Welcome to **Principles of Machine Learning** IDS 705

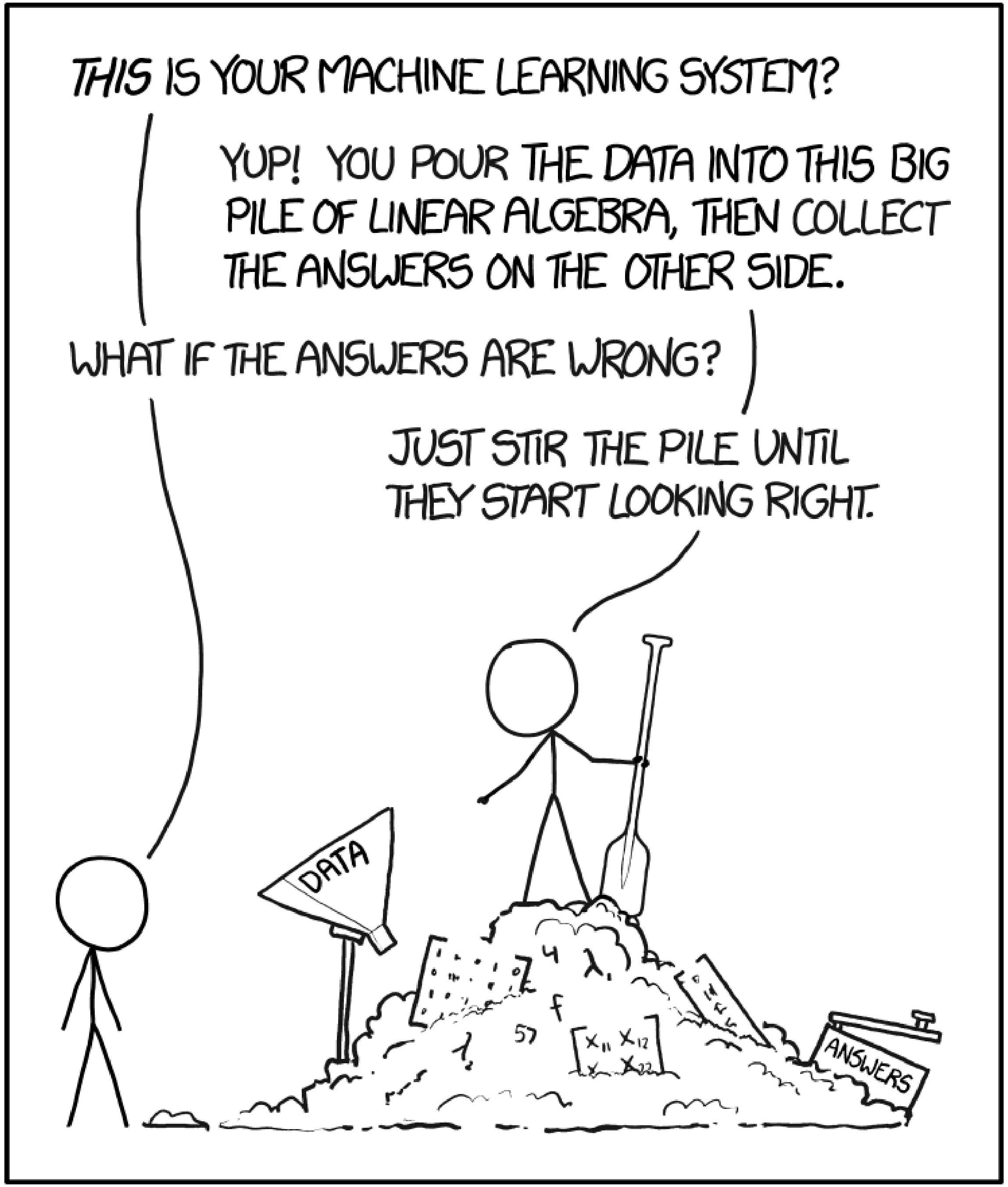

THIS IS YOUR MACHINE LEARNING SYSTEM?
YUP! YOU POUR THE DATA INTO THIS BIG PILE OF LINEAR ALGEBRA, THEN COLLECT THE ANSWERS ON THE OTHER SIDE.
WHAT IF THE ANSWERS ARE WRONG?
JUST STIR THE PILE UNTIL THEY START LOOKING RIGHT.
DATA
ANSWERS

