Reflections on Safety and Artificial Intelligence

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Exploratory Technical Workshop on Safety and Control for AI
Carnegie Mellon University

Pittsburgh, PA
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AI & Safety

Constellation of methods referred to as Artificial Intelligence will touch our lives more closely and intimately

AI moving into high-stakes applications

Healthcare
Transportation
Finance
Public policy
Defense

→ Much to do on principles, methods, and best practices

Relevance of Multiple Subdisciplines

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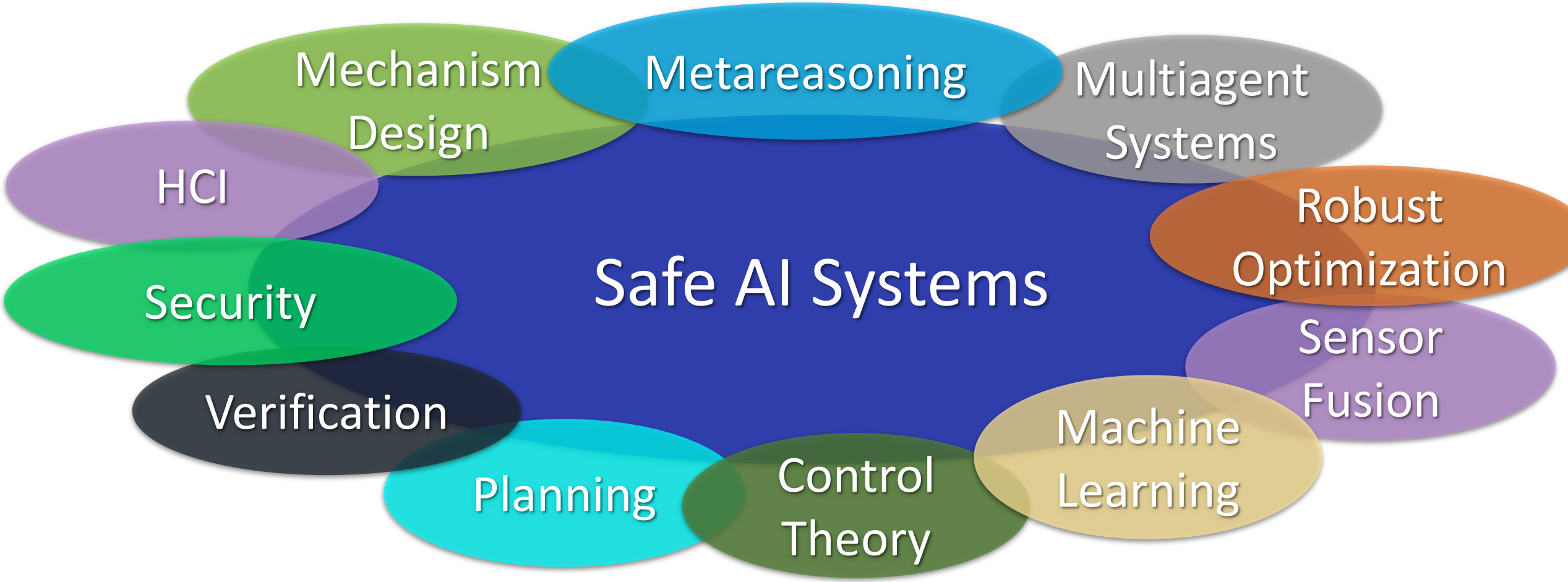

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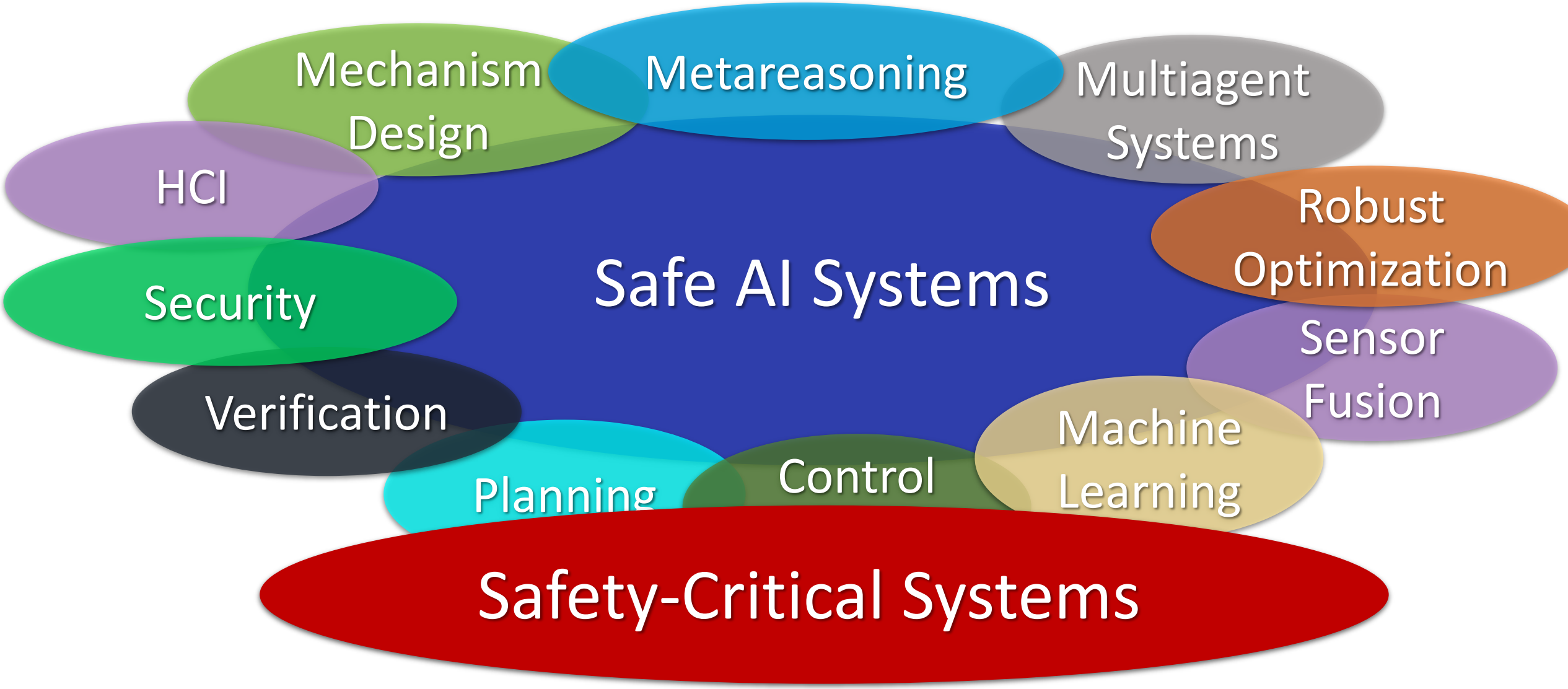


safety

ˈsāftē/

noun

1. the condition of being protected from or unlikely to cause danger, risk, or injury

safety-critical ˈsāftēˌkridək(ə)l/

adjective

1. systems whose failure could result in loss of life, significant property damage, or damage to the environment.

2. designed or needing to be fail-safe for safety purposes.

fail-safe \ˈfāl-ˌsāf\

noun

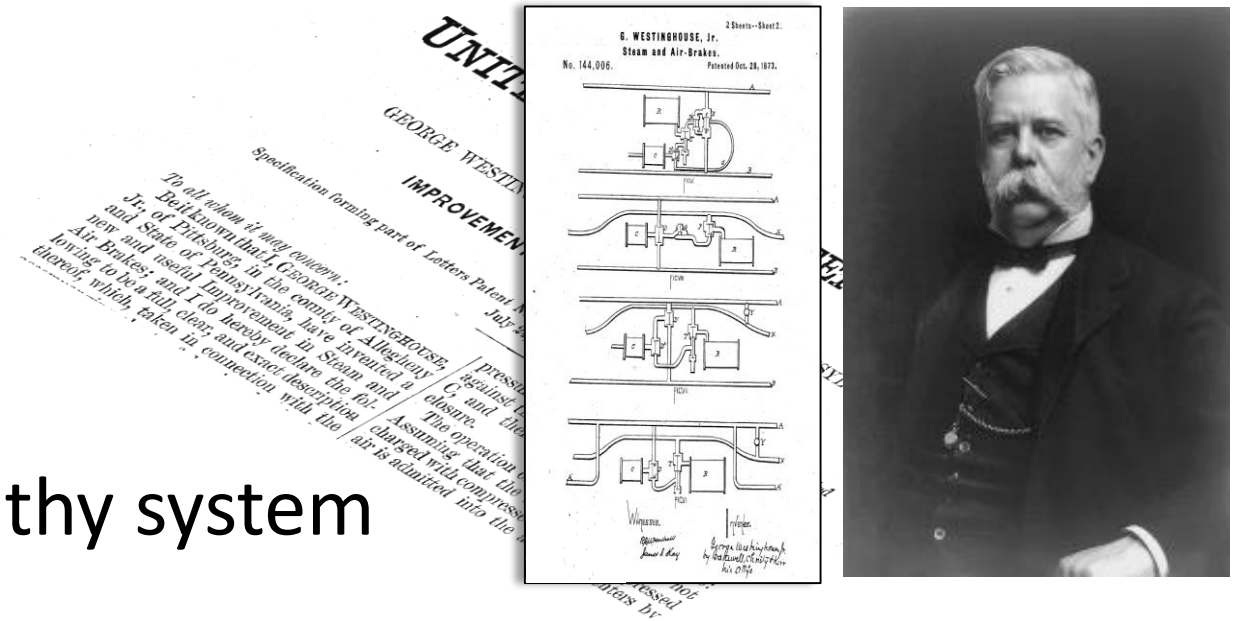
device or practice that, in the event of a failure, responds or results in a way that will cause no harm, or at least minimizes harm.

adjective

incorporating some feature for automatically counteracting the effect of an anticipated possible source of failure

Fail-safe

George Westinghouse, 1869
Train braking system



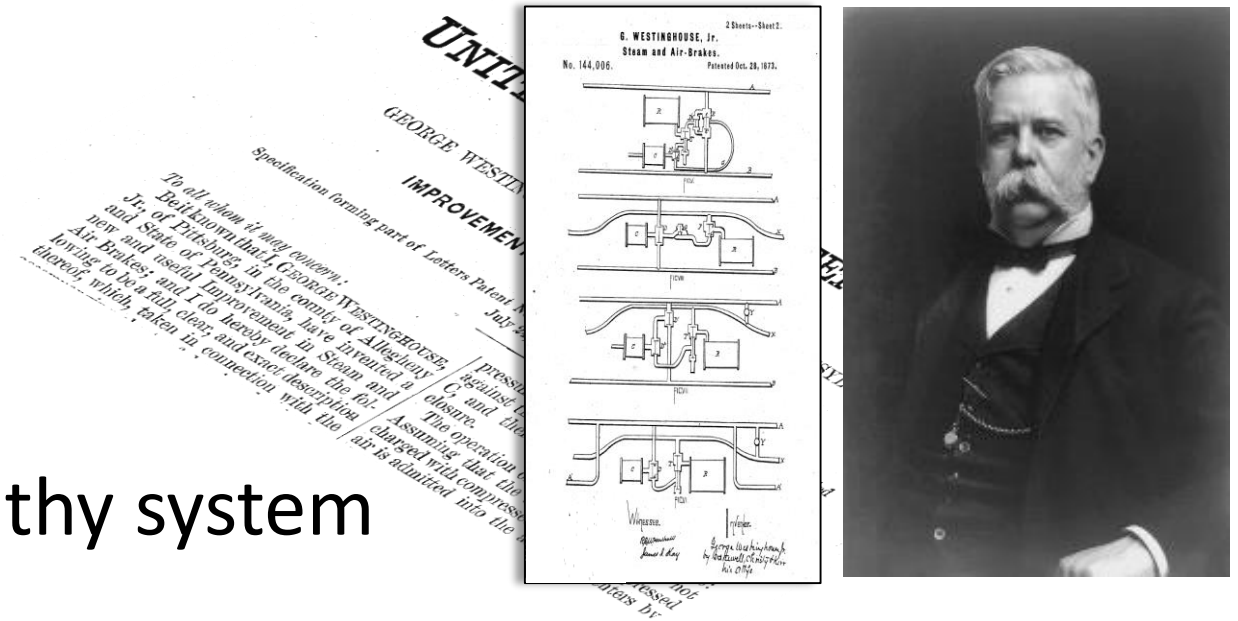
Brakes held "off" actively by healthy system

Brakes naturally resort to “on” if any failure of braking system

Fail-safe design
Air brakes

Fail-safe

George Westinghouse, 1869
Train braking system



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Fail-safe practice
Full-power throttle on arrested landing

Fail-safe

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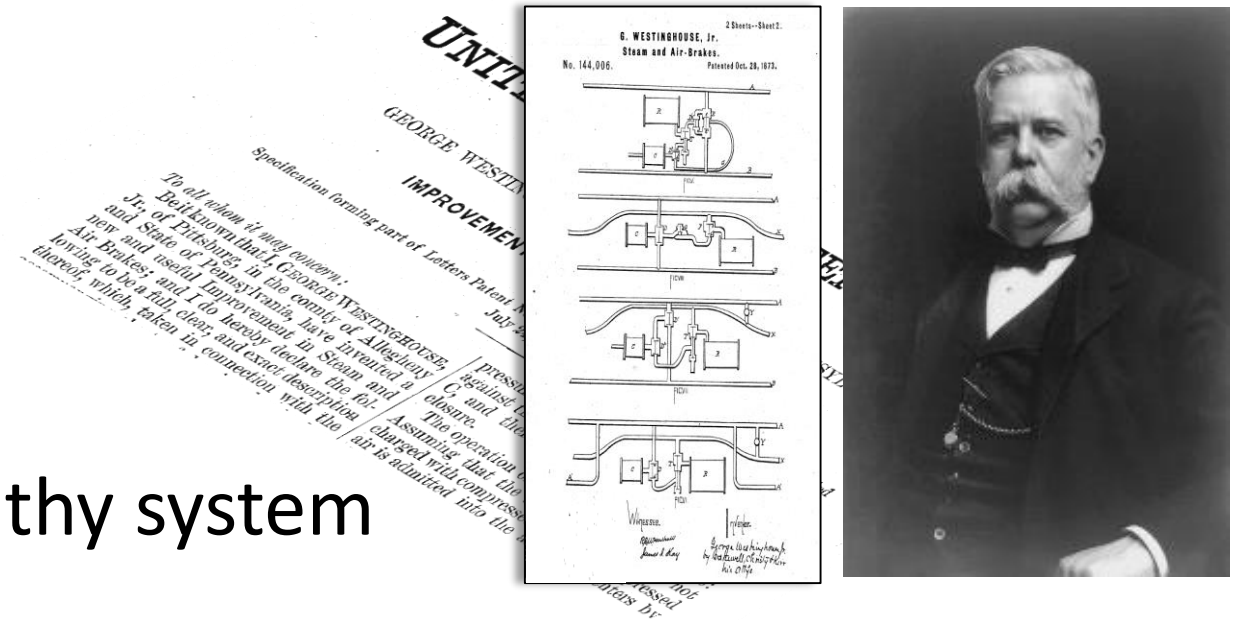

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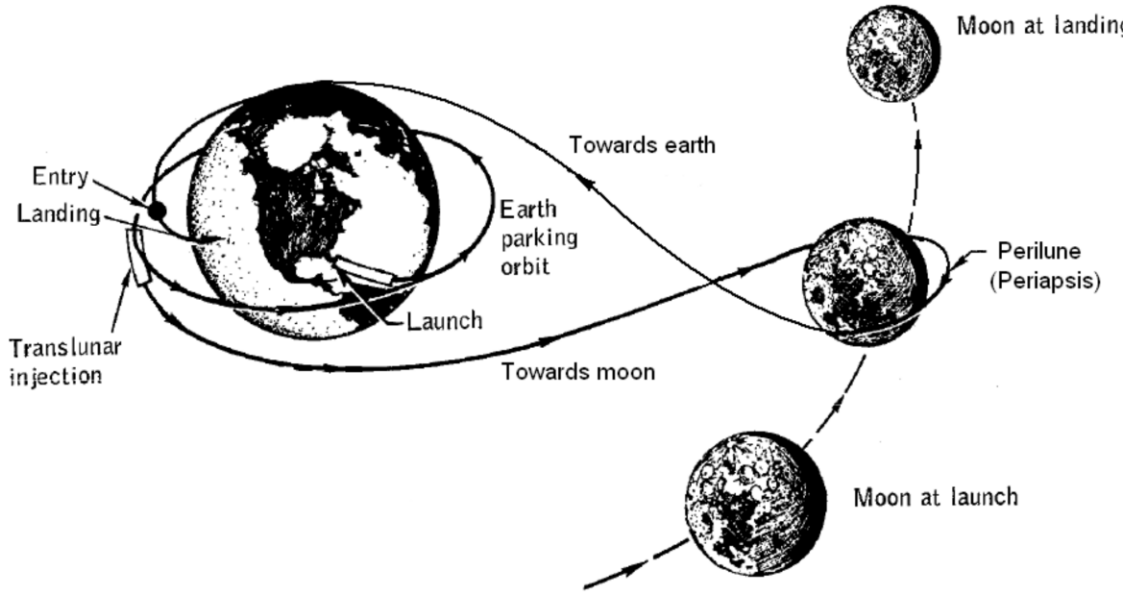
Fail-safe plan
Free return trajectory



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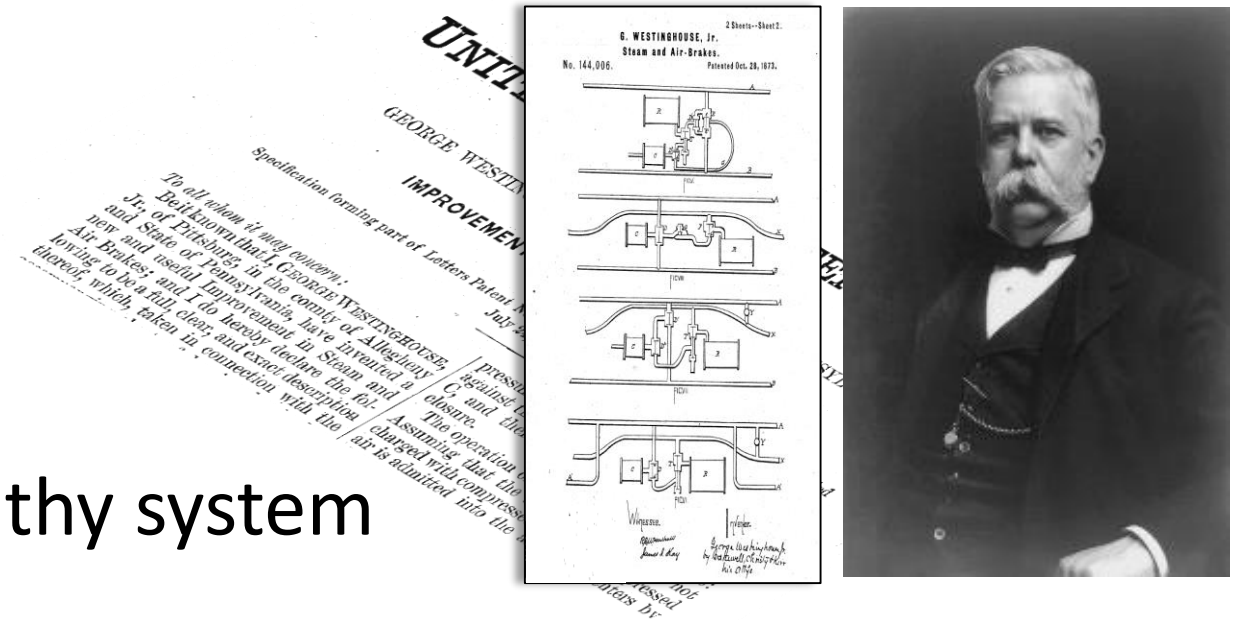

Brakes held "off" actively by healthy system

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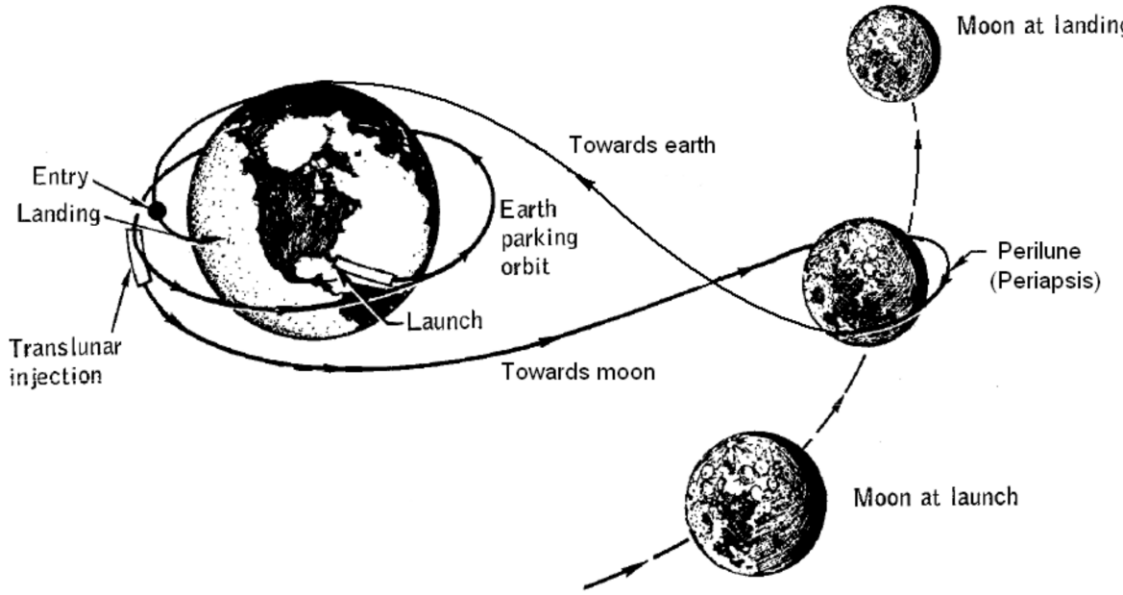
- ✓ Mechanism
- ✓ Practice
- ✓ Plan

Fail-safe plan

Free return trajectory



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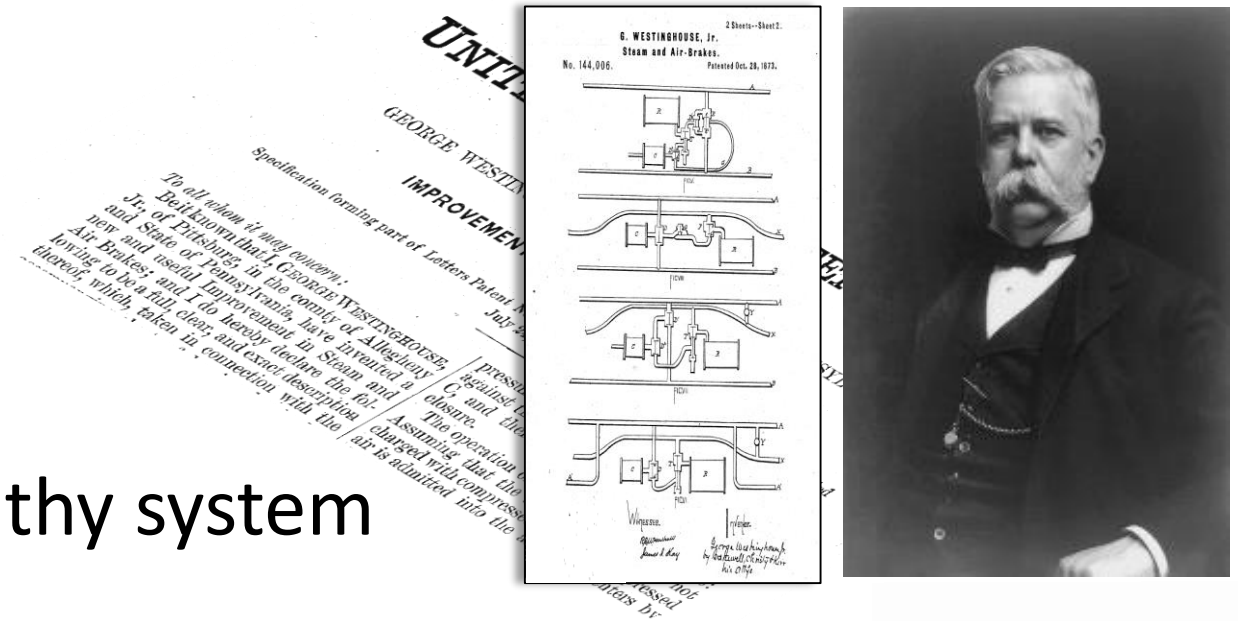


Brakes held "off" actively by healthy system

Brakes naturally resort to “on” if any failure of braking system

- ✓ Mechanism
- ✓ Practice
- ✓ Plan
- ✓ Monitoring

AI in the Open World

Growing interest in issues & directions with AI in real-world settings

Grappling with uncertainty and more general incompleteness

AAAI President's address (2008), "Artificial Intelligence in the Open World."

AAAI President's address (2016), "Steps Toward Robust Artificial Intelligence."

E. Horvitz. Artificial Intelligence in the Open World, *AAAI President's Address*, Chicago, IL, July 2008.

T. Dietterich, Steps Toward Robust Artificial Intelligences, *AAAI President's Address*, Phoenix, AX. February, 2016.

Special Considerations with AI

Open-world complexity → incomplete understanding

Uncertainties & poor-characterization of performance
Poor operating regimes, unfamiliar situations

Rich ontology of failures

Numerous failure modalities
New attack surfaces (e.g., *machine learning attack*)
Self-modification & gaming (e.g., *modify reward fcn*)
Unmodeled influences

Challenges of transfer across time & space

Challenge of coordinating human-machine collaborations

Operational opacity

AI & Open-World Complexity

Frame problem

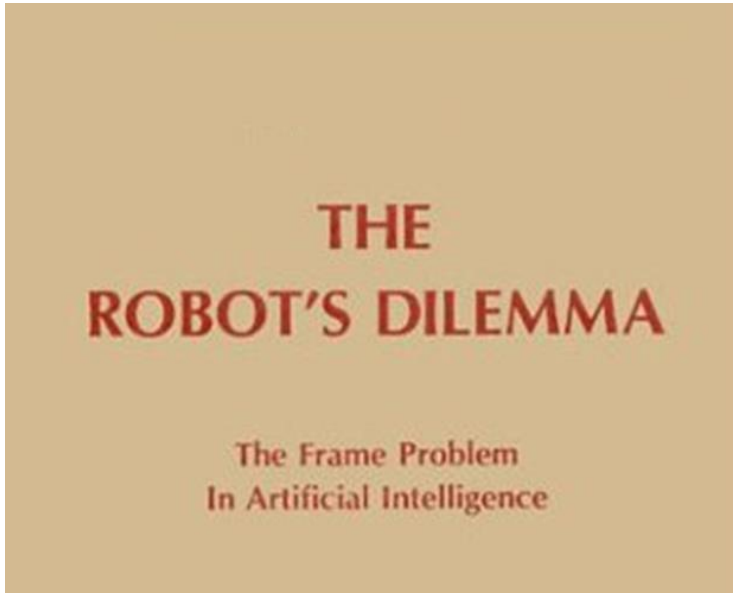
How to tractably derive consequences of an action?

