A Path to AI

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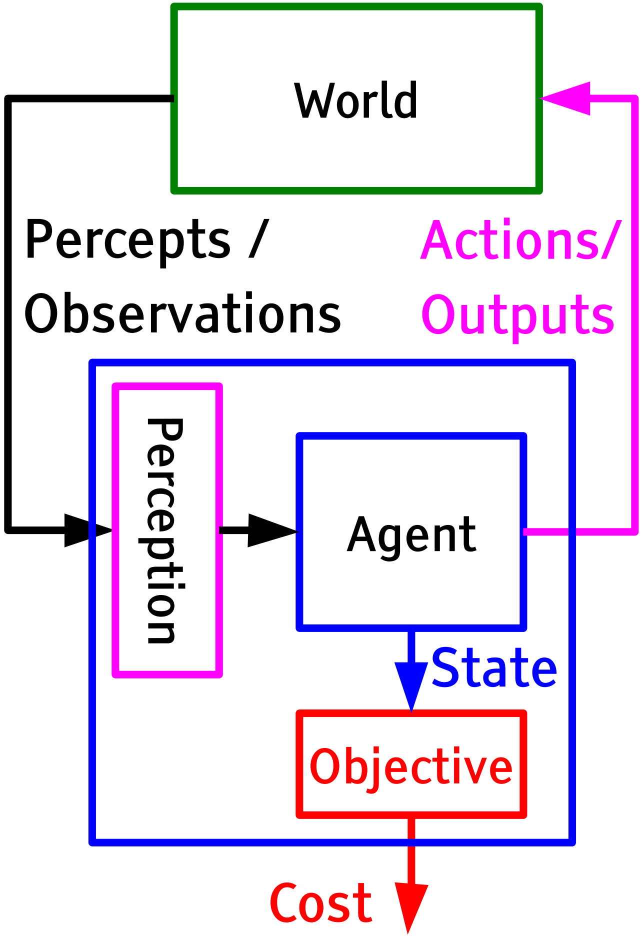
How can machines be intelligent and beneficial

The Architecture of an AI system

- **Perception:** estimates the state of the world
  - Vision, Speech, Audio
- **Agent**
  - Prediction, Causal Inference
  - Planning, Reasoning, Working Memory
- **Objective:** Measures the agent's "happiness"
  - Agent acts to optimize the objective
  - Drives the system to do what we want
  - Parts of it are hardwired and immutable
  - Parts of it is trainable

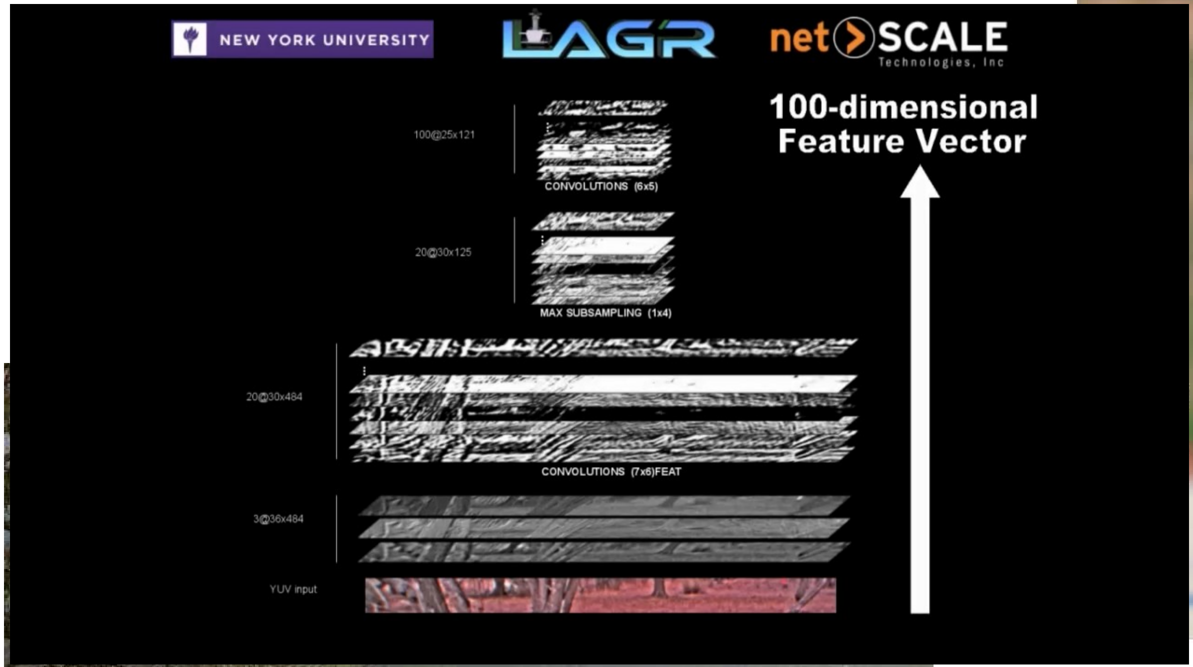


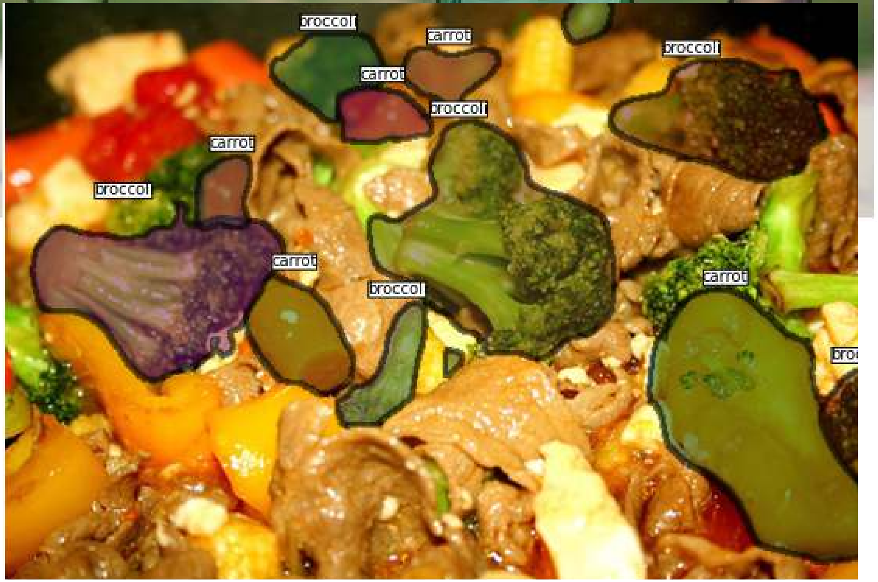
Obstacles to AI

How could machines acquire common sense?

