Introduction

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Outline

- What is AI
- Brief History of AI
- Personal Experience with AI
- Demos
- Learning Paradigms
- Learning Pipeline

What is AI

- Intelligence is essential to us. We call ourselves *Home sapiens*—man the wise.
- Our brain can perceive, understand, predict, and manipulate a world, which is one of the greatest scientific mysteries.

- Artificial Intelligence: understand and build intelligent agent.
- One of the most interesting and fastest-growing fields (especially the last decade).
- Over a trillion dollars a year in revenue (=Netherlands's GDP, 17th in the world)
- AI expert Kai-Fu Lee predicts AI's impact will be "more than anything in the history of mankind."
- Not like other fields such as physics, AI research is still wide open.

Brief History of AI

- Turning (1950): "Computing Machinery and Intelligence" introduced Turning test, machine learning, genetic algorithms, and reinforcement learning
- Minsky (1969) and McCarthy (1971): defining the foundations based on representation and reasoning
- Newell and Simon (1975): symbolic models of problem solving and human cognition
- Feigenbaum and Reddy (1994): expert systems that encode human knowledge to solve real-world problems
- Pearl (2011): probabilistic reasoning
- Bengio, Hinton, LeCun (2019): deep learning

- General Problem Solver (Newell and Simon), RL checkers player (Samuel), Lisp programming language (McCarthy), Microworlds (Minsky), Perceptrons (Rosenblatt), ...

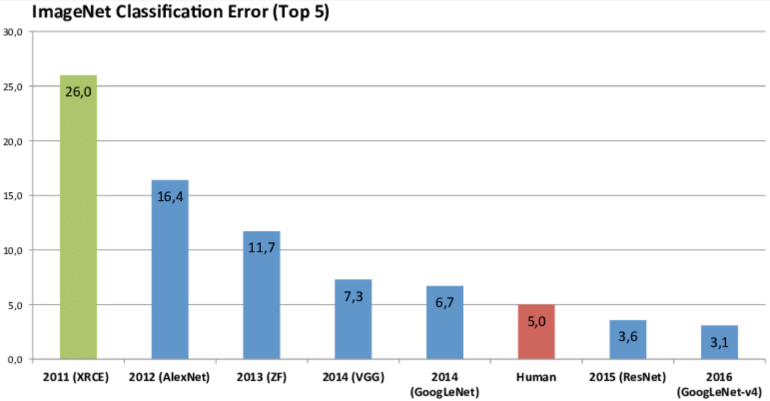
- Early systems found fail more difficult problems due to 1) the lack of analysis of specific tasks and 2) intractability of the tasks
- Minsky and Papert (1969) showed limitations of neural networks causing the first winter for these architectures

- The rising of expert systems: domain knowledge + reasoning
- The AI industry went from a few million dollars in 1980 to billions of dollars in 1988
- However, expert systems are difficult to built for complex domains due to the reasoning methods broke down in the face of uncertainty and the systems could not learn from experience
- Many companies failed to deliver their promises, causing the second AI winter until 1997

- Backpropagation (first developed in the early 1960s) is reinvented.
- Hinton: skeptical about symbolic AI research
- Probabilistic reasoning: hidden markov models, Bayesian networks, ...
- Reinforcement learning: TD-GAMMON, temporal-difference learning

- Big data: internet (text, images, videos), ubiquitous sensors, ...

- Deep learning: the breakthroughs of convolutional neural networks on ImageNet competition started everything



- By 2019, AI has reported to exceed human-level performance on various domains.
- Computer vision: ImageNet object detection
- Language processing: speech recognition in a limited domain, Chinese-to-English translation in a restricted domain
- Games (classic and video): chess, Go, poker, Pac-Man, Jeopardy!, Quake III, Dota 2, StarCraft II, various Atari games
- Biology: skin cancer detection, prostate cancer detection, protein folding, and diabetic retinopathy diagnosis

- Major improvements have been achieved on many other domains: autonomous vehicles (ground and air), autonomous planning and scheduling, recommendations, medicine discovery, climate change, ...