Image: xkcd.com

TA's

Lilah
DuBoff

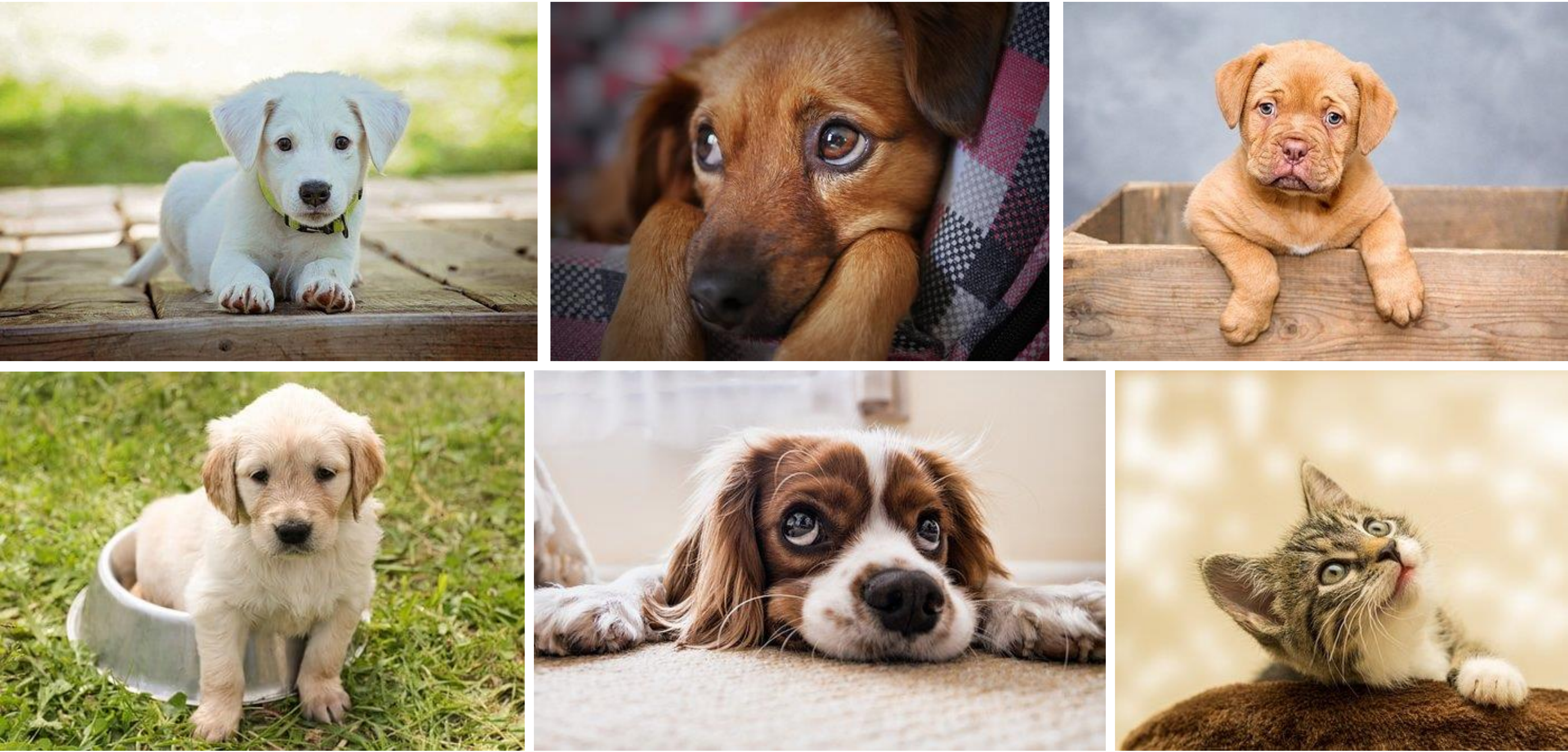
Kayla
Haeussler

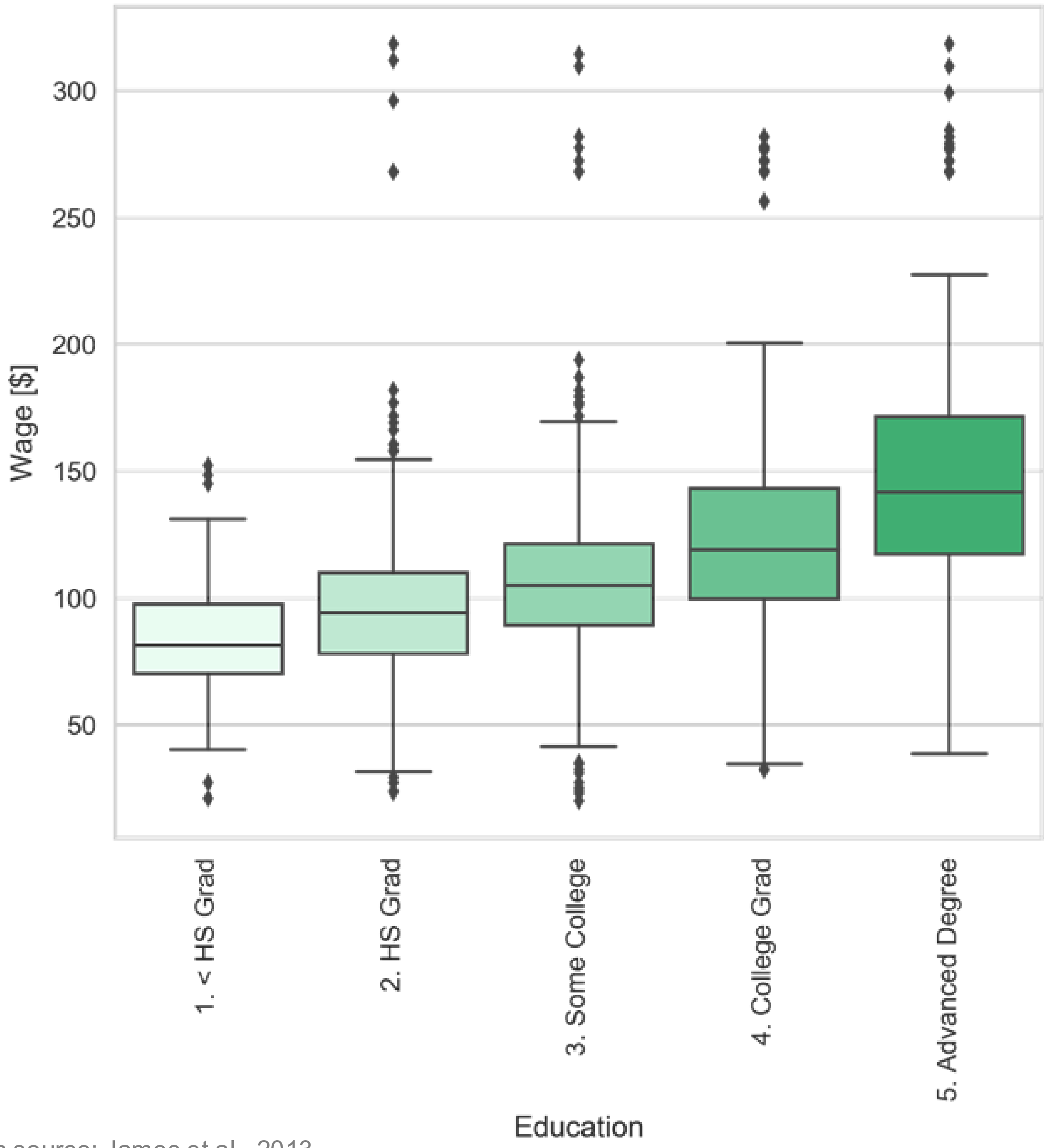