- TL;DR:
  - Machines don’t have common sense
  - To acquire it, they must learn how the world works by observation
  - Predictive/unsupervised learning is the missing link

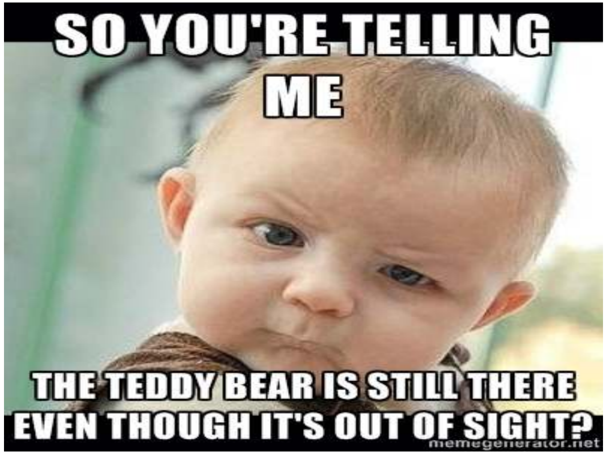
Today, AI = Supervised (Deep) Learning





But Supervised Learning is Insufficient for "Real" AI

- **Most of animals and humans learning is unsupervised, through interaction with the world**
- **We learn how the world works by observing it**
  - We learn many simple things: depth and 3-dimensionality, gravity, object permanence, ...
- **We build models of the world through predictive unsupervised learning**
- **World models give us "common sense"**



What is Common Sense?

- “The trophy doesn’t fit in the suitcase because it’s too large/small”
  - (Winograd Schema)

- “Mike picked up his bag and left the room”

- We have common sense because we know how the world works

- How do we get machines to learn that?

Common Sense is the ability to fill in the blanks

- Infer the state of the world from partial information
- Infer the future from the past and present
- Infer past events from the present state

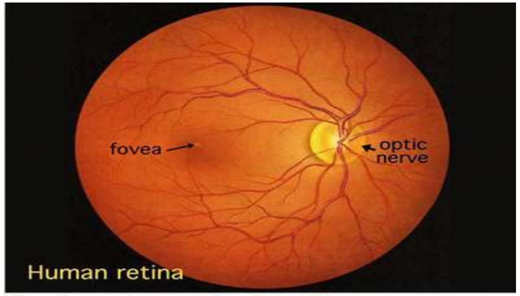


Fig. 1. Human retina as seen through an opthalmoscope.

- Filling in the visual field at the retinal blind spot
- Filling in occluded images
- Fillling in missing segments in text, missing words in speech.
- Predicting the consequences of our actions
- Predicting the sequence of actions leading to a result

- **Predicting any part of the past, present or future percepts from available information.**

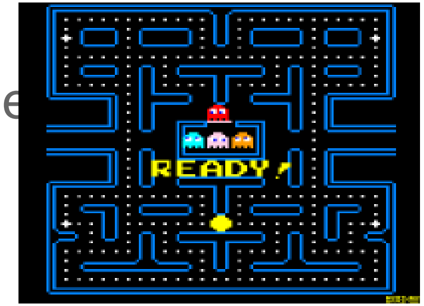
- That's what **predictive unsupervised learning** is

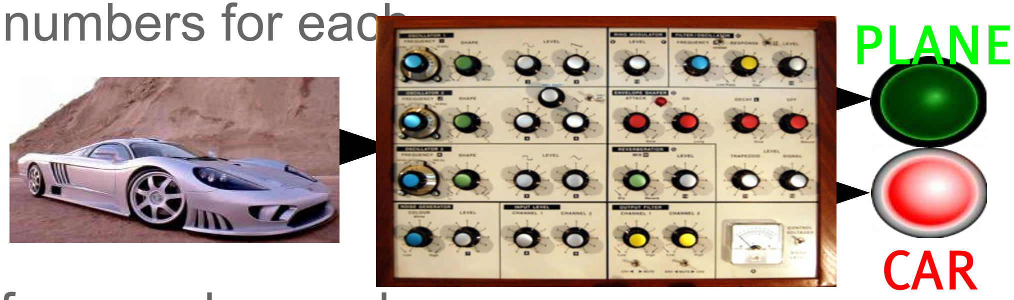
The Necessity of Unsupervised / Predictive Learning

- **The number of samples required to train a large learning machine (for any task) depends on the amount of information that we ask it to predict.**
  - The more you ask of the machine, the larger it can be.
- **"The brain has about 10^14 synapses and we only live for about 10^9 seconds. So we have a lot more parameters than data. This motivates the idea that we must do a lot of unsupervised learning since the perceptual input (including proprioception) is the only place we can get 10^5 dimensions of constraint per second."**
  - Geoffrey Hinton (in his 2014 AMA on Reddit)
  - (but he has been saying that since the late 1970s)
- **Predicting human-provided labels is not enough**
- **Predicting a value function is not enough**

Three Types of Learning

- **Reinforcement Learning**
  - The machine predicts a scalar reward given once in a while
  - **A few bits trial**
- **Supervised Learning**
  - The machine predicts a category or a few numbers for each input
  - **10→10,000 bits per trial**
- **Unsupervised Learning**
  - The machine predicts any part of its input for any observed part.
  - Predicts future frames in videos
  - **Millions of bits per trial**
    - **But these are unreliable bits!**





How Much Information does the Machine Need to Predict?