- These successes have stimulated huge interest in AI in both academia and industry.
- AI papers increased 20-fold between 2010 and 2019 to 20,000 a year. The most popular category is machine learning.
- Course enrollment increased 5-fold in the U.S. and 16-fold internationally from a 2010 baseline. AI is the most popular specialization in CS.
- AI startups increased 20-fold in the U.S. to over 800.
    - OpenAI and DeepMind are leading companies on deep learning.

Personal Experience with AI

- 2009: study AI in graduate school: Lisp programming, expert systems, linear temporal logic, etc.
- 2010: study ML in graduate school: Bayesian inference, graphical models, HMMs, CRFs, topic modeling, nonparametric approaches, etc.
- Until 2015: "data-driven" is a hot keyword to put into paper titles for computer graphics research
- 2015: during internship at Disney research, support vector machines are still widely used (even deep learning revolution has started).
- 2016: start to use deep neural networks
- 2018: start to use deep reinforcement learning

- 2013–2016: besides AI and ML, other branches of CS are slowly picking up deep learning.
- 2016–Present: all CS branches (except for a few such as theoretical CS and systems) have adopted deep learning.
- 2018–Present: other fields are adopting deep learning at an increased speed depending on the technical barriers such as programming.

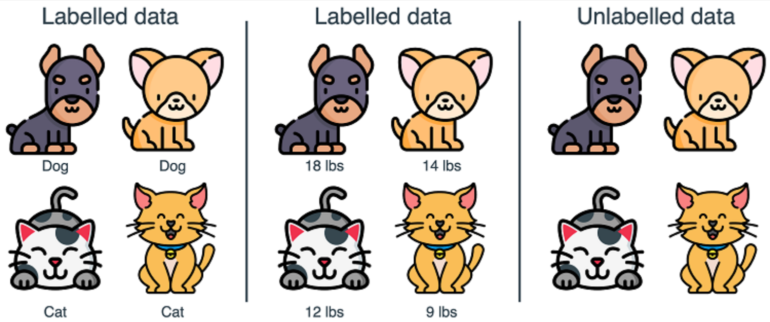
Demos

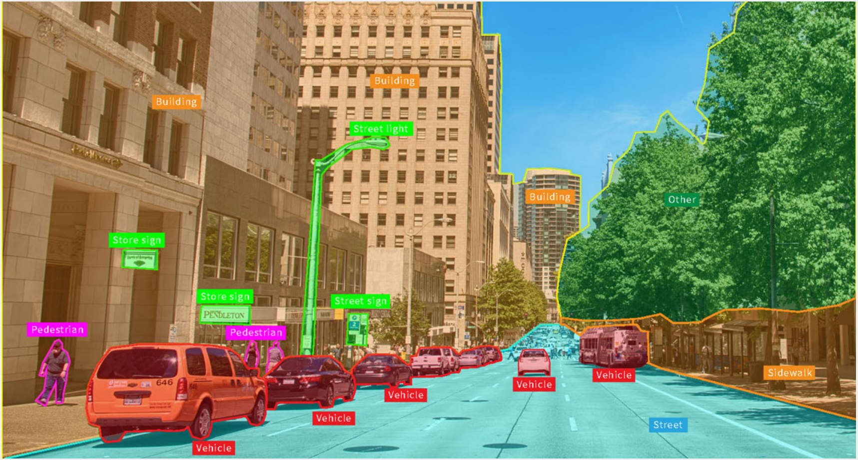
- Atari games (link)
- AlphaZero (link), AlphaGo documentary (link)
- AlphaStar (link)
- AlphaFold (link)
- OpenAI Five (link)
- Hide and Seek (link)
- Rubik's Cube (link)