Qualification problem

Understanding preconditions required for actions to have intended effects

Ramification problem

Understanding all important effects of action



AI & Open-World Complexity

Rise of probabilistic methods: *known unknowns*

Recent attention to *unknown unknowns*

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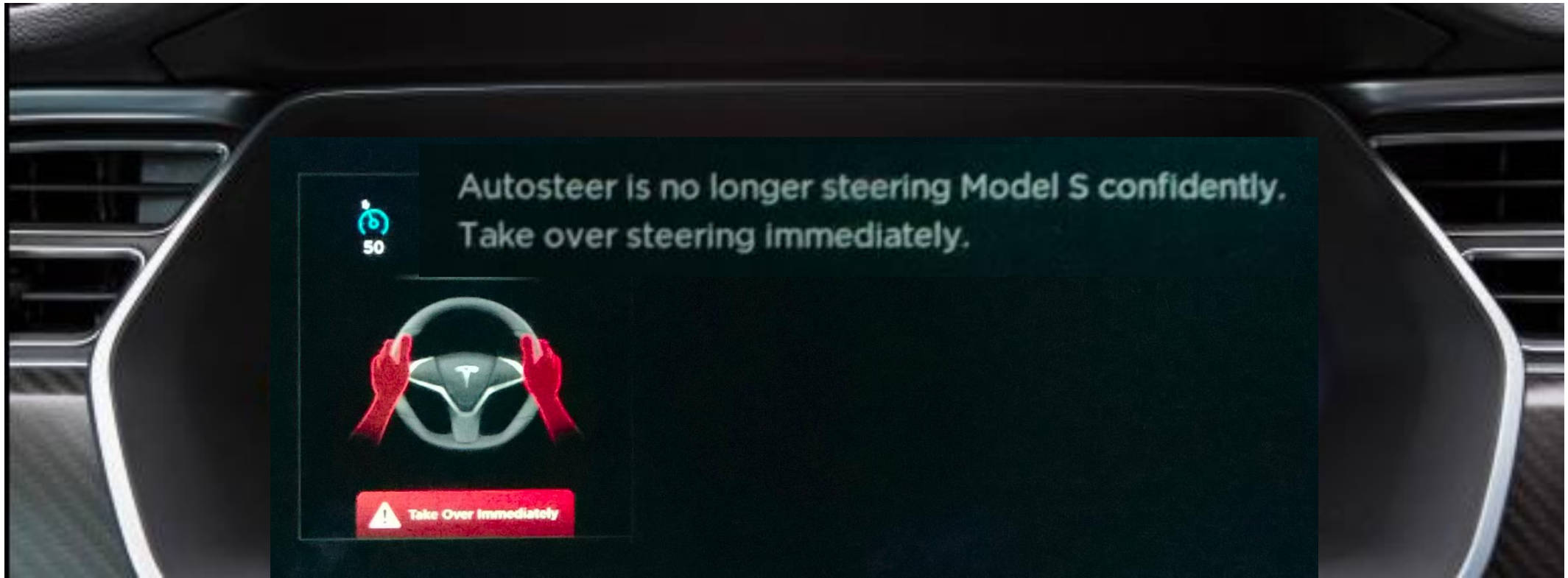

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Decision making under uncertainty & incompleteness

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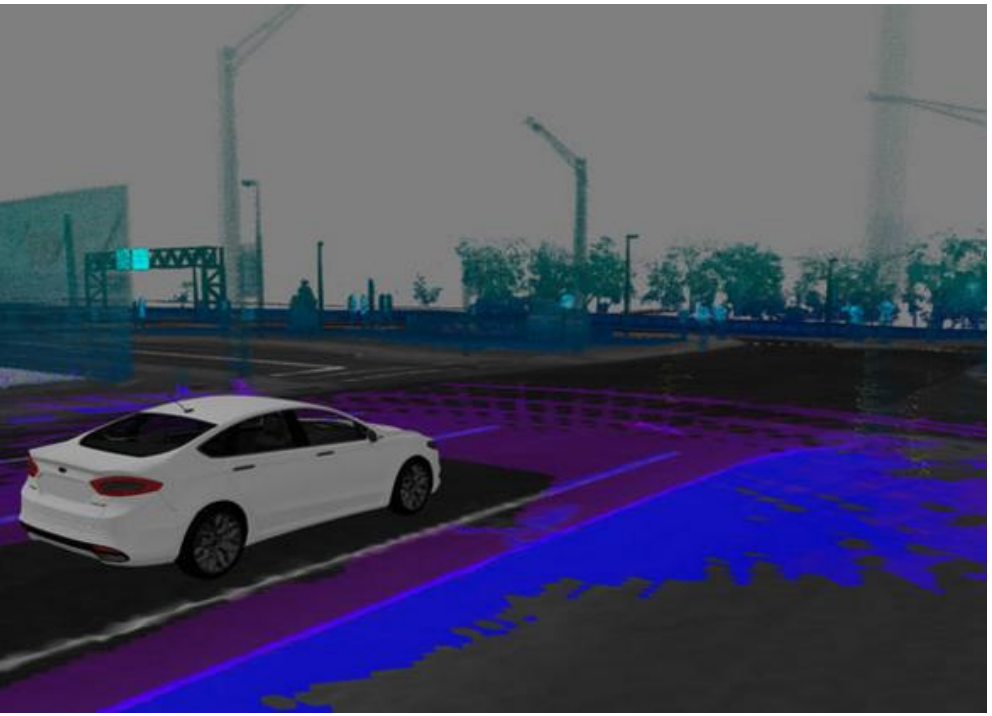

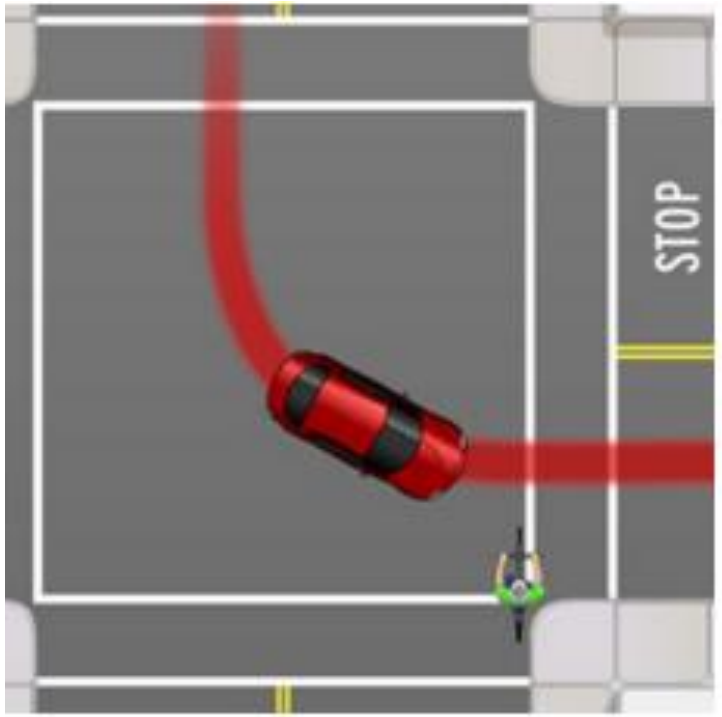

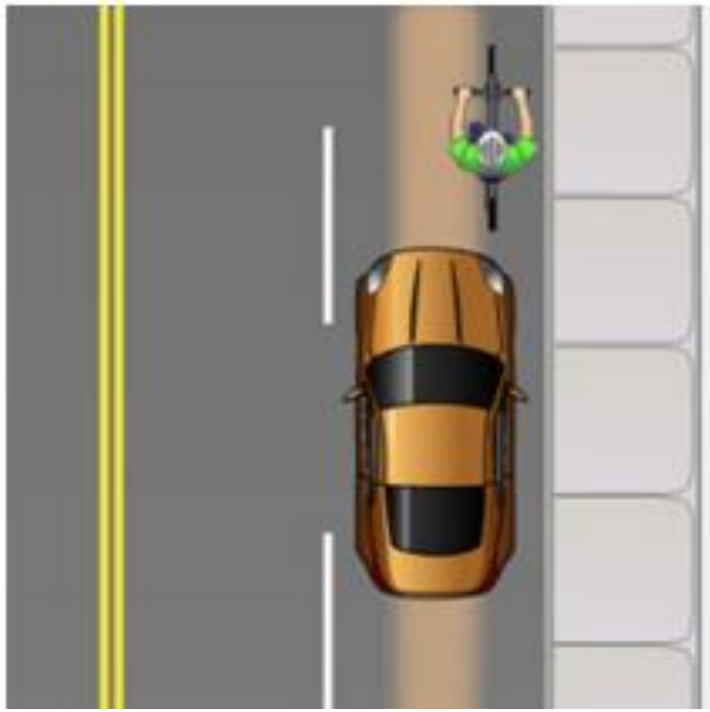

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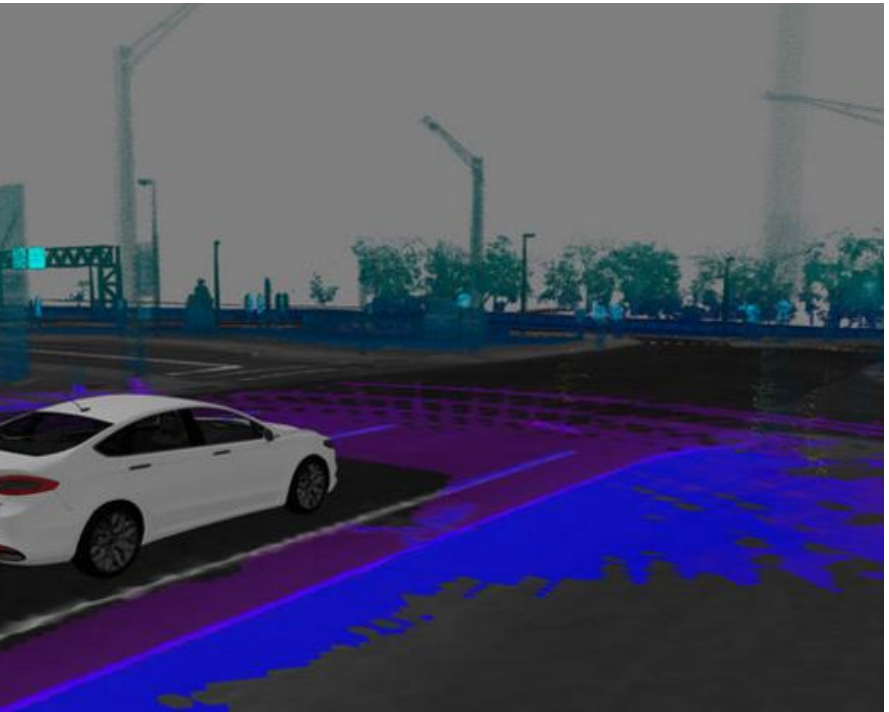

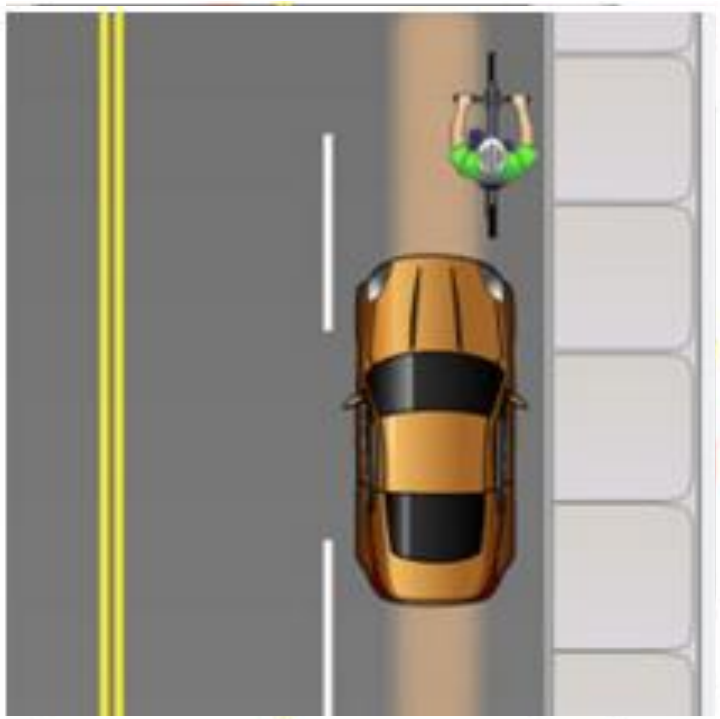

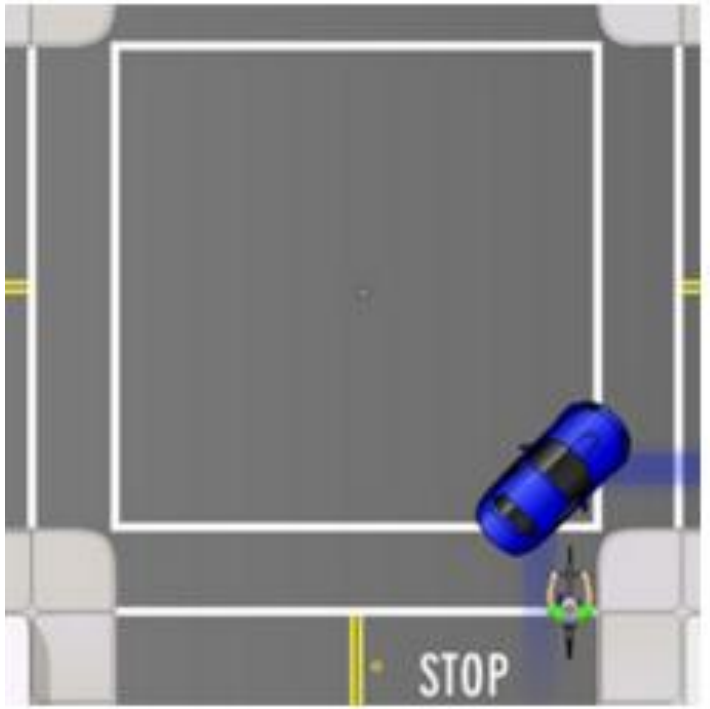

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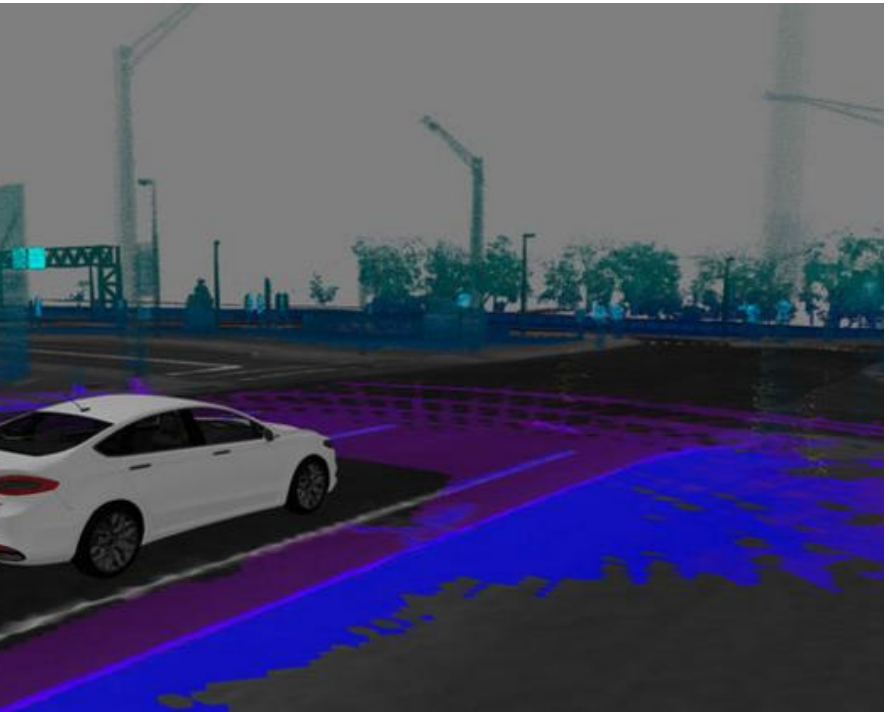

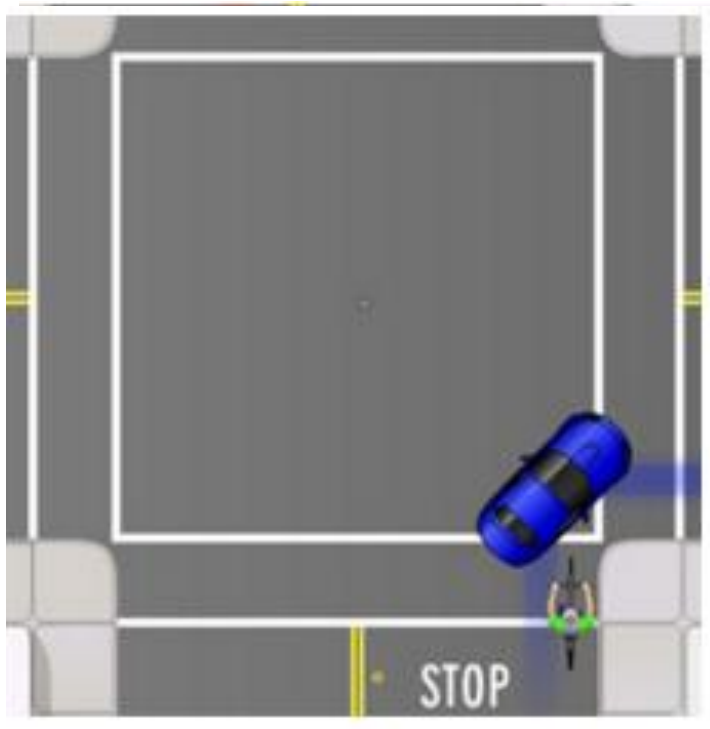

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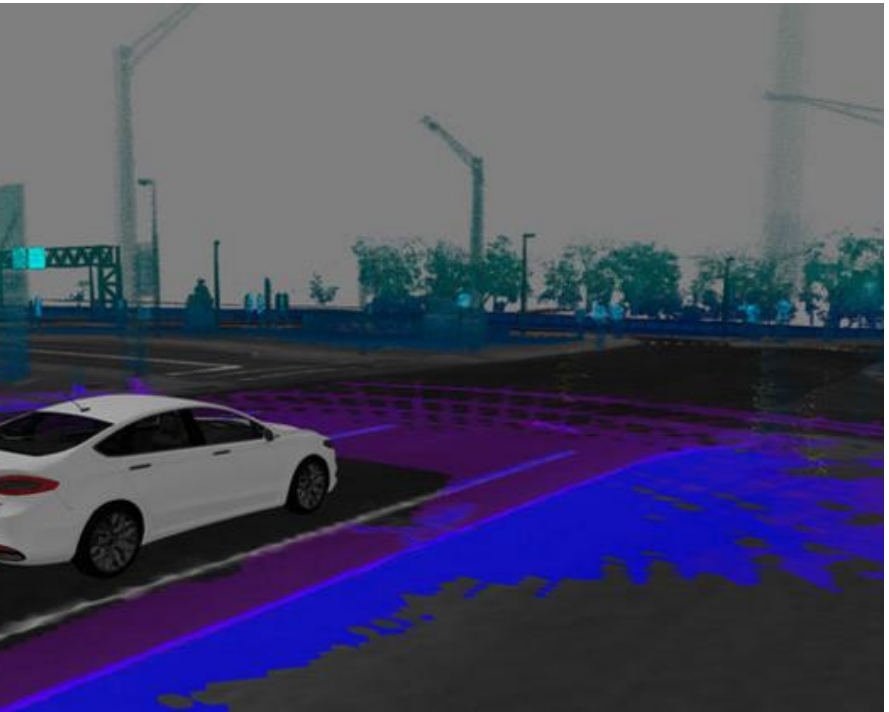

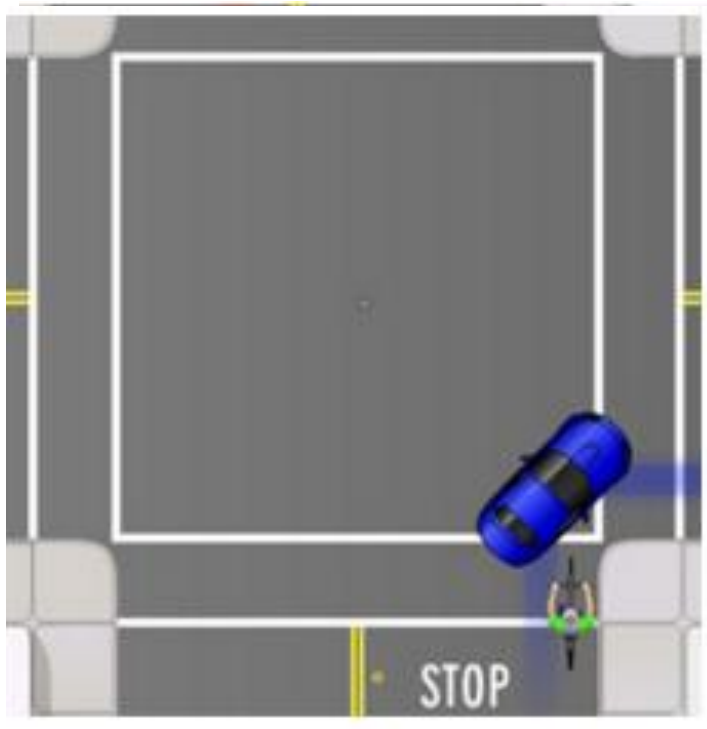

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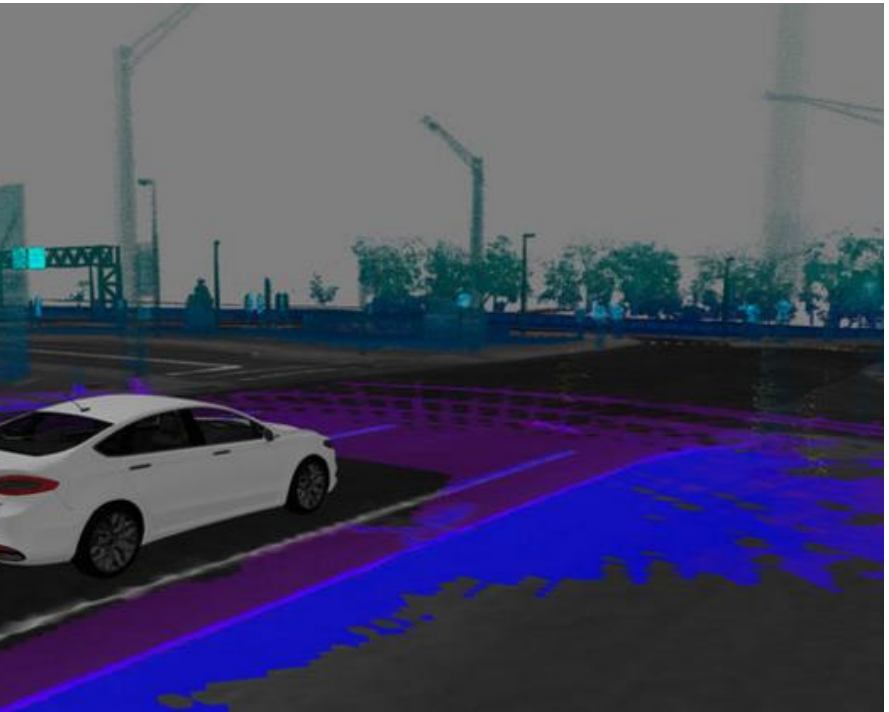
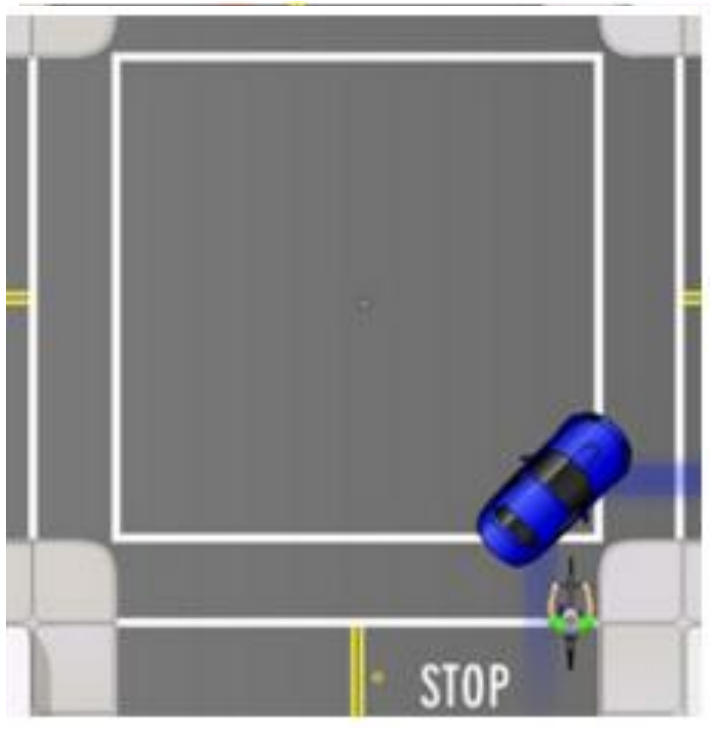
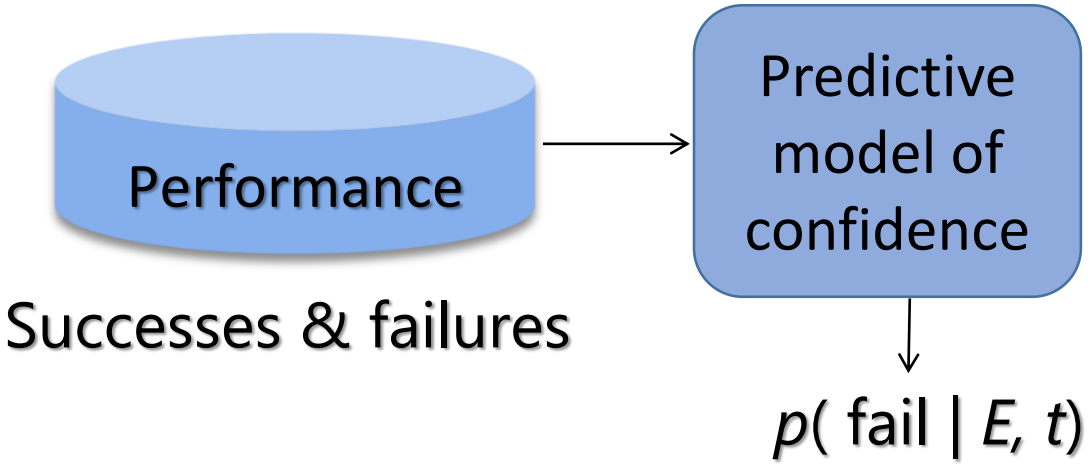
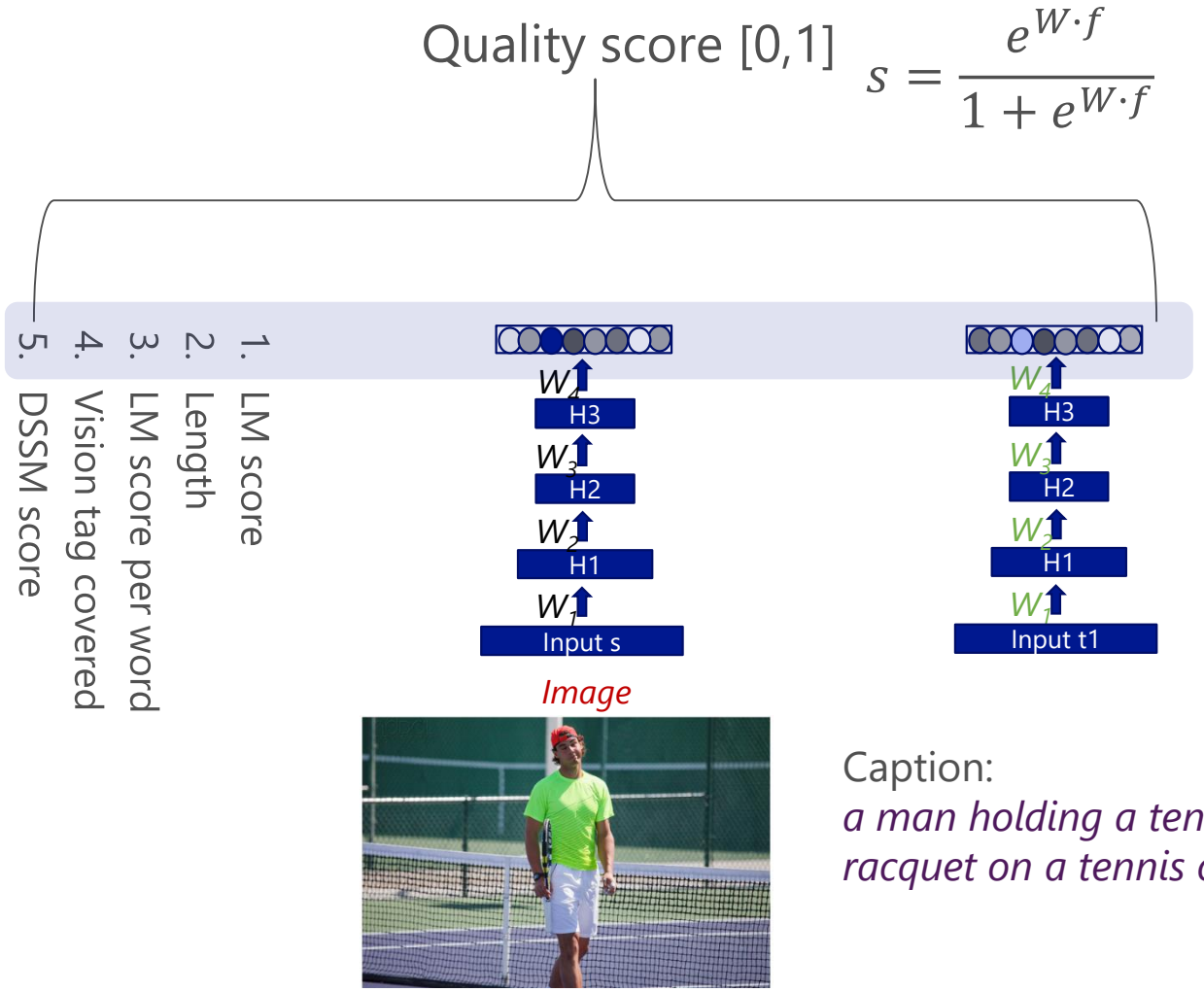




