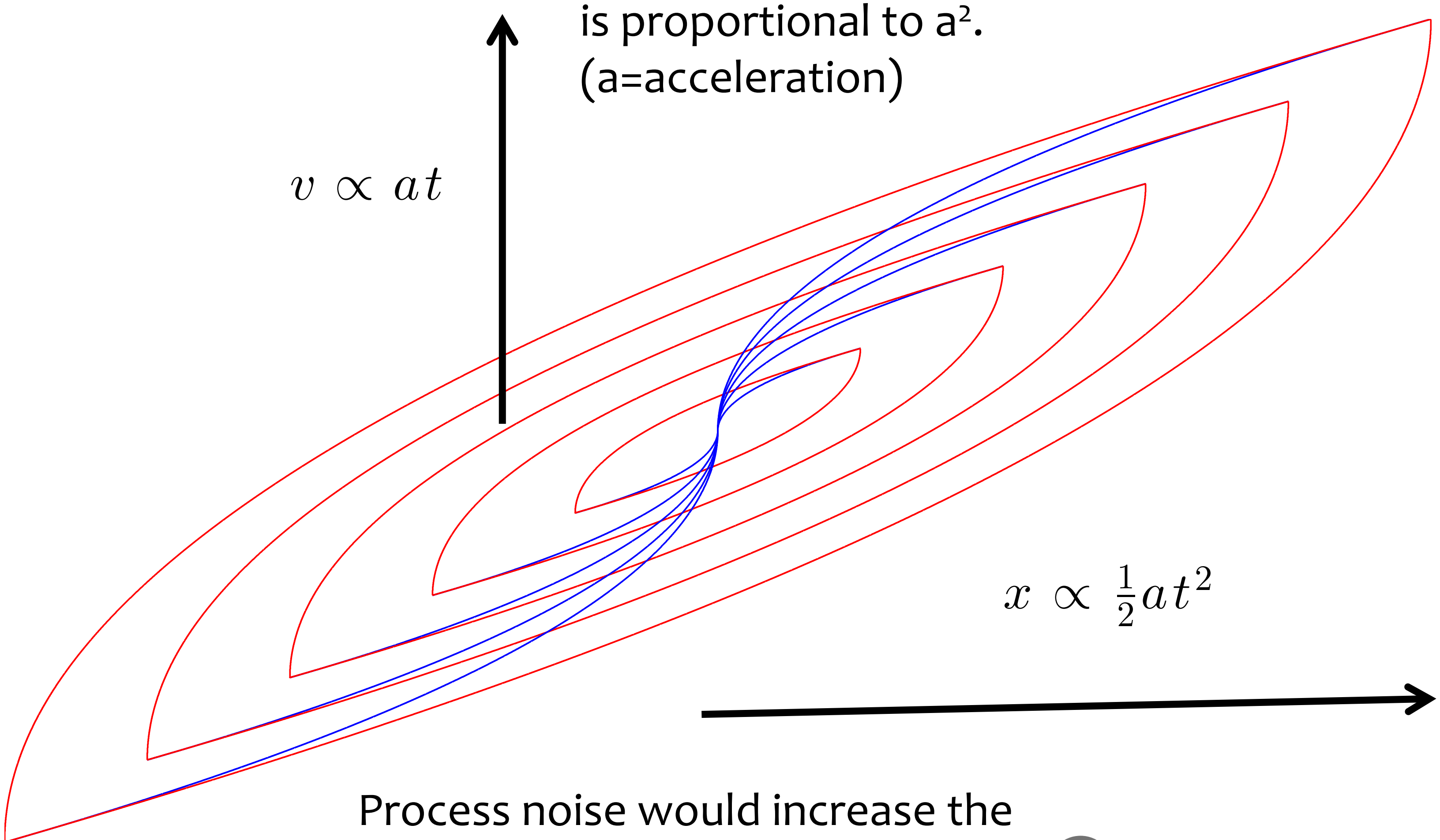
Bang-bang control analogy

Reachable area, within a given time, is proportional to a². (a=acceleration)



Process noise would increase the expected time to a goal state.

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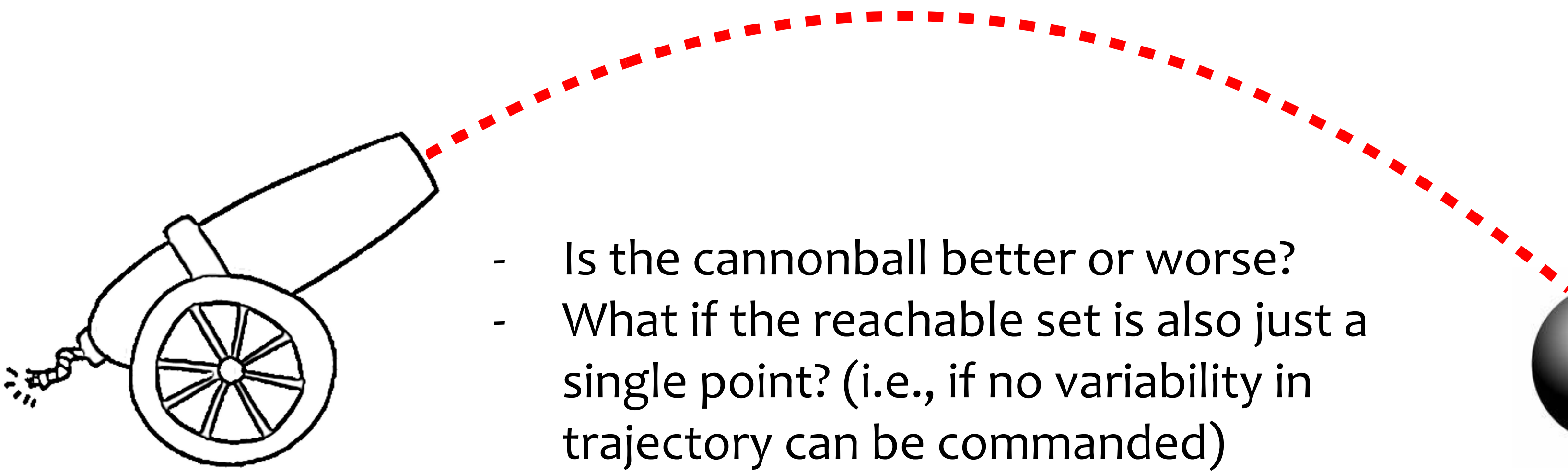
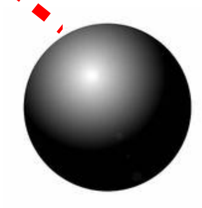
Rock vs. Cannonball

Rock never moves.
Zero agility, since reachable set has zero area.



- Is the cannonball better or worse?
- What if the reachable set is also just a single point? (i.e., if no variability in trajectory can be commanded)
- What if this is not entirely repeatable?



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Golf analogy

Hitting the ball further can reduce the total number of shots required.

But bad aim on a long shot will result in a greater expected number of total swings to sink the ball, on average.

In metrics for agility, effects of greater speed and greater inaccuracy should be mapped to the net effect on average "time to reach a given state" and/or "volume of states reachable in some time".

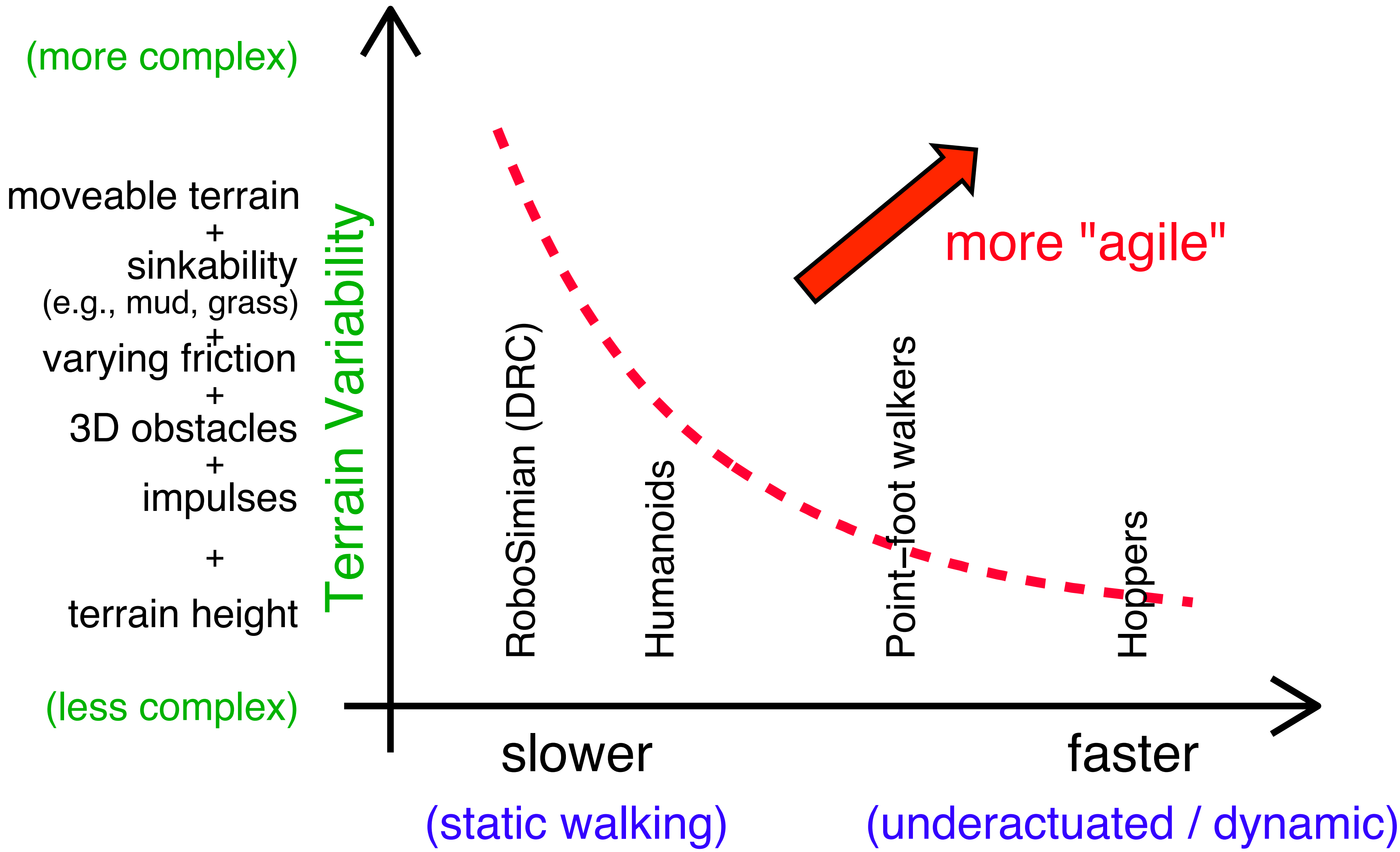
(Analogies with balancing financial risk vs reward? With information theory?)

Current Agility Metrics?

Flight dynamics and human dynamics seem to value twisting and turning…

Perhaps point-to-point mobility is more key, with turning useful iff it enables that goal.

Range of Locomotion Research



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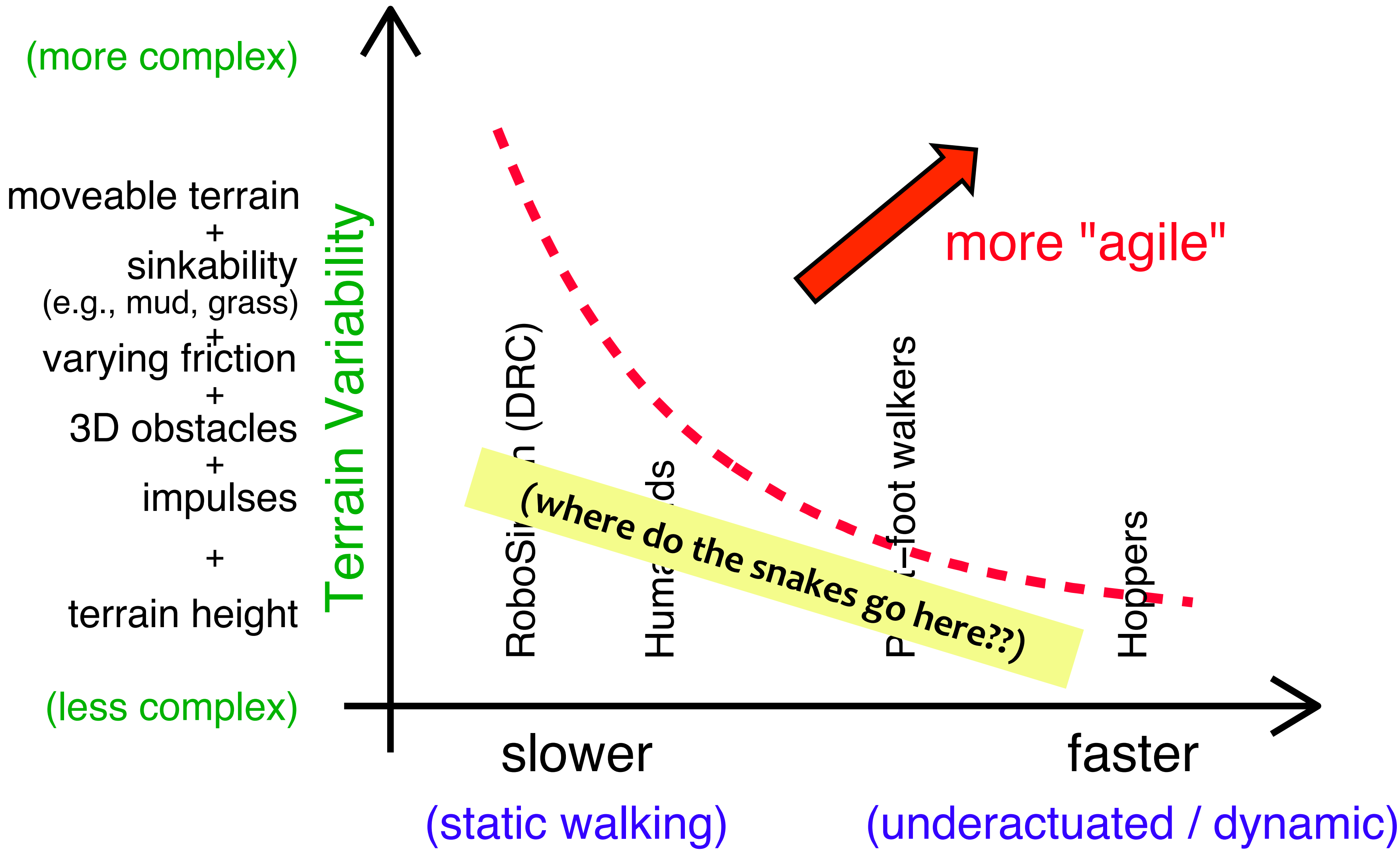