Learning Paradigms

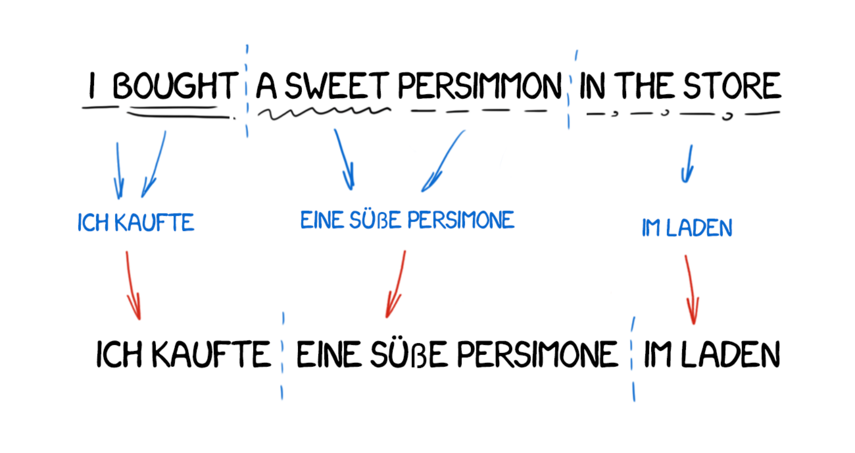
- Supervised learning
- Unsupervised learning
- Reinforcement learning

- Uses labelled data, hence "supervised"

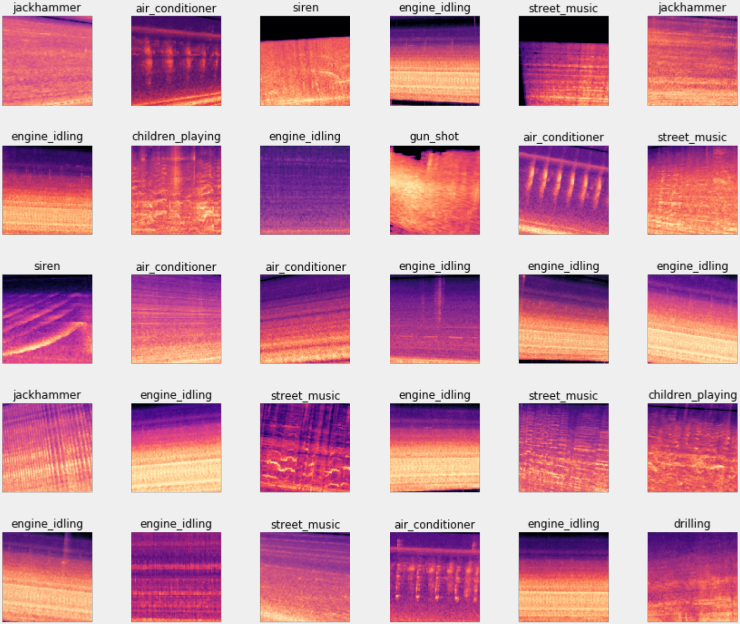




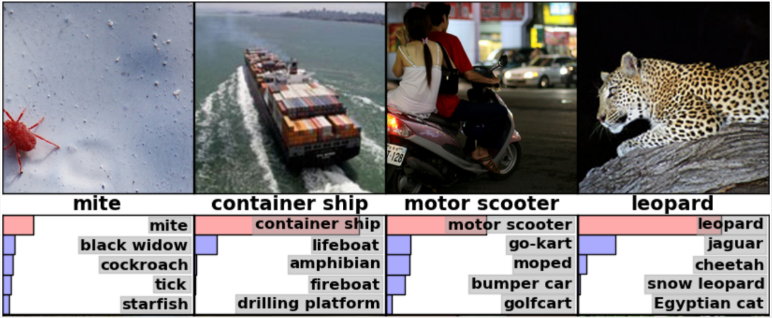
Building
Building
Street light
Building
Other
Store sign
Store sign
PENDLETON
Street sign
Pedestrian
Pedestrian
646
Vehicle
Vehicle
Vehicle
Vehicle
Vehicle
Sidewalk
Street
Vehicle


I BOUGHT
A SWEET PERSIMMON
IN THE STORE
ICH KAUFTE
EINE SÜßE PERSIMONE
IM LADEN
ICH KAUFTE
EINE SÜßE PERSIMONE
IM LADEN

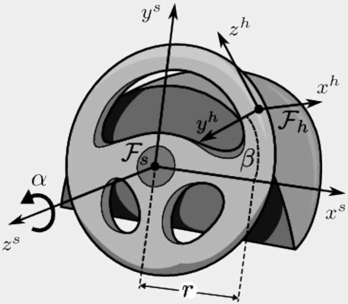
Supervised Learning: Labelled Data



- Classification: predict categorical labels (discrete values)
- E.g., ImageNet: 1,000 object classes (categories), 1M+ images, labels are crowd-sourced