- **Pure Reinforcement Learning (cherry)**
  - The machine predicts a scalar reward given once in a while.
  - **A few bits for some samples**
- **Supervised Learning (icing)**
  - The machine predicts a category or a few numbers for each input
  - **10→10,000 bits per sample**
- **Unsupervised/Predictive Learning (génoise)**
  - The machine predicts any part of its input for any observed part.
  - Predicts future frames in videos
  - **Millions of bits per sample**

- **Unsupervised Learning is the Dark Matter (or Dark Energy) of AI**

Not a jab at RL (we do RL at FAIR)

- **Model-free RL worsk in games, but it doesn't really work in the real world**

FAIR won the VizDoom 2016 competition.
[Wu & Tian, submitted to ICLR 2017]

TorchCraft: interface between Torch and StarCraft (on github)
[Usunier et al, submitted to ICLR 2017]

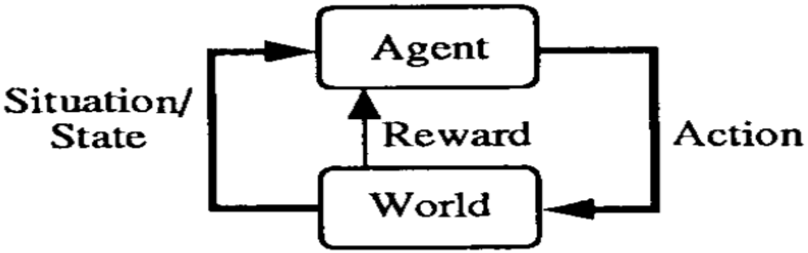
Sutton's Dyna Architecture: "try things in your head before acting"

- **Dyna: an Integrated Architecture for Learning, Planning and Reacting**
  - [Rich Sutton, ACM SIGART 1991]

The main idea of Dyna is the old, commonsense idea that planning is 'trying things in your head,' using an internal model of the world (Craik, 1943; Dennett, 1978; Sutton & Barto, 1981). This suggests the existence of a more primitive process for trying things *not* in your head, but through direct interaction with the world. *Reinforcement learning* is the name we use for this more primitive, direct kind of trying, and Dyna is the extension of reinforcement learning to include a learned world model.

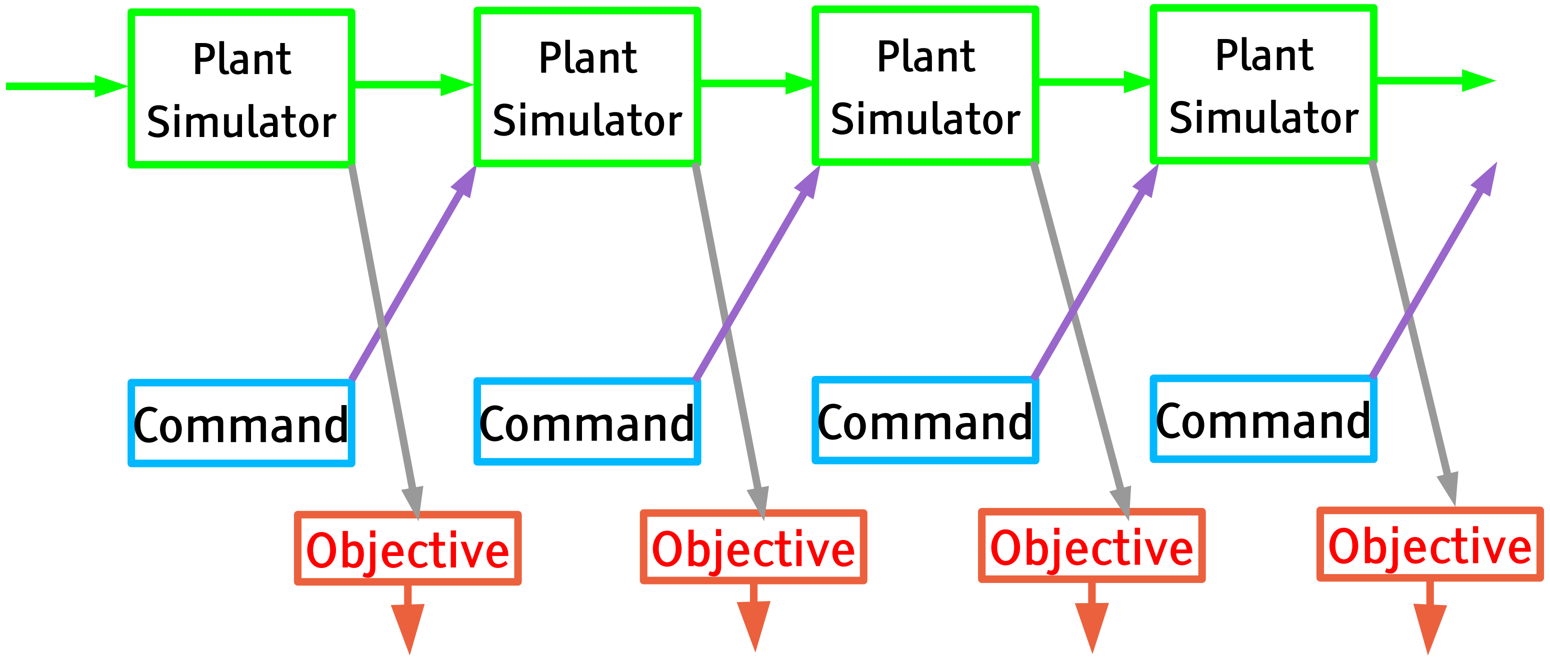
REPEAT FOREVER:

1. Observe the world's state and reactively choose an action based on it;
2. Observe resultant reward and new state;
3. Apply reinforcement learning to this experience;
4. Update action model based on this experience;
5. Repeat K times:
   - 5.1 Choose a hypothetical world state and action;
   - 5.2 Predict resultant reward and new state using action model;
   - 5.3 Apply reinforcement learning to this hypothetical experience.



Classical model-based optimal control

- **Simulate the world (the plant) with an initial control sequence**
- **Adjust the control sequence to optimize the objective through gradient descent**
- **Backprop through time was invented by control theorists in the late 1950s**
  - it's sometimes called the adjoint state method
  - [Athans & Falb 1966, Bryson & Ho 1969]