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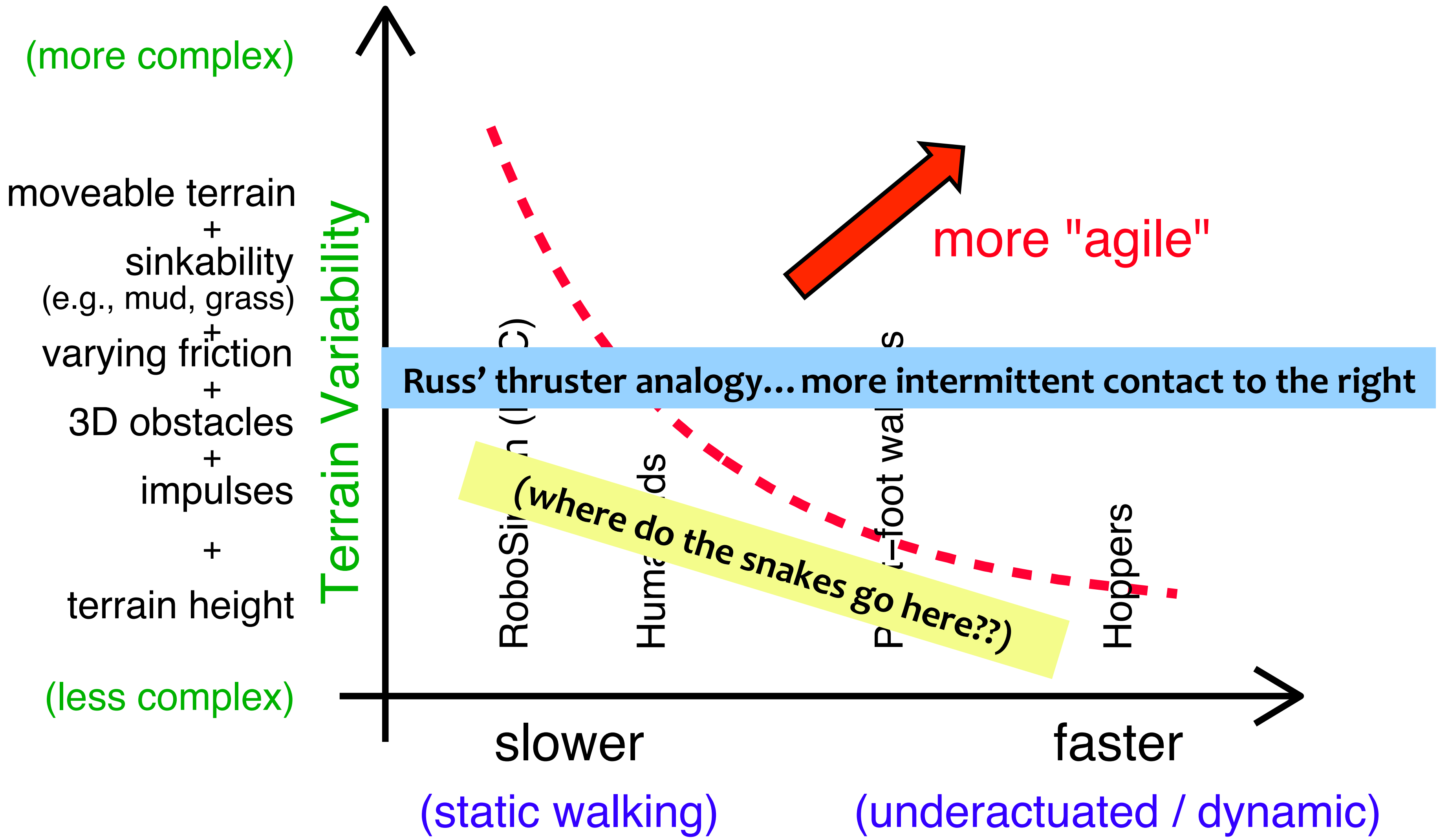

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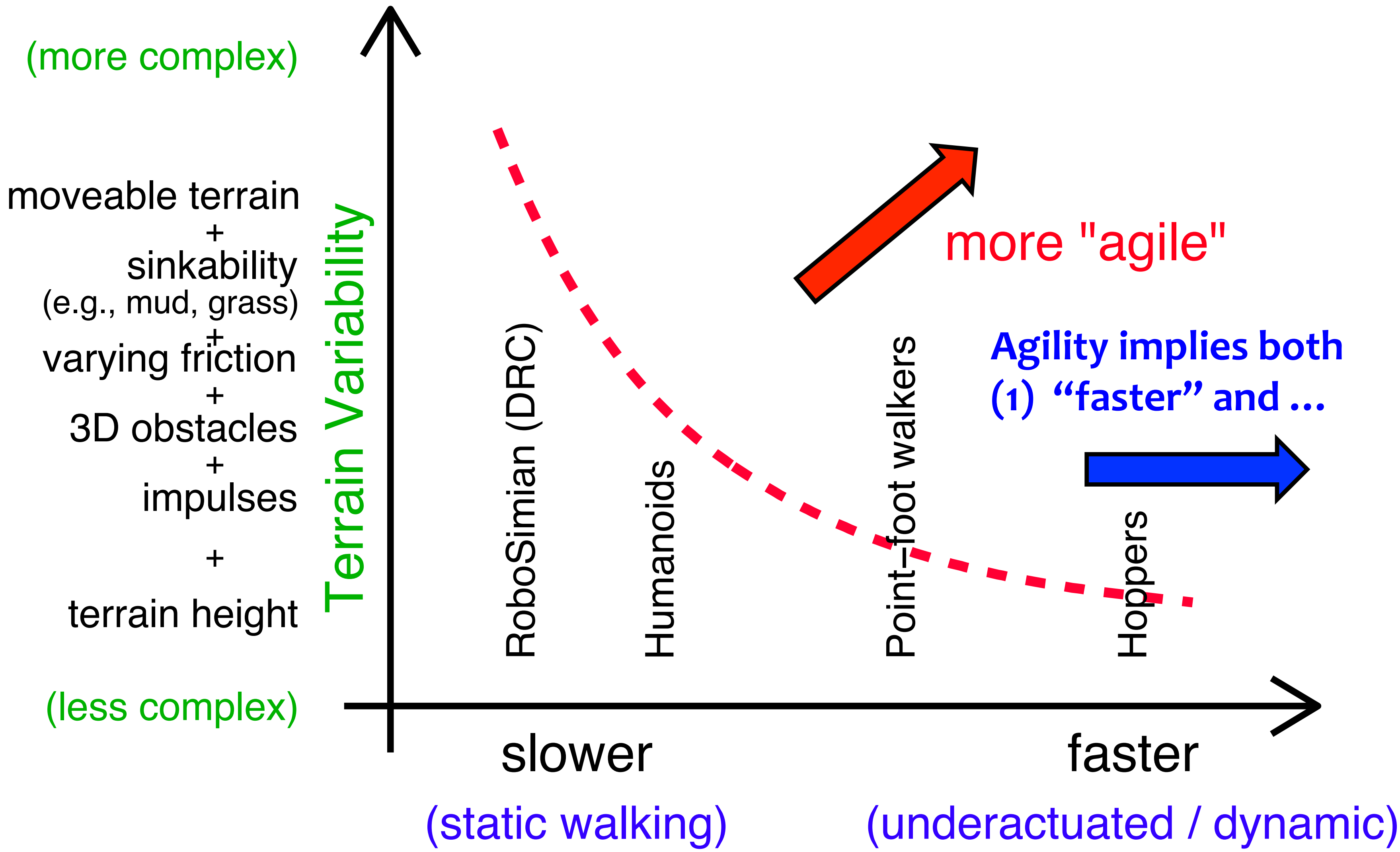

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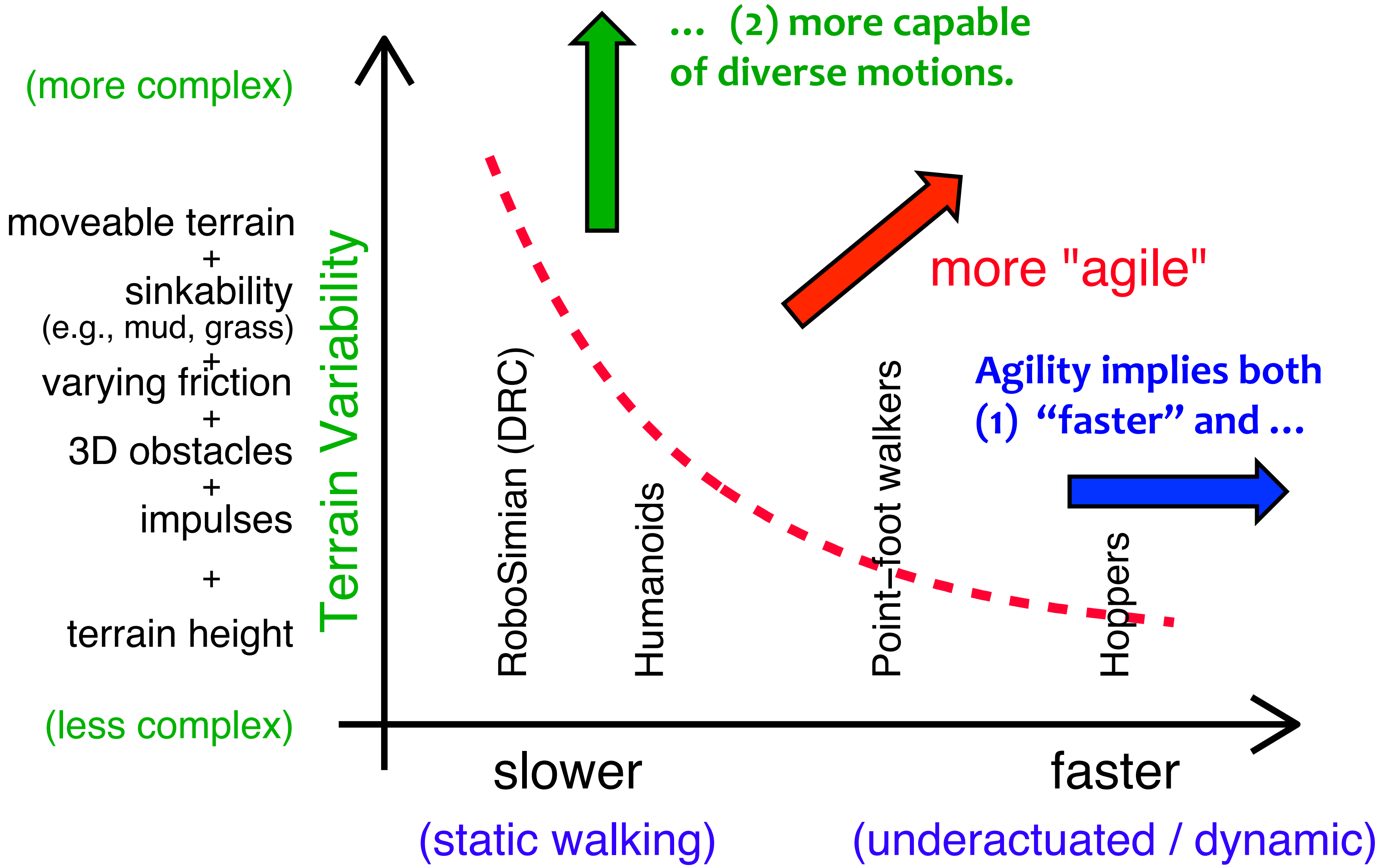
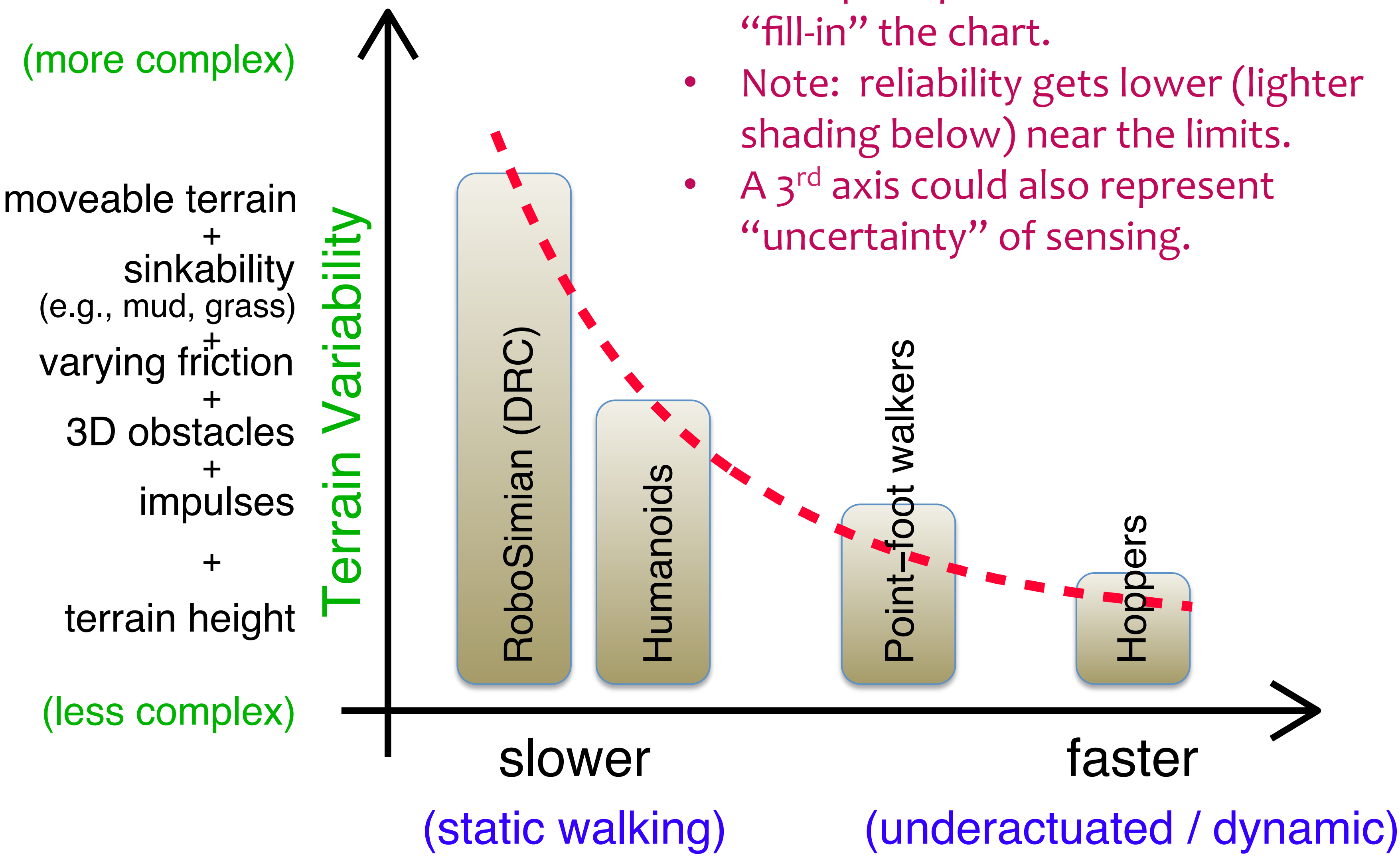