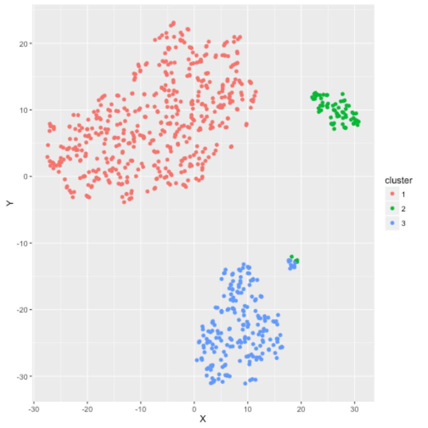


- Regression: predict numerical labels (continuous values)
- E.g., stock price, temperature, continuous control commands, etc.

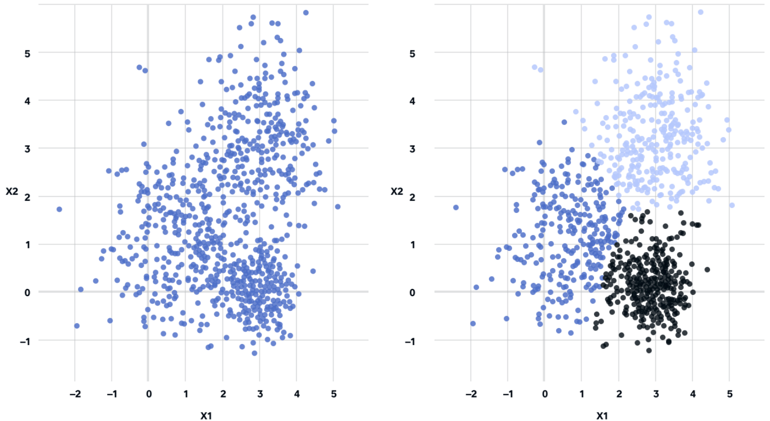


- Training set: train a model
- Validation set: tune a model through its hyperparameters
- Test set: test a model
- Example ratio: 6:2:2

- Assumption 1: training and test data are from the same distribution (the distribution is usually unknown)



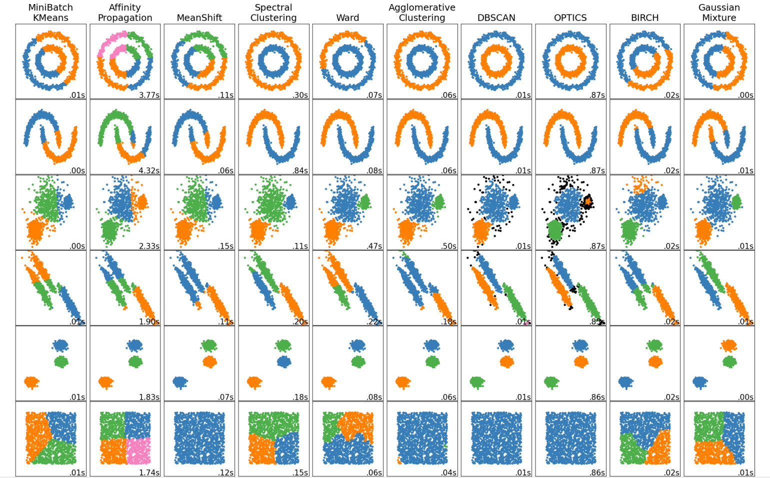
- Assumption 2: training and test data are i.i.d. (independent and identically distributed)