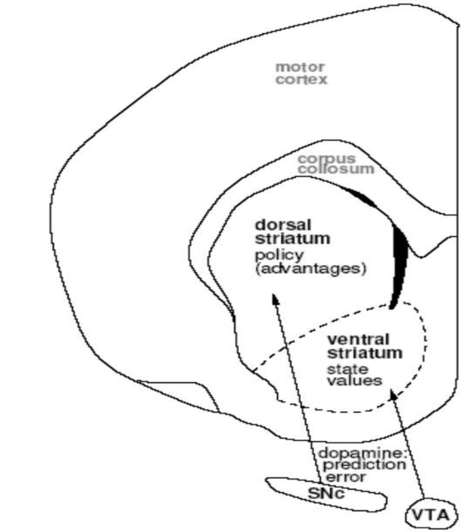


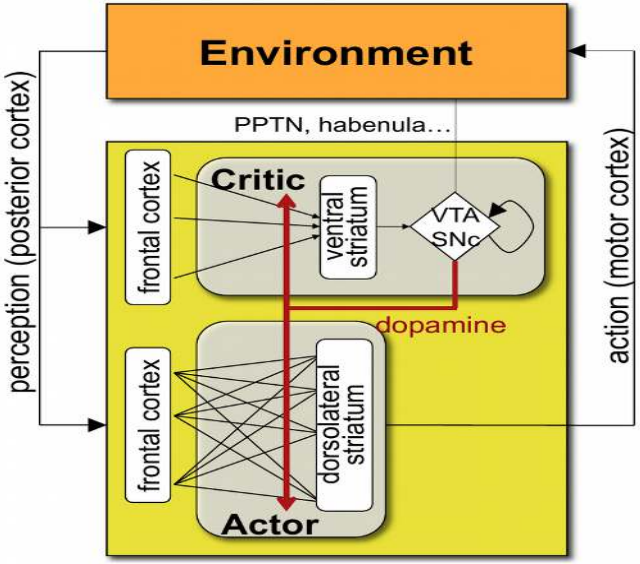
Architecture of an AI Agent

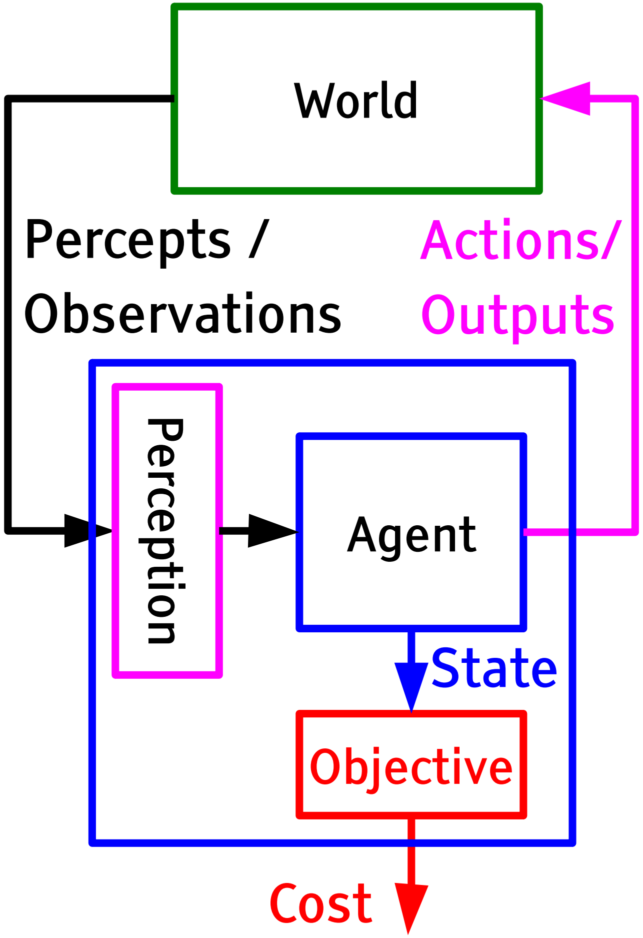
- TL;DR:
  - AI Agent = perception + world model + actor + critic + objective

AI System: Learning Agent + Objective

- The agent gets percepts from the world
- The agent acts on the world
- The agents tries to minimize the long-term expected cost.
- Objective has immutable and trainable parts

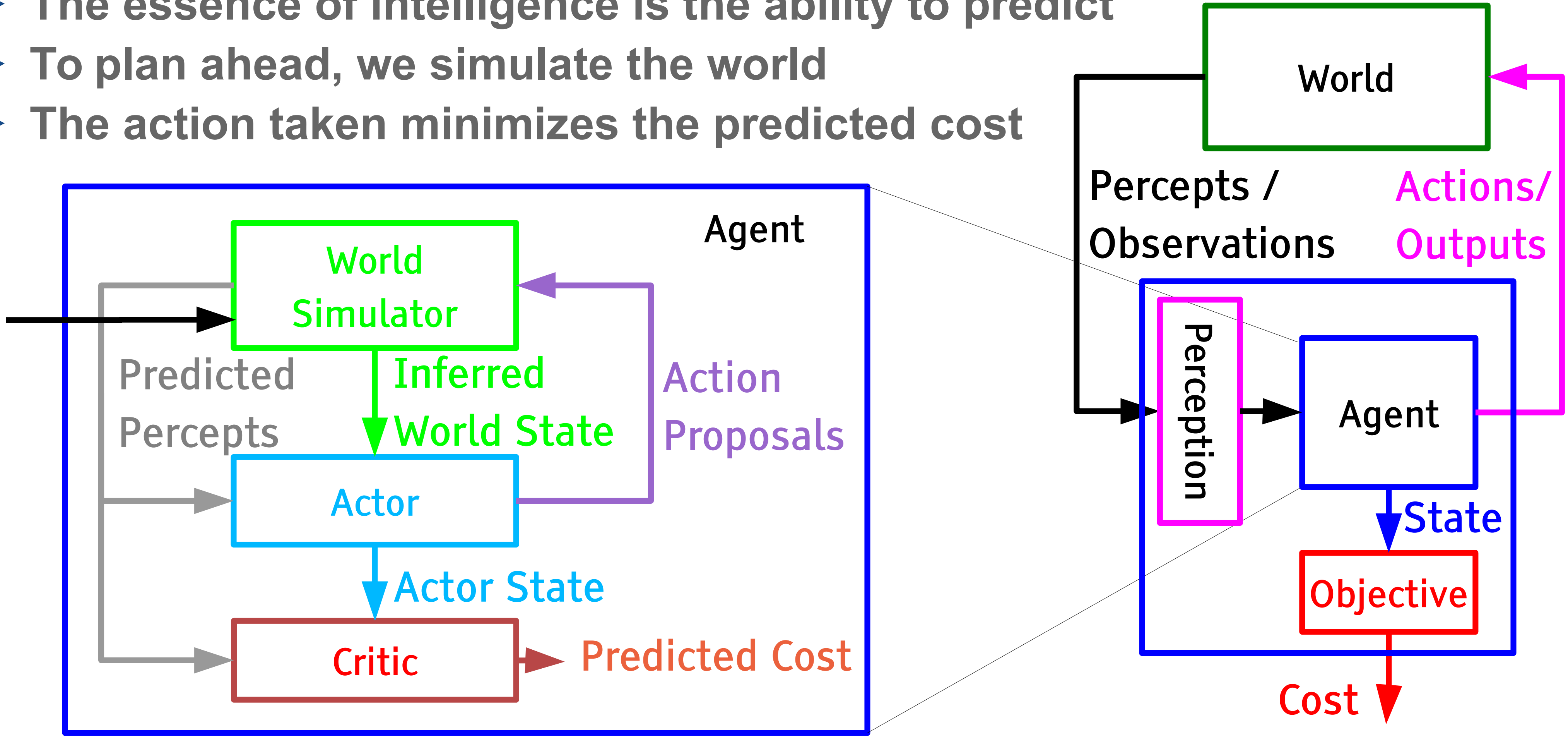






AI Agent: Reasoning = Prediction + Planning

- The essence of intelligence is the ability to predict
- To plan ahead, we simulate the world
- The action taken minimizes the predicted cost