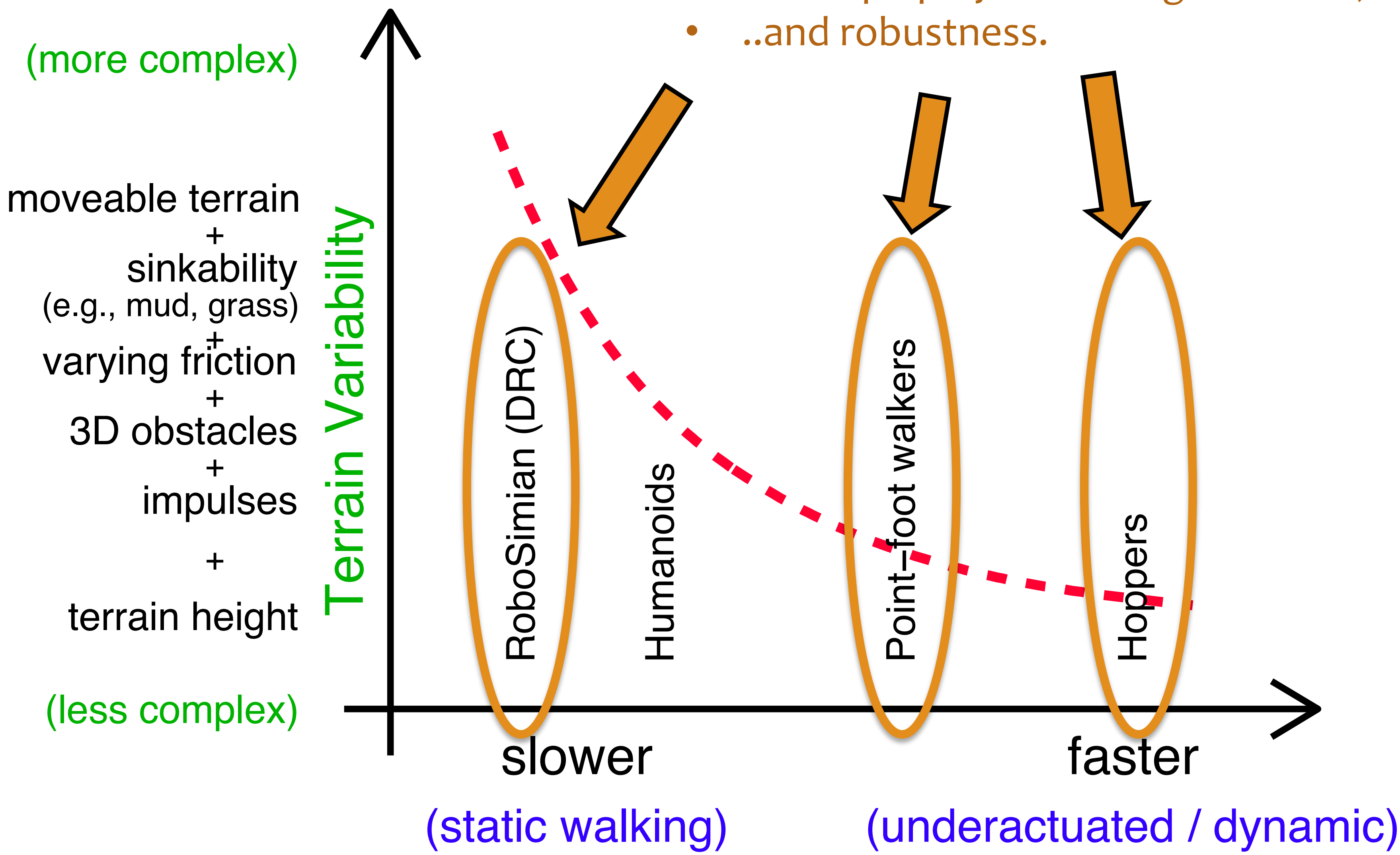
Range of Locomotion Research

- Goal: push performance limits to "fill-in" the chart.
- Note: reliability gets lower (lighter shading below) near the limits.
- A 3rd axis could also represent "uncertainty" of sensing.



Our Locomotion Research

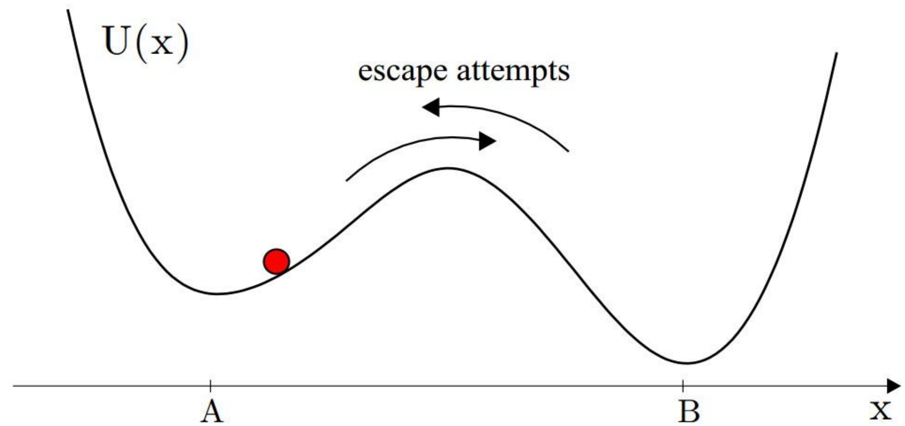
- I'll wrap up by discussing our work,
- ..and robustness.



Robustness

Robustness: Rarely Failing

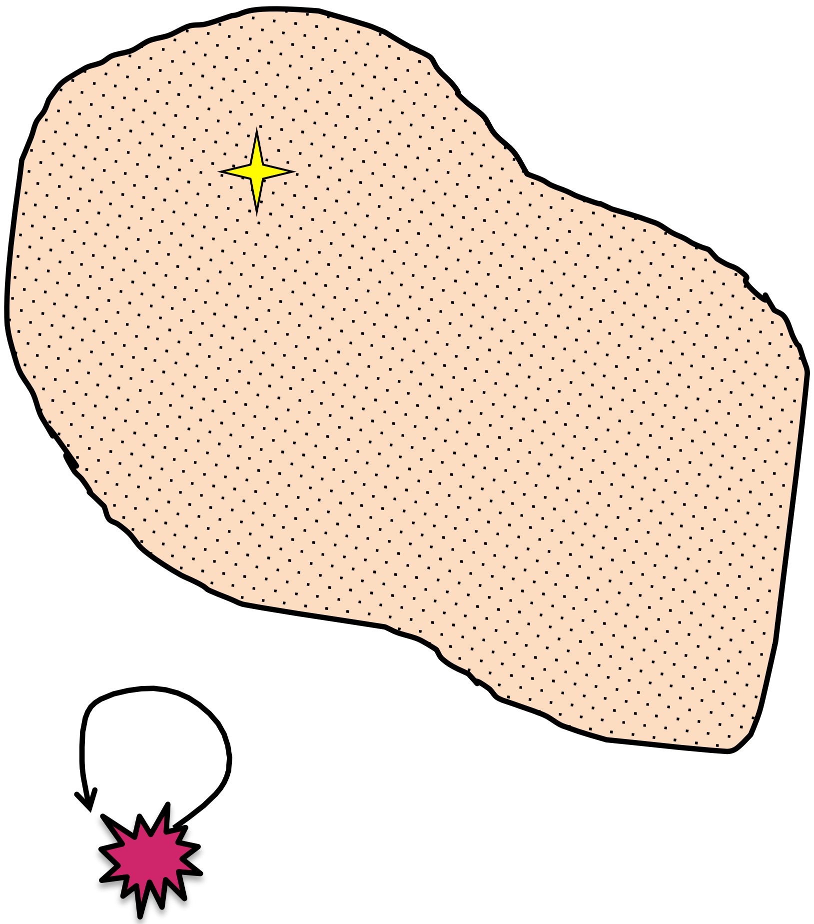
1. Achieve **metastable** locomotion



Metastable:
Not strictly stable, but exhibiting long-living behaviors. (literally, "beyond stable".)

Probabilistic framework. Want to discretize things, to use machine learning.

How to estimate MFPT???



- A single, absorbing failure state capture all failure events.

- Start with the fixed point for a given gait, on level ground.
- Create a mesh (deterministically) of reachable (Poincare) states, i.e., of snapshots at some point of the gait cycle, given some range of variability – e.g., terrain height.
- **This can be done, because a gait controller drives the dynamics to low-dimensional manifolds within the full state space.**
- Build a transition matrix, which describes the stochastic dynamics of rough terrain walking.

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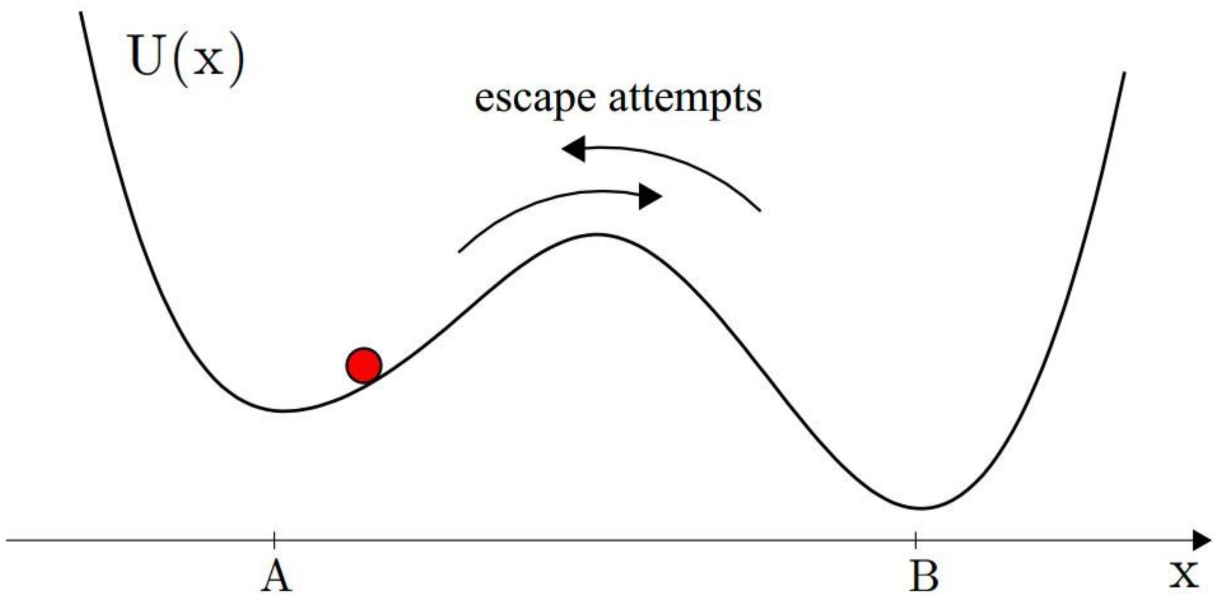
Mean first-passage time (MFPT)



$$M \approx \frac{1}{1-\lambda_2}$$

A system-wide metric

(Based on 2nd-largest eigenvalue of transition matrix.)

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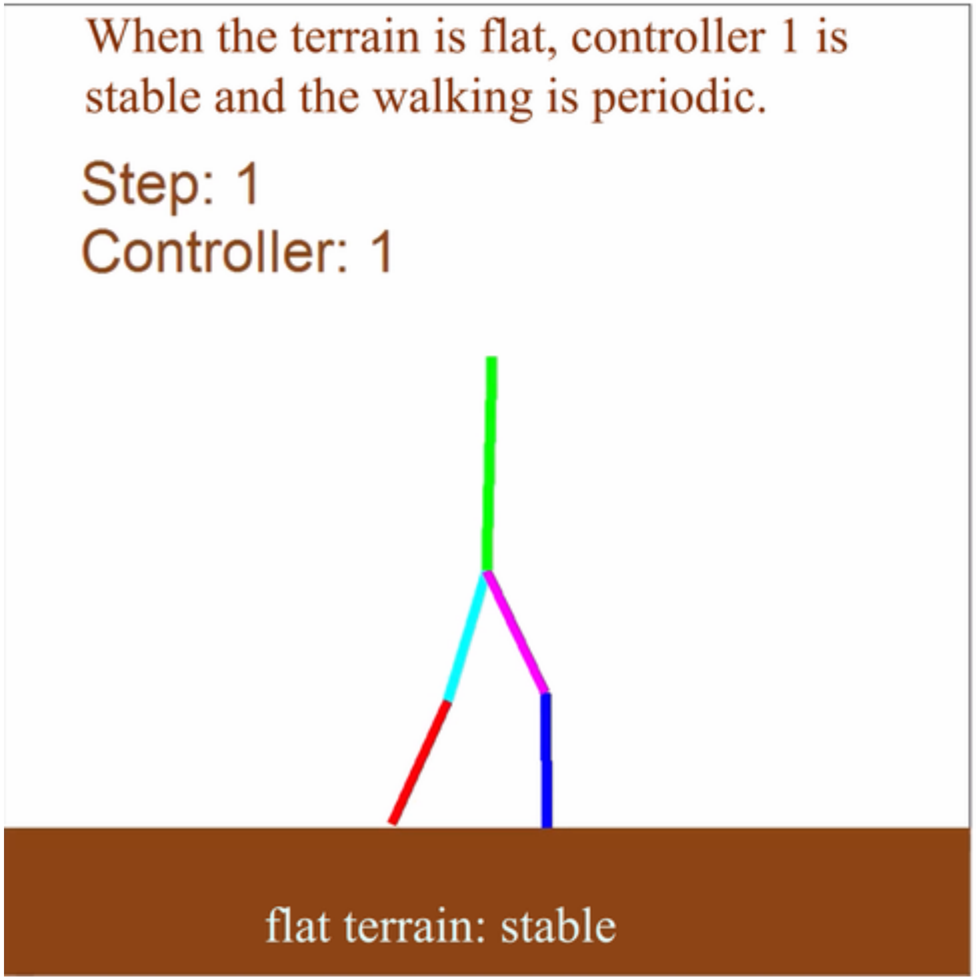
Look-ahead: known variability



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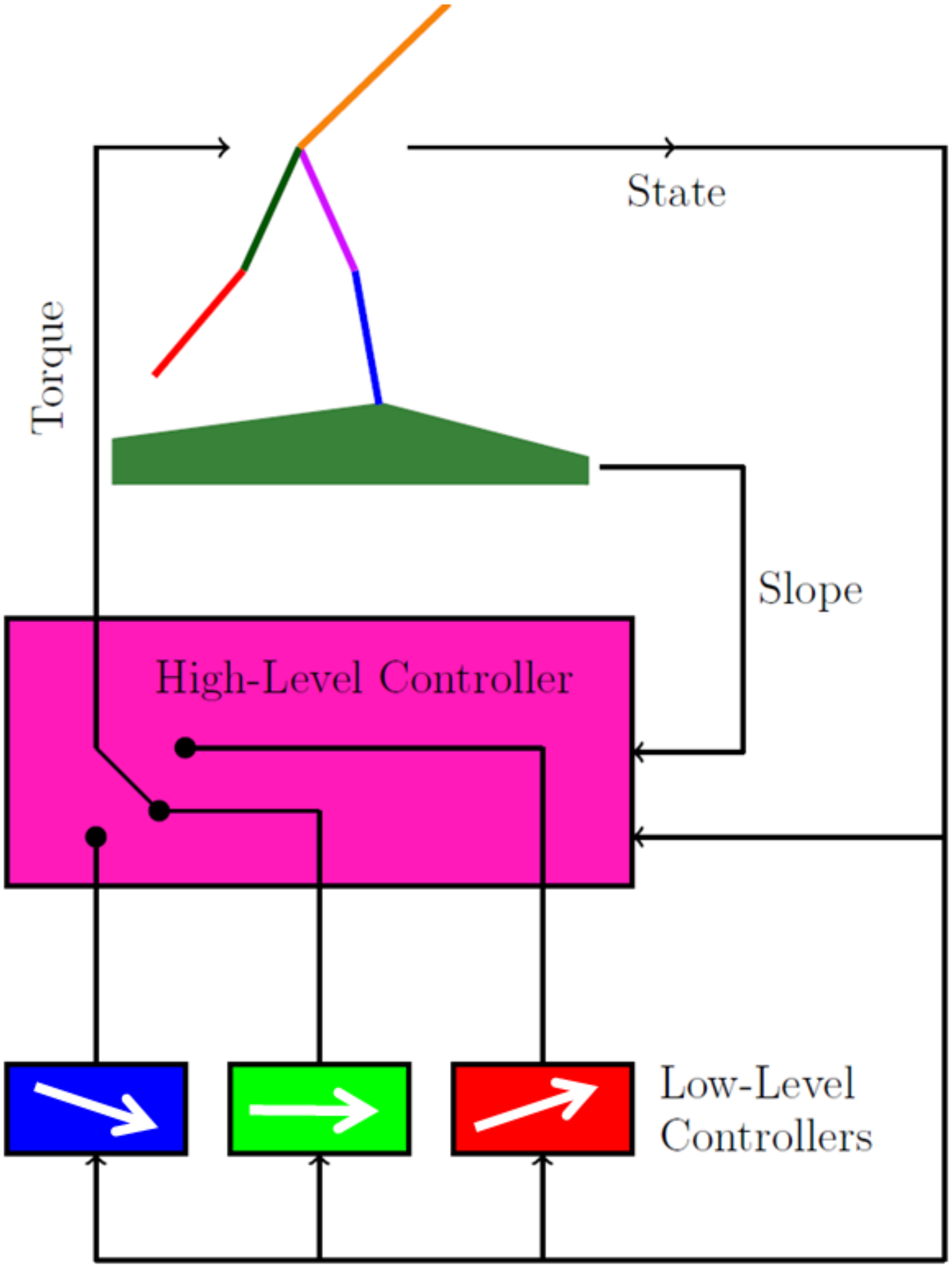

Framework

Having a robustness metric enables OPTIMIZATION! (that is pretty much the whole point…)

One can optimize:
- High-level switching control
- Parameterizations of low-level controllers
- Morphology of the robot

The high-level switching policy will be globally optimal, while other searches find locally optimal solutions.