- Note: non-i.i.d. data may or may not break supervised learning

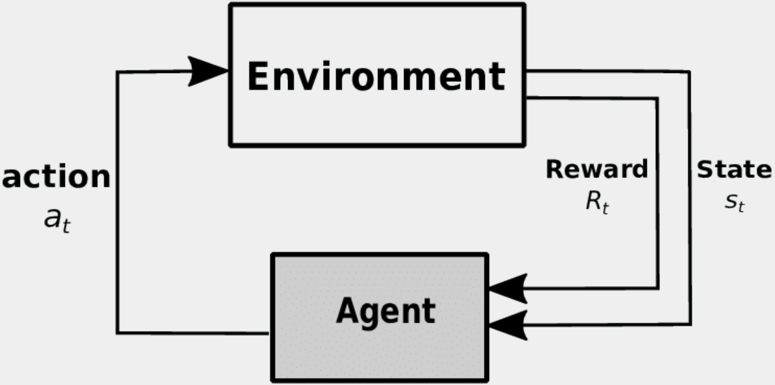
- Uses unlabelled data, hence “unsupervised”
- Tasks: clustering, generative models, ...

- Goal: discover hidden structures

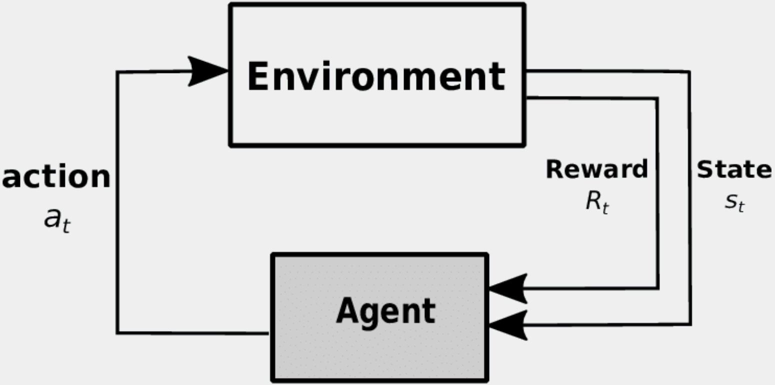


- Goal: generate synthetic data (image, sound, etc)

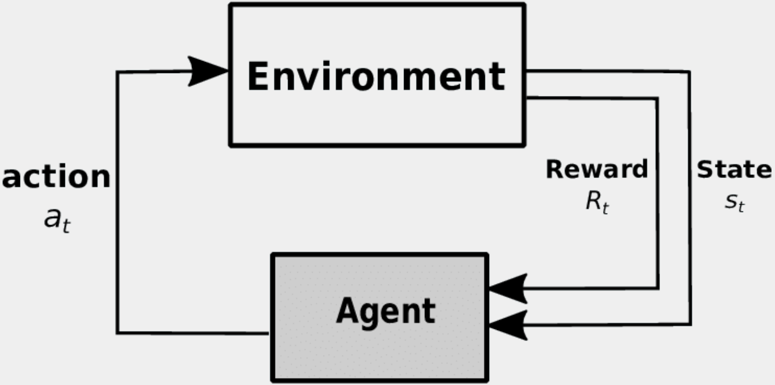
- Sequential decision making: interactions between Agent and Environment



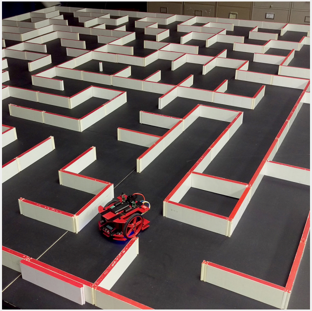
- Agent chooses an action to execute in the current state of Environment



- Environment provides reward to Agent and transits Agent to the next state



- Agent performs a sequence of actions, observes their "rewards," and learns an optimal policy
- E.g., Go, robot and maze, Atari game, etc.

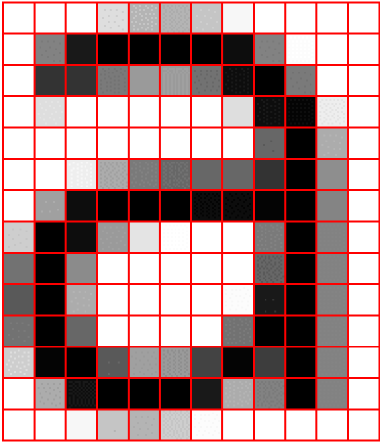


- Supervised learning
  - Solve the recognition problem
  - Assume i.i.d. data
  - Cannot pass human performance (i.e., ground truth)
    - Although for ImageNet: human 5% error, best model 3.57% error
- Reinforcement learning
  - Solve the decision problem
  - Learn via trial and error, no explicit supervisor only indirect, delayed feedback
  - Action order (time) matters $\rightarrow$ non-i.i.d. data
    - E.g., autonomous driving via a front-facing camera (image at t affects action at $t+1$ then affects image at $t+1$)
  - Superhuman potential

Learning Pipeline

Machine Learning is Difficult!