Direction: Learn about abilities & failures

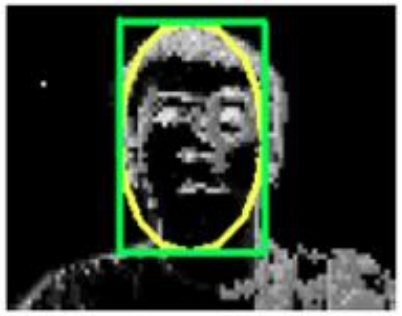
Deep learning about deep learning performance

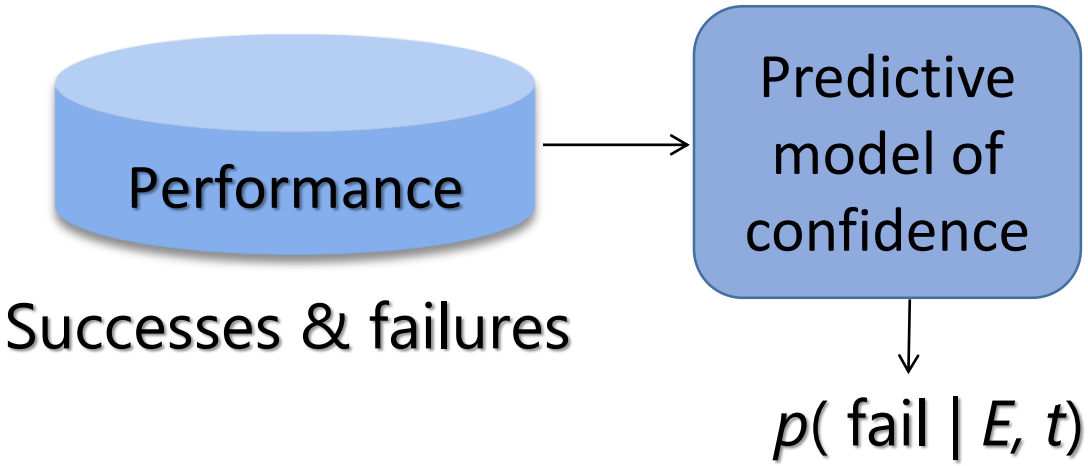




Fang, et al., 2015

Direction: Learn about abilities & failures





Toyama & H. 2000

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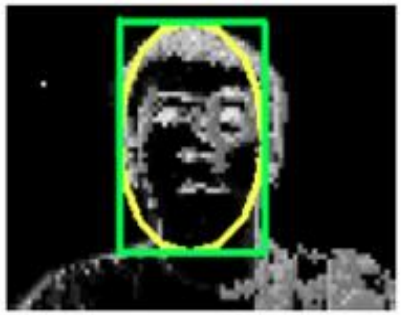
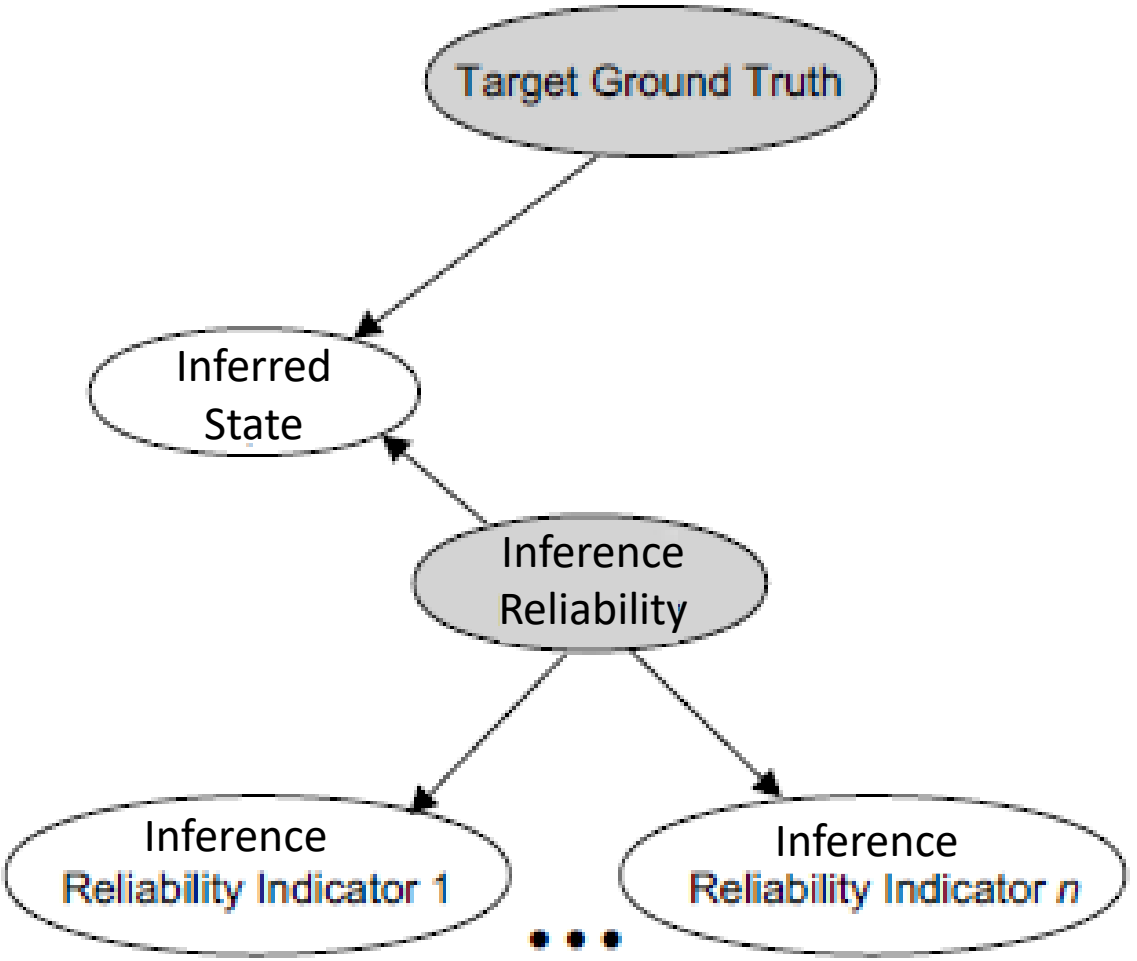
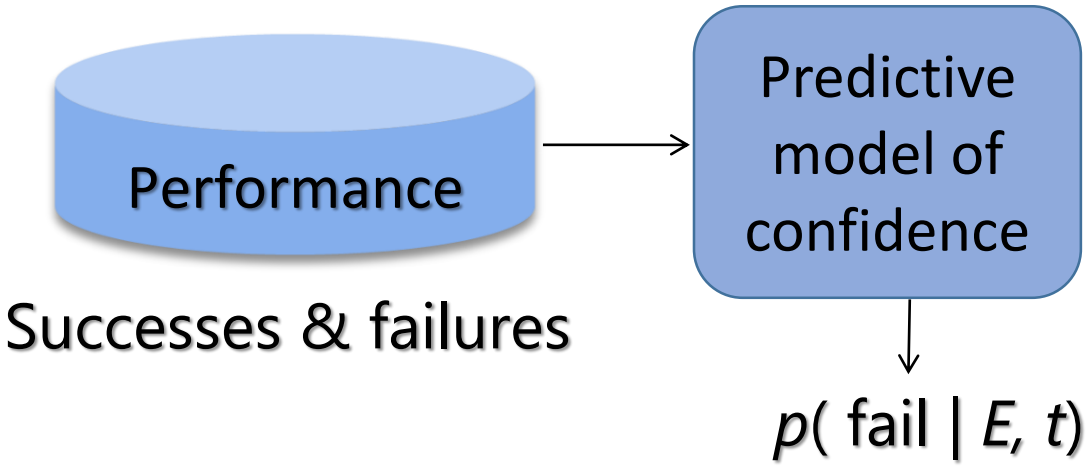
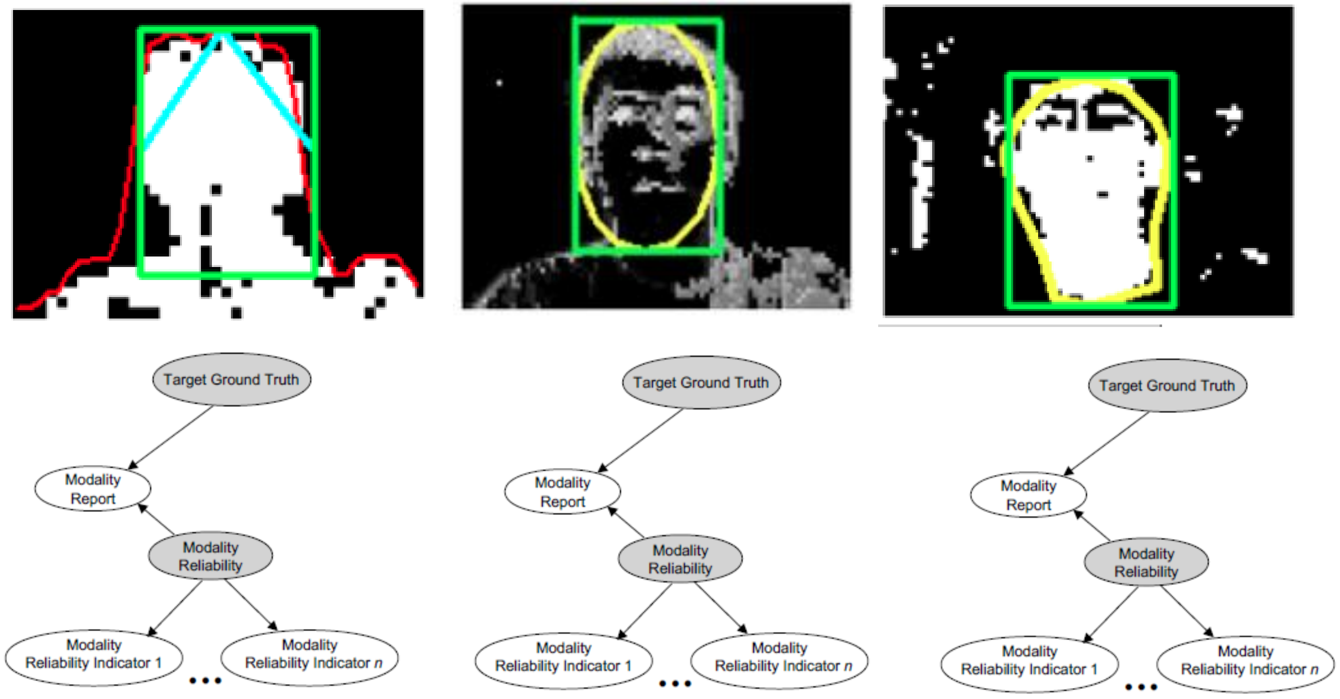


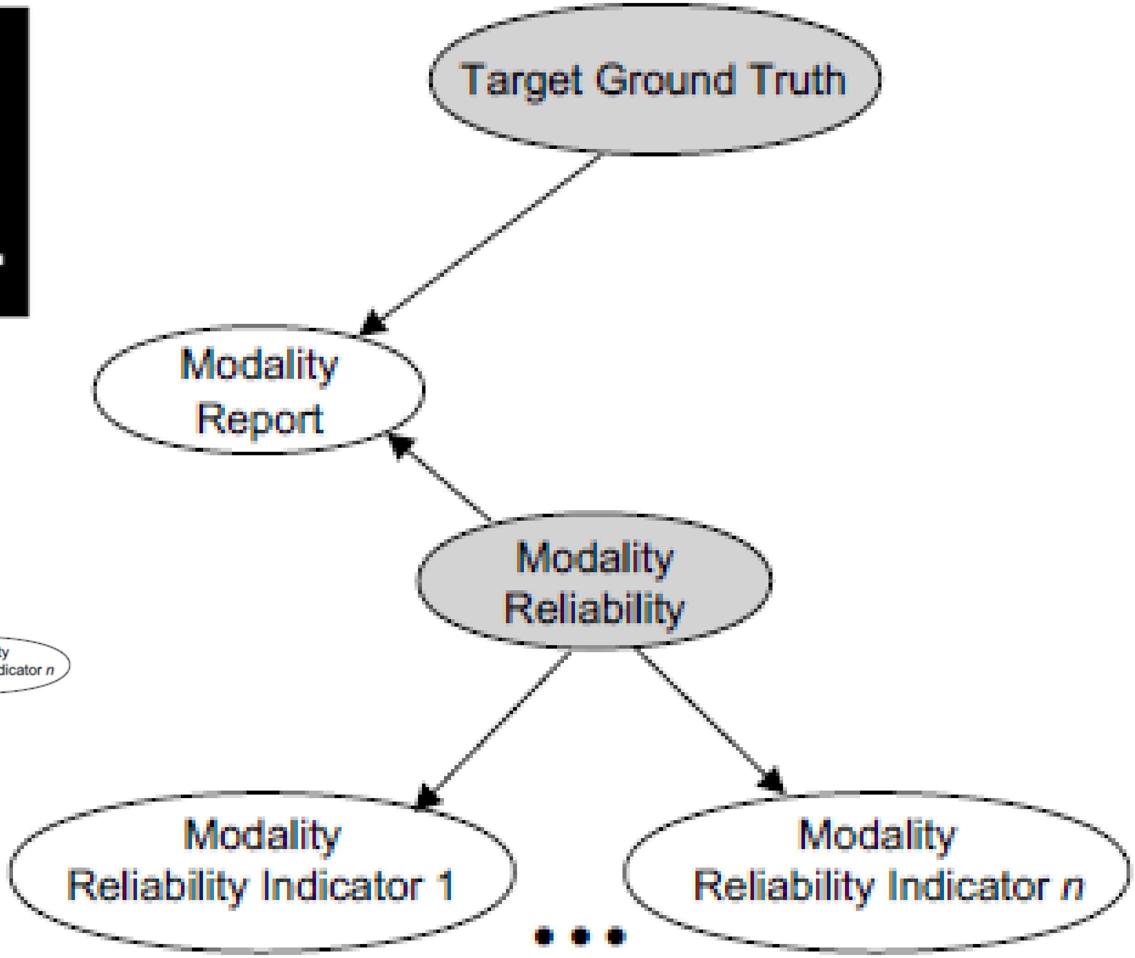




Toyama & H. 2000

Direction: Robustness via analytical portfolios





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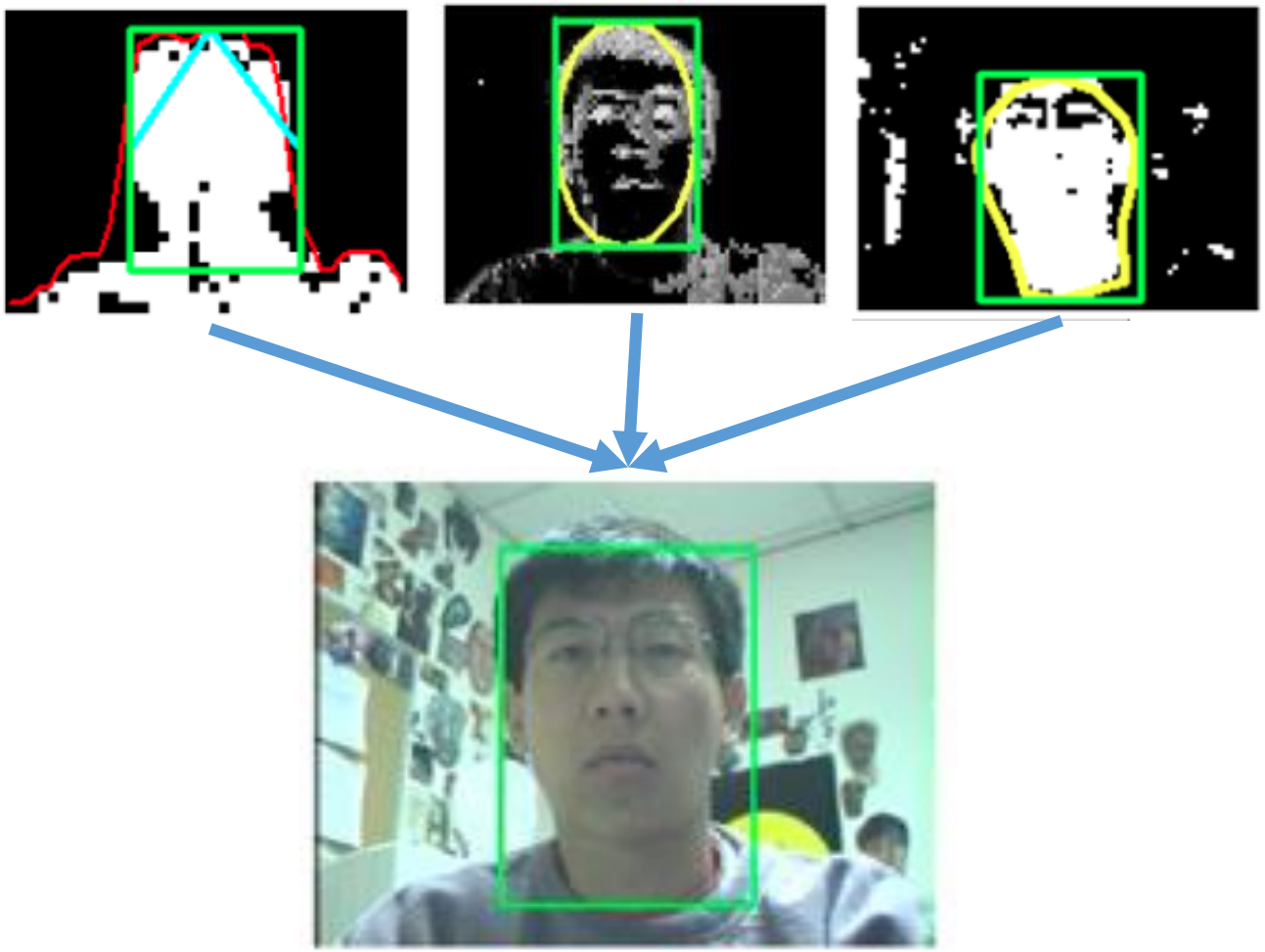

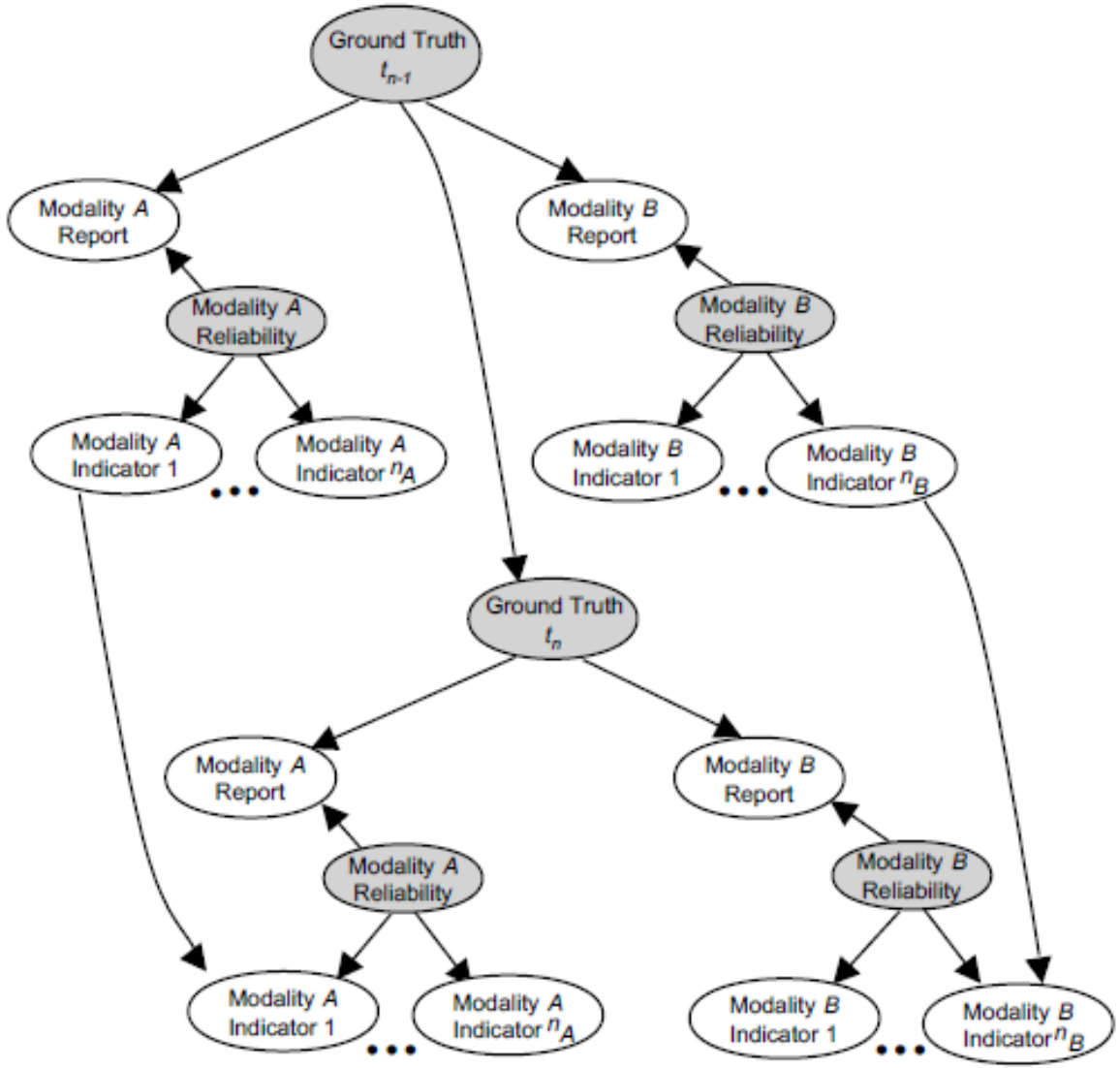

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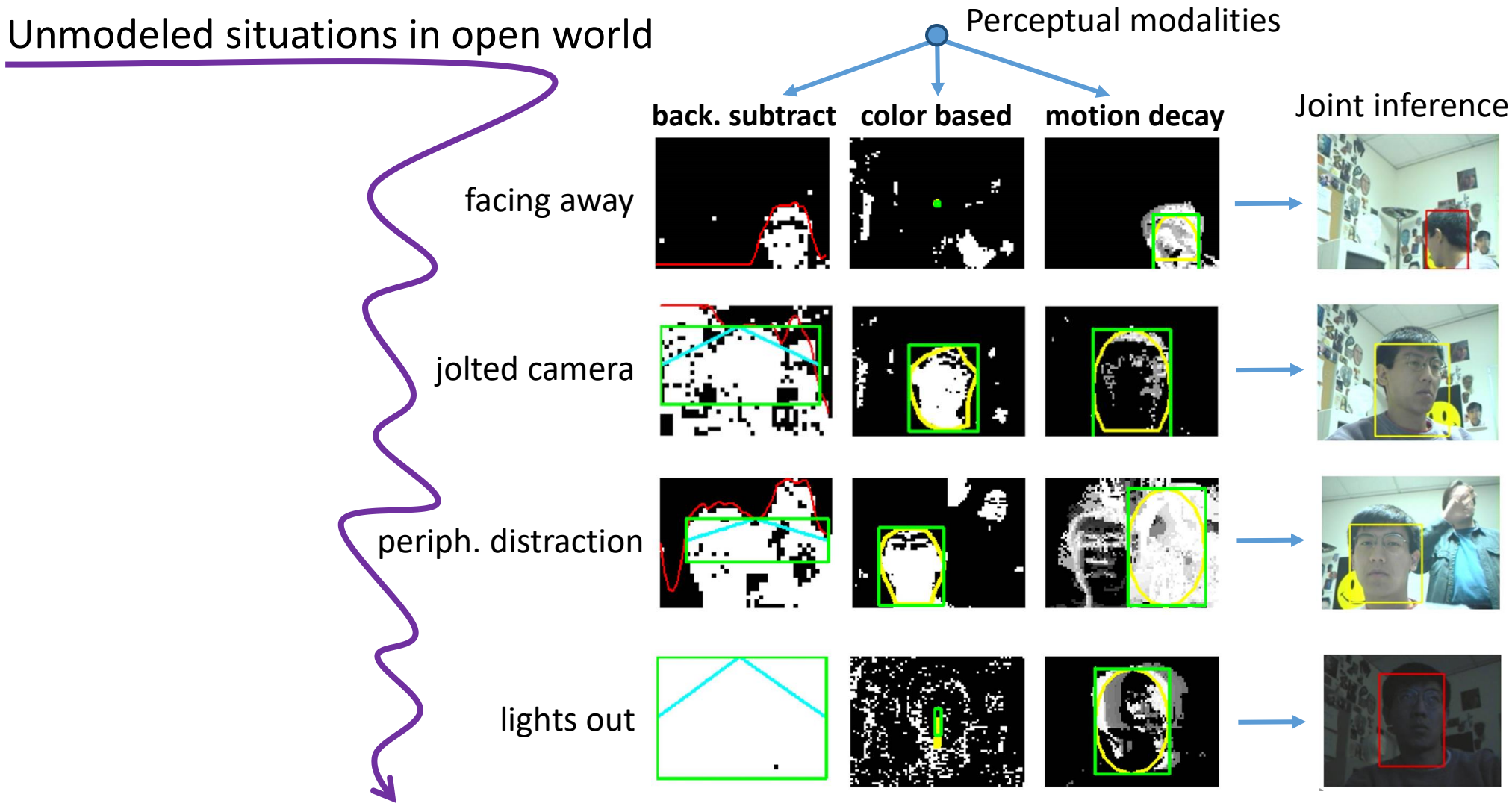
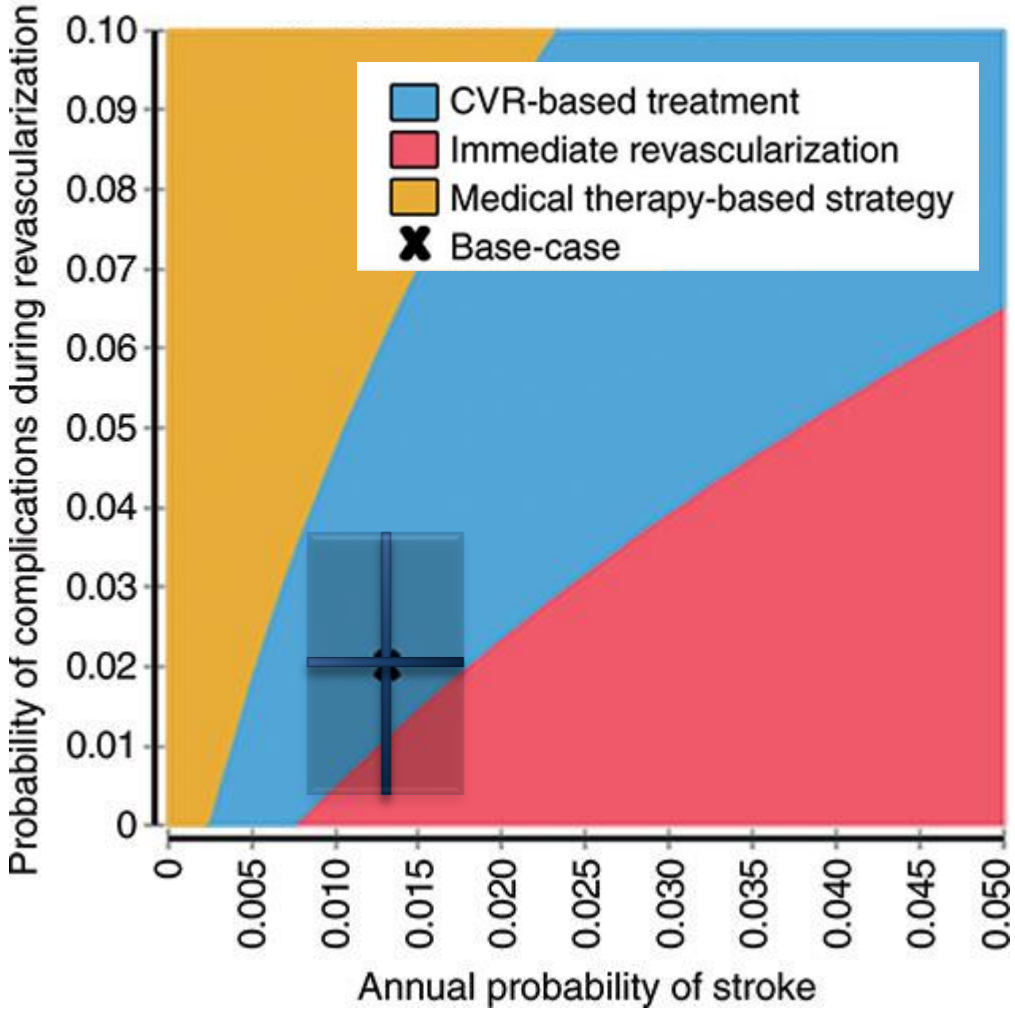