Paul
Markakis

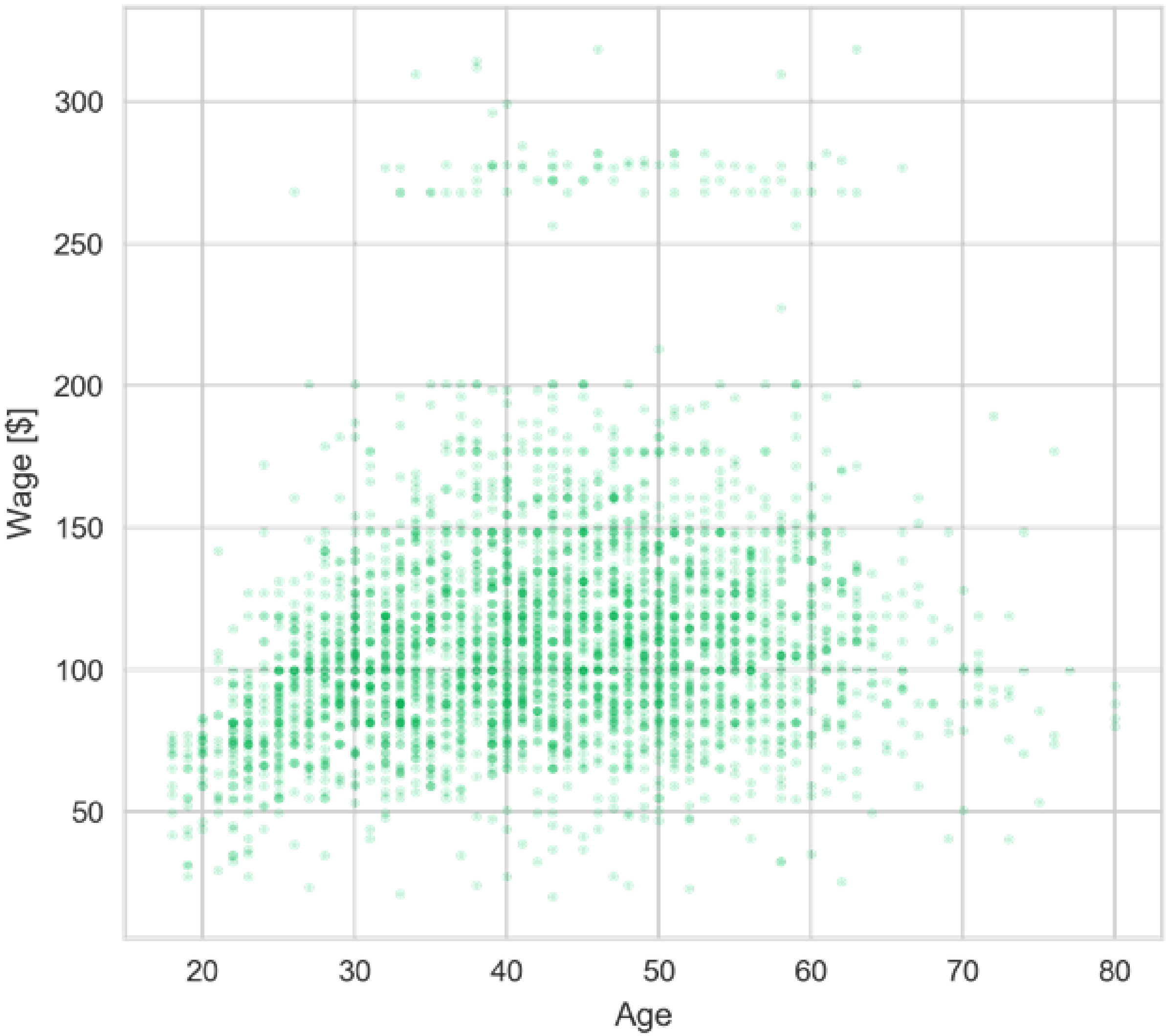
What is machine learning?

Lecture 01