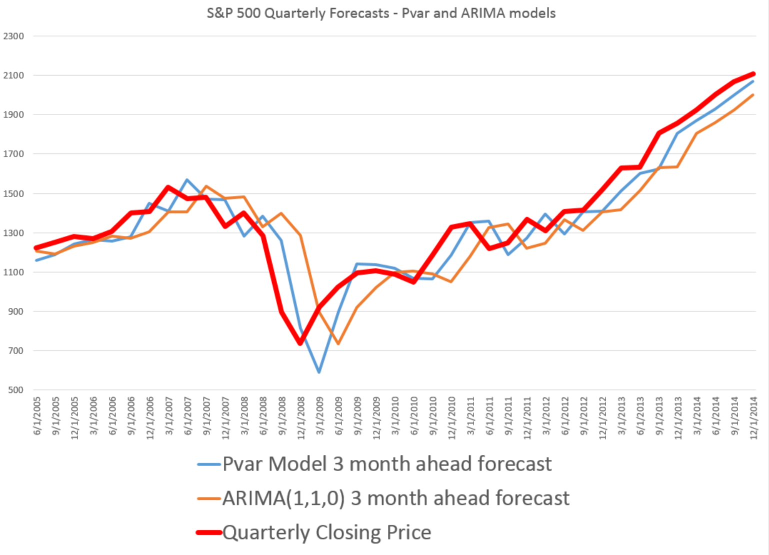
a



1.0	1.0	1.0	0.9	0.6	0.6	0.6	1.0	1.0	1.0	1.0	1.0
1.0	0.5	0.0	0.0	0.0	0.0	0.0	0.0	0.5	1.0	1.0	1.0
1.0	0.2	0.2	0.5	0.6	0.6	0.5	0.0	0.0	0.5	1.0	1.0
1.0	0.9	1.0	1.0	1.0	1.0	1.0	0.9	0.0	0.0	0.9	1.0
1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.5	0.0	0.5	1.0
1.0	1.0	1.0	0.5	0.5	0.5	0.5	0.5	0.4	0.0	0.5	1.0
1.0	0.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.5	1.0
0.9	0.0	0.0	0.6	1.0	1.0	1.0	1.0	0.5	0.0	0.5	1.0
0.5	0.0	0.6	1.0	1.0	1.0	1.0	1.0	0.5	0.0	0.5	1.0
0.5	0.0	0.7	1.0	1.0	1.0	1.0	1.0	0.0	0.0	0.5	1.0
0.6	0.0	0.6	1.0	1.0	1.0	1.0	0.5	0.0	0.0	0.5	1.0
0.9	0.1	0.0	0.6	0.7	0.7	0.5	0.0	0.5	0.0	0.5	1.0
1.0	0.7	0.1	0.0	0.0	0.0	0.1	0.9	0.8	0.0	0.5	1.0
1.0	1.0	1.0	0.8	0.8	0.9	1.0	1.0	1.0	1.0	1.0	1.0

- raw data $\rightarrow$ feature engineering via human experts $\rightarrow$ model training and tuning $\rightarrow$ outcome


Affenpinscher
Brussels Griffon
Cavalier King Charles Spaniel
Chihuahua
Chinese Crested
English Toy Spaniel
Havanese
Italian Greyhound
Japanese Chin
Maltese
Manchester Terrier
Miniature Pinscher
Papillon
Pekingese
Pomeranian
Pug
Shih Tzu
Silky Terrier
Toy Fox Terrier
Toy Poodle
Yorkshire Terrier