Toyama & H. 2000

Direction: Understanding robustness via sensitivity analyses

Vary model structure, parameters, inferences



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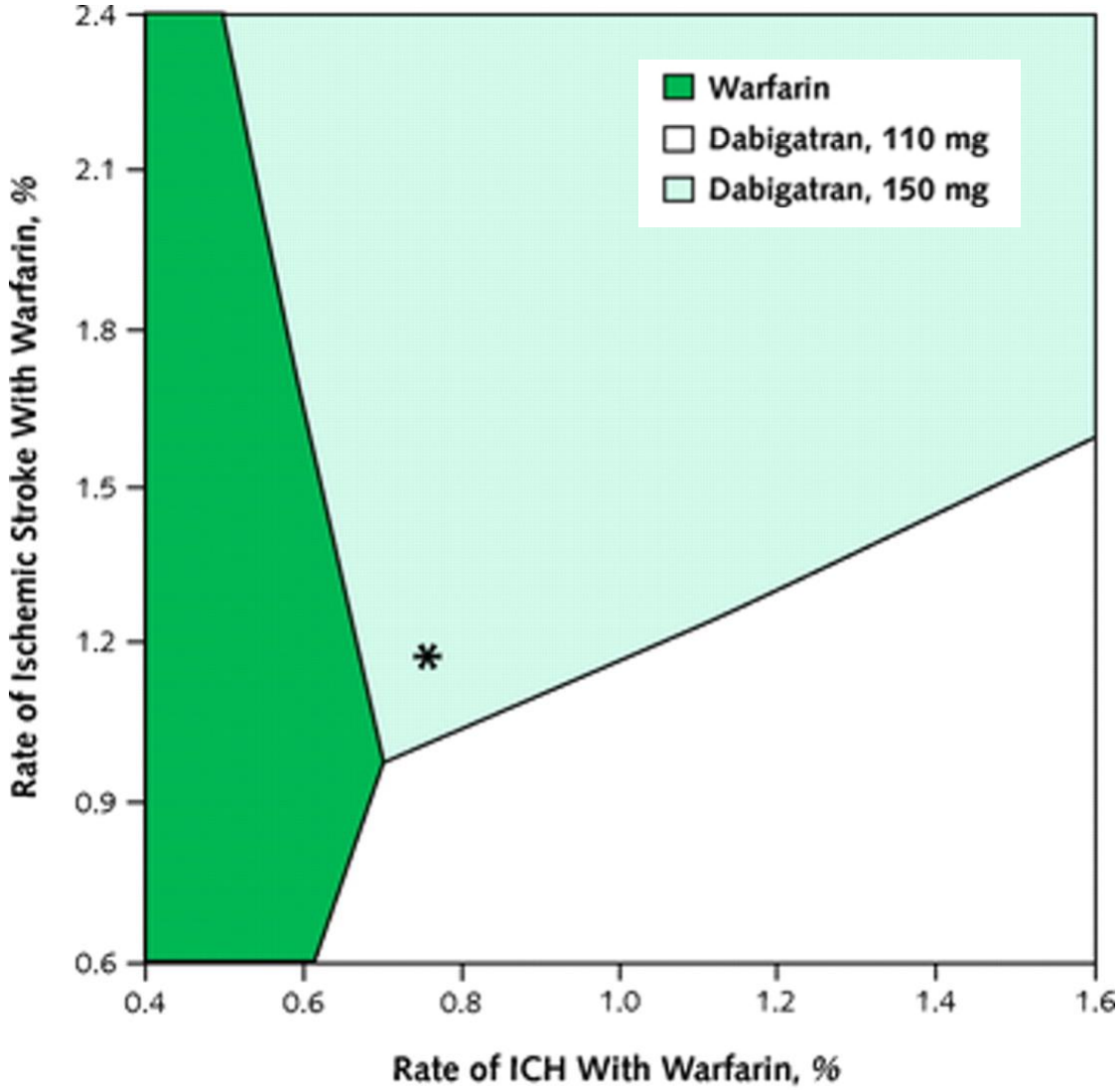


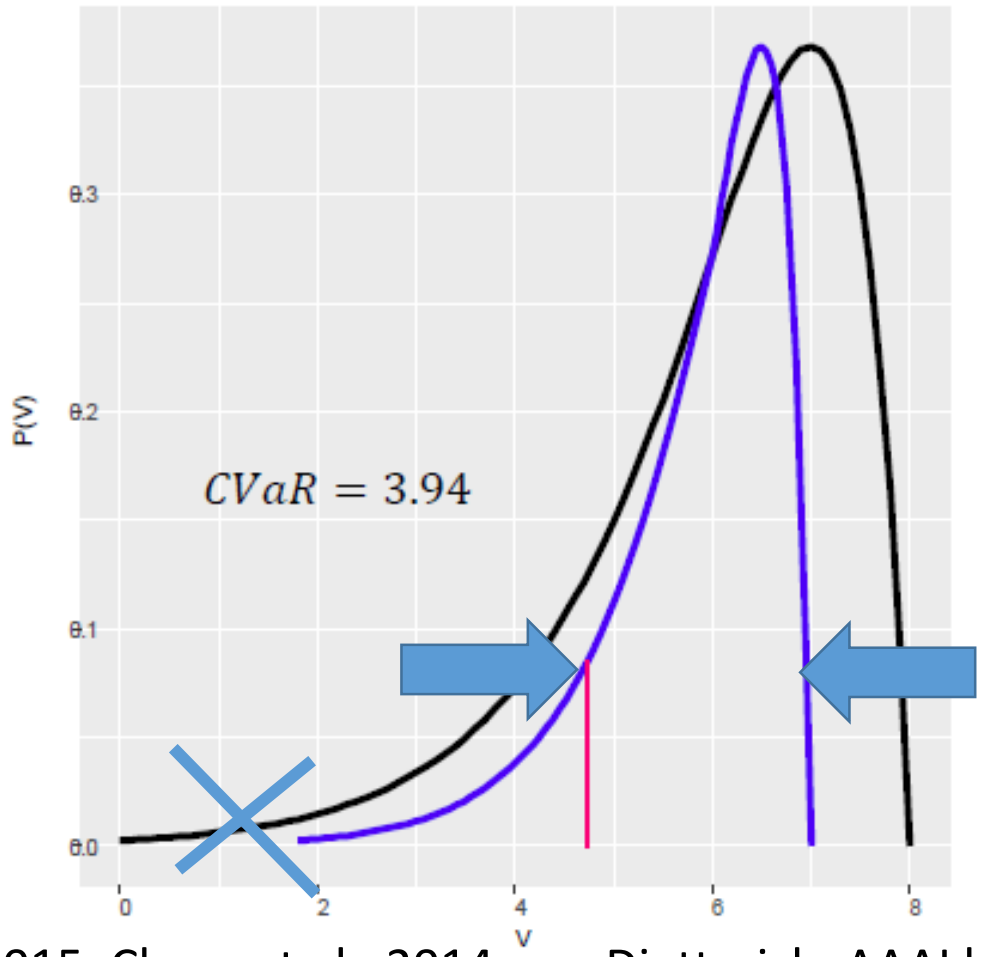
Direction: Robust optimization to minimize downside

Robust optimization under uncertain parameters

Risk-sensitive objective

e.g., conditional-value-at-risk budget

Methods trade upside value for reducing probability of costly outcomes



Tamar, 2015; Chow, et al., 2014; per Dietterich, AAAI lect. 2016

Direction: Learn about unknown unknowns

Data, experience, rich simulations

Detect anomalies, unexpected variations, distributional shifts

Meta-analysis & transfer

Human engagement

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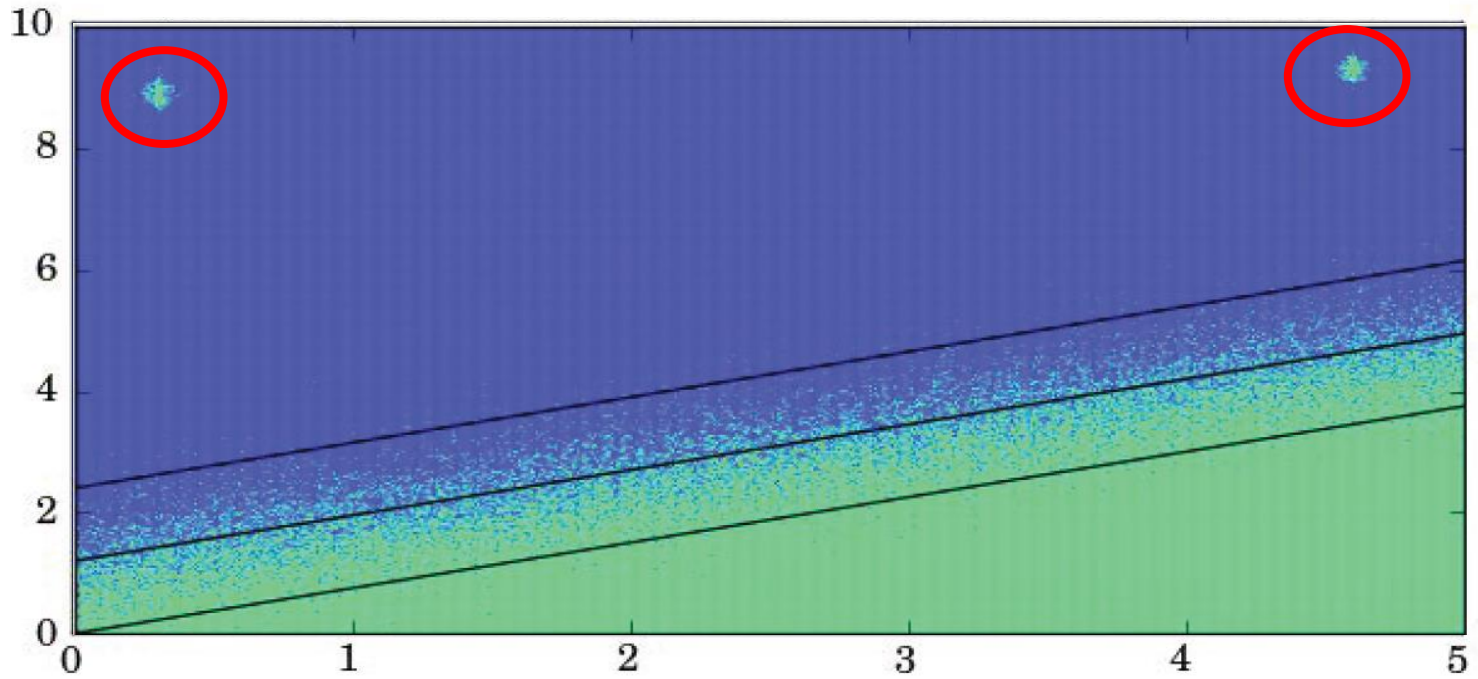
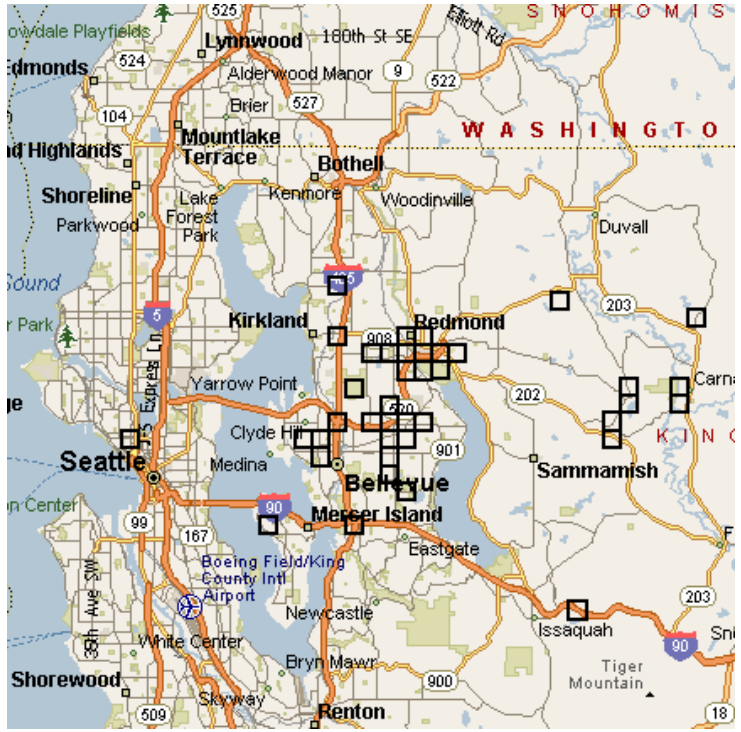
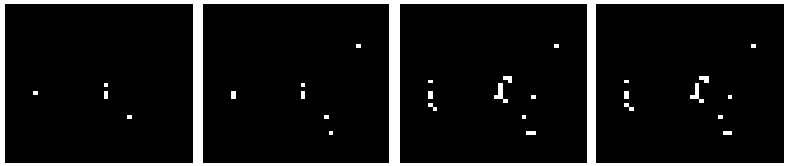
"Beat the Machine" (Attenberg, Ipeirotis, Provost 2015)



Direction: Learn about unknown unknowns

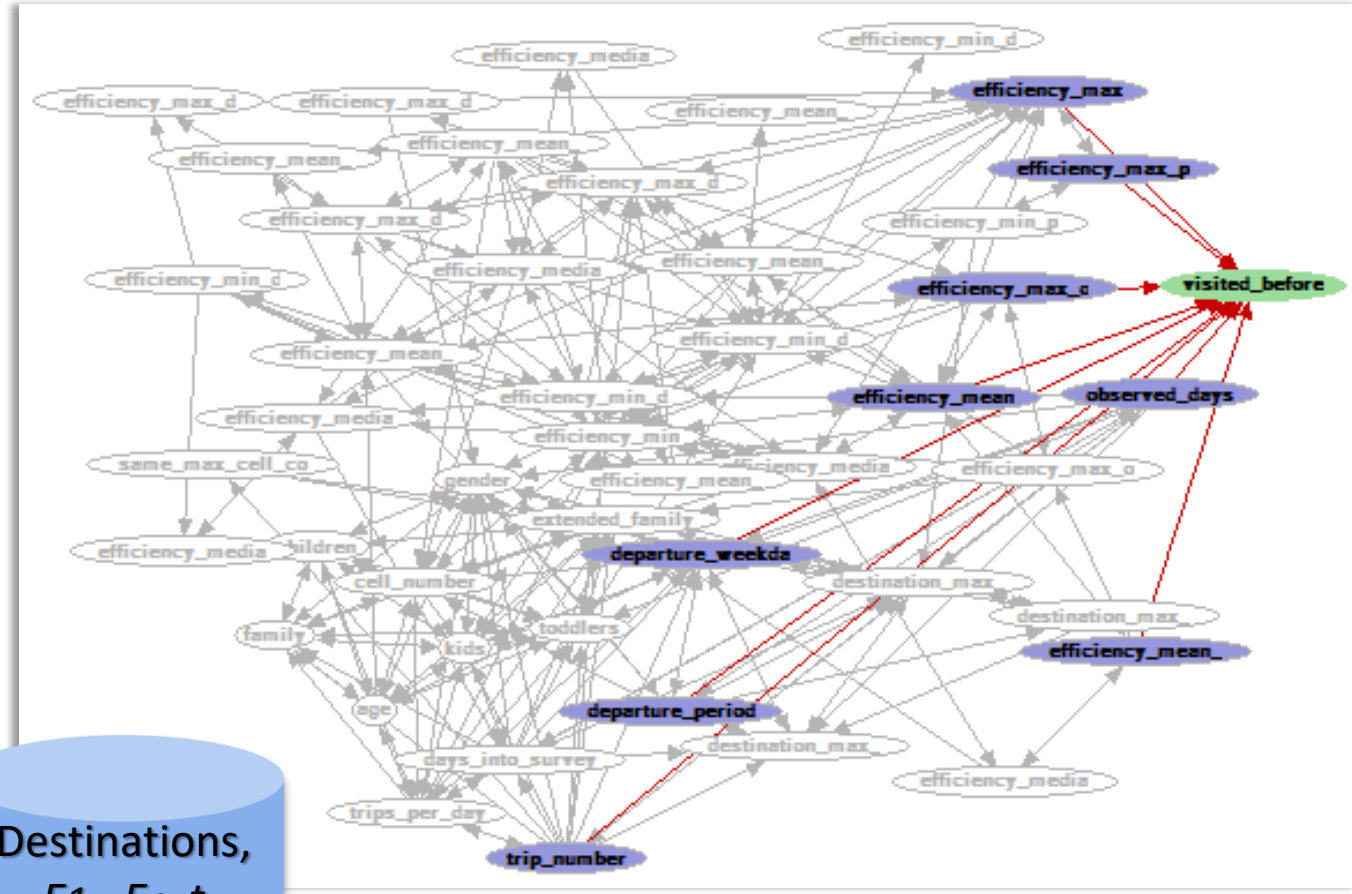
Predict new distinctions, combine open- & closed-world models





Destinations, *E1..,En, t*

Predict previously unseen destination



[Krumm, H., 2006]

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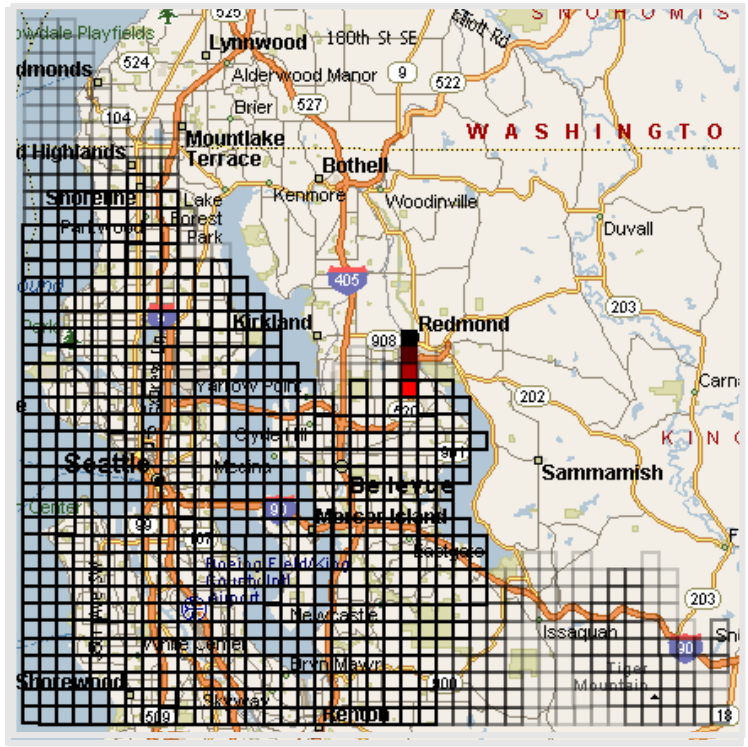

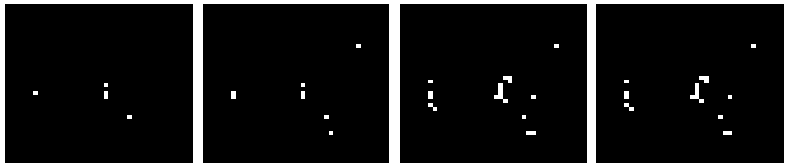

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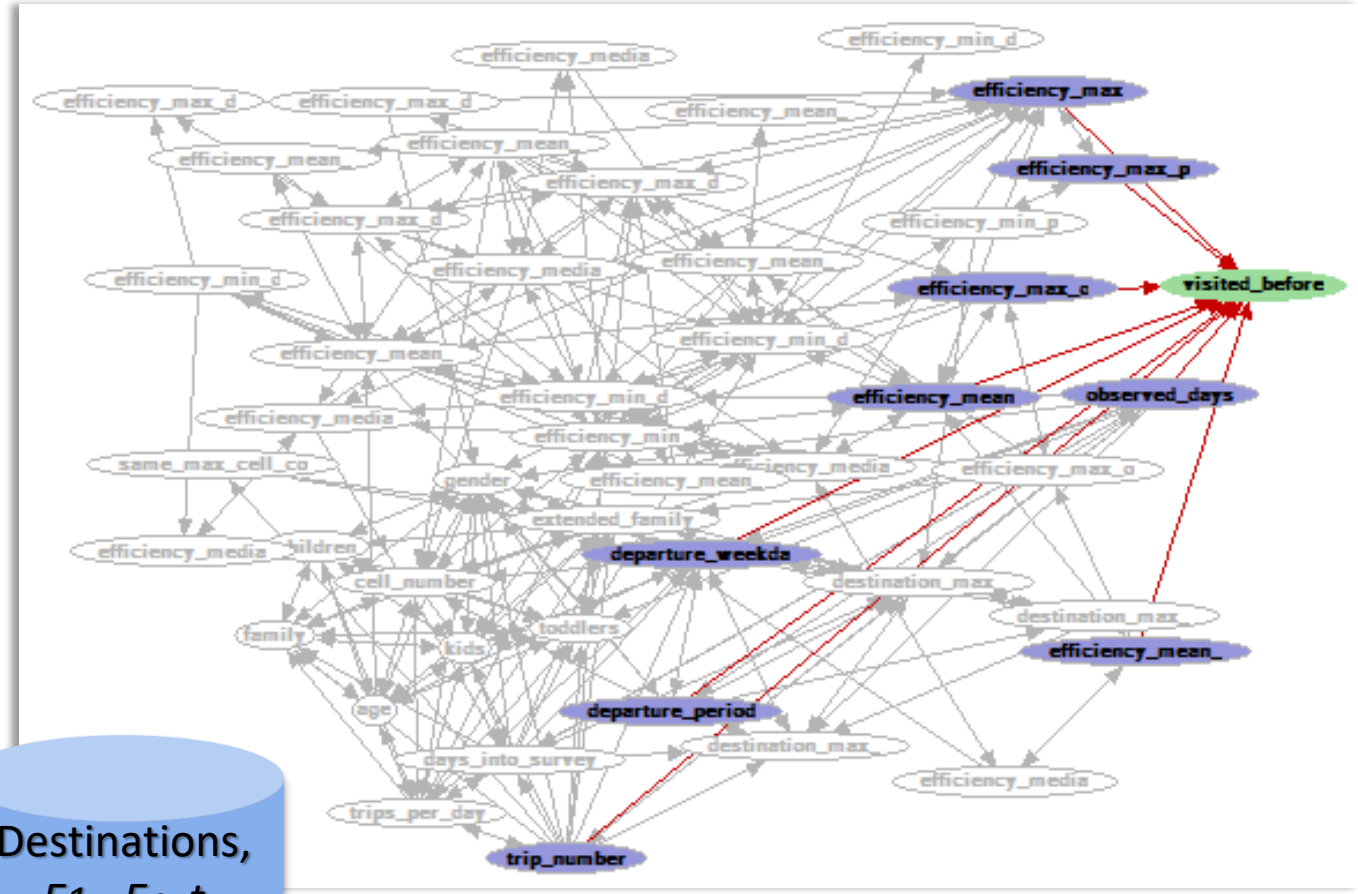