AI Agent: Reasoning = Simulating

- The essence of intelligence is the ability to predict
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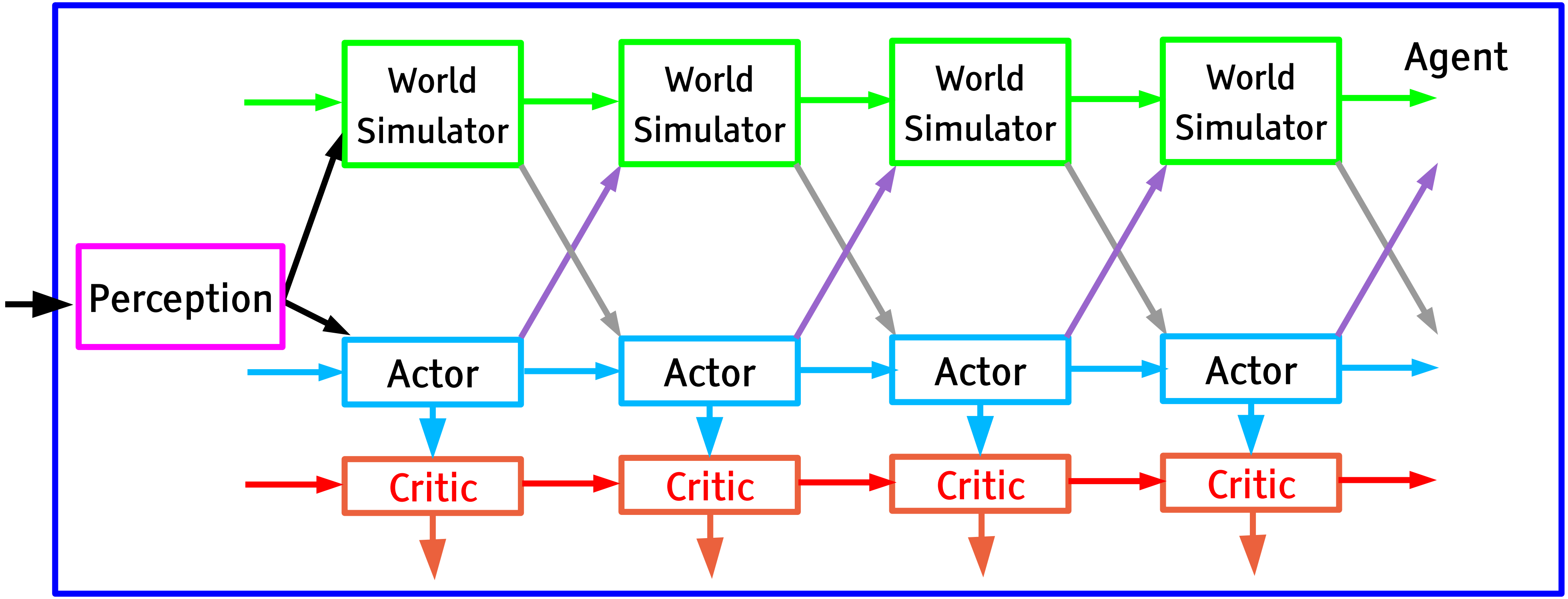


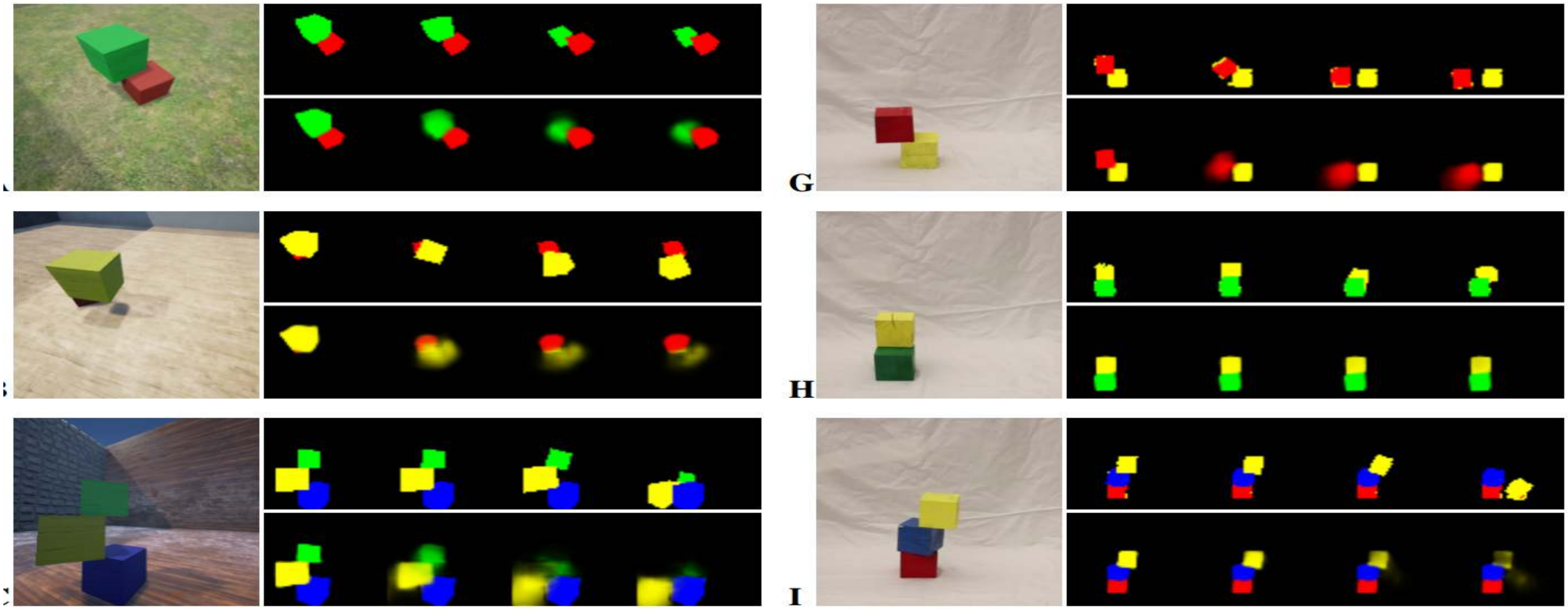
Learning predictive models

The missing link to AI

- TL;DR:
  - Generative Adversarial Networks are extremely promising

Learning Physics (PhysNet) [Lerer, Gross, Fergus, ICML'16]