One can optimize for a metric considering MFPT *and* energy.

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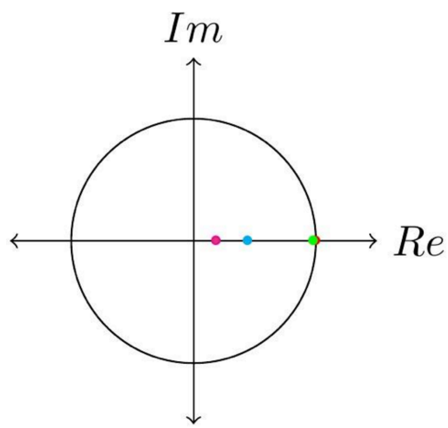
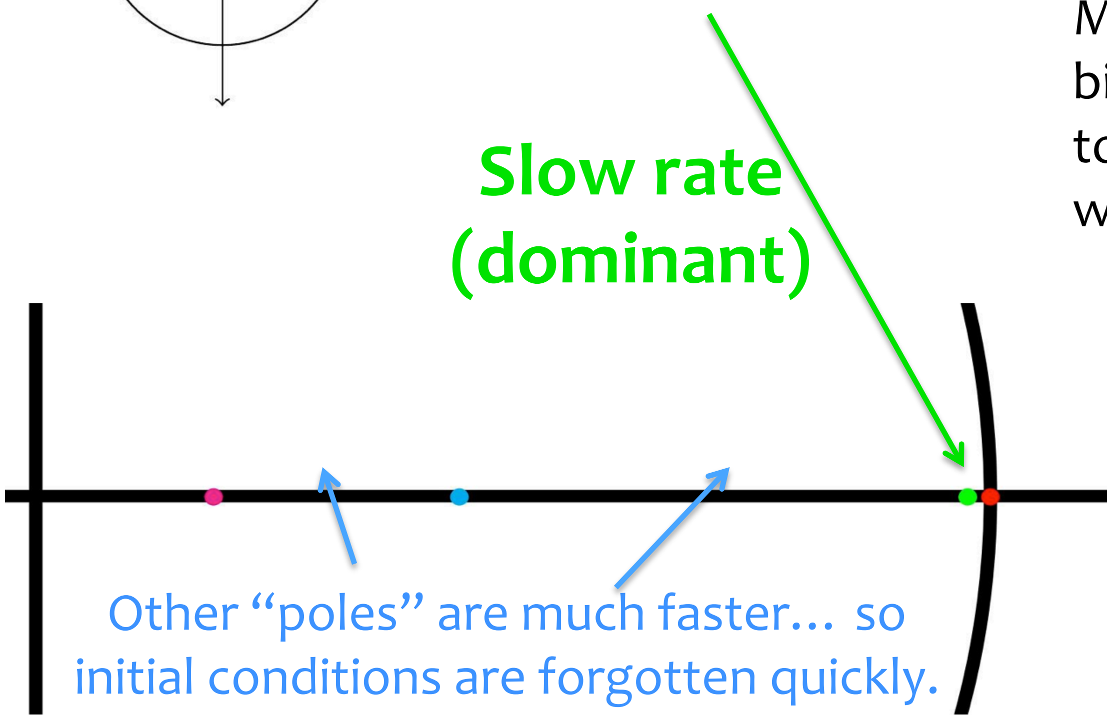
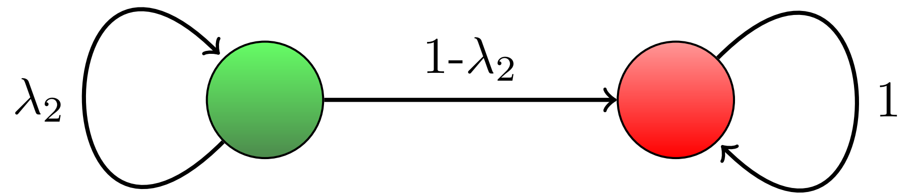
Eigenvalues: Discrete-time system



λ_2





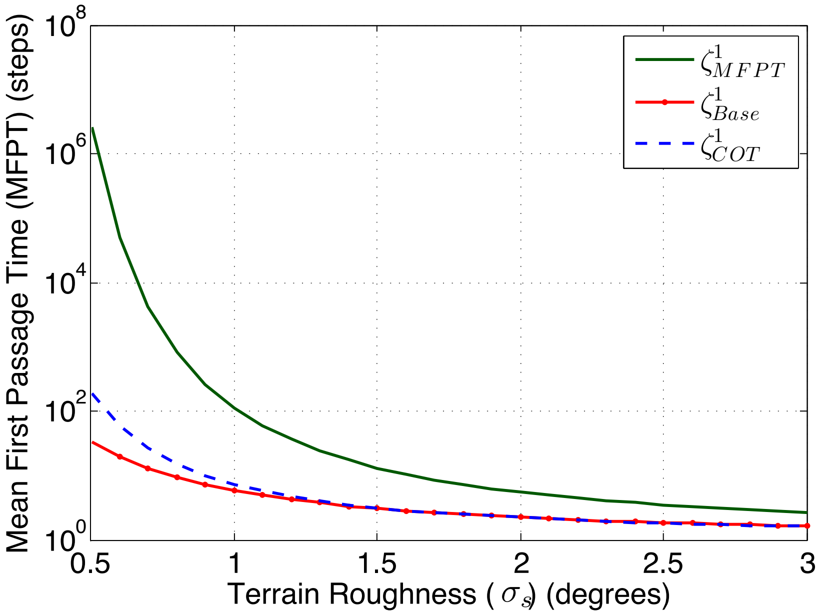
Metastable system is like a very biased coin toss: Usually returns to a metastable neighborhood, with very rare failures.

Example Benchmarking

Optimizing each of two low-level controller

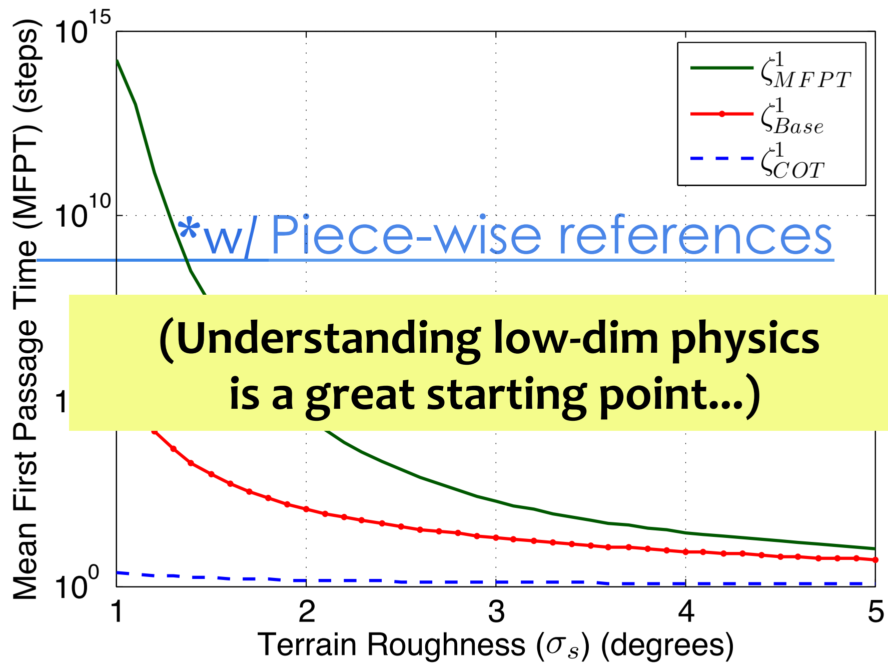
Hybrid Zero Dynamics

Grizzle et al. (Umich)



Sliding Mode Control*

Saglam and Byl (UCSB)



*w/ Piece-wise references

(Understanding low-dim physics is a great starting point...)

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Example Benchmarking

Optimizing each of two low-level controller

Hybrid Zero Dynamics

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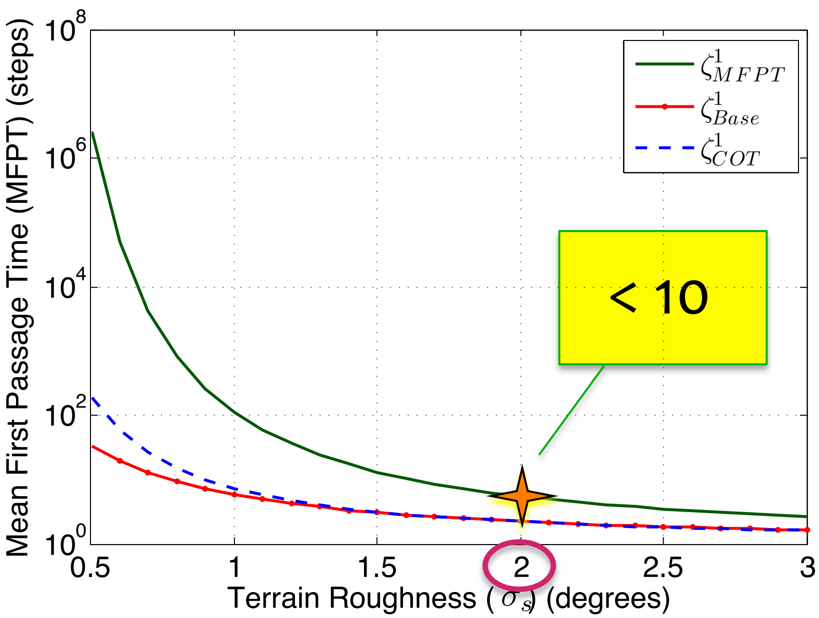
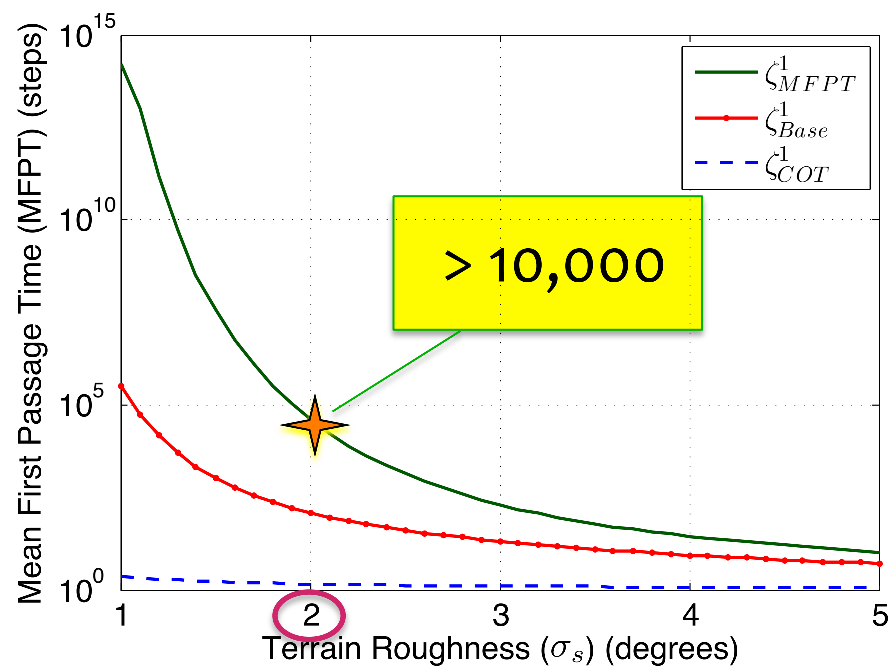


"Sliding Mode Control"

Saglam and Byl (UCSB)



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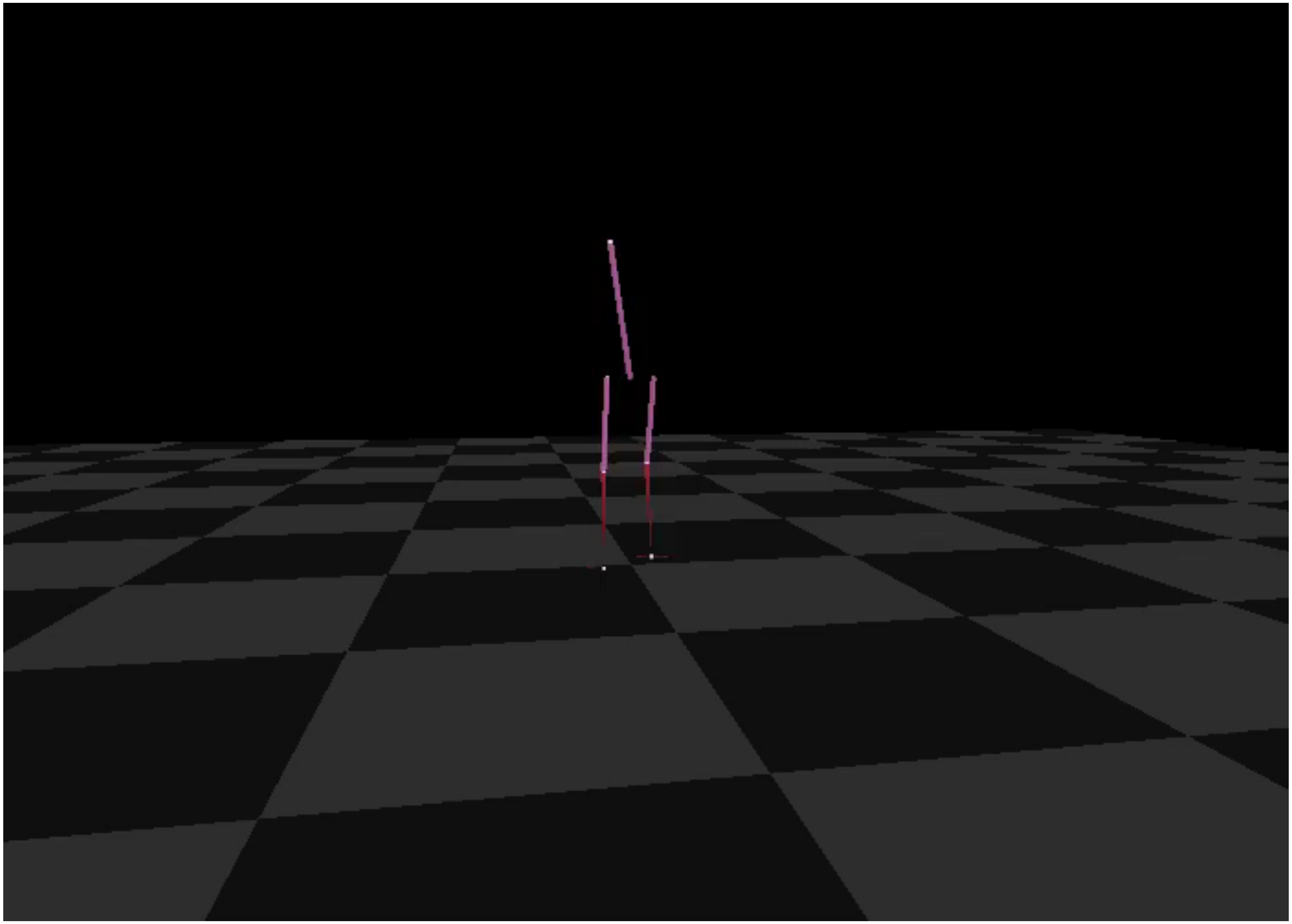
Goal is to control higher-DOF system



MuJoCo – Emo Todorov. (Thanks Emo!!)