Krumm, H., 2006

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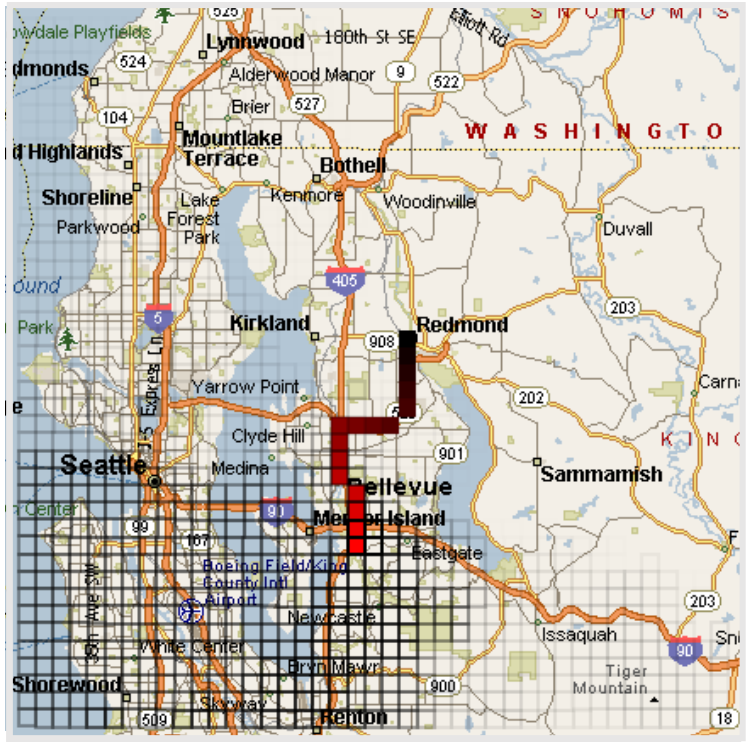

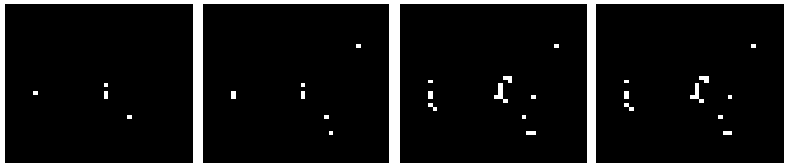

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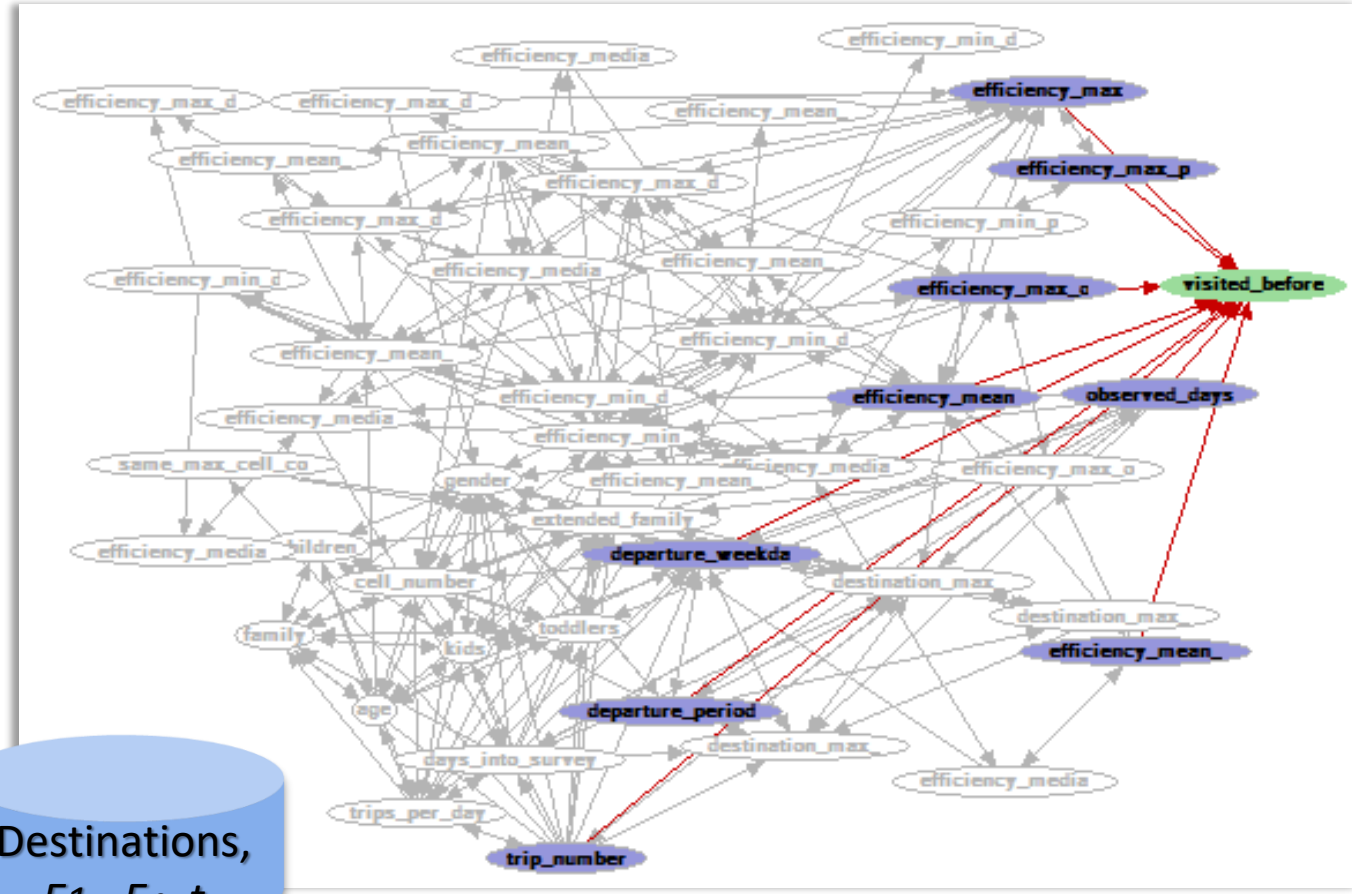
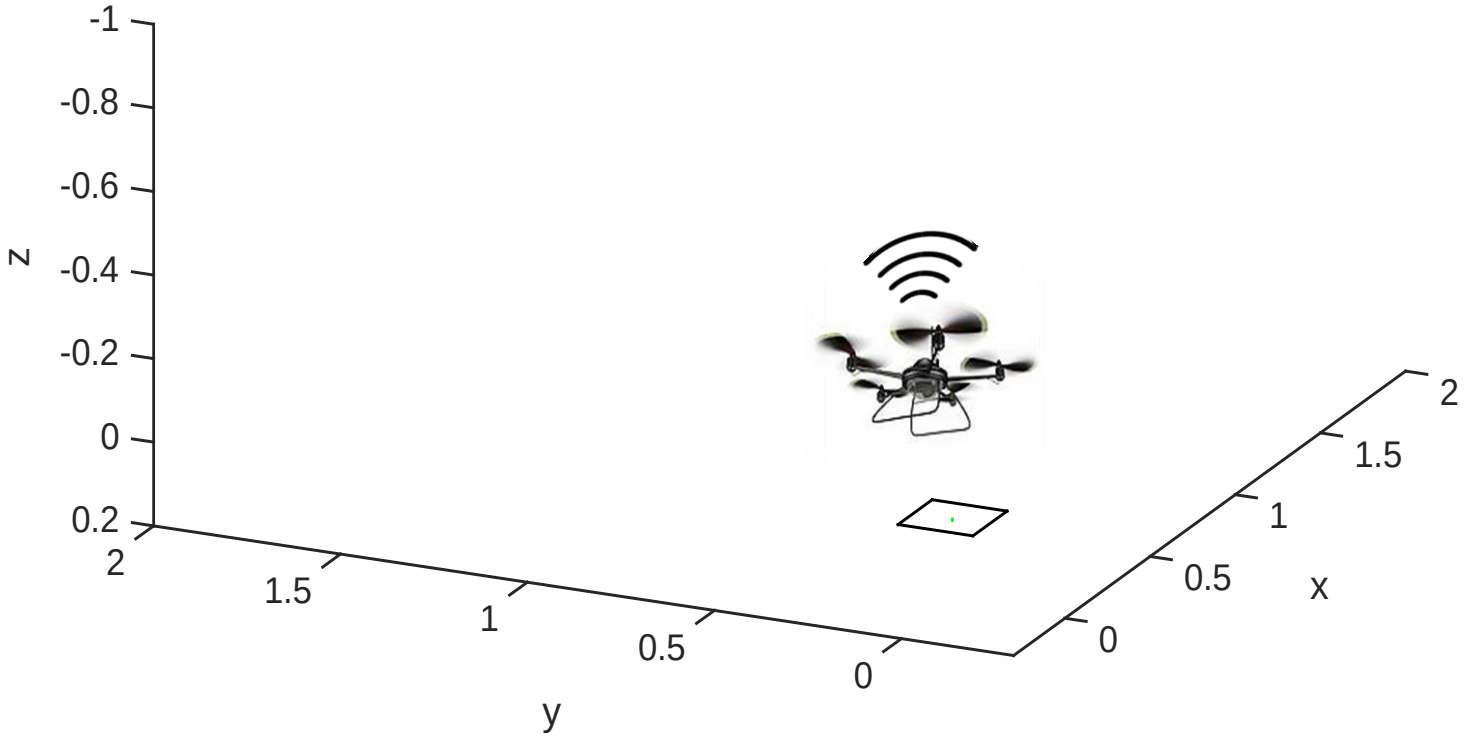


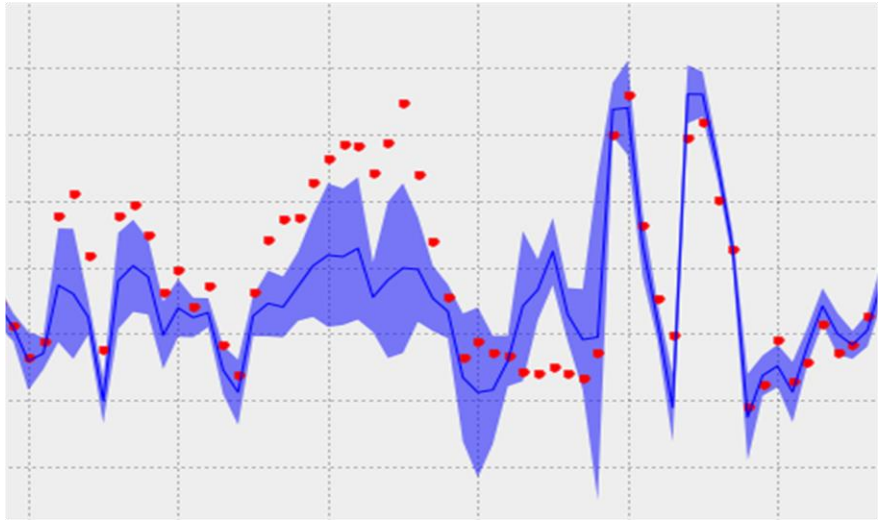
[Krumm, H., 2006]

Direction: Joint modeling of key dimensions of error

Example: Learn about errors of perception & control

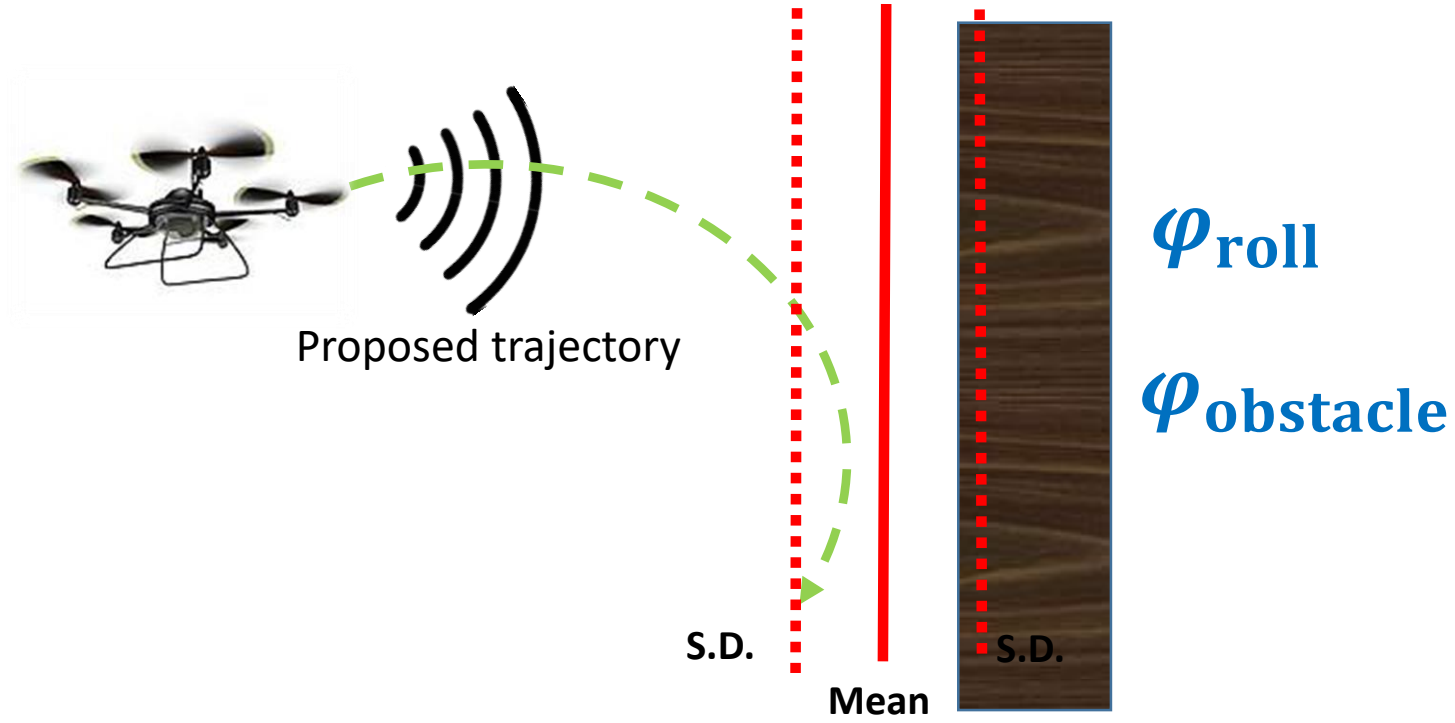
- Probabilistic models of control $\varphi_{\mathbf{roll}}$
- Probabilistic models of sensing $\varphi_{\mathbf{obstacle}}$

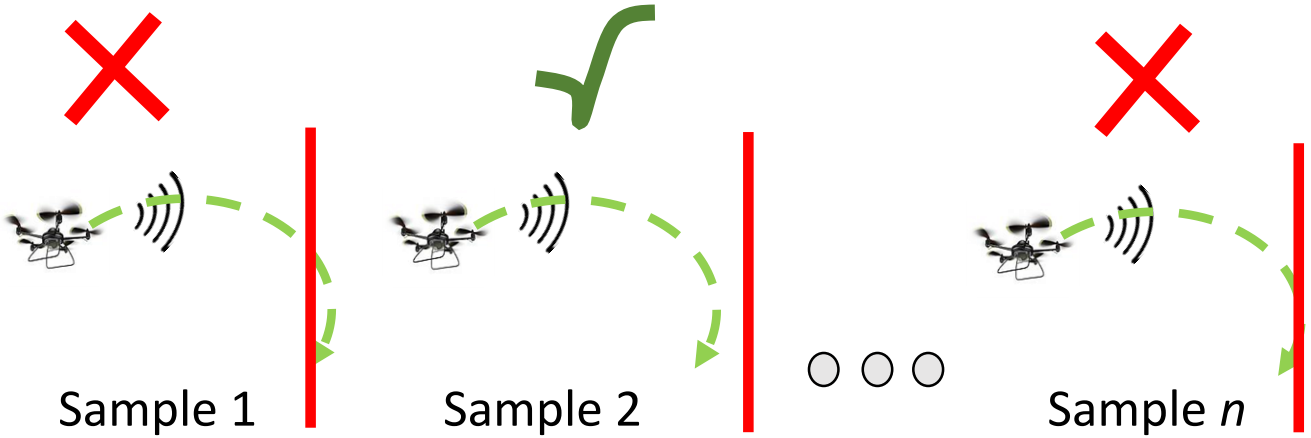




Sadigh & Kapoor, 2016

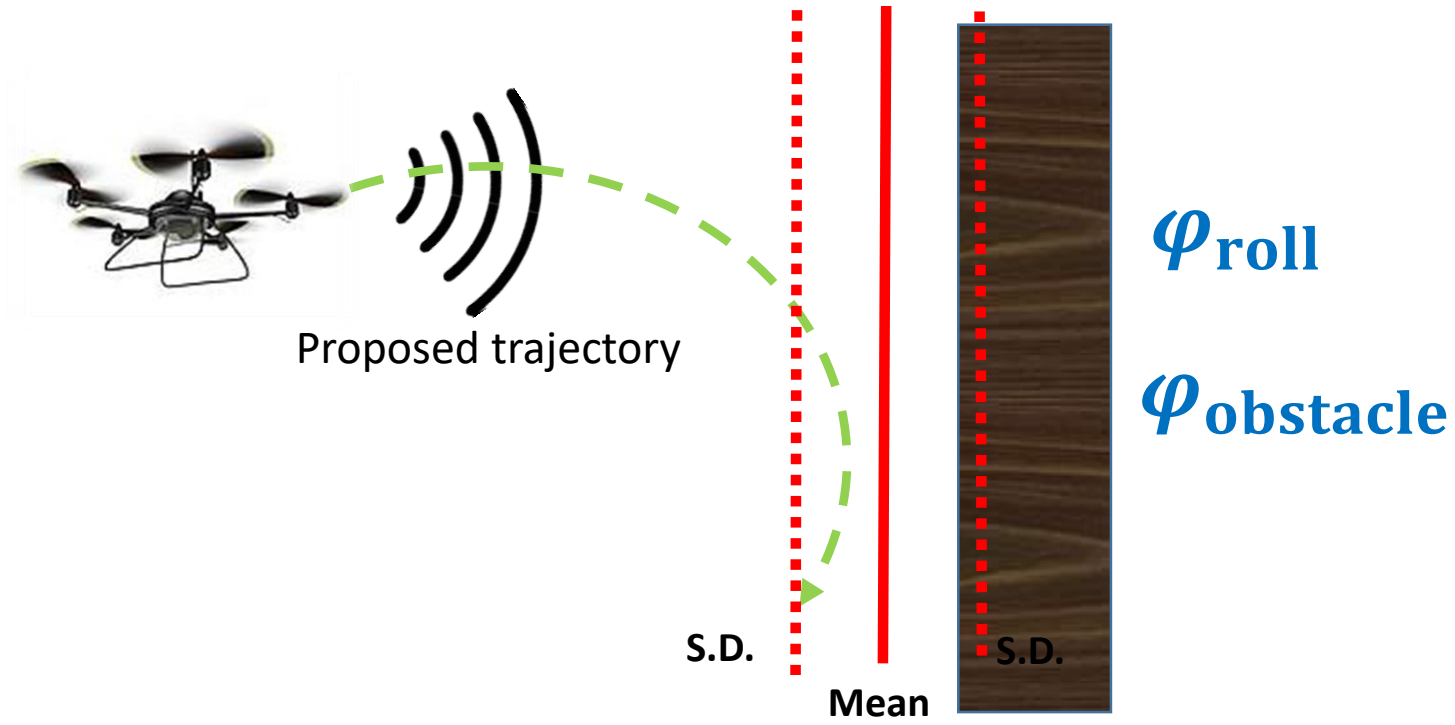
Direction: Joint modeling of key dimensions of error





Sadigh & Kapoor, 2016

Direction: Joint modeling of key dimensions of error



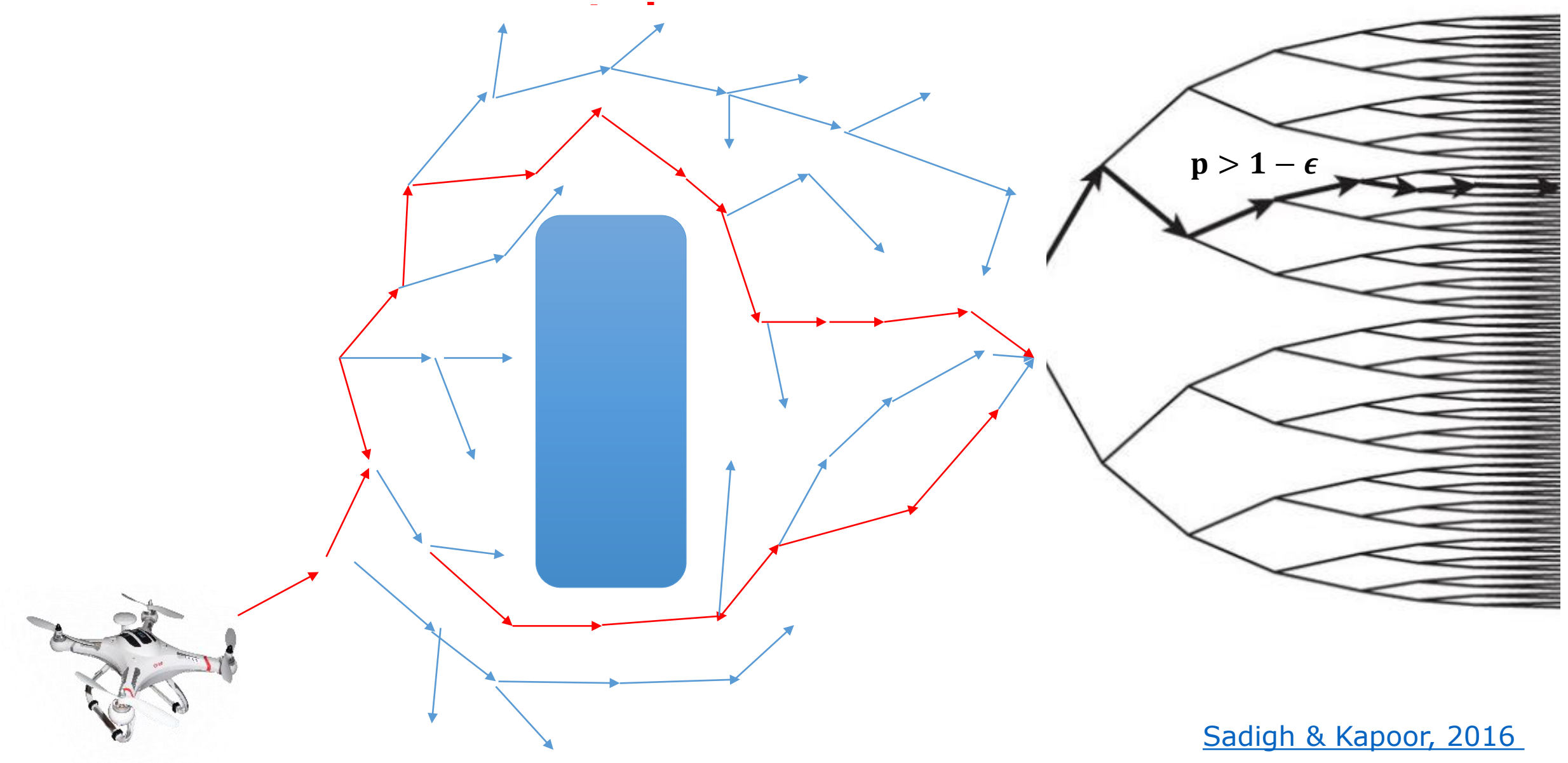
Trajectory safe if:

$$\frac{\Sigma \checkmark}{\Sigma \checkmark + \Sigma \times} > 1 - \epsilon$$

Σ ✓✓✓✓✓✓✗✓✓✓✗✓✓✓✓✓✓✗✓✓✓✗✓✗✓✓✓

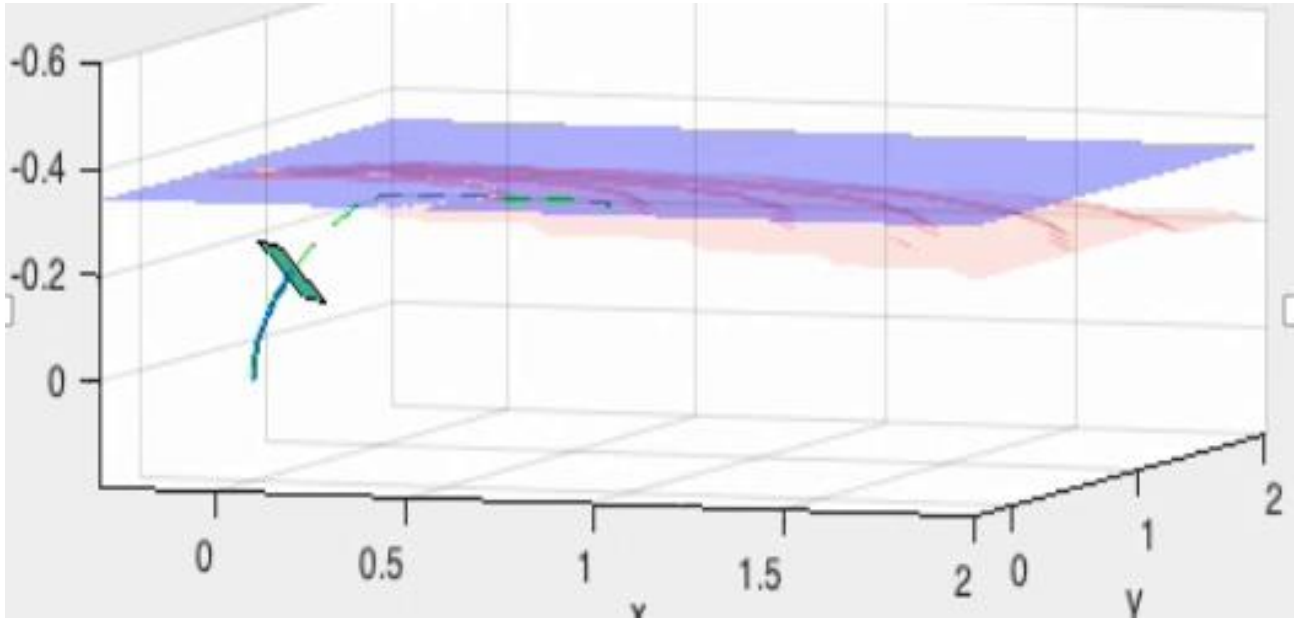
Sadigh & Kapoor, 2016

Direction: Joint modeling of key dimensions of error



Sadigh & Kapoor, 2016

Direction: Joint modeling of key dimensions of error



(video)

Value of refining models & system

- Value of additional data
- Value of enhancing sensors
- Value of better controller

Sadigh & Kapoor, 2016

Direction: Joint modeling of key dimensions of error

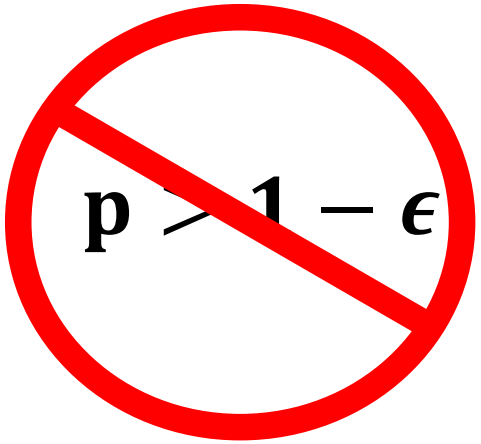
$$\mathbf{p} > \mathbf{1} - \boldsymbol{\epsilon}$$

(video)