What are these?







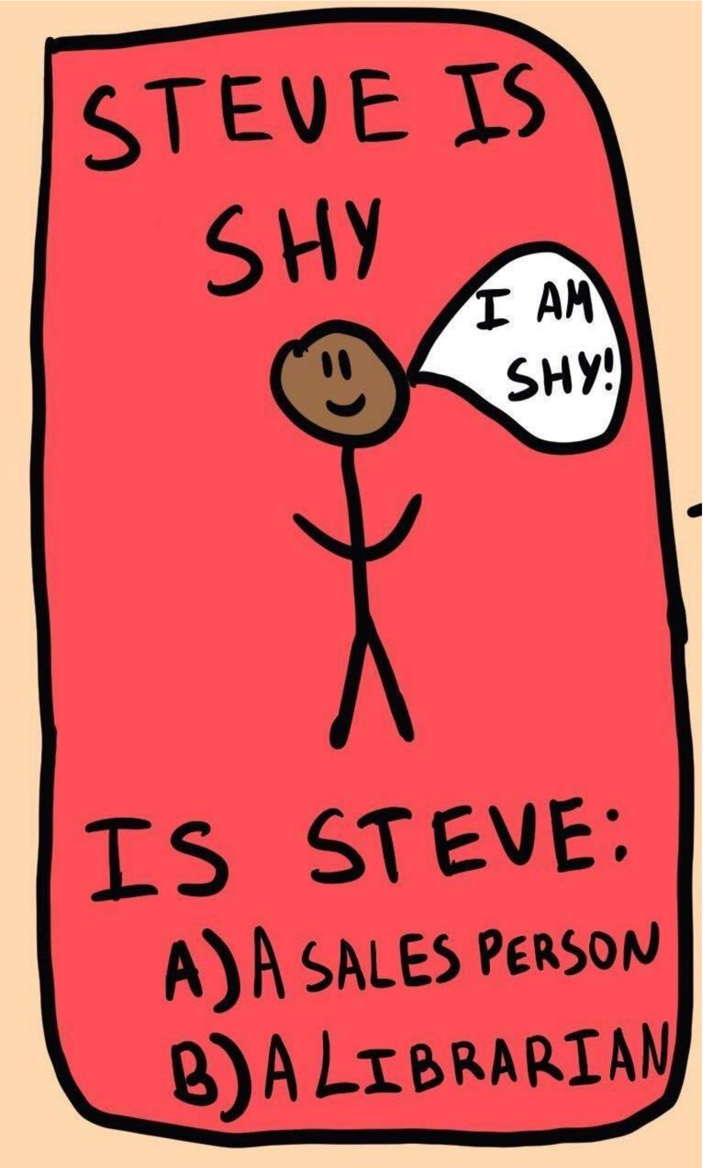
Wage data from workers in the mid-Atlantic region in one field