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(Understanding low-dim physics is a great starting point...)

Reachability

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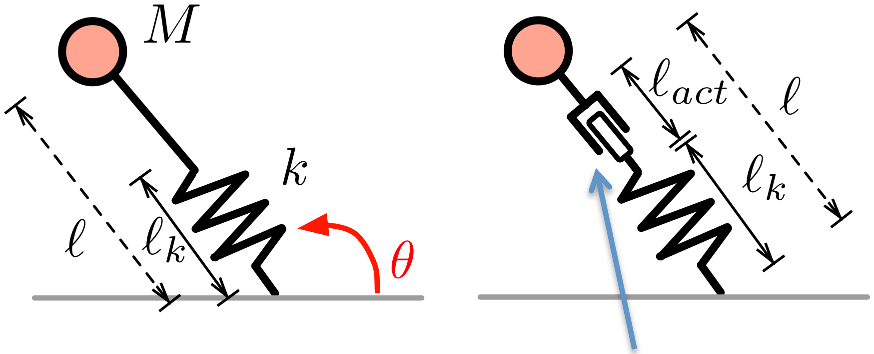
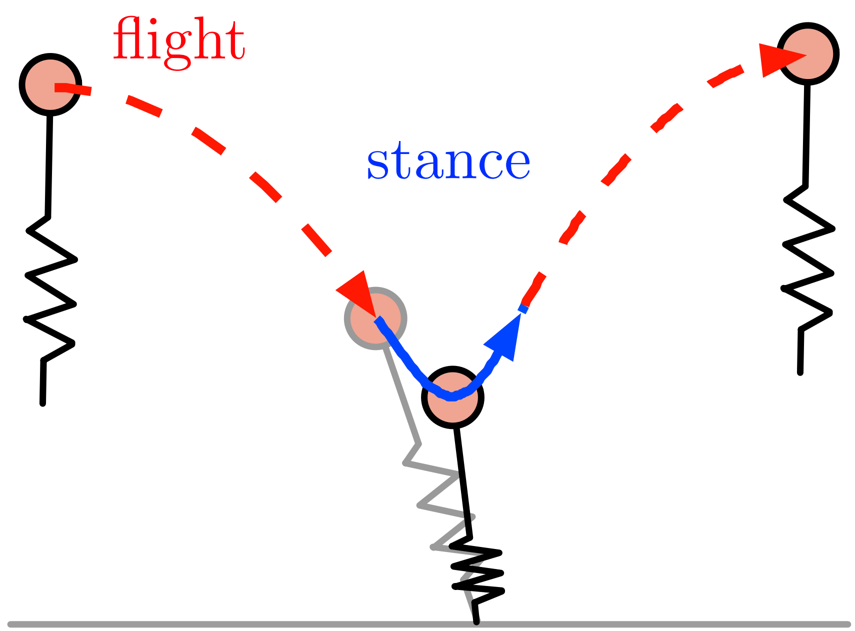
Planar Hopper Model

Motivation: enable MPC (model predictive control), by accurately steering toward desired next apex states.

- Spring-Loaded Inverted Pendulum (**SLIP**)



Passive vs **Active**



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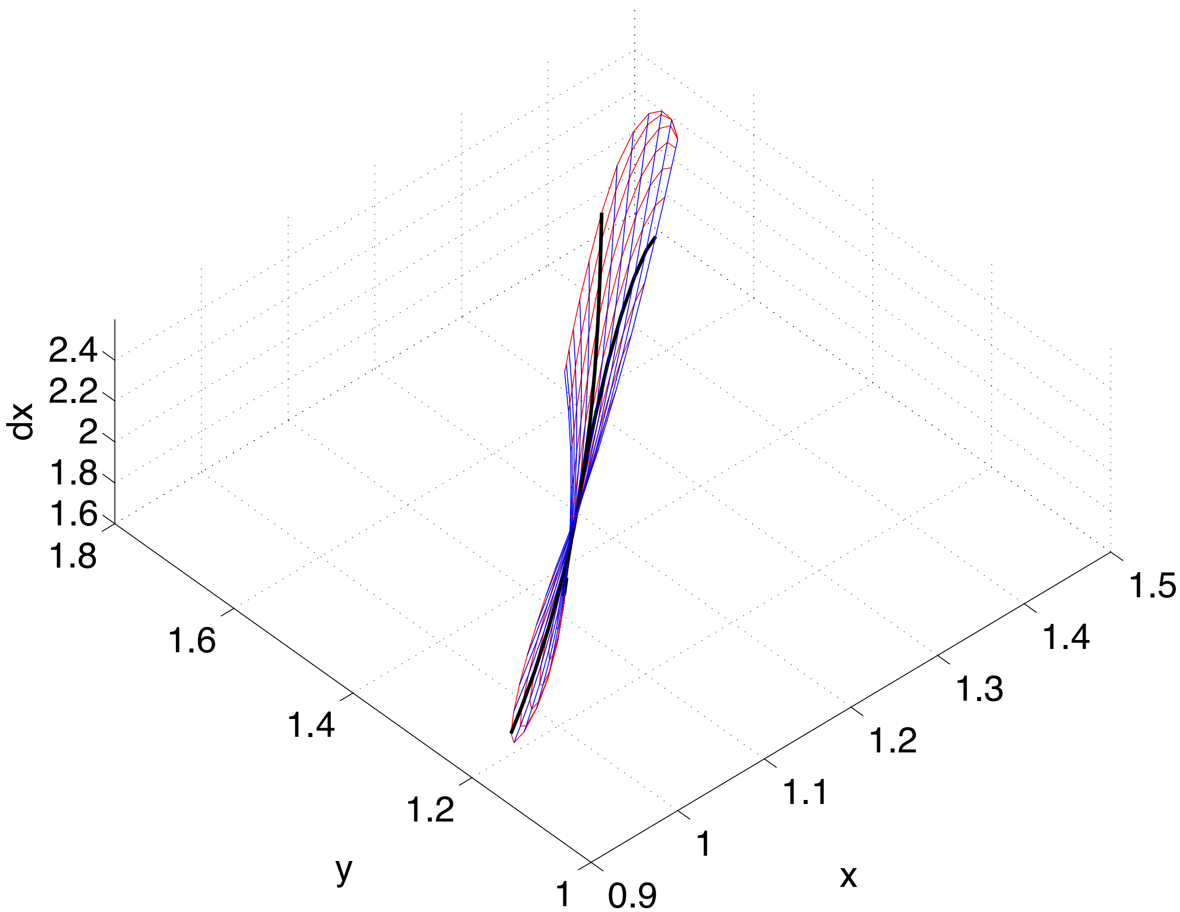
Reachable set ?



Next apex states:
dy/dt=0, leaving
x, y, and dx/dt.

Once touch-down angle is set, reachable states for a 2D set (approximately).

Spanning this region requires 2 "knobs to twiddle" in active control during stance.

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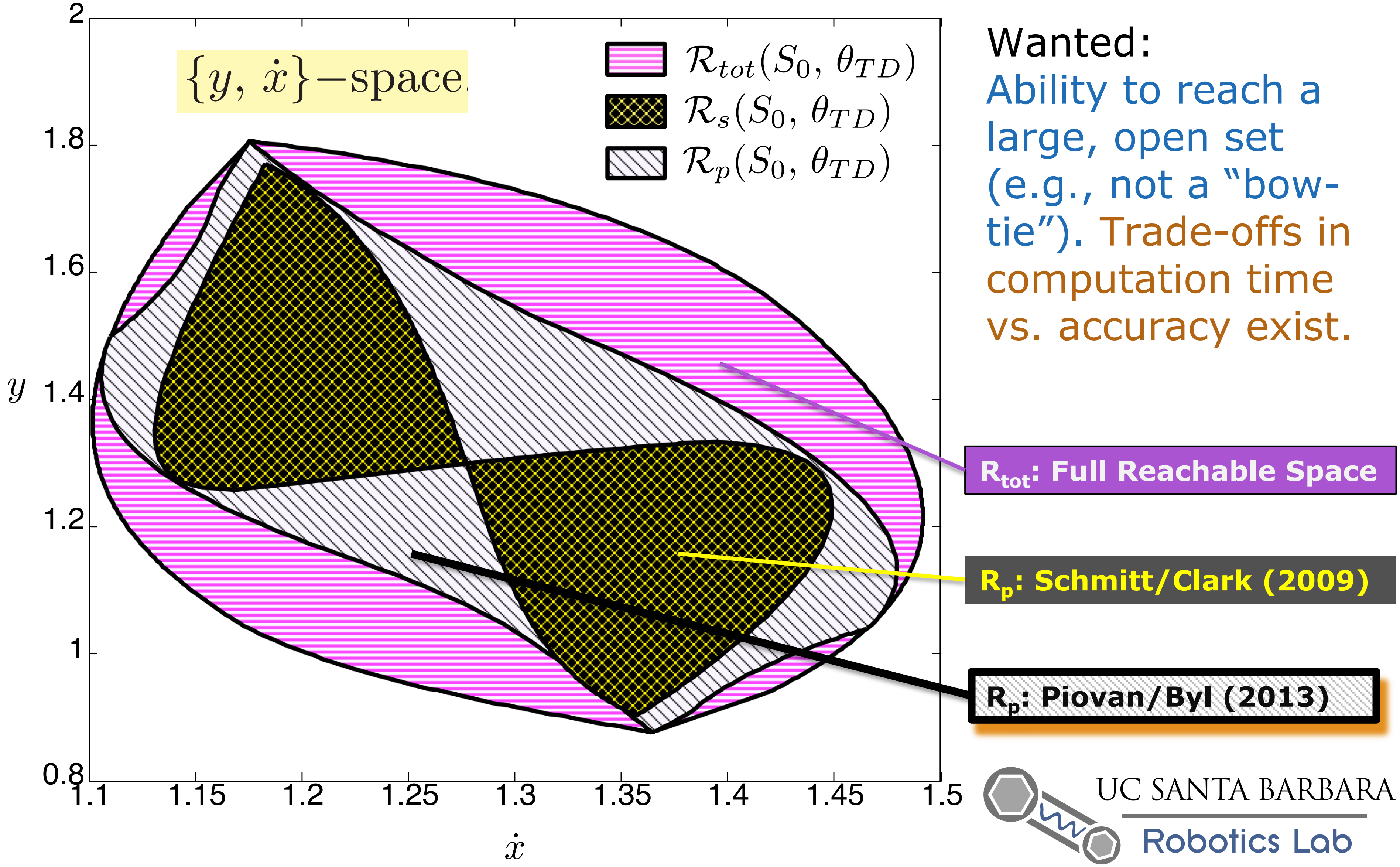
Reachability of Control Laws



Wanted:
Ability to reach a large, open set (e.g., not a "bow-tie"). Trade-offs in computation time vs. accuracy exist.

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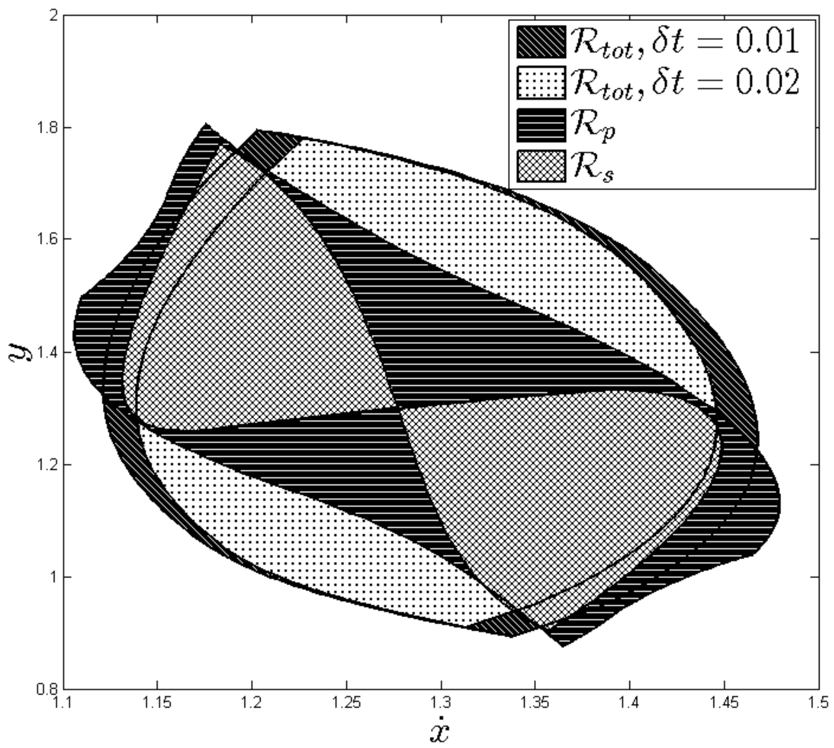
Computational Time Delay

- **Let's say we cannot act for the first dt, while initial computations are done.**
  - Motivation: We are uncertain about terrain.