Sadigh & Kapoor, 2016

Direction: Joint modeling of key dimensions of error

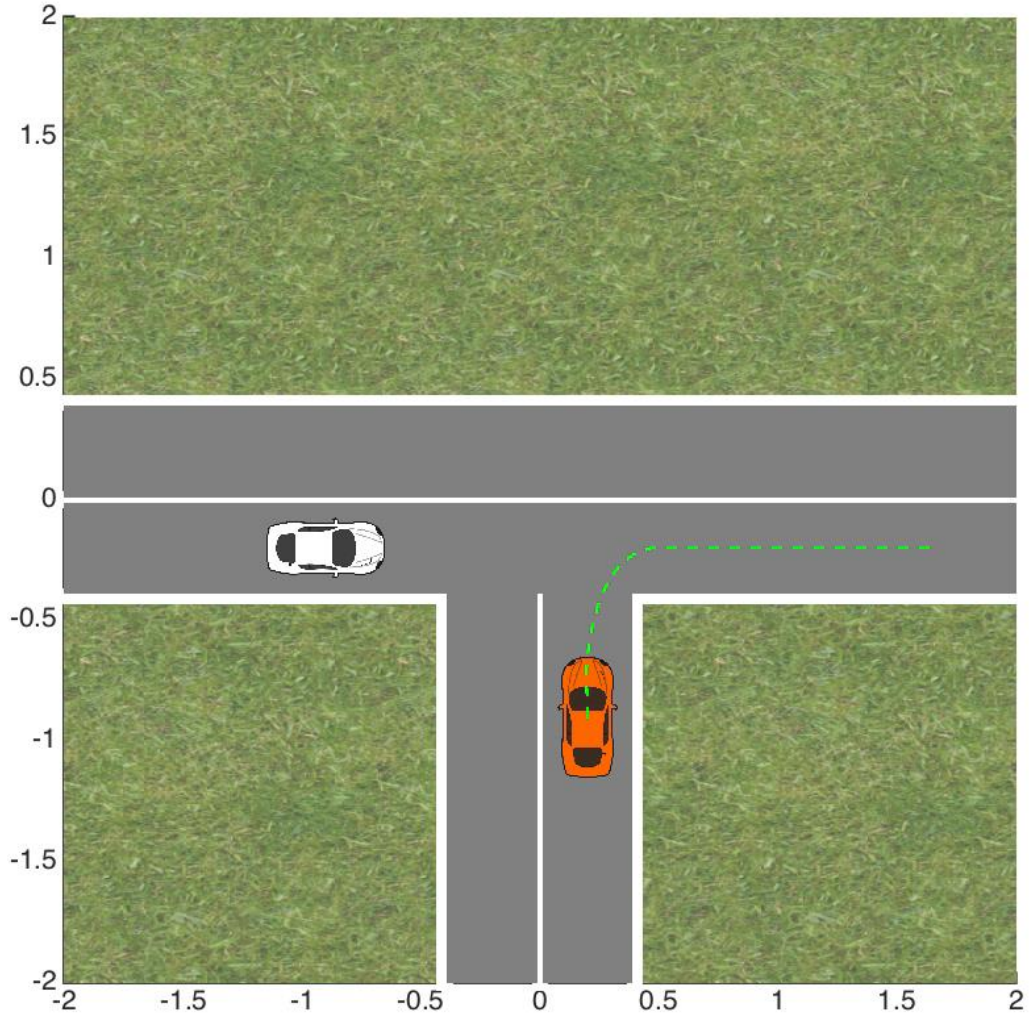
Fail-safe



(video)

Sadigh & Kapoor, 2016

Direction: Joint modeling of key dimensions of error

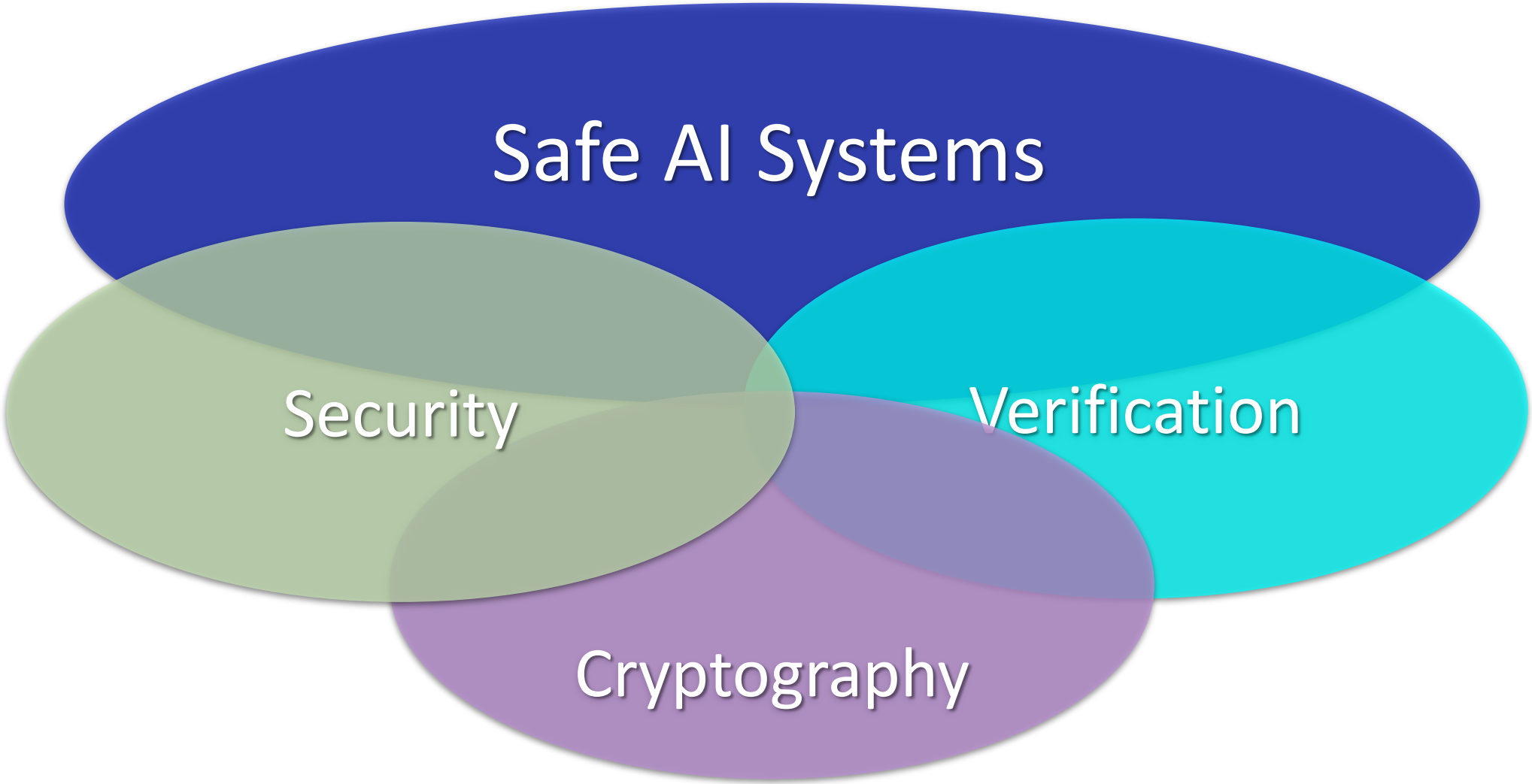


(video)

```
bool AvoidCarCrash(double[] x, double[] y, double[] t, double mu_x, ..
  .., double mu_y, double mu_sx, double mu_sy, double sigma_sq,
  .., double Thresh)
{
  //Sample location and velocities for the other vehicle
  x_other  = Gaussian(mu_x, sigma_sq);
  y_other  = Gaussian(mu_y, sigma_sq);
  sx_other = Gaussian(mu_sx, sigma_sq);
  sy_other = Gaussian(mu_sy, sigma_sq);

  bool isSafe = True;
  for (int i = 0; i < x.GetLength(0); i++)
  {
      //Compute distances to the ego vehicle at each time step
      Xdistance = x[i] - (x_other + time[i]*sx_other);
      Ydistance = y[i] - (y_other + time[i]*sy_other);

      //Safety invariants that require min threshold distance
      SafeInX = (Xdistance > Thresh) || (Xdistance < -Thresh);
      SafeInY = (Ydistance > Thresh) || (Ydistance < -Thresh);
      isSafeNow = (SafeInX || SafeInY)

      isSafe = isSafe && isSafeNow;
  }

 return isSafe;
}
```

Sadigh & Kapoor, 2016

Direction: Verification, security, cryptography



Direction: Verification, security, cryptography

Static analysis

Run-time verification

Whitebox fuzzing

Cybersecurity to protect attack surfaces

Appropriate use of physical security, isolation

Encryption for data integrity, protection of interprocess comms.

Direction: Runtime verification

Difficult to do formal analysis of large-scale system

→ Analysis & execution considers info. from running system

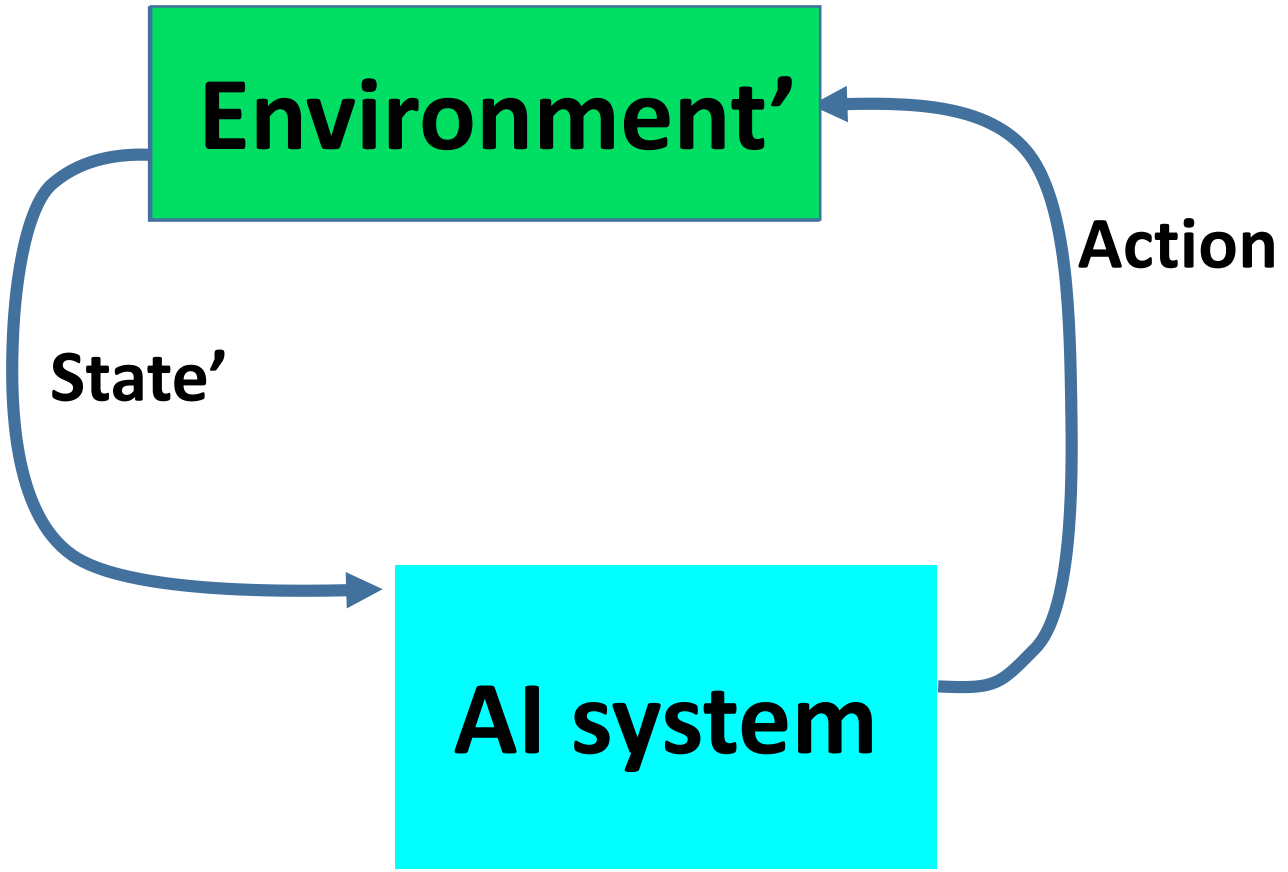
Satisfy or violate desired properties?

Identify problem, future problem

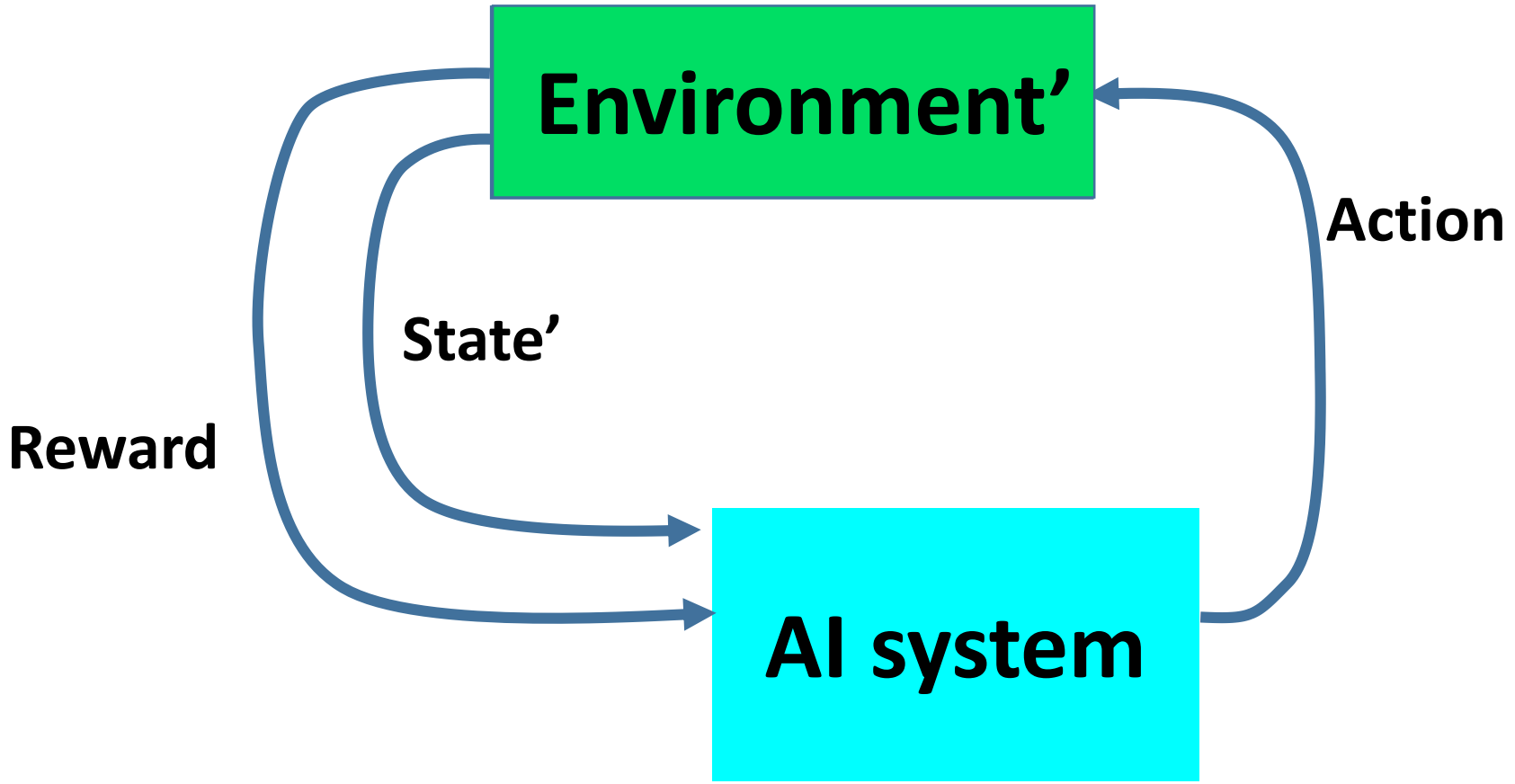
Engage human

Take fail-safe action

Direction: Metalevel analysis, monitoring, assurance



Direction: Metalevel analysis, monitoring, assurance



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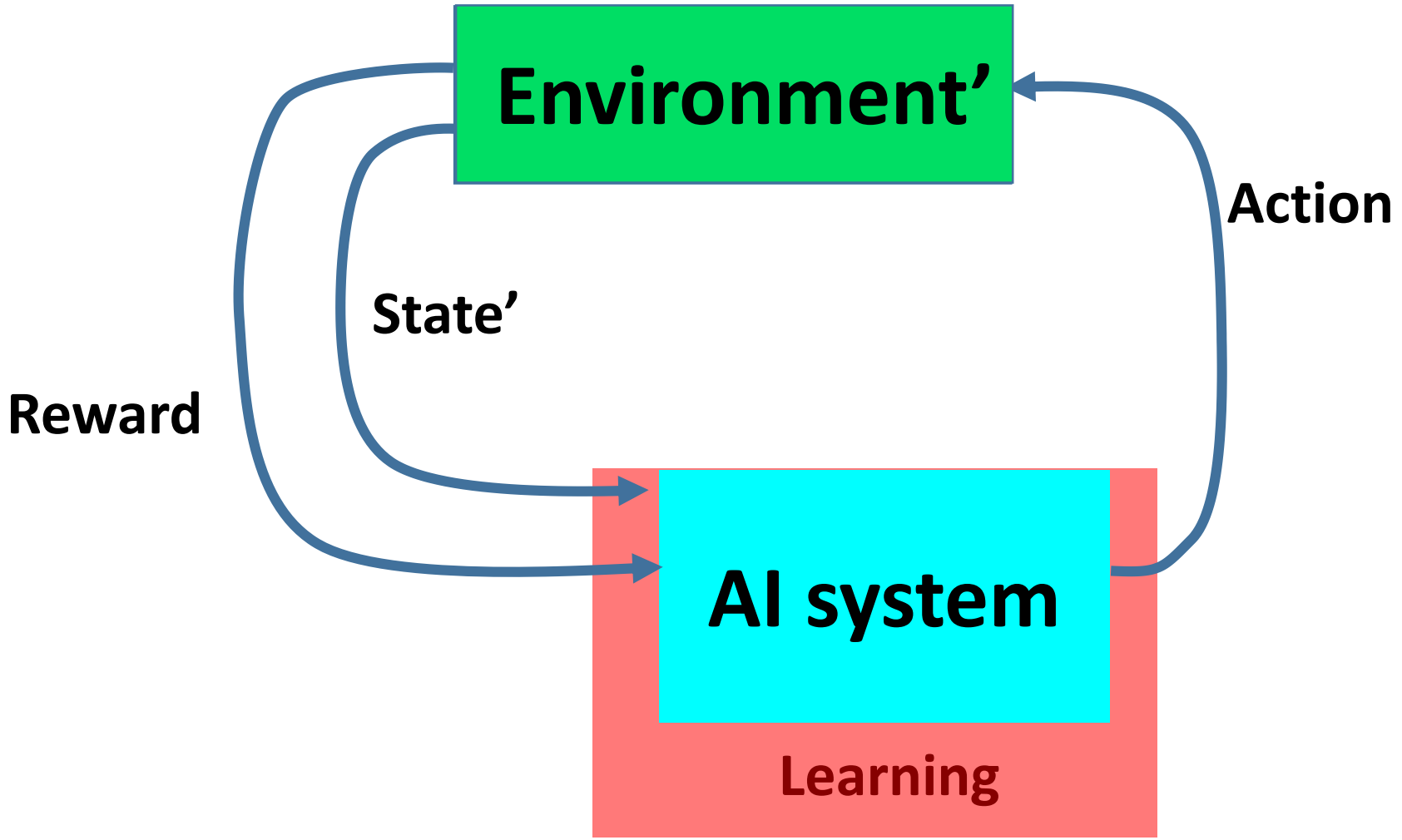
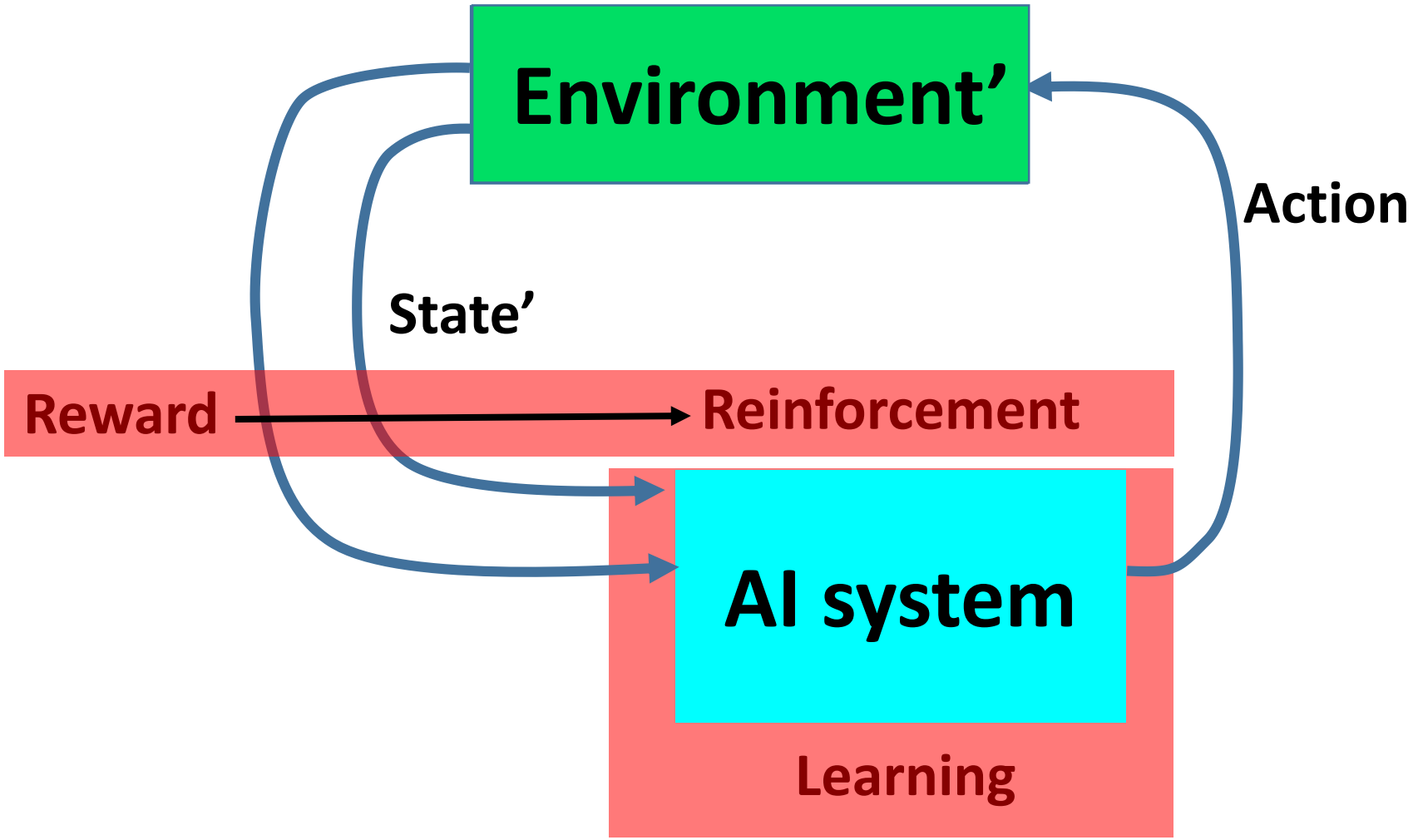
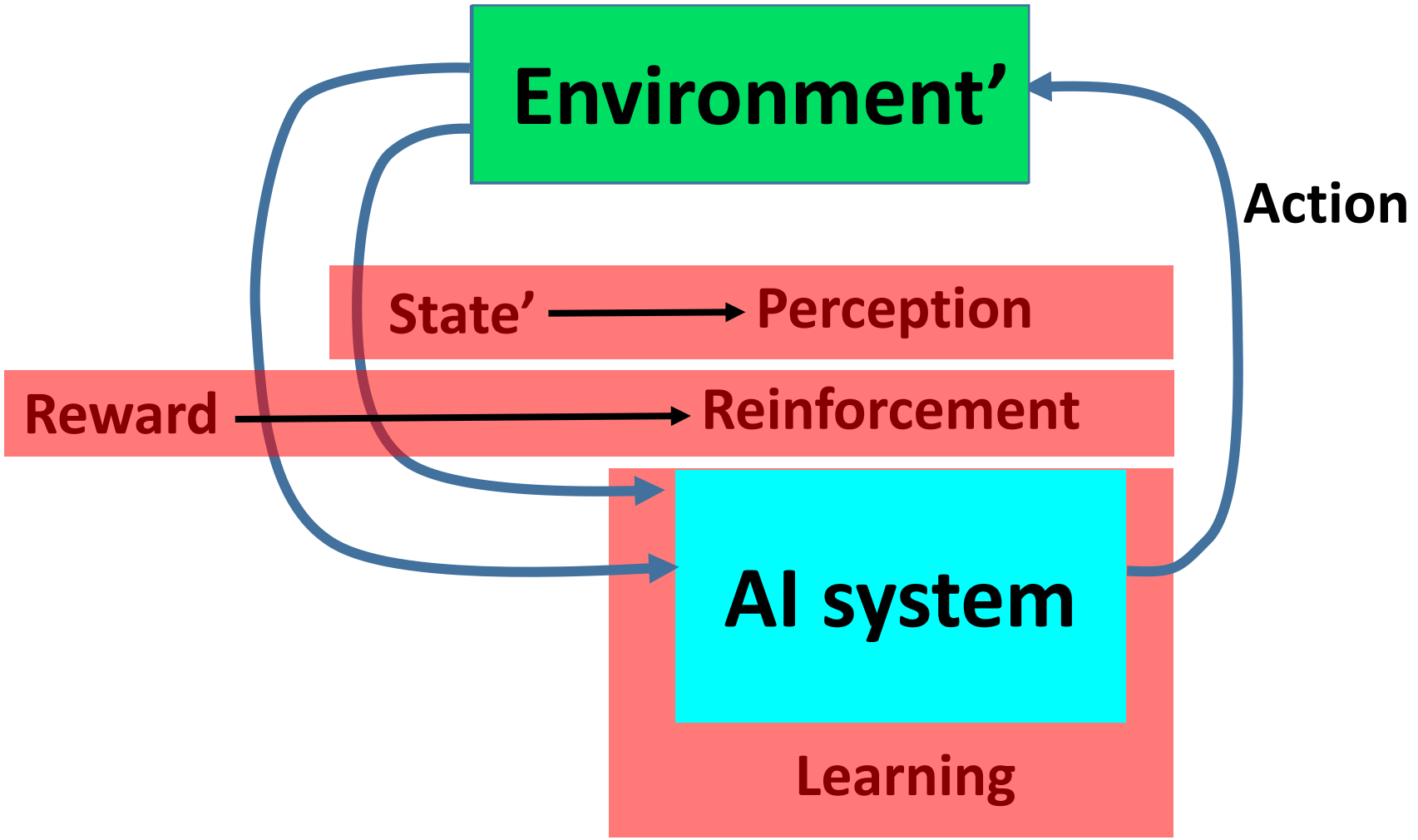