S&P 500 Quarterly Forecasts - Pvar and ARIMA models
2300
2100
1900
1700
1500
1300
1100
900
700
500
6/1/2005
9/1/2005
12/1/2005
3/1/2006
6/1/2006
9/1/2006
12/1/2006
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12/1/2014
Pvar Model 3 month ahead forecast
ARIMA(1,1,0) 3 month ahead forecast
Quarterly Closing Price

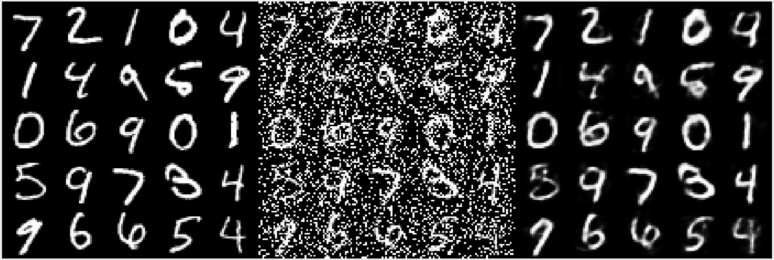
- raw data $\rightarrow$ model training and tuning $\rightarrow$ outcome (a.k.a. "end-to-end learning")

- Pros: easy to set-up, powerful (if works)

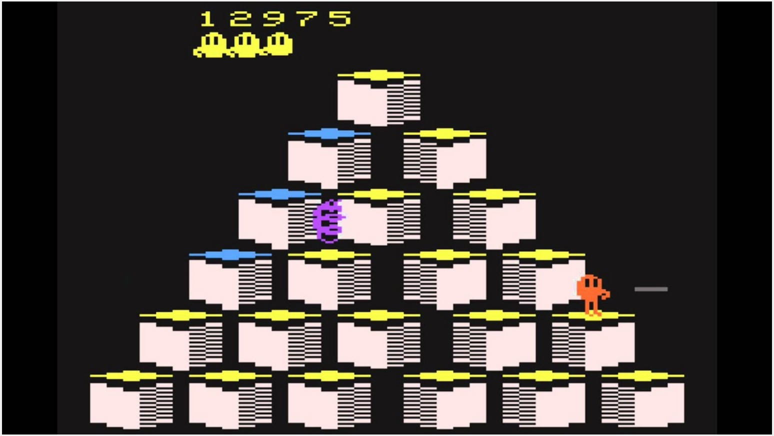
- Cons:
  - blackbox (no human-interpretable features)
  - difficult to defend adversarial attacks
  - data hungry
  - computation intensive
  - hyperparameter search is a pain

- Steering angle prediction = 90k images + 3080 (GPU) + 16 hours

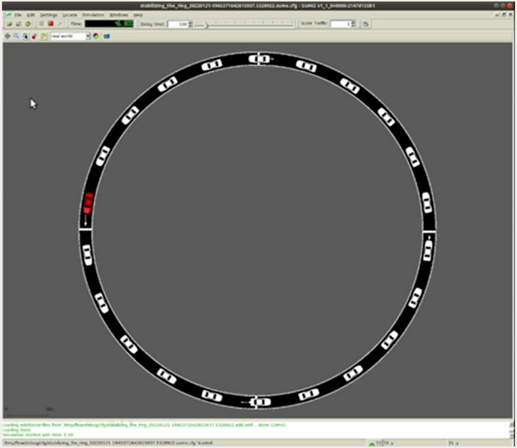
- De-noising Autoencoder: 75k images + 3080 (GPU) + 4 hours



- Q-bert: DQN (algorithm) + 3070 TI (GPU) + 2–3 hours



- Traffic on a ring: PPO (algorithm) + Intel core-i9 11900k (CPU) + 6 hours



- Pattern recognition (reporting in accuracy) $\rightarrow$ supervised learning
  - How to obtain (at least 20k) labelled data?
- Pattern discovery or generation (show the found or generated patterns) $\rightarrow$ unsupervised learning
  - How to obtain (at least 20k) pattern-specific data?
- Sequential decision making (show agent-environment interactions) $\rightarrow$ reinforcement learning
  - How to build the environment?
- computing resources required vs. computing resources possessed