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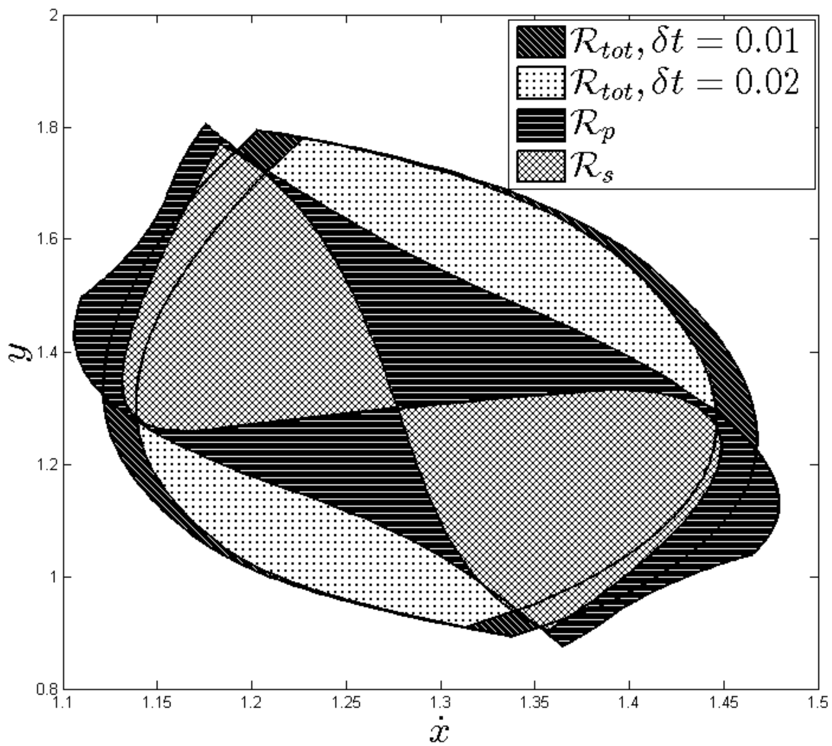
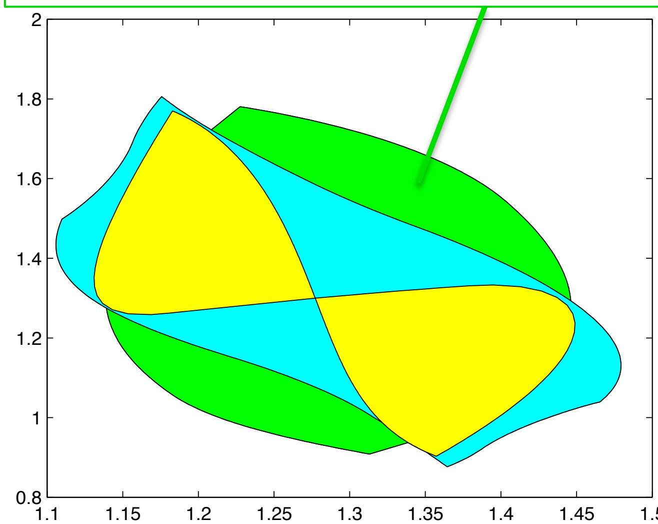


Our numeric approach (with time delay) is in green.



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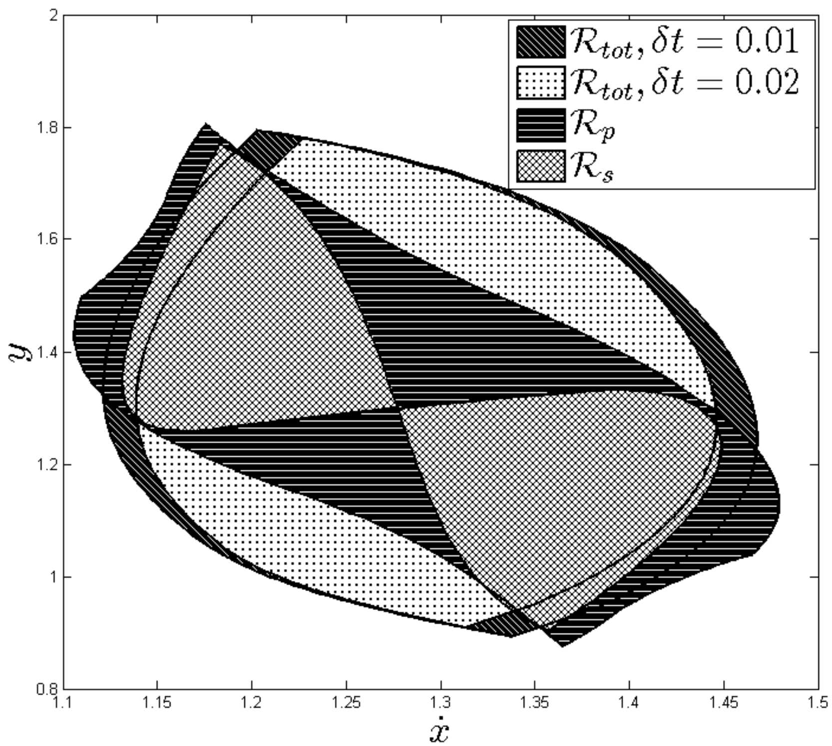

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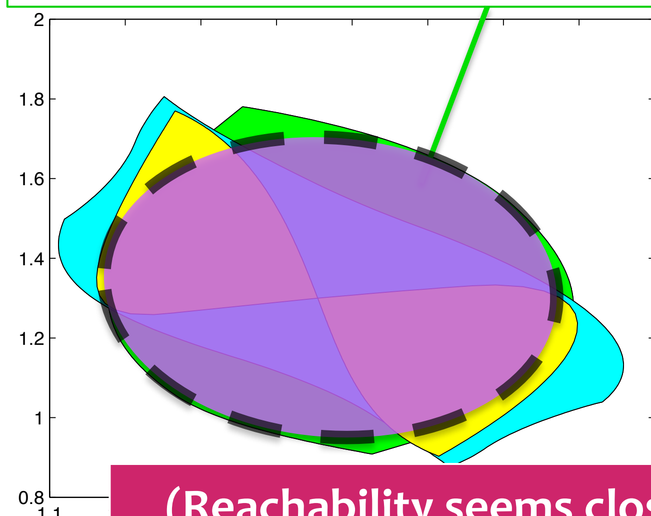

(Reachability seems closely related to "agility"... See slide 15 again.)

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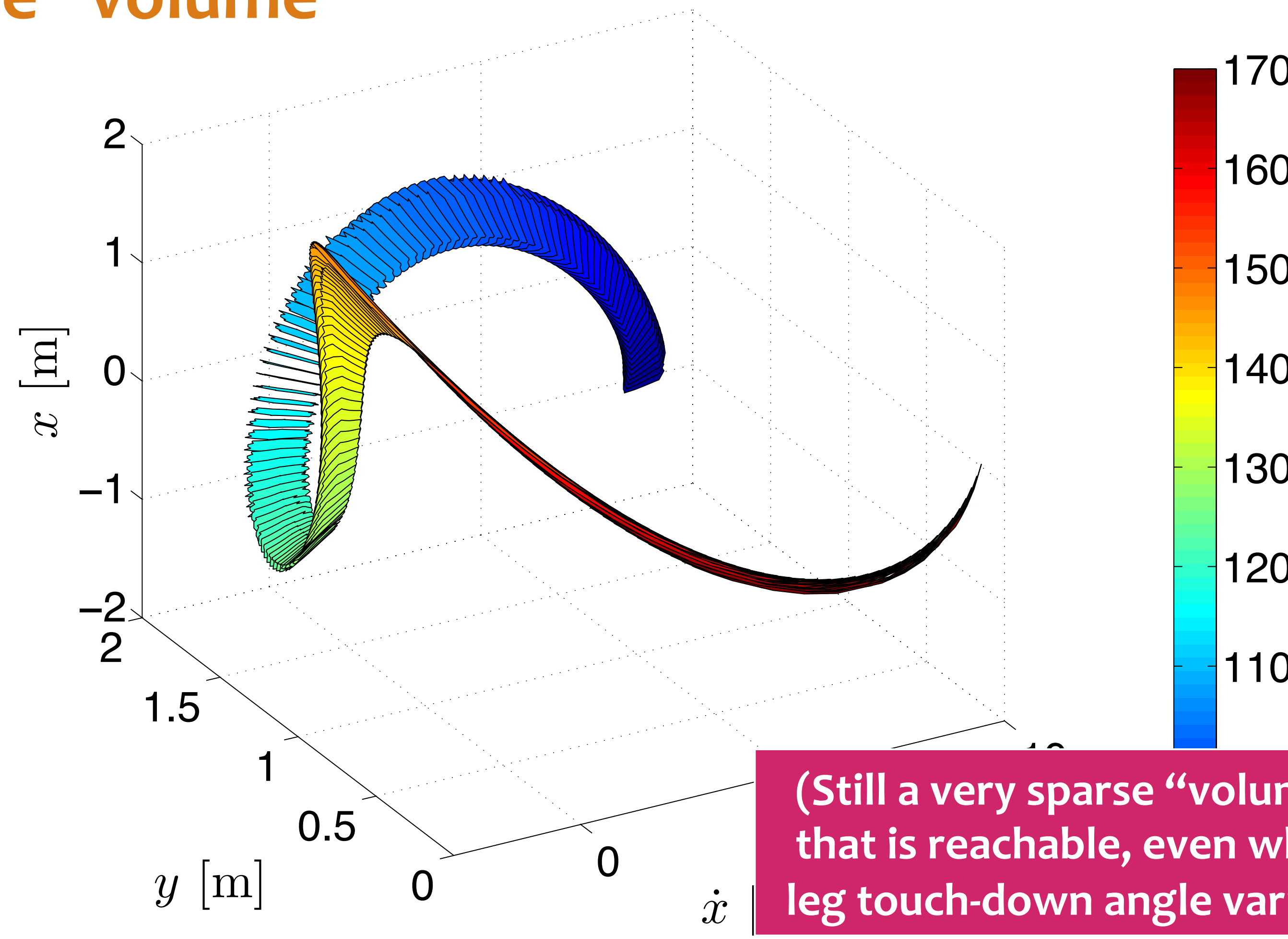
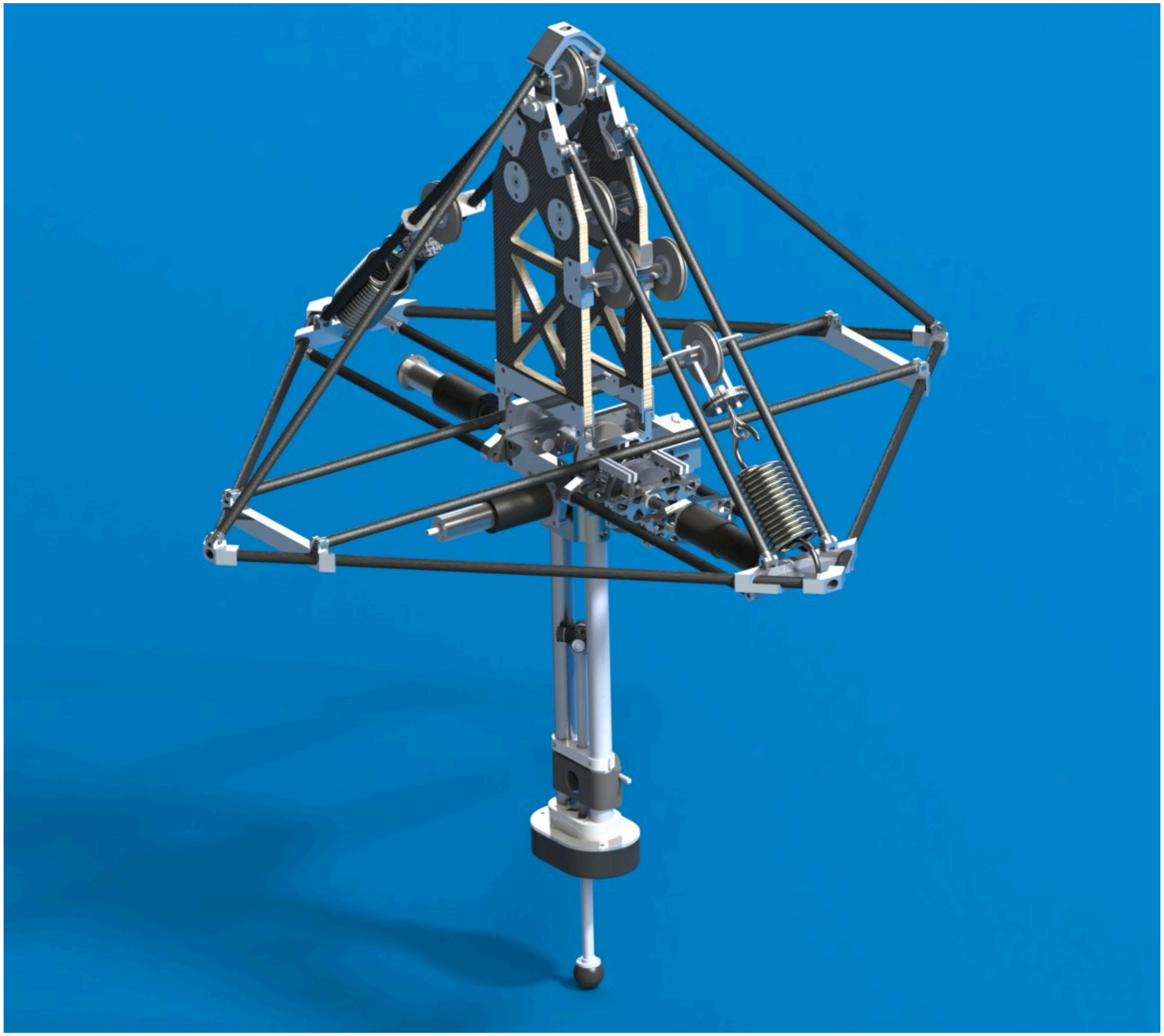
Varying touchdown angle

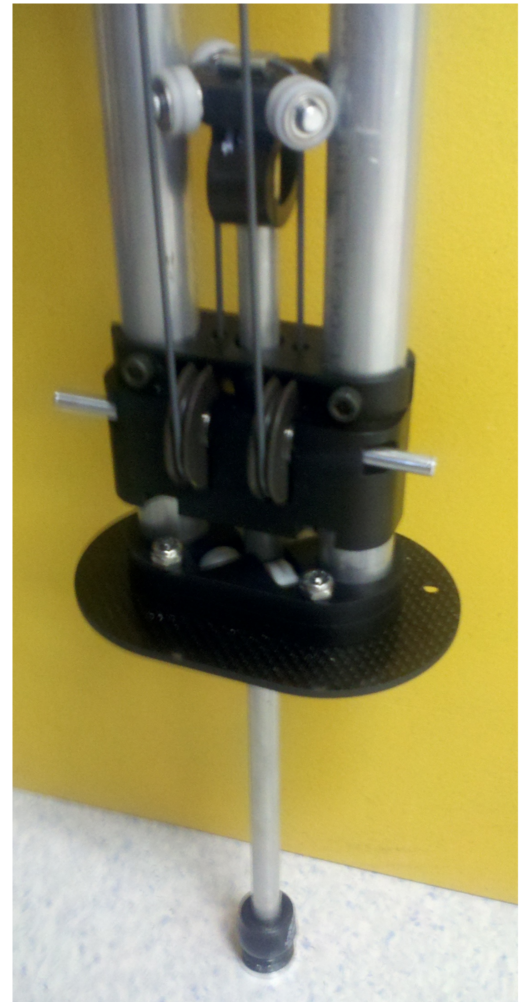
- **Reachable "volume"**



(Still a very sparse "volume" that is reachable, even when leg touch-down angle varies.)