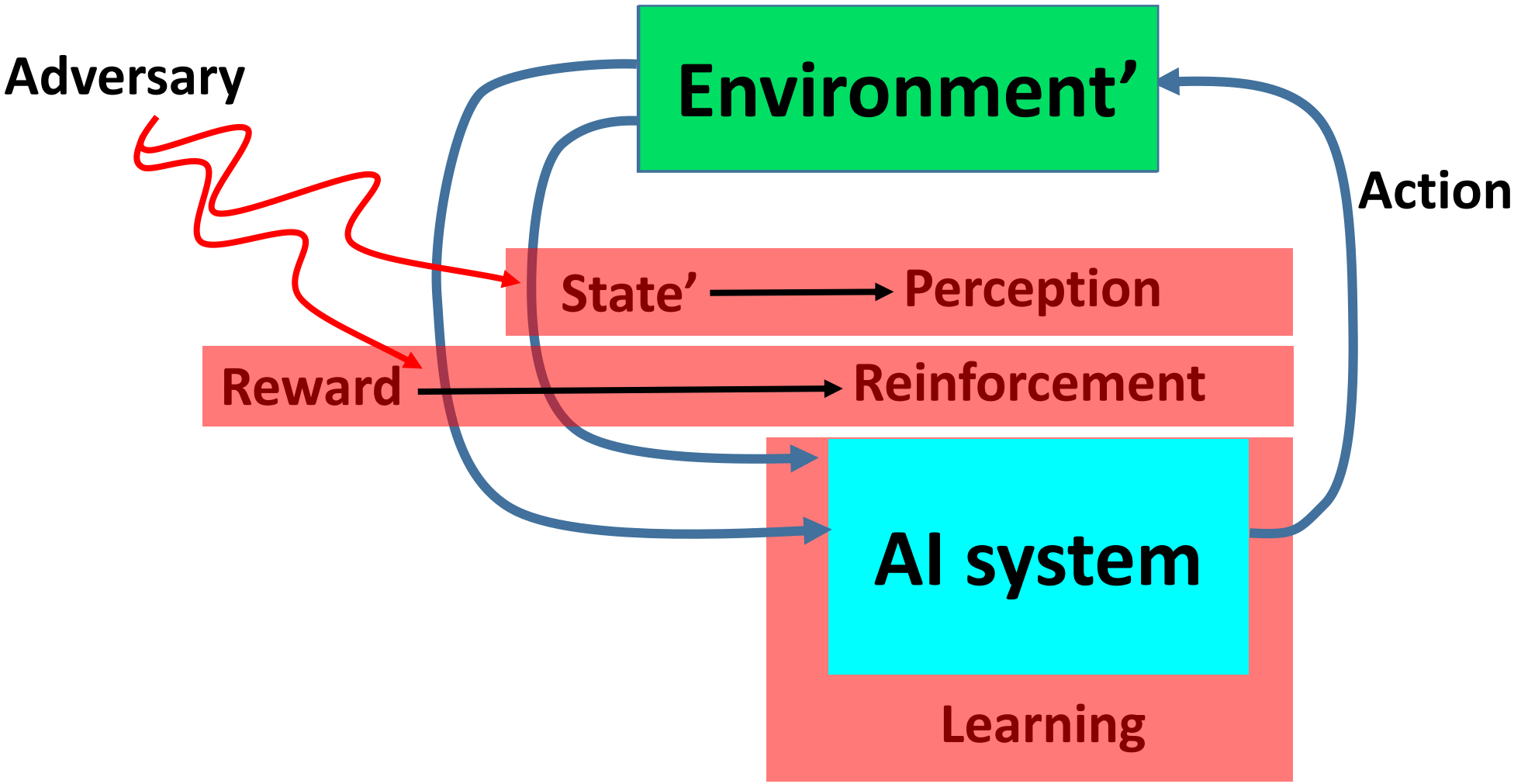
Direction: Metalevel analysis, monitoring, assurance



Direction: Metalevel analysis, monitoring, assurance



Direction: Metalevel analysis, monitoring, assurance



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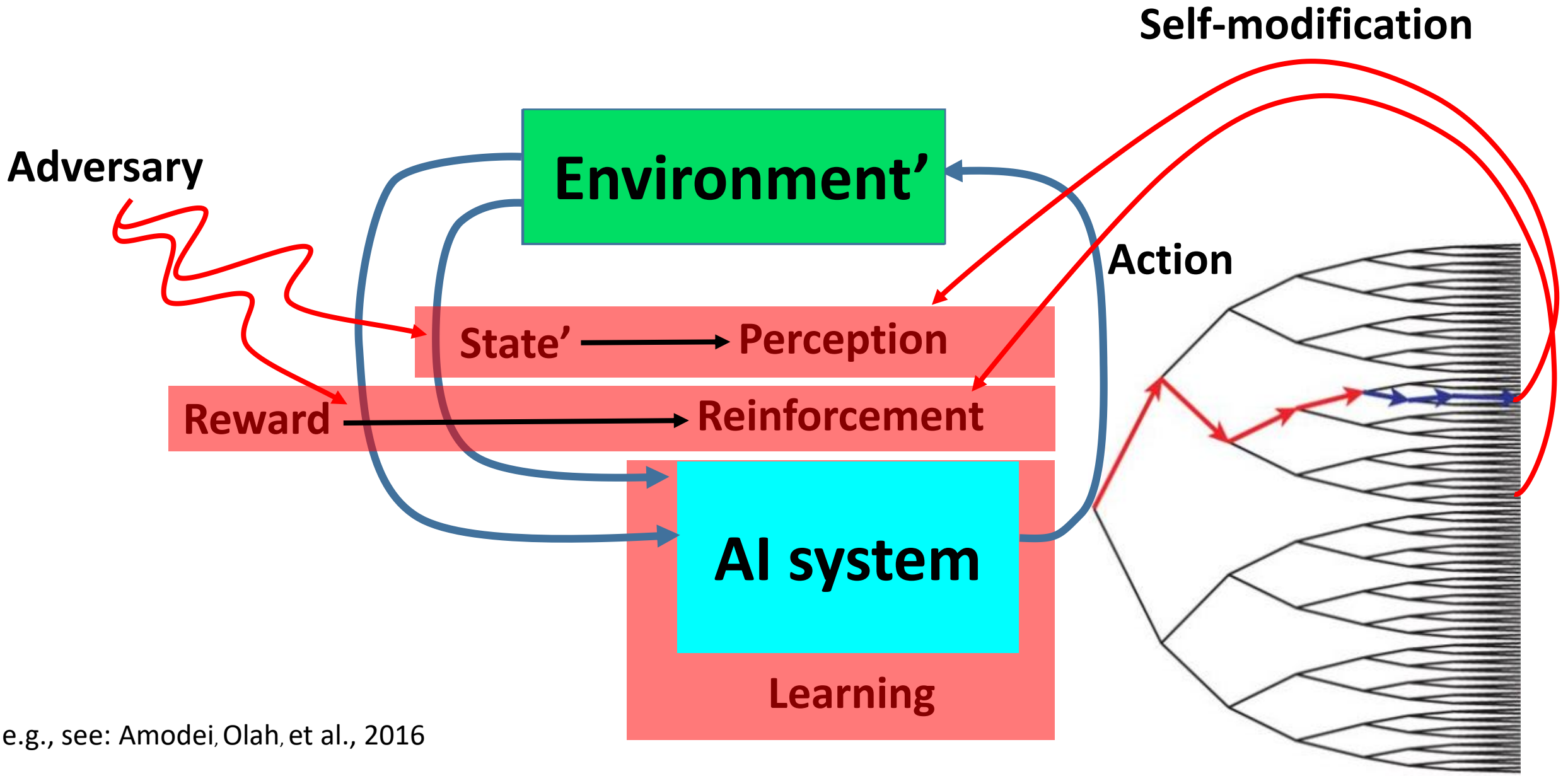
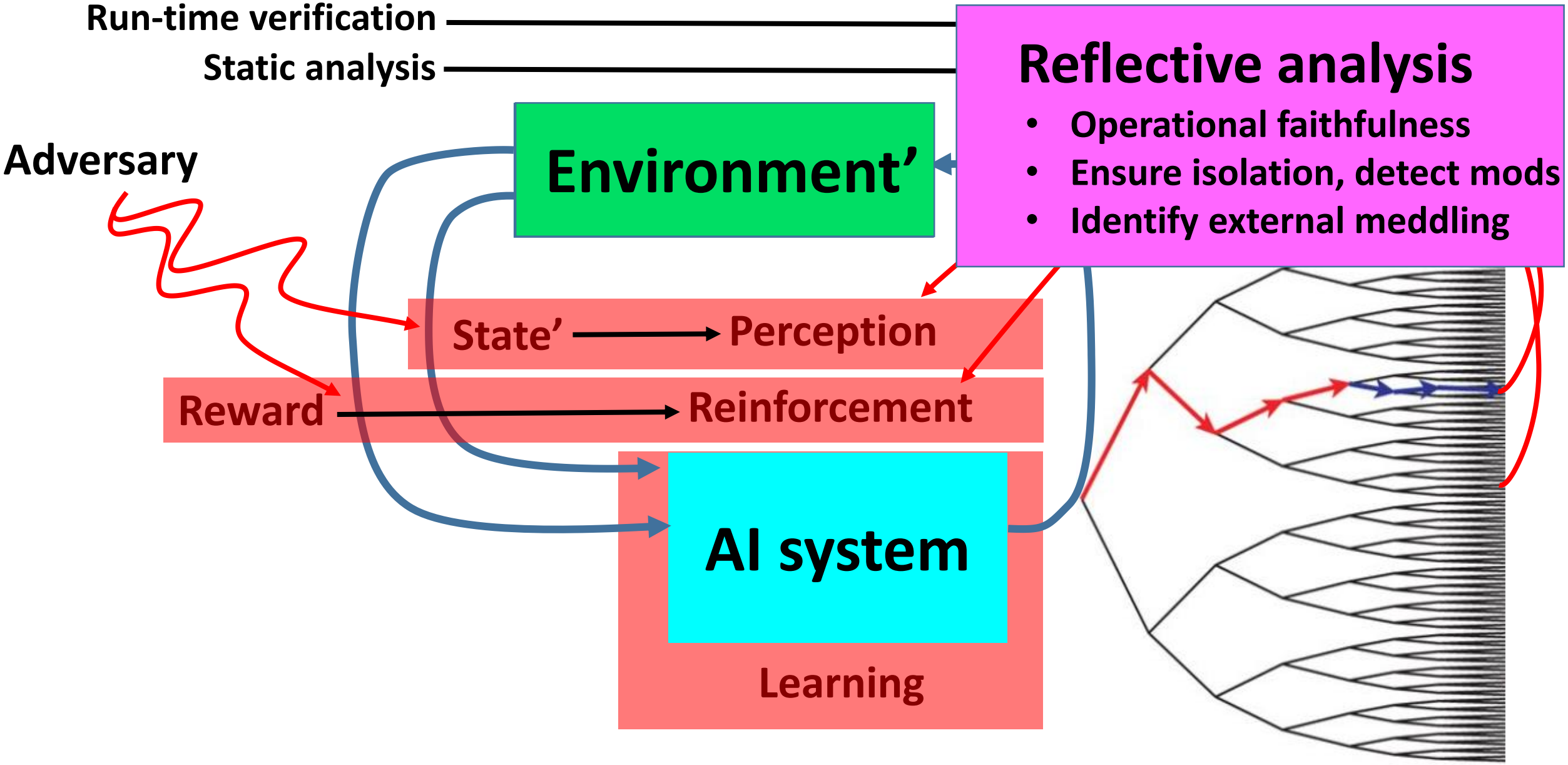


e.g., see: Amodei, Olah, et al., 2016

Direction: Metalevel analysis, monitoring, assurance



Direction: Human-machine collaboration

Models of human cognition

Transparency of state, explanation

Mastering coordination of initiatives

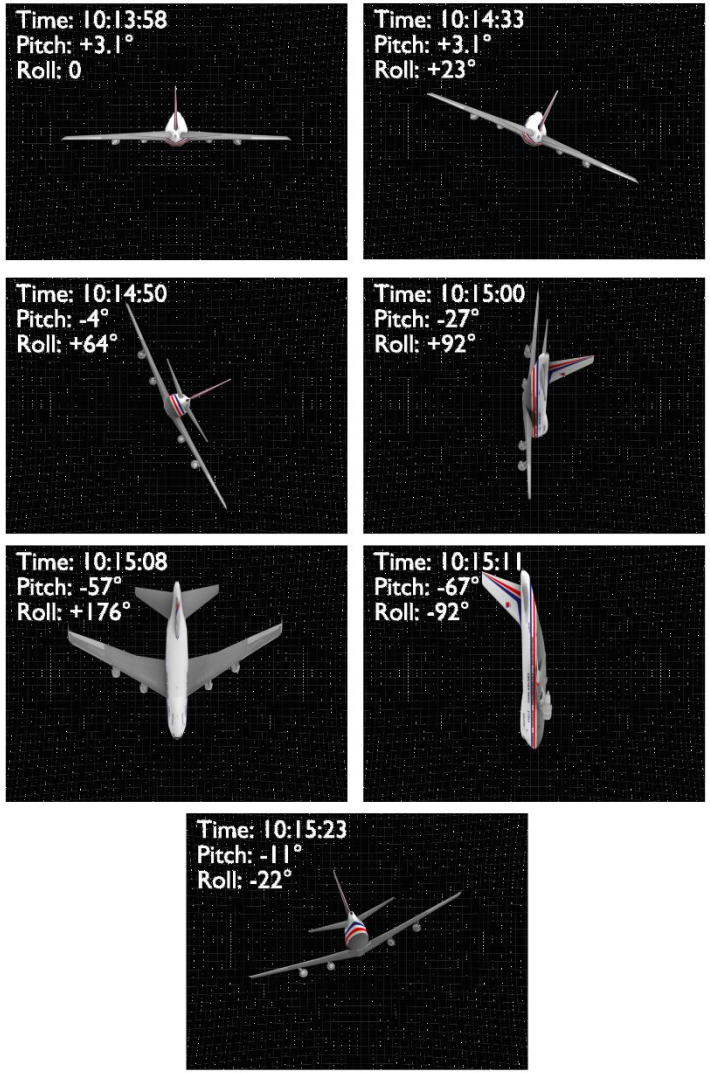
Direction: Human-machine collaboration

China Airlines 006 (Feb 1985)

747 dives 10,000 in 20 seconds. 5g, supersonic.

Air France 447 (June 2009)

Unrecoverable stall.



Direction: Human-machine collaboration

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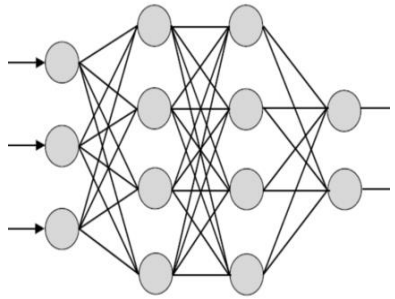
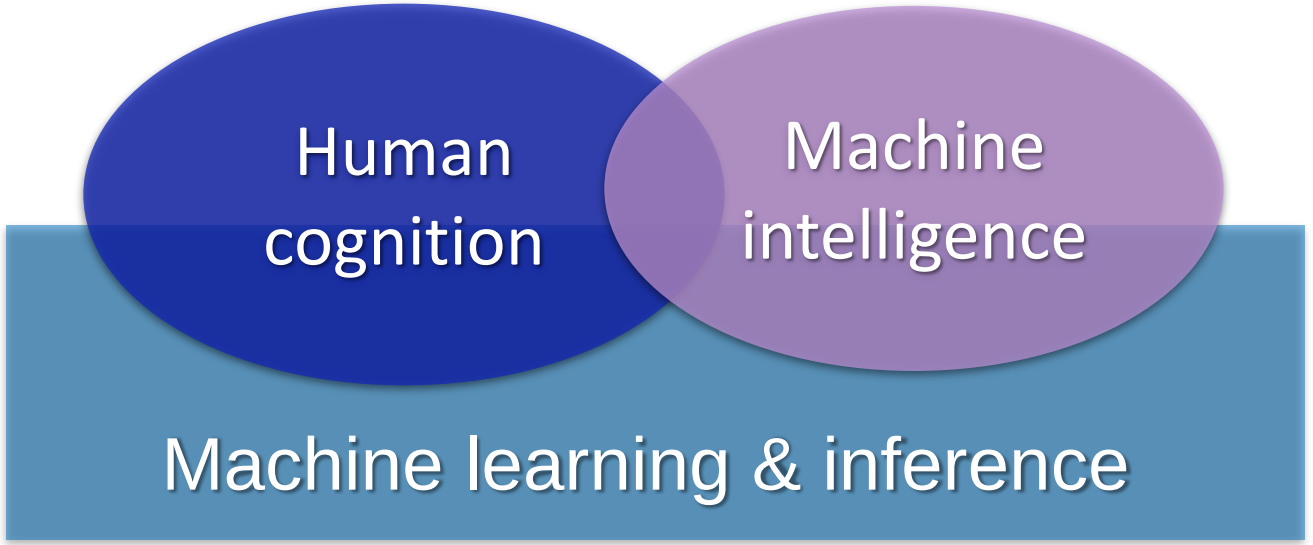
Direction: Human-machine collaboration

- Rich spectrum of autonomy
- How to best work together for safety?







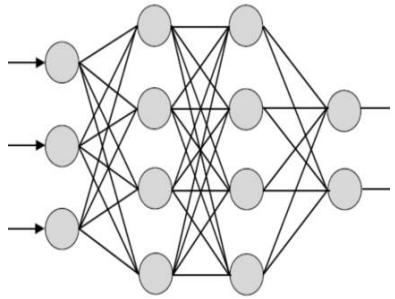


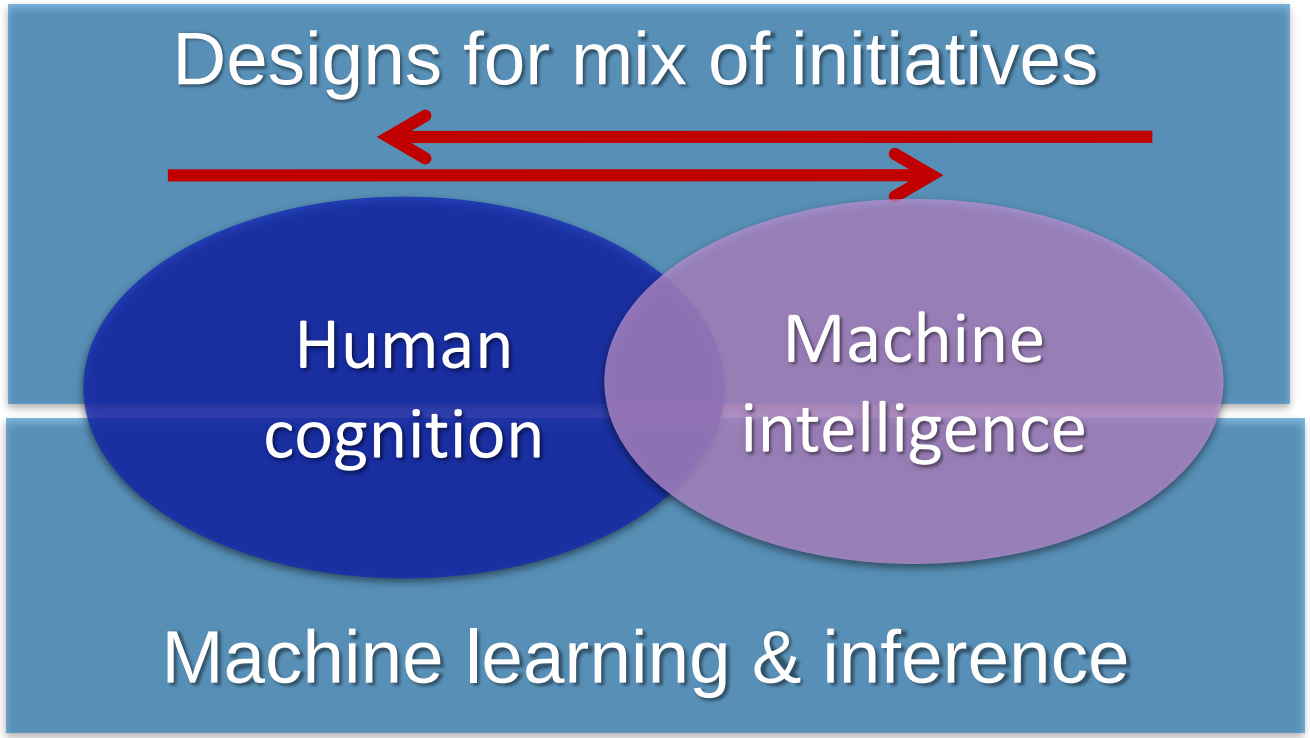
Kamar, Hacker, H., 2012

Direction: Human-machine collaboration

Rich spectrum of autonomy

How to best work together for safety?