- **ConvNet predicts the trajectories of falling blocks**
- **Uses the Unreal game engine hooked up to Torch.**



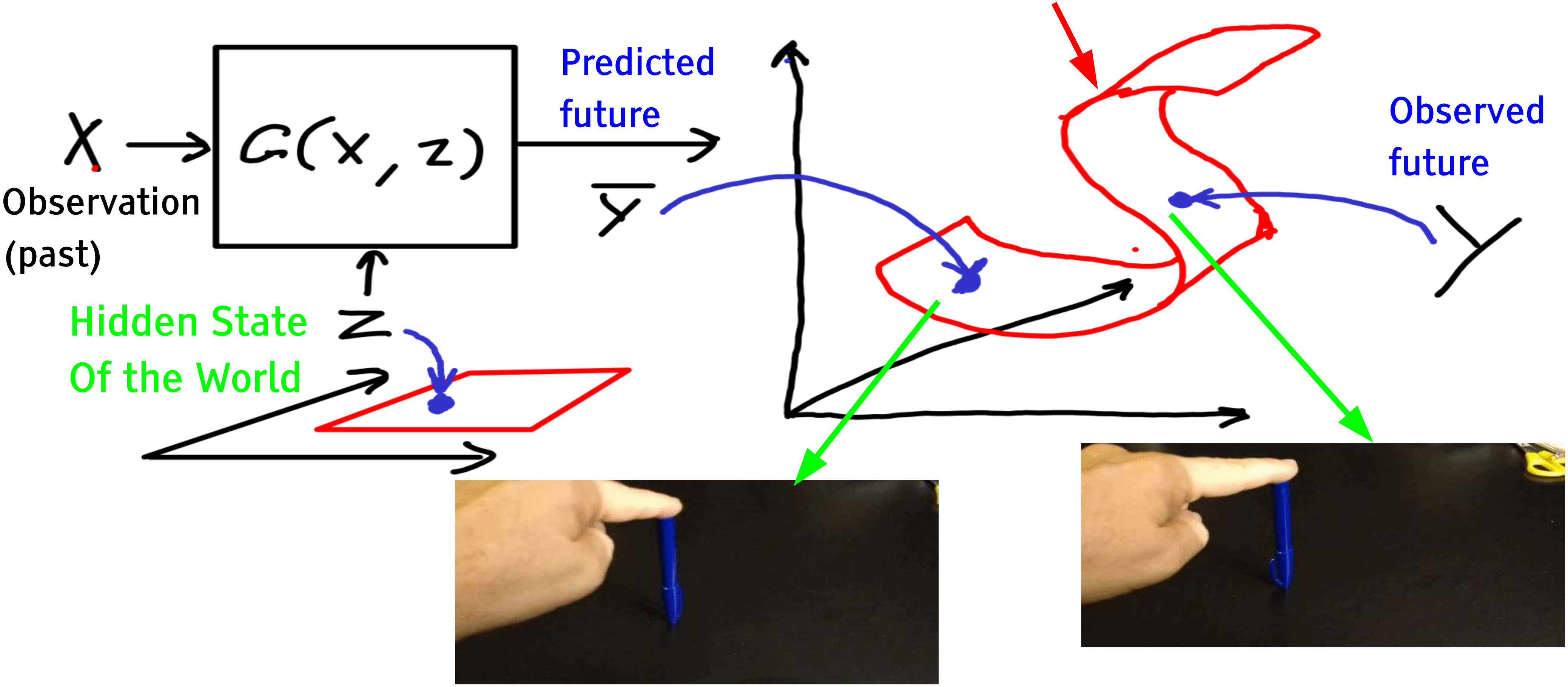
But in the real world, the future is uncertain…

- **Naïve predictive learning**
  - Minimize the prediction error
  - Predict the average of all plausible futures
  - Blurry results

- **Better predictive learning**
  - Learning the loss function
  - Predict one plausible future among many
  - Sharper results