“Hopper **C**” (Jason **C**ortell)





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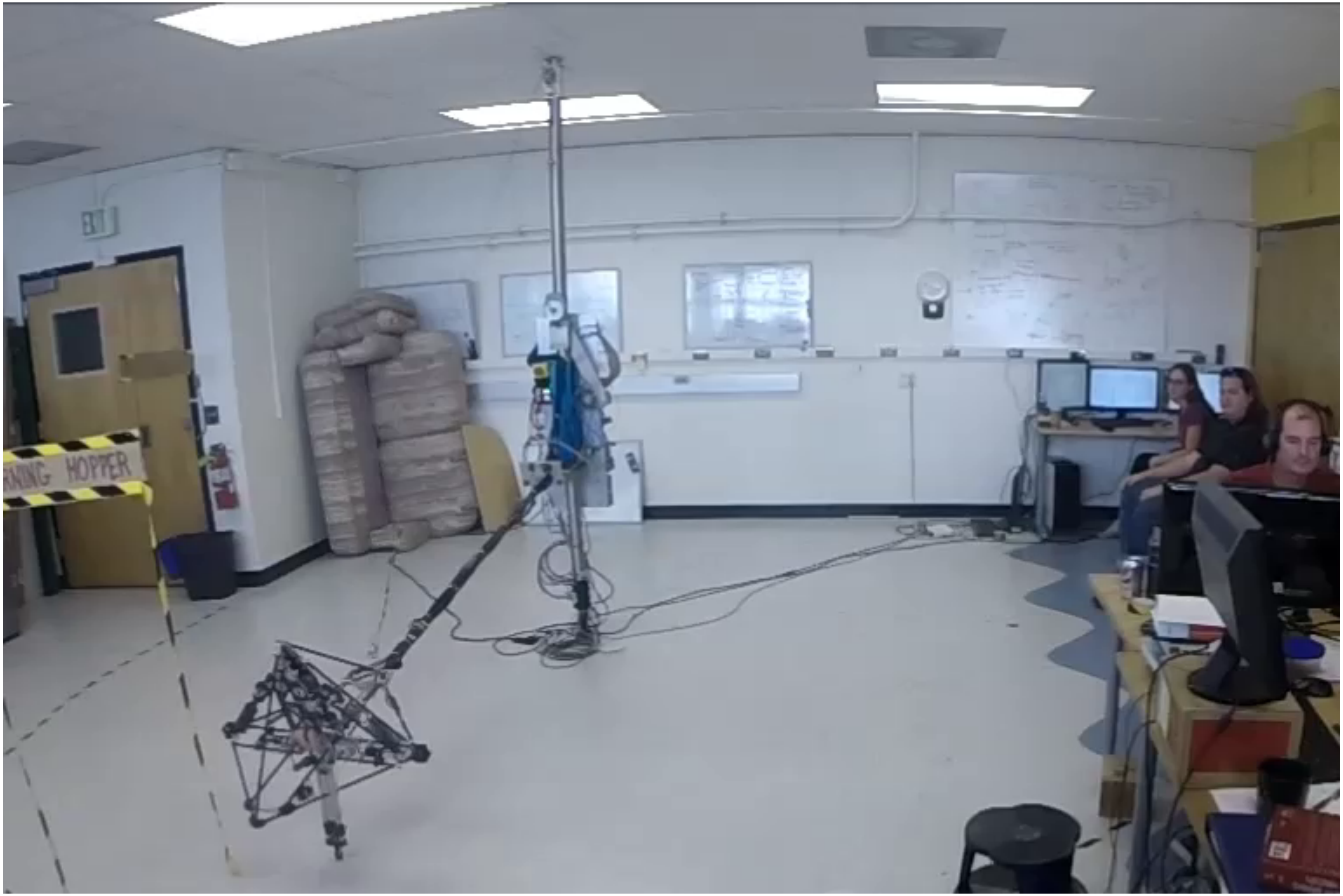

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Robustness and Agility… and the DRC?

DARPA Robotics Challenge (DRC)

- **Humanitarian Rescue, inspired by Fukushima**

DARPA ROBOTICS CHALLENGE

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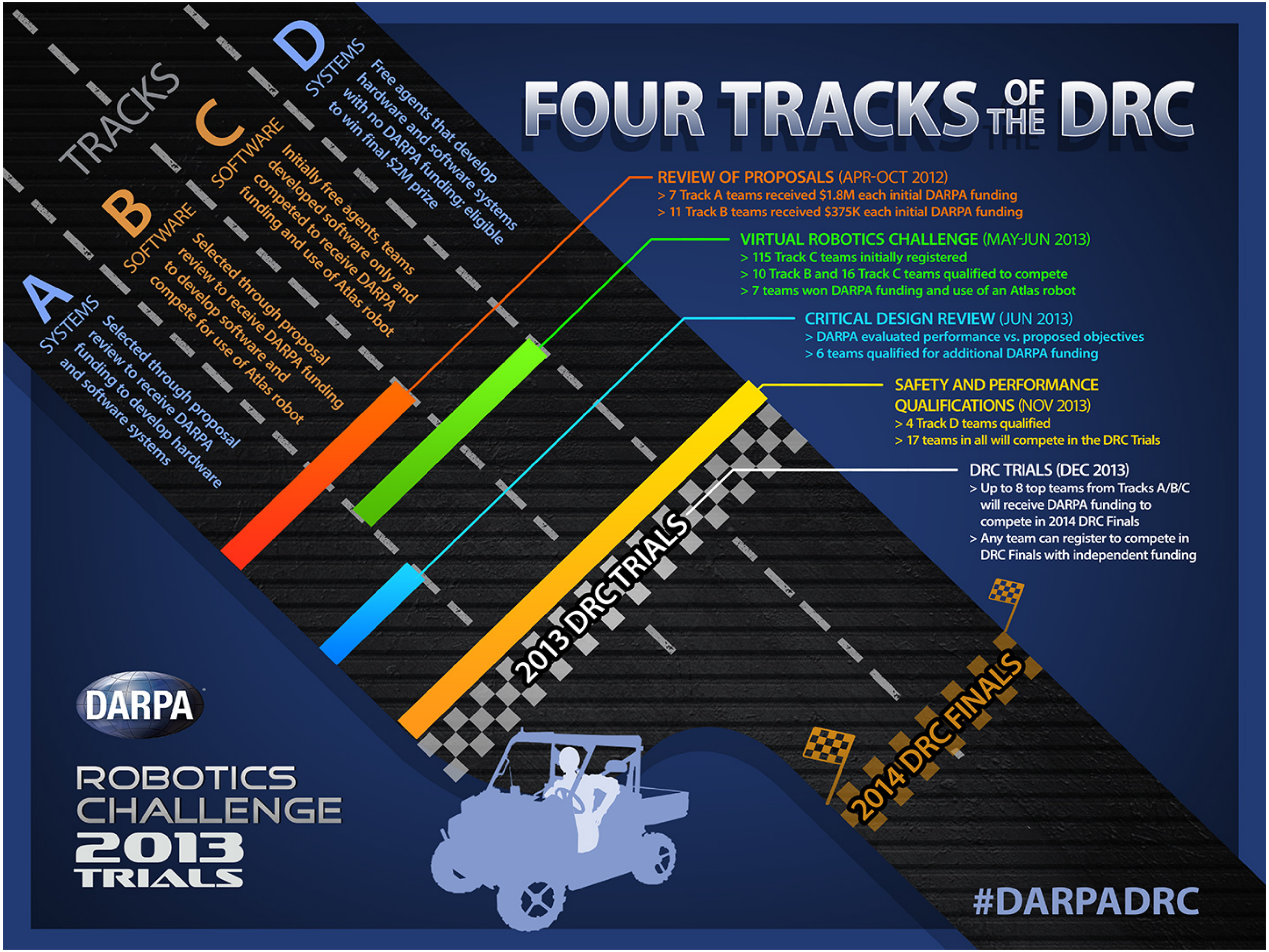
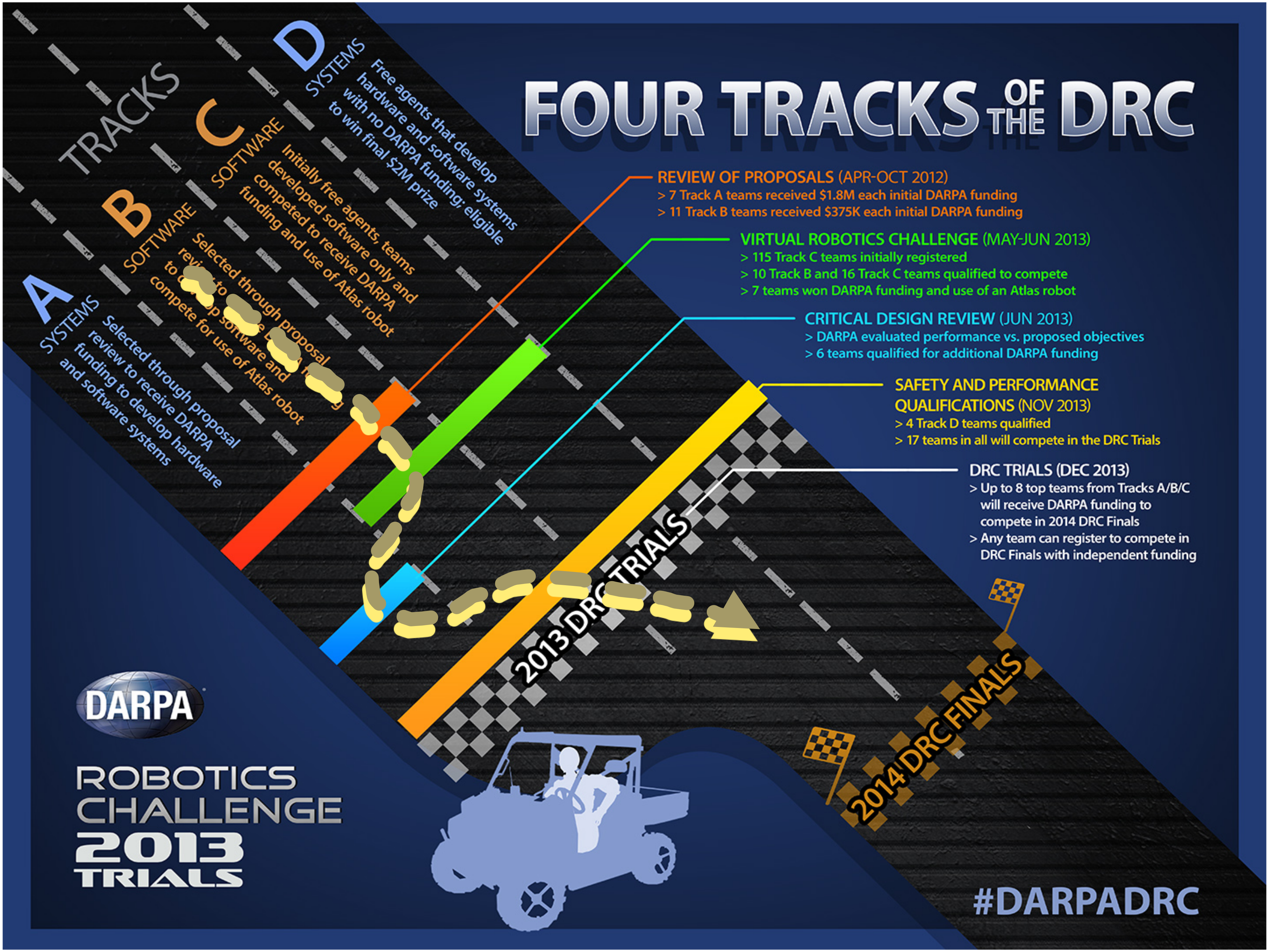

FOUR TRACKS OF THE DRC
TRACKS
A
SYSTEMS
Selected through proposal review to receive DARPA funding to develop hardware and software systems
B
SOFTWARE
Selected through proposal review to receive DARPA funding to develop software and compete for use of Atlas robot
C
SOFTWARE
Initially free agents, teams developed software only and competed to receive DARPA funding and use of Atlas robot
D
SYSTEMS
Free agents that develop hardware and software systems with no DARPA funding; eligible to win final $2M prize
REVIEW OF PROPOSALS (APR-OCT 2012)
> 7 Track A teams received $1.8M each initial DARPA funding
> 11 Track B teams received $375K each initial DARPA funding
VIRTUAL ROBOTICS CHALLENGE (MAY-JUN 2013)
> 115 Track C teams initially registered
> 10 Track B and 16 Track C teams qualified to compete
> 7 teams won DARPA funding and use of an Atlas robot
CRITICAL DESIGN REVIEW (JUN 2013)
> DARPA evaluated performance vs. proposed objectives
> 6 teams qualified for additional DARPA funding
SAFETY AND PERFORMANCE QUALIFICATIONS (NOV 2013)
> 4 Track D teams qualified
> 17 teams in all will compete in the DRC Trials
DRC TRIALS (DEC 2013)
> Up to 8 top teams from Tracks A/B/C will receive DARPA funding to compete in 2014 DRC Finals
> Any team can register to compete in DRC Finals with independent funding
2013 DRC TRIALS
2014 DRC FINALS
DARPA
ROBOTICS CHALLENGE 2013 TRIALS
#DARPADRC



FOUR TRACKS OF THE DRC
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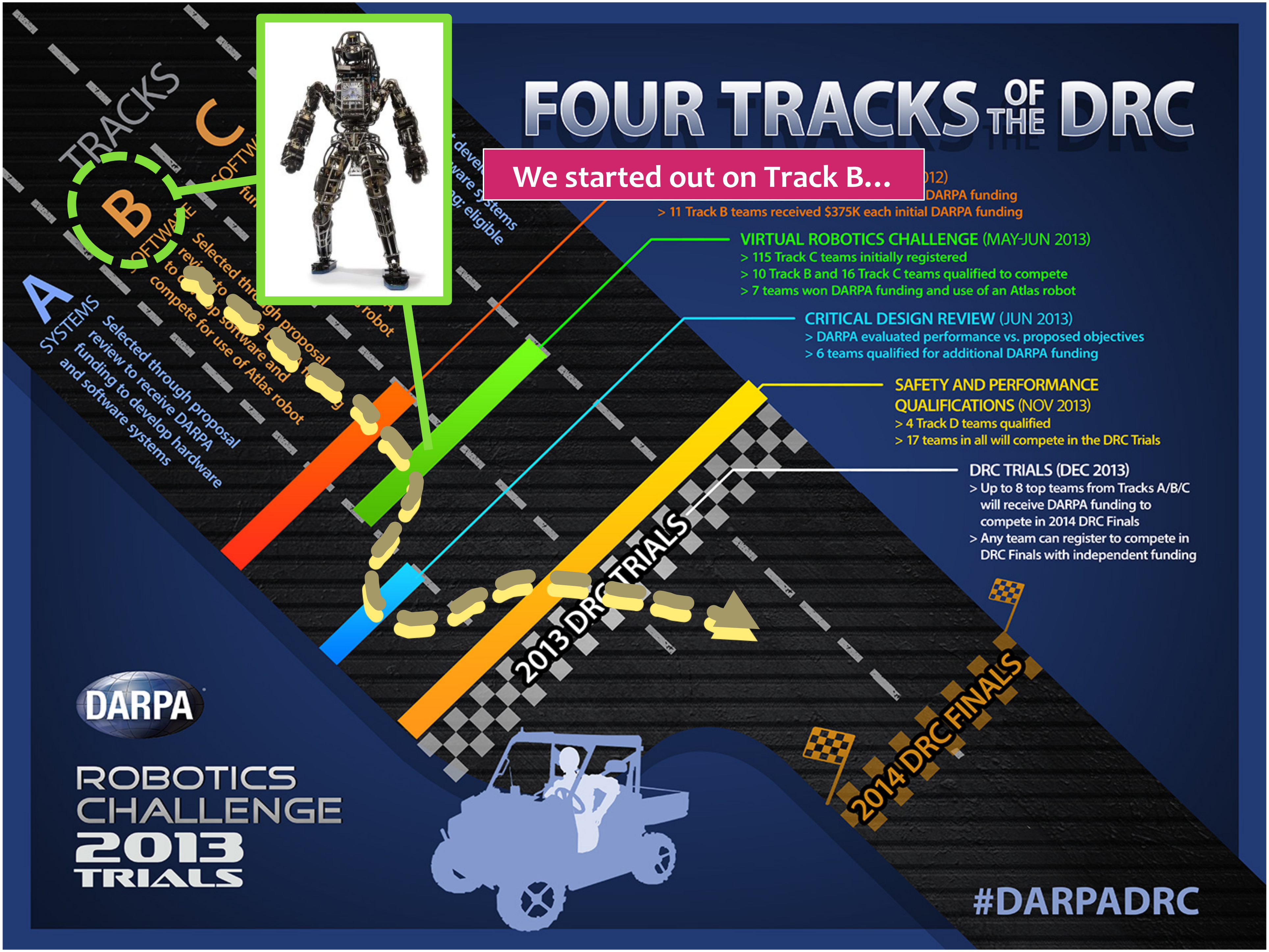