How much will someone with some college education make? What if they're 20 years old?

Data source: James et al., 2013

We use heuristic rules from past experiences and data to make decisions and understand the world daily

Machine learning enhances that process, making it scalable



STEVE IS SHY
I AM SHY!
IS STEVE:
A) A SALES PERSON
B) A LIBRARIAN

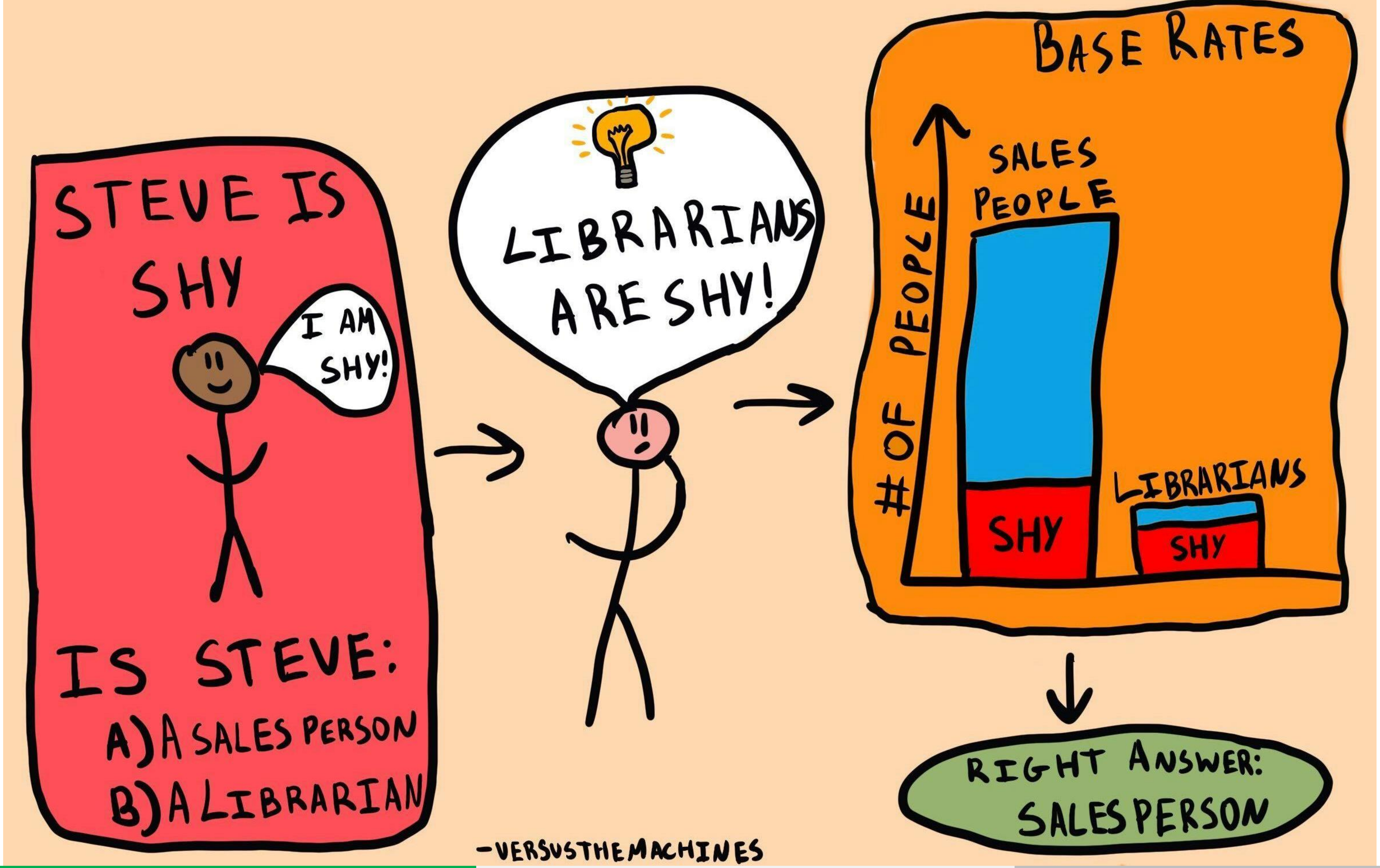
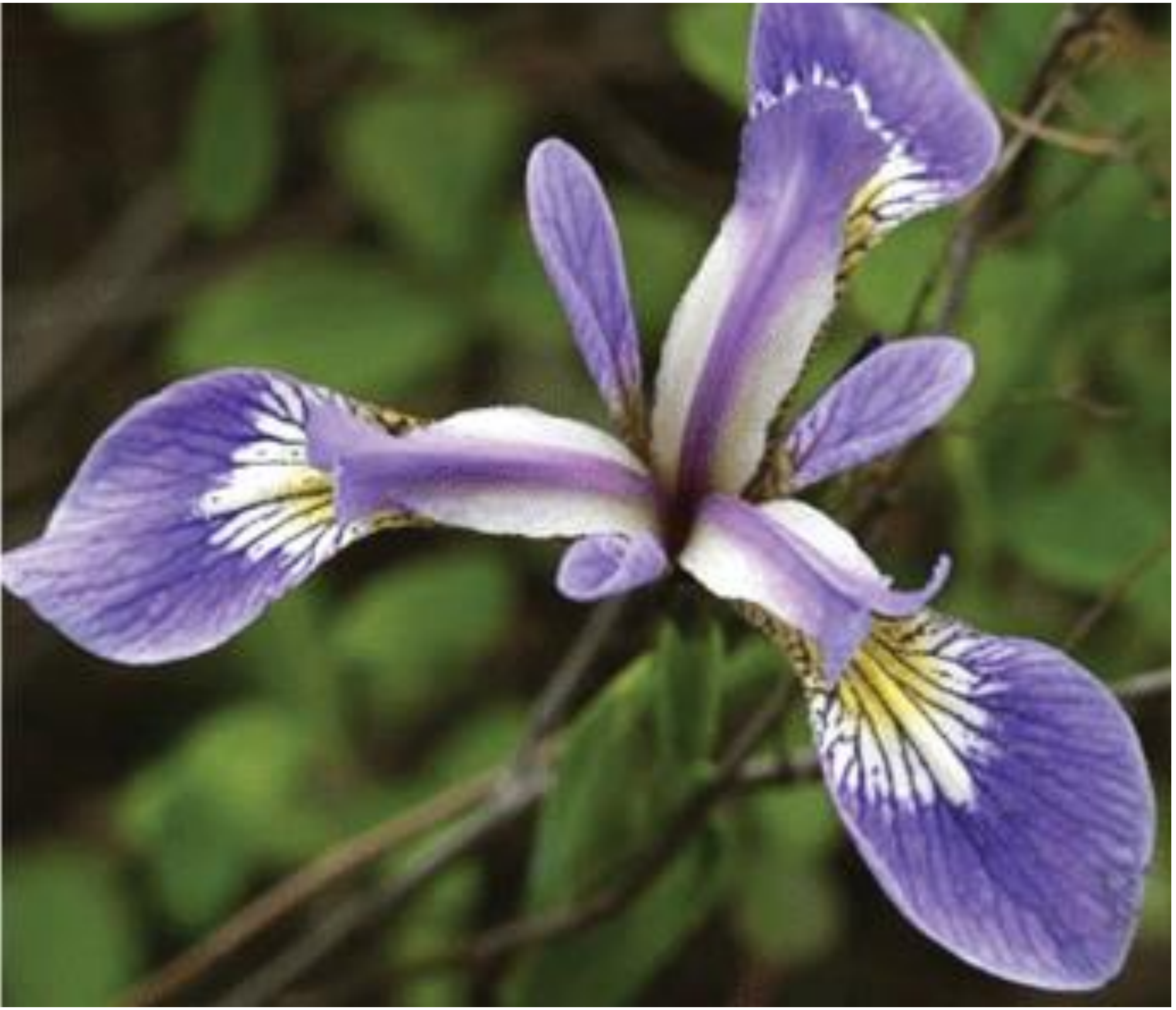