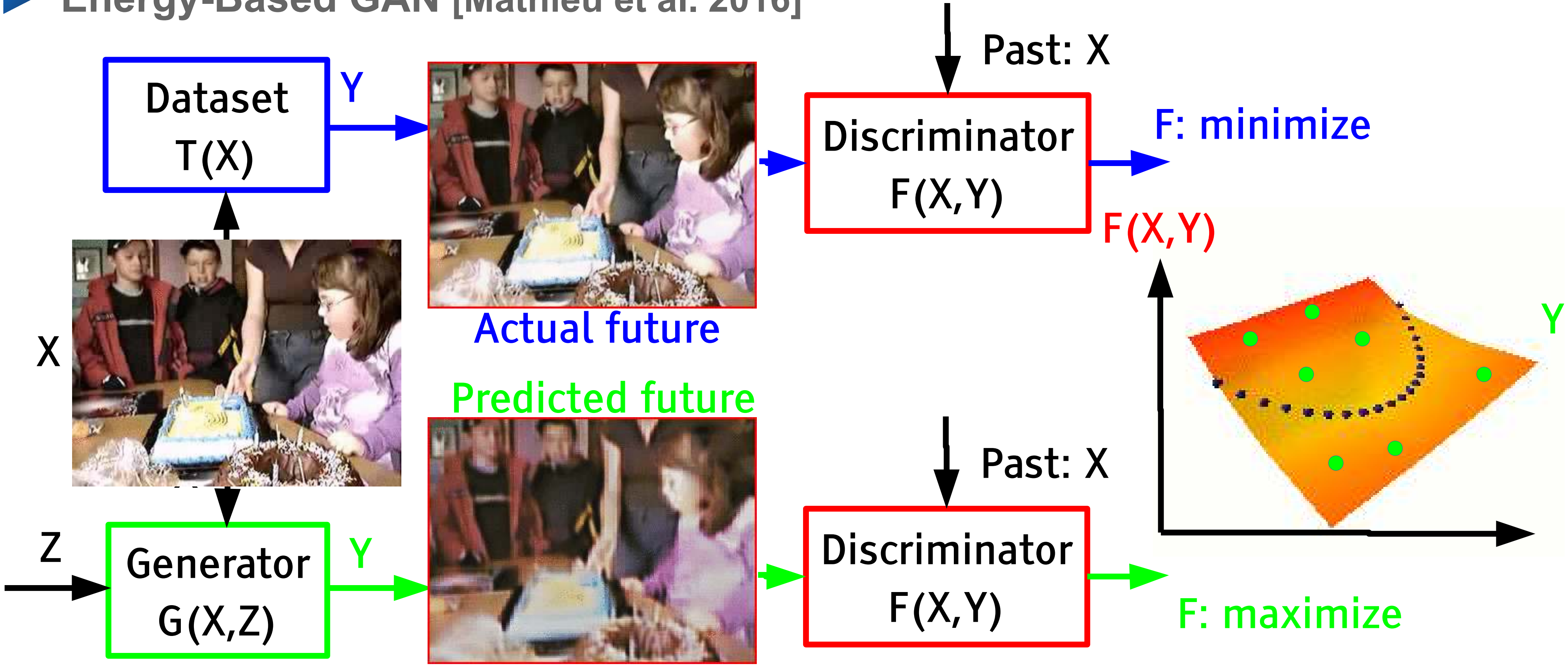
The Hard Part: Prediction Under Uncertainty

- The observed future is a representative of a **set of plausible futures**



Adversarial Training: the key to predicting under uncertainty

- Generative Adversarial Networks (GAN) [Goodfellow et al. NIPS 2014],
- Energy-Based GAN [Mathieu et al. 2016]



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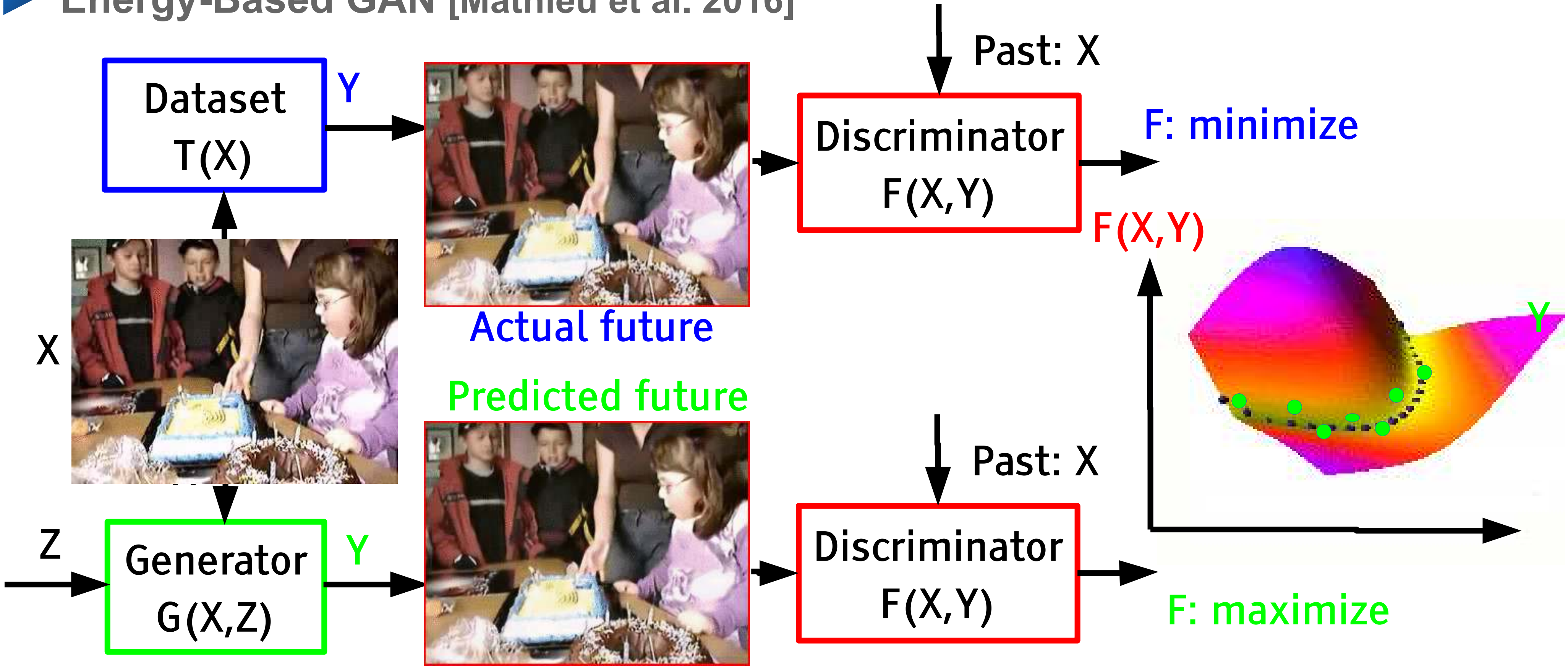
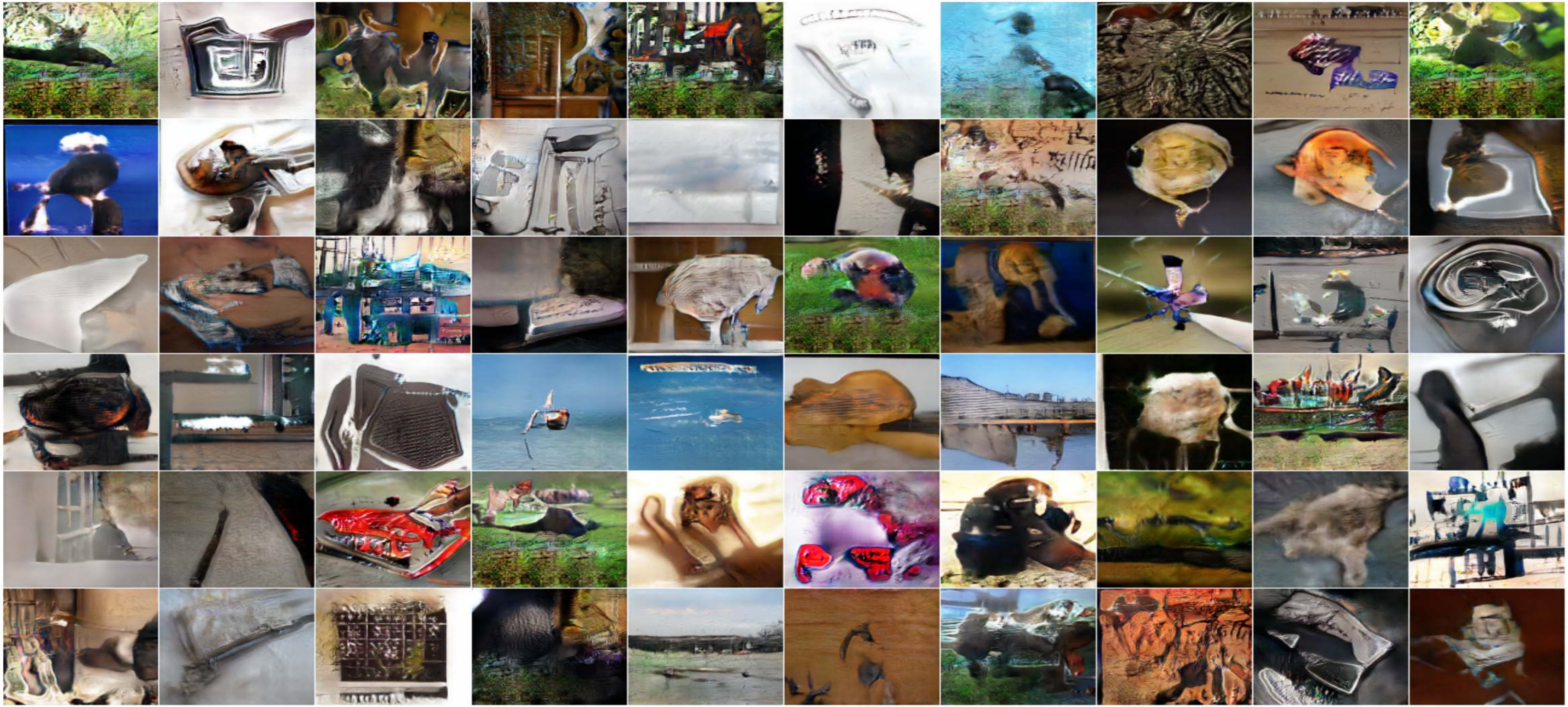