FOUR TRACKS OF THE DRC
We started out on Track B…
TRACKS
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Selected through proposal review to receive DARPA funding to develop hardware and software systems
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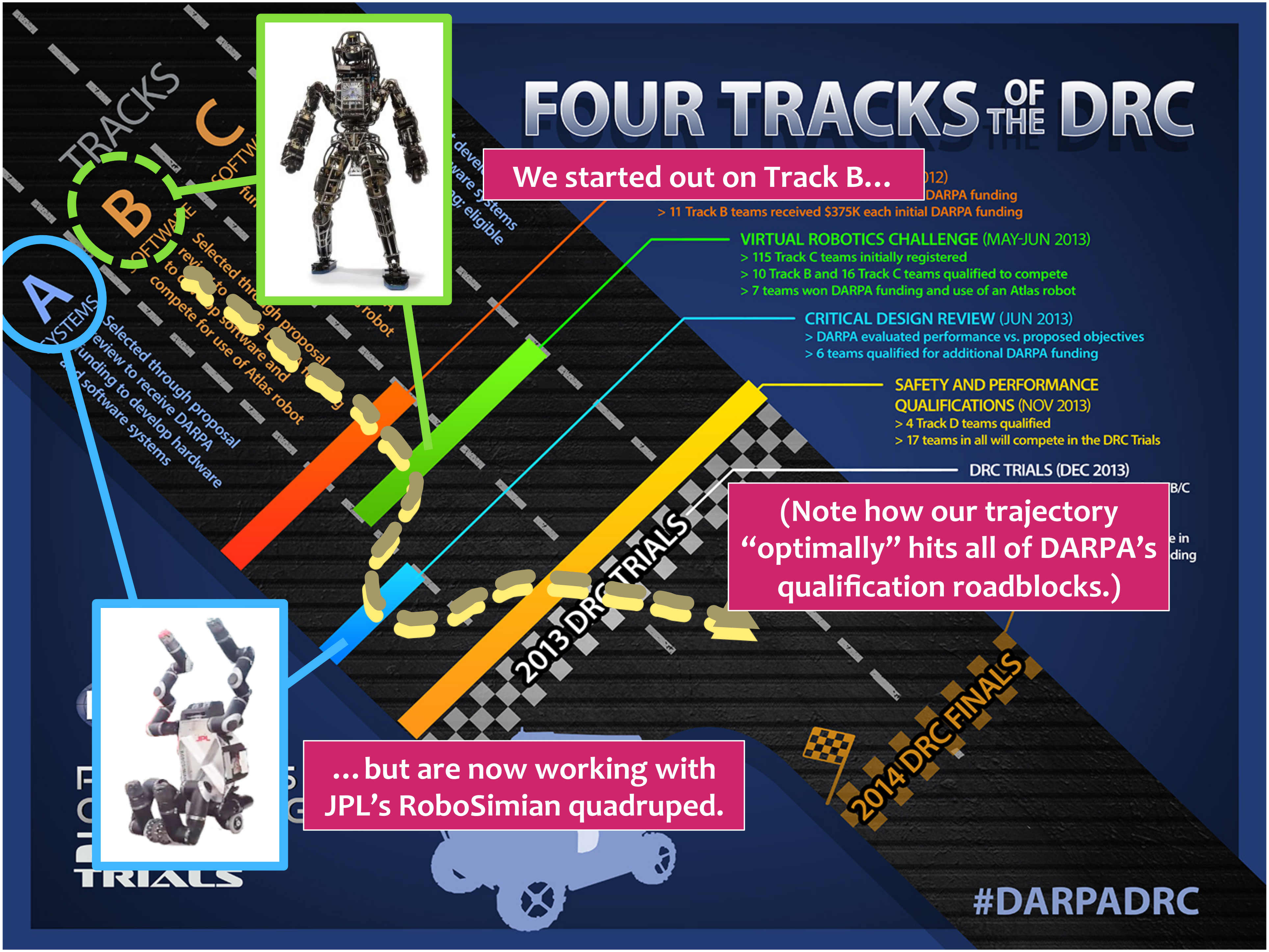
ROBOTICS CHALLENGE 2013 TRIALS
#DARPADRC


FOUR TRACKS OF THE DRC
We started out on Track B…
> 11 Track B teams received $375K each initial DARPA funding
VIRTUAL ROBOTICS CHALLENGE (MAY-JUN 2013)
> 115 Track C teams initially registered
> 10 Track B and 16 Track C teams qualified to compete
> 7 teams won DARPA funding and use of an Atlas robot
CRITICAL DESIGN REVIEW (JUN 2013)
> DARPA evaluated performance vs. proposed objectives
> 6 teams qualified for additional DARPA funding
SAFETY AND PERFORMANCE QUALIFICATIONS (NOV 2013)
> 4 Track D teams qualified
> 17 teams in all will compete in the DRC Trials
DRC TRIALS (DEC 2013)
(Note how our trajectory "optimally" hits all of DARPA's qualification roadblocks.)
A SYSTEMS
Selected through proposal review to receive DARPA funding to develop hardware and software systems
B SOFTWARE
Selected through proposal review to develop software and compete for use of Atlas robot
TRACKS
C
2013 DRC TRIALS
2014 DRC FINALS
…but are now working with JPL's RoboSimian quadruped.
TRIALS
#DARPADRC

RoboSimian

JPL
Jet Propulsion Laboratory
California Institute of Technology

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DARPA
ROBOTICS
CHALLENGE

Asides on DRC Status

- RoboSimian's design is robust on variable terrain. As for agility: dexterous 7-DOF limbs are slow.
- JPL's approach/viewpoint (with DARPA)
  - Not trying to "game things"
  - Trying to keep "in the spirit DARPA intends"
- High robotics personnel turn-over lately…
  - Google, Apple, etc. hiring a lot of roboticists lately

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And a *really* quick update…

RoboSimian: Coping with Variability

- End-on-contact limb trajectories; then replan.
- Lot of pre-processing (e.g., kinematics):
  - IK tables map 3-DOF location (x,y,z) of end effector to 7-DOF joint solution.
  - Solutions give efficient/fast motions.
  - Designed for minimal collisions due to uncertainty.
- Very strong hands are *very* useful (occasionally).
- For very complex mobility, we're NOT generalizing "behaviors" – instead trying to demonstrate robot capabilities.

R2T2, at UCSB: Going Up...

7x true speed.

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R2T2, at UCSB: ...and Down.

7x true speed.

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IK Tables Alone – Fast Walk

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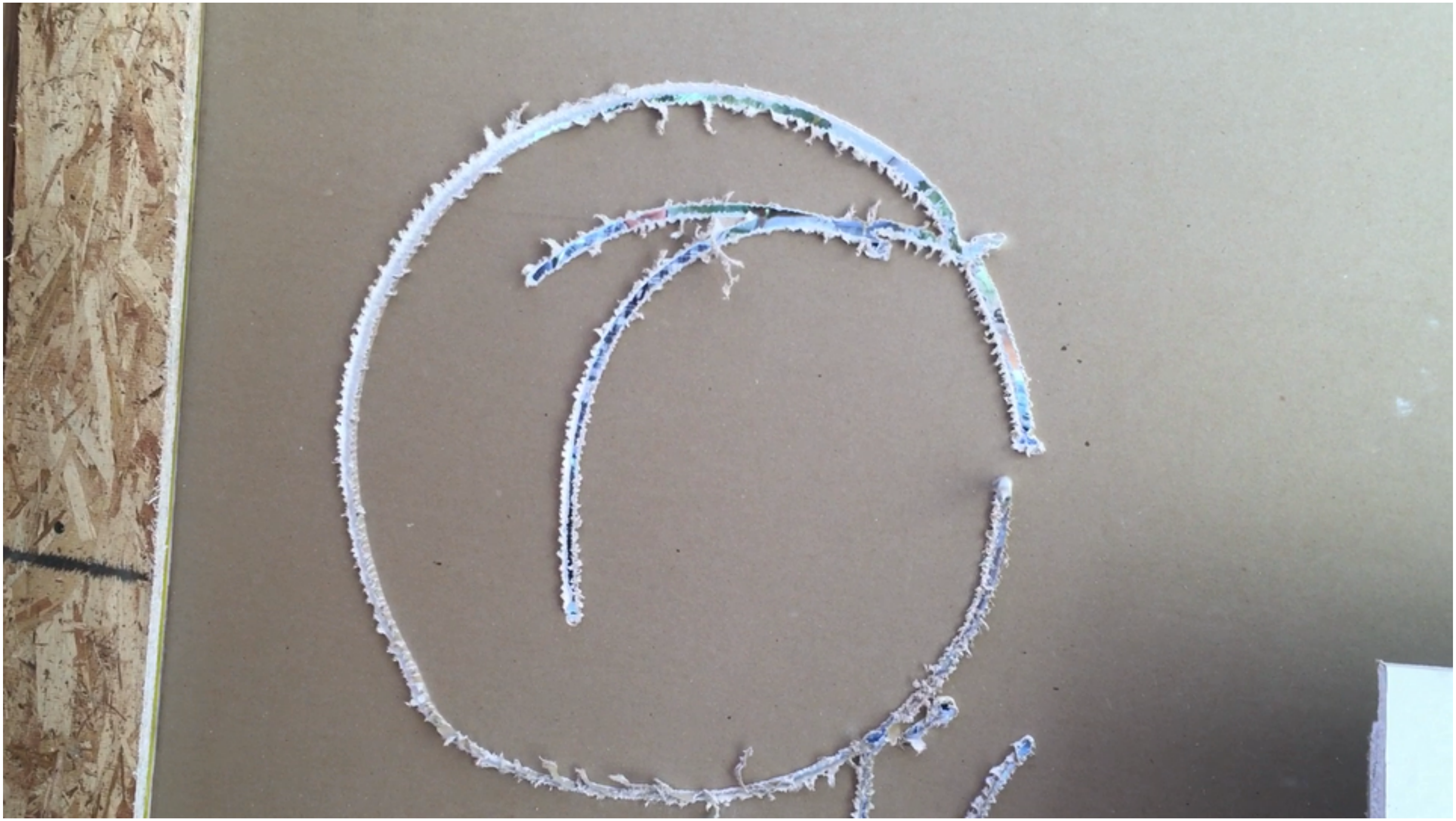
More RoboSimian



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More RoboSimian

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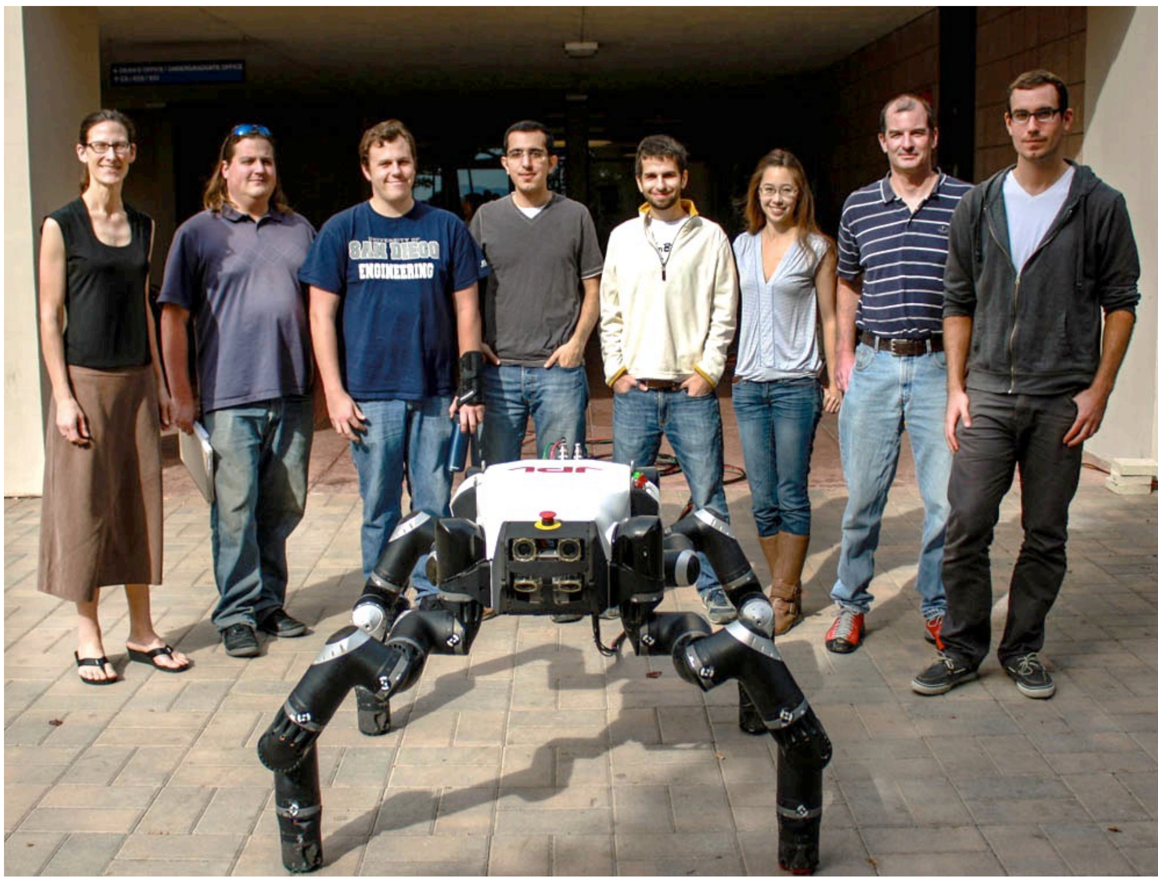

Katie Byl

UCSB

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More Rabbit Agility

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Other metrics of interest

How do we quantify:

- Terrain challenge / complexity ?