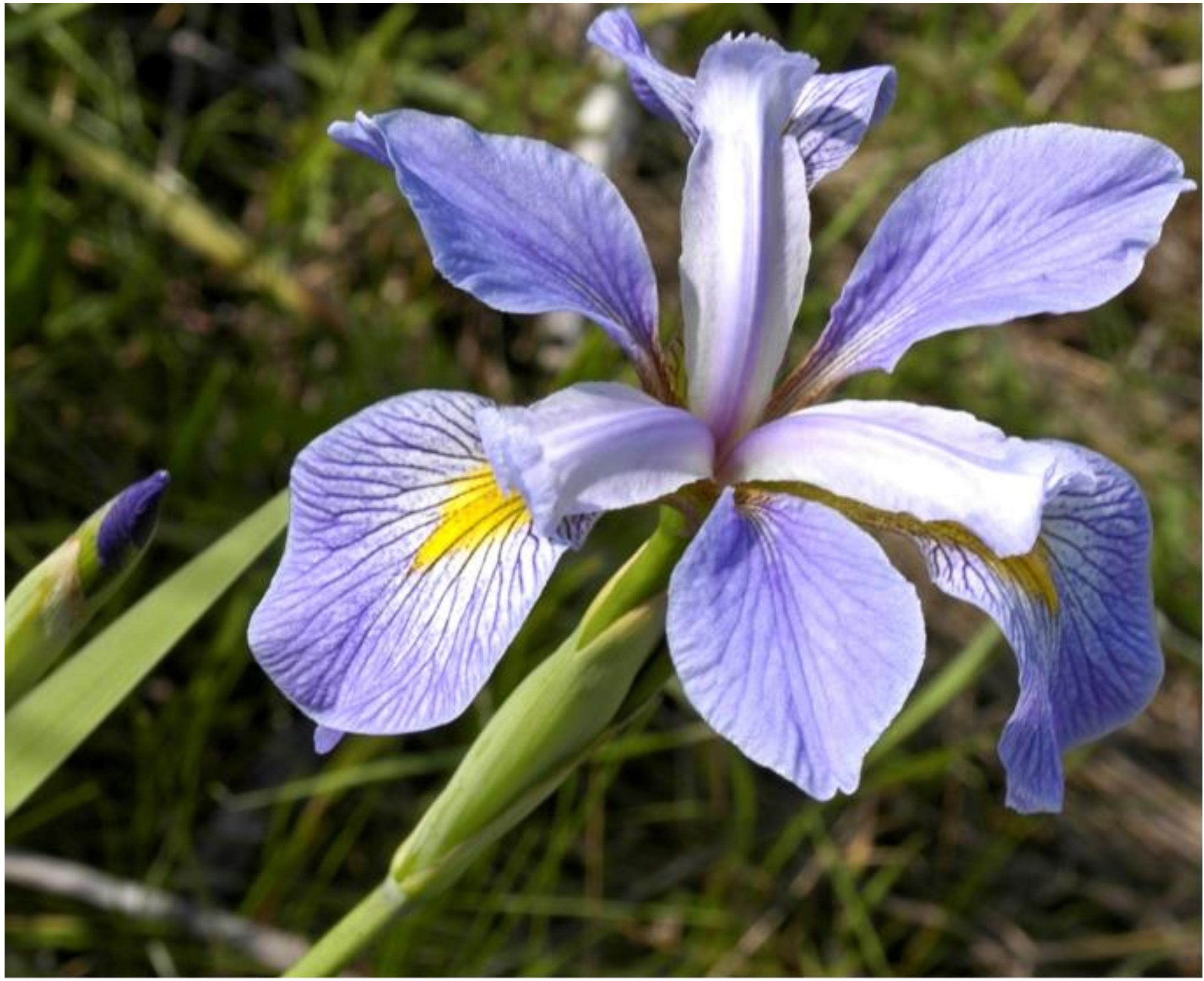
Image from the Decision Lab: https://thedecisionlab.com/biases/base-rate-fallacy

We also seek to ensure that our solutions don't suffer from the same logical fallacies and cognitive biases as we do!

How can you tell these flowers apart?

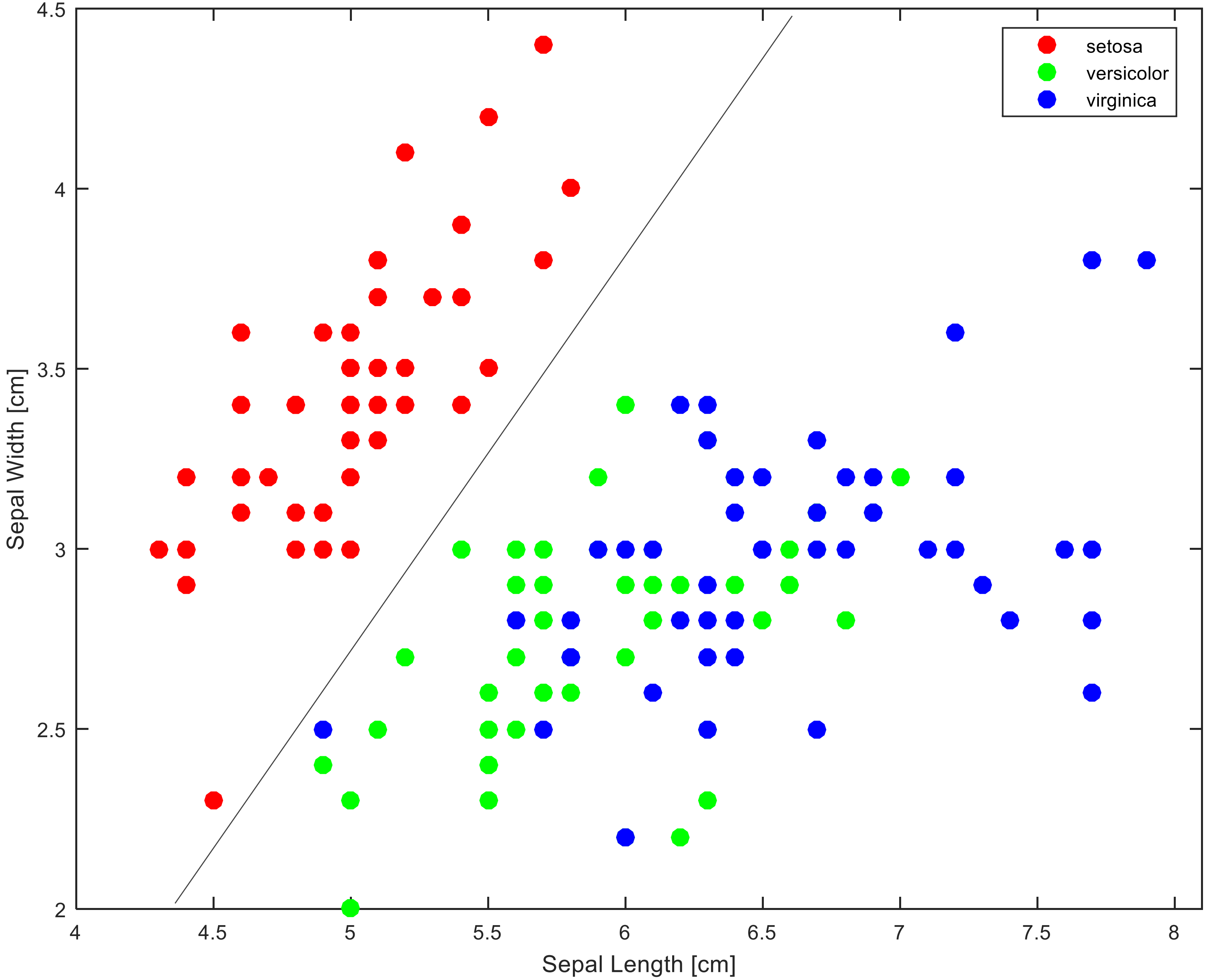


Iris setosa



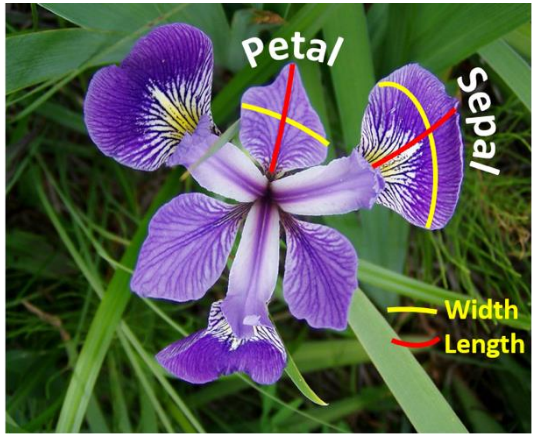
Iris virginica

Image Sources: Srishti Sawla (setosa) and Ivo Dinov, University of Michigan SOCR (versicolor and verginica)



setosa

versicolor



virginica

Data Source: Fisher Iris Data

Image Sources: Srishti Sawla (setosa) and Ivo Dinov, University of Michigan SOCR (versicolor and verginica)