Energy-Based GAN trained on ImageNet at 128x128 pixels



Energy-Based GAN trained on ImageNet at 256x256 pixels

- Trained on dogs

Video Prediction with GAN

- [Mathieu, Couprie, LeCun arXiv:1511:05440]
- But we are far from a complete solution.

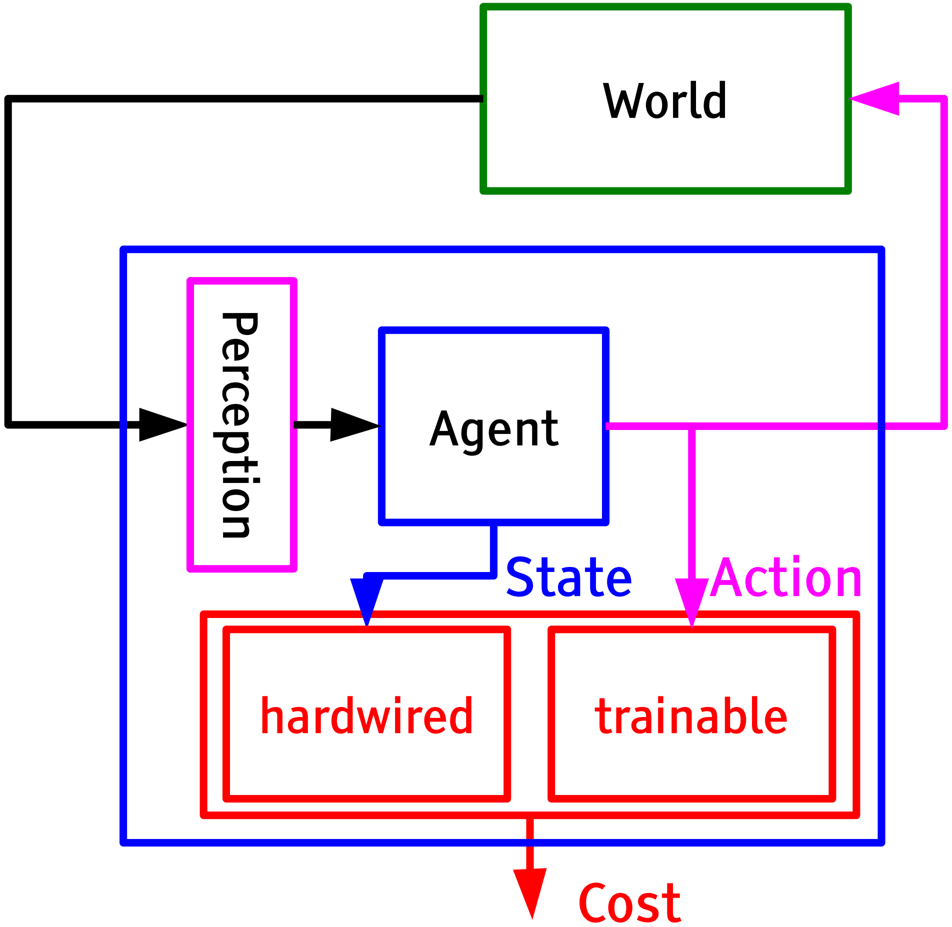
Video Prediction: predicting 5 frames

Video Prediction: predicting 5 frames

Video Prediction: predicting 50 frames

Aligning the Objective with Human Values

- **Make the objective have two components**
- **1. A hardwired, immutable “safeguard” objective**
  - Call it the instinct
- **2. A Trainable objective that estimates the value function of its human trainers**
  - It’s trained through adversarial training / Inverse RL.
  - (for once, I’m agreeing with Stuart Russel)



Inverse RL through Adversarial Training

- Train the objective to emulate the (unknown) objectives of the human trainers
- Objective trains to distinguish trainer actions from agent actions
- Agent plans/trains to minimize objective