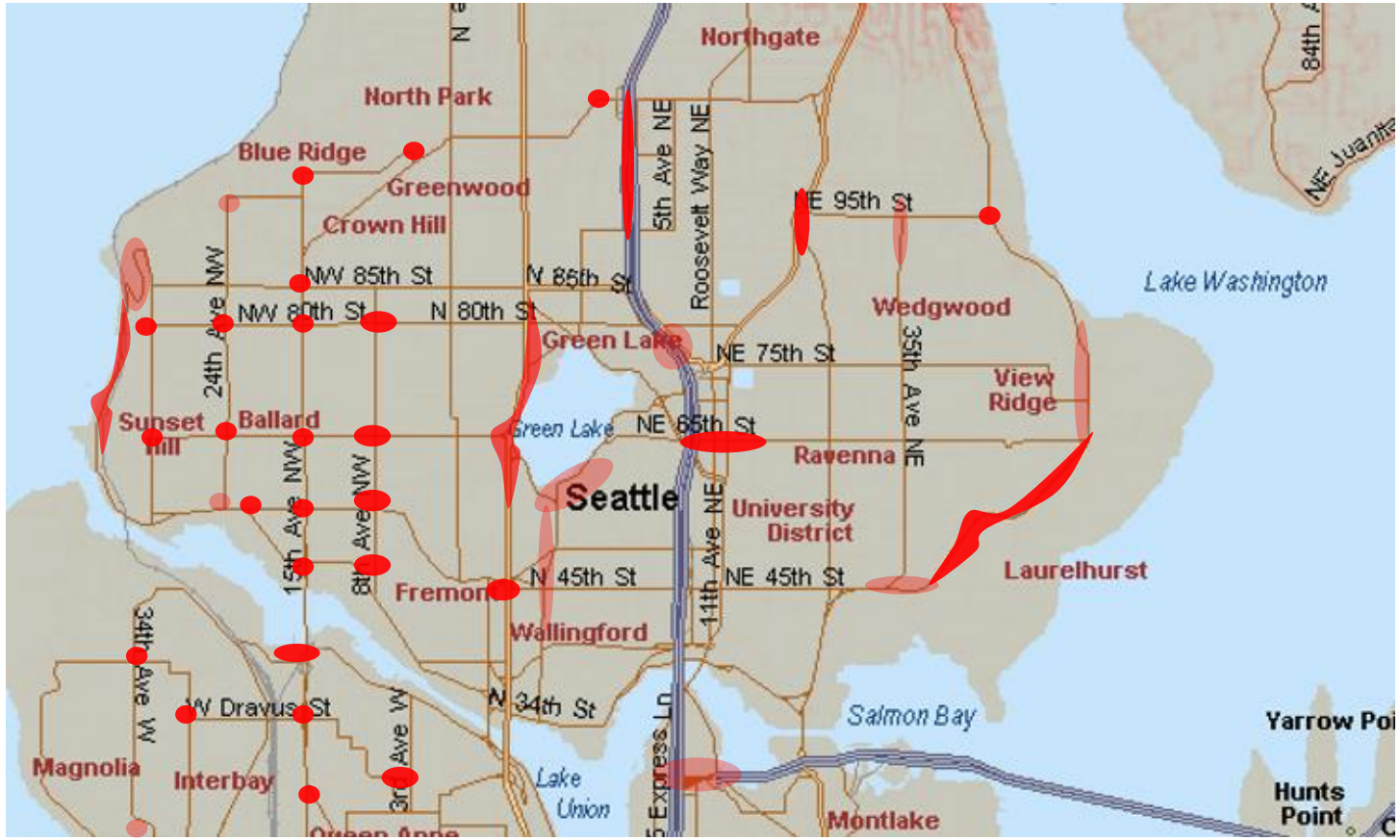


Kamar, Hacker, H., 2012

Direction: Human-machine collaboration

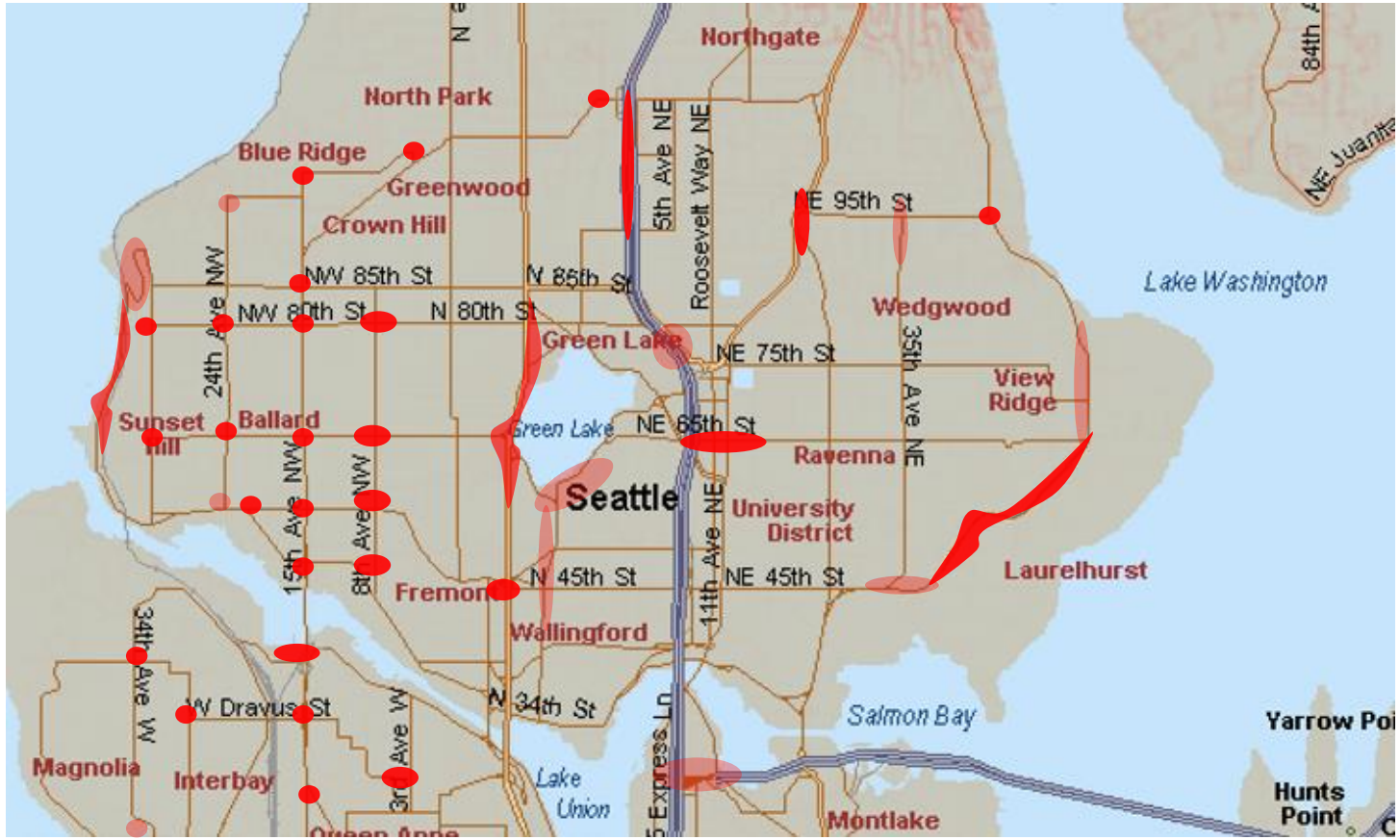
Direction: Human-machine collaboration

Infer challenges with machine competency

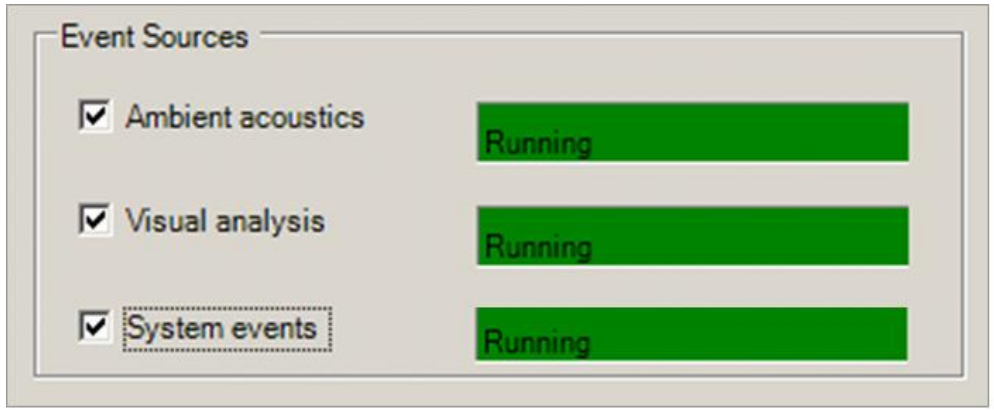


Direction: Human-machine collaboration

Infer challenges with machine competency

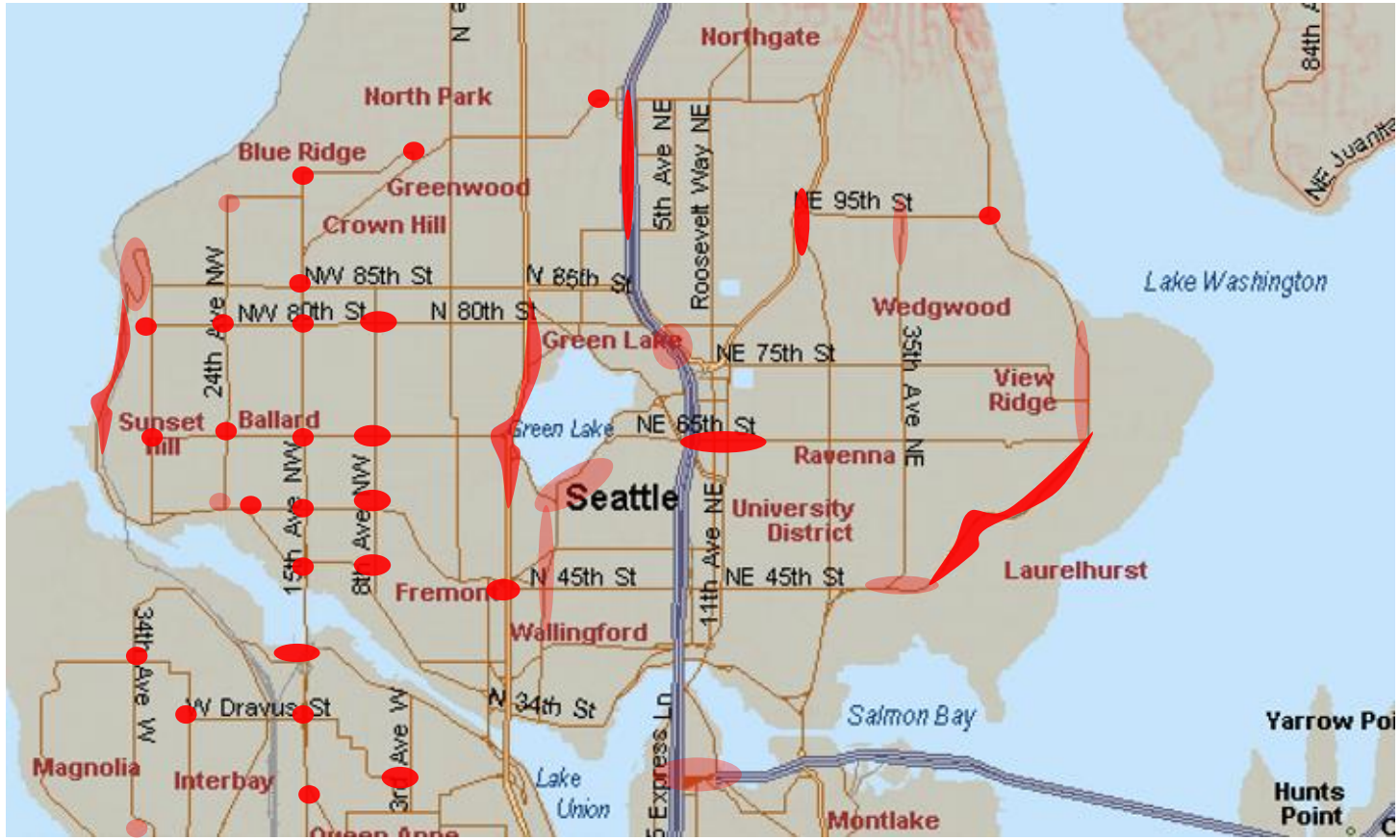


Infer human attention



Direction: Human-machine collaboration

Infer challenges with machine competency



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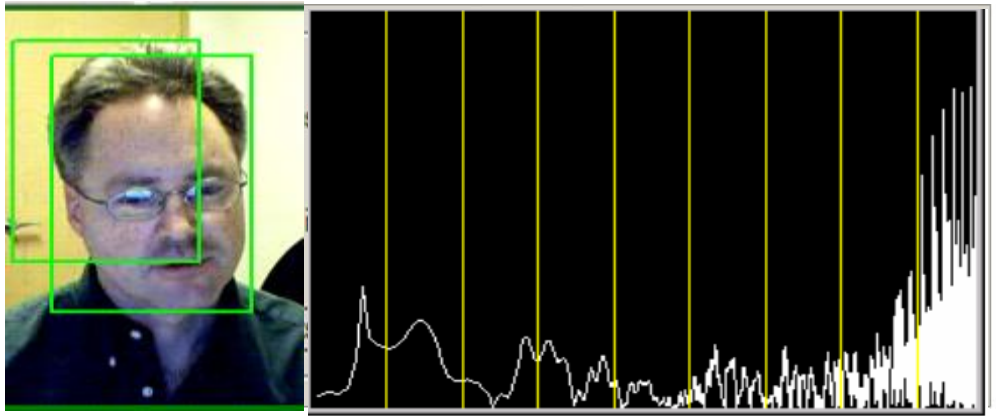
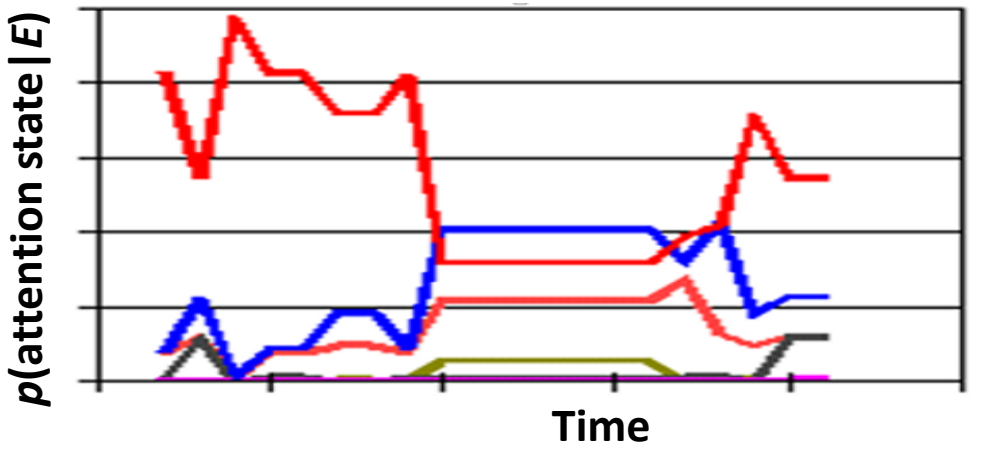
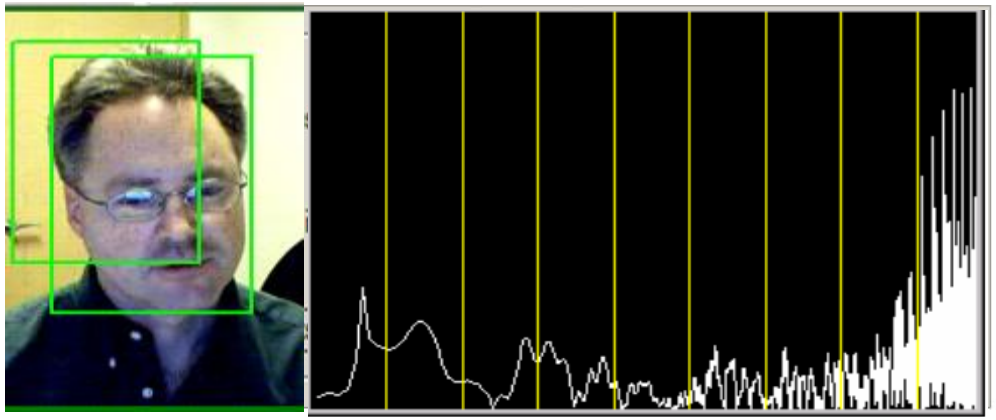


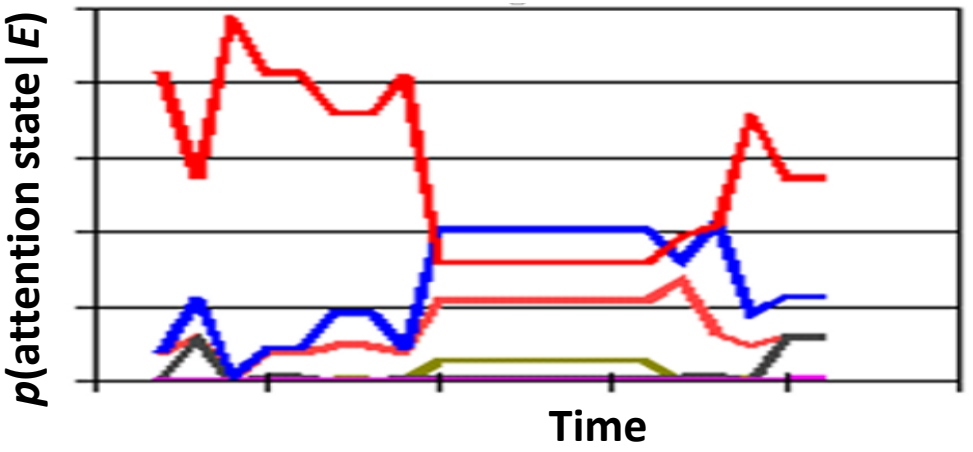


Direction: Human-machine collaboration

Continual prediction of trajectories

Infer human attention

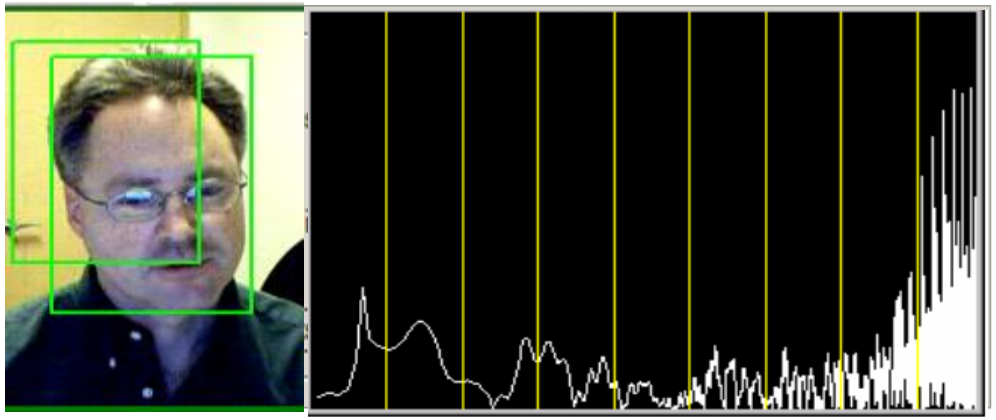


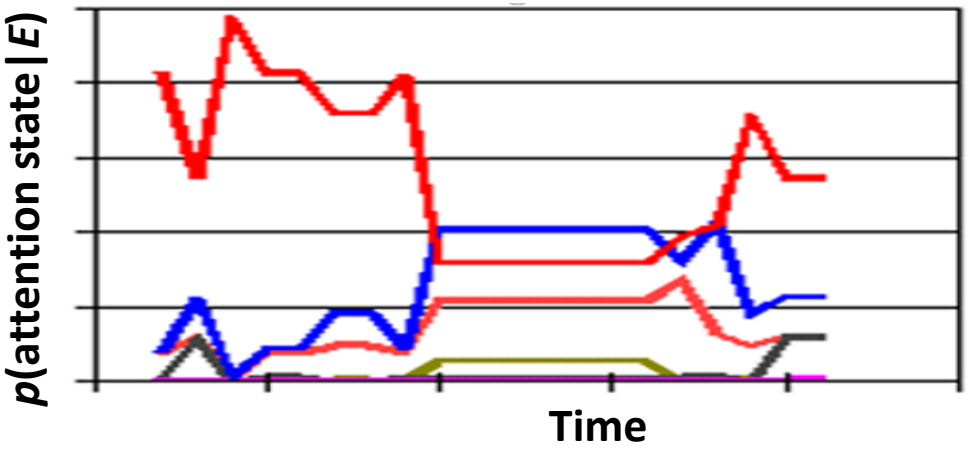


Direction: Human-machine collaboration

Continual prediction of trajectories

Infer human attention





Direction: Human-machine collaboration

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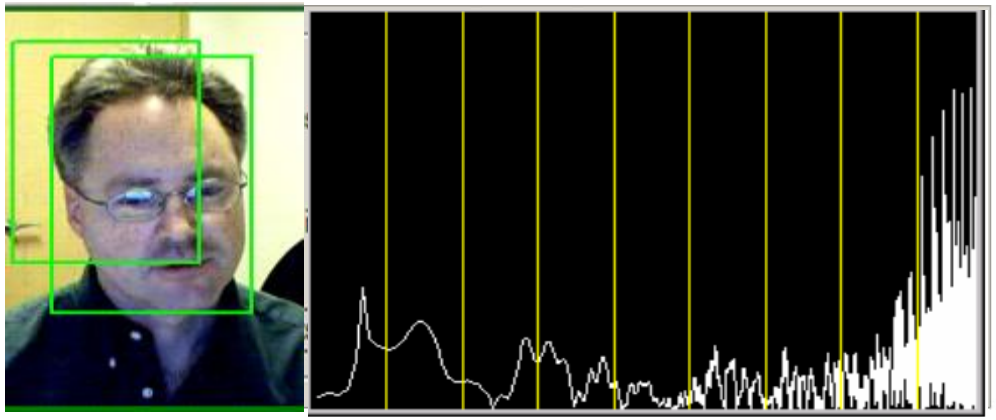
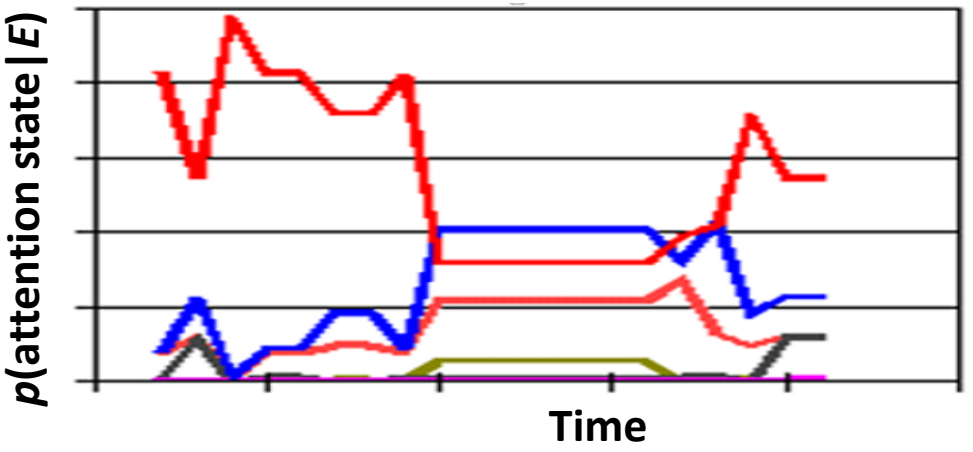
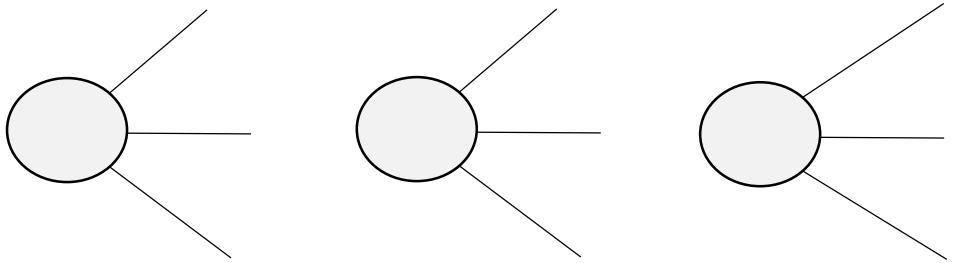




Direction: Human-machine collaboration

Safety-assuring mixed-initiative planner

- Driver's attention over time
- Latency of human input
- Latency tolerance of situation
- Cost & influence of alerting driver
- Custom language, ongoing dialog



Gain driver attention *t*

Slow to defer need *t'*

Implement failsafe *t''*

Direction: Develop Best Practices for Safe AI

- Phases of study, testing, reporting for rolling out new capabilities in safety-critical domains (akin to FDA clinical trials, post-marketing surveillance)
- Disclosure & control of parameters on failure rates, tradeoffs, preferences
- Transparency & explainability of perception, inference, action
- System self-monitoring & reporting machinery
- Isolation of components in intelligence architectures
- Detecting & addressing feedback of system's influence on self

Direction: Develop Best Practices for Safe AI

- Standard protocols for handoffs, attention, awareness, warning, in human-machine collaborations
- Policies for visible disclosure of autonomy to others (e.g., indication to others that a car is currently on automated policy)
- Fail-safe actions & procedures given predicted or sensed failures
- Enhancing robustness via co-design of environment & systems
- Testing for drift of assumptions, distributions in domains
- Special *openness* & *adherence to best practices* for data, learning, decision making for applications in governance & public policy

Direction: Address concerns about “superintelligences”

Addressing concerns of public

Significant differences of opinion, including experts

Stephen Hawking, Elon Musk, and Bill Gates Warn About Artificial Intelligence

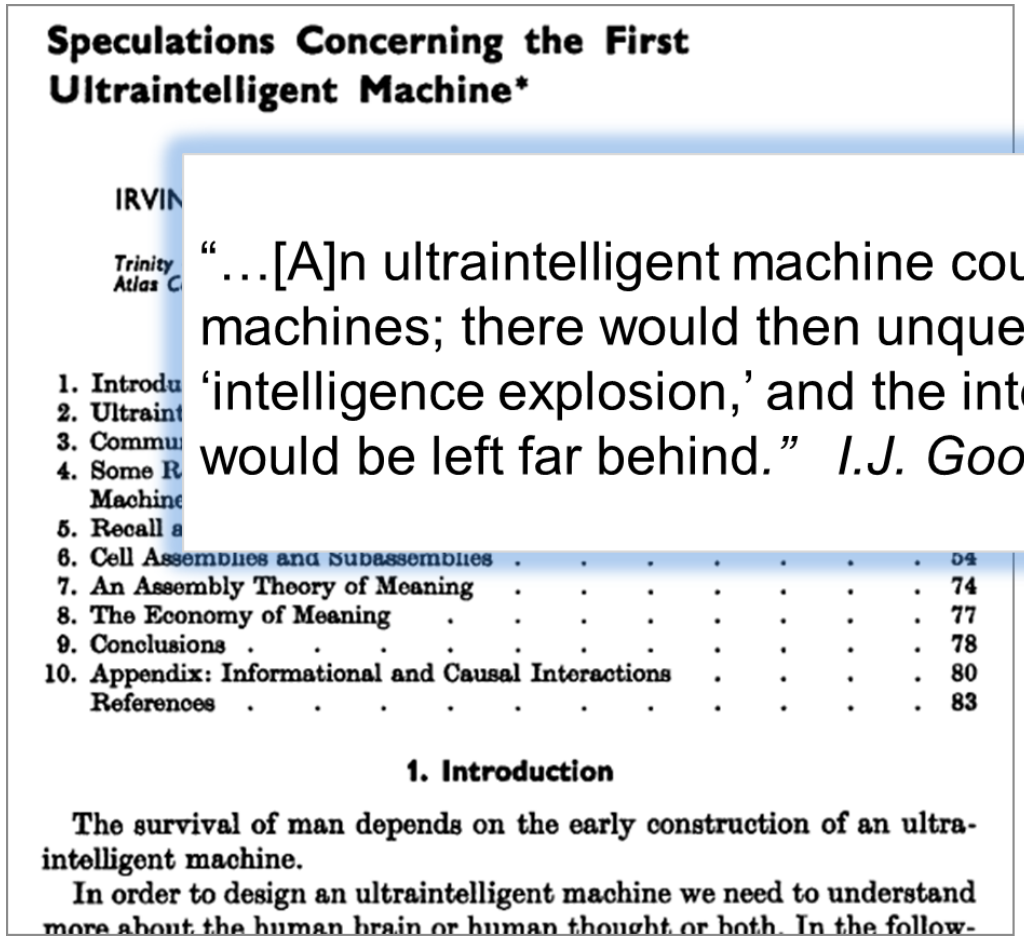
Google-owned Boston Dynamics released a video showing a 6′ tall 320-lb humanoid robot named Atlas running freely in the woods

By Michael Sainato • 08/19/15 12:30pm

Direction: Address concerns about “superintelligences”

Addressing concerns of public

Significant differences of opinion, including among experts



Speculations Concerning the First Ultraintelligent Machine*

IRVIN

Trinity Atlas C

1. Introdu
2. Ultraint
3. Commu
4. Some R
   Machine
5. Recall a
6. Cell Assemblies and Subassemblies 84
7. An Assembly Theory of Meaning 74
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    References 83

1. Introduction

The survival of man depends on the early construction of an ultra-intelligent machine.

In order to design an ultraintelligent machine we need to understand more about the human brain or human thought or both. In the follow-

“…[A]n ultraintelligent machine could design even better machines; there would then unquestionably be an ‘intelligence explosion,’ and the intelligence of man would be left far behind.” *I.J. Good* (1965)

Direction: Address concerns about “superintelligences”

Let us now assume, for the sake of argument, that these machines are a genuine possibility, and look at the consequences of constructing them. To do so would of course meet with great opposition, unless we have advanced greatly in religious toleration from the days of Galileo. There would be great opposition from the intellectuals who were afraid of being put out of a job. It is probable though that the intellectuals would be mistaken about this. There would be plenty to do, trying to understand what the machines were trying to say, ~~in trying to say~~, i.e. in trying to keep ones

seems probable that once the machine thinking method had started, it would not take long to outstrip our feeble powers. There would be no question of the machines dying, and they would be able to converse with each other to sharpen their wits. At some stage therefore we should have to expect the machines to take control, in the way that is mentioned in Samuel Butler's 'Erewhon'.

Alan Turing
Script, BBC broadcast, 1951

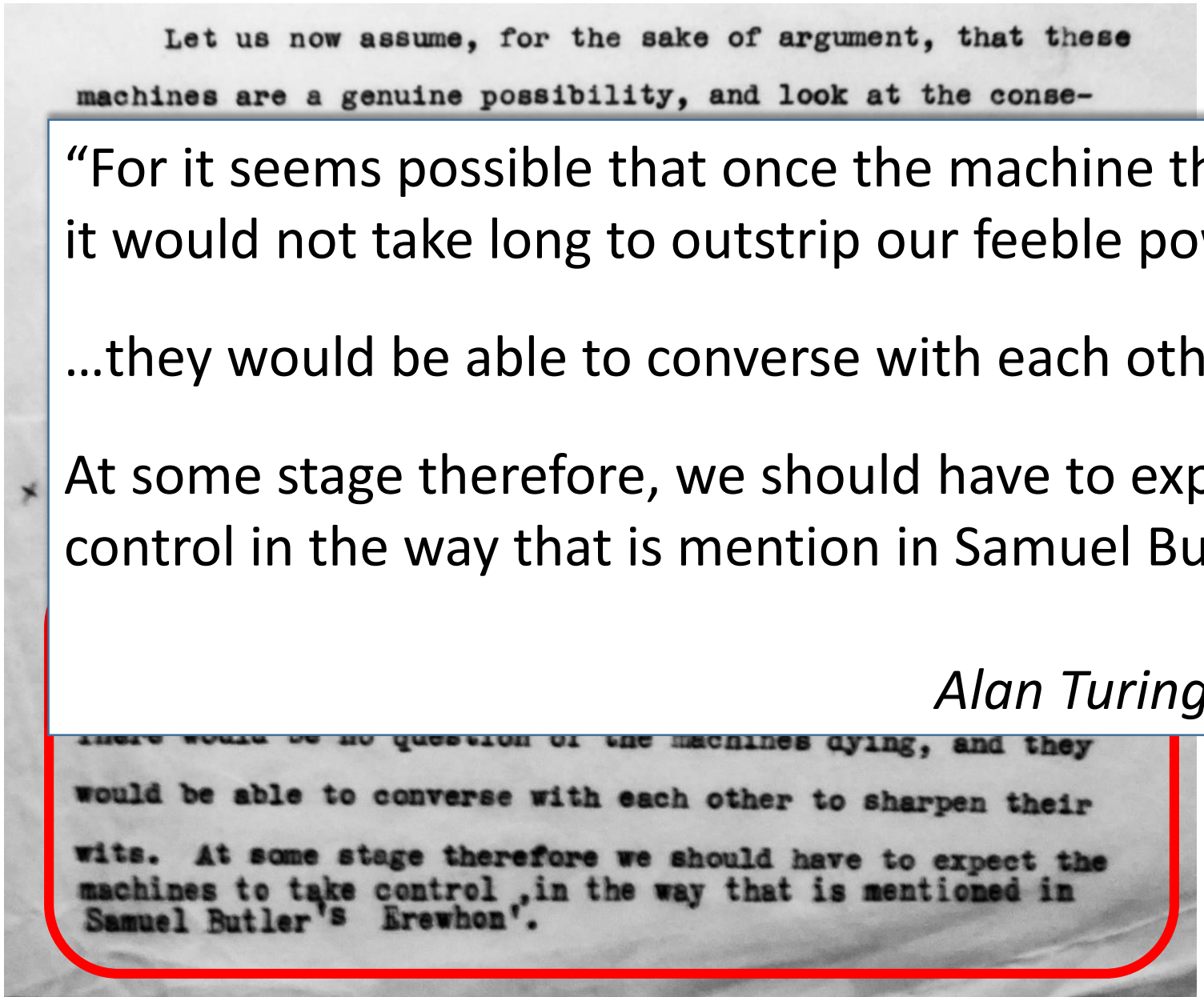
Direction: Address concerns about “superintelligences”

“For it seems possible that once the machine thinking method had started, it would not take long to outstrip our feeble powers.

…they would be able to converse with each other to sharpen their wits.

At some stage therefore, we should have to expect the machines to take control in the way that is mention in Samuel Butler’s Erewhon.”

Alan Turing, 1951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would be able to converse with each other to sharpen their wits. At some stage therefore we should have to expect the machines to take control, in the way that is mentioned in Samuel Butler's Erewhon'.

Direction: Address concerns about “superintelligences”

Addressing concerns of public

Significant differences of opinion, including experts

- Do we understand possibilities?
- What kind of research should done proactively?
- Can we “backcast” from imagined poor outcomes
- Designs of clear ways to thwart possibilities, ease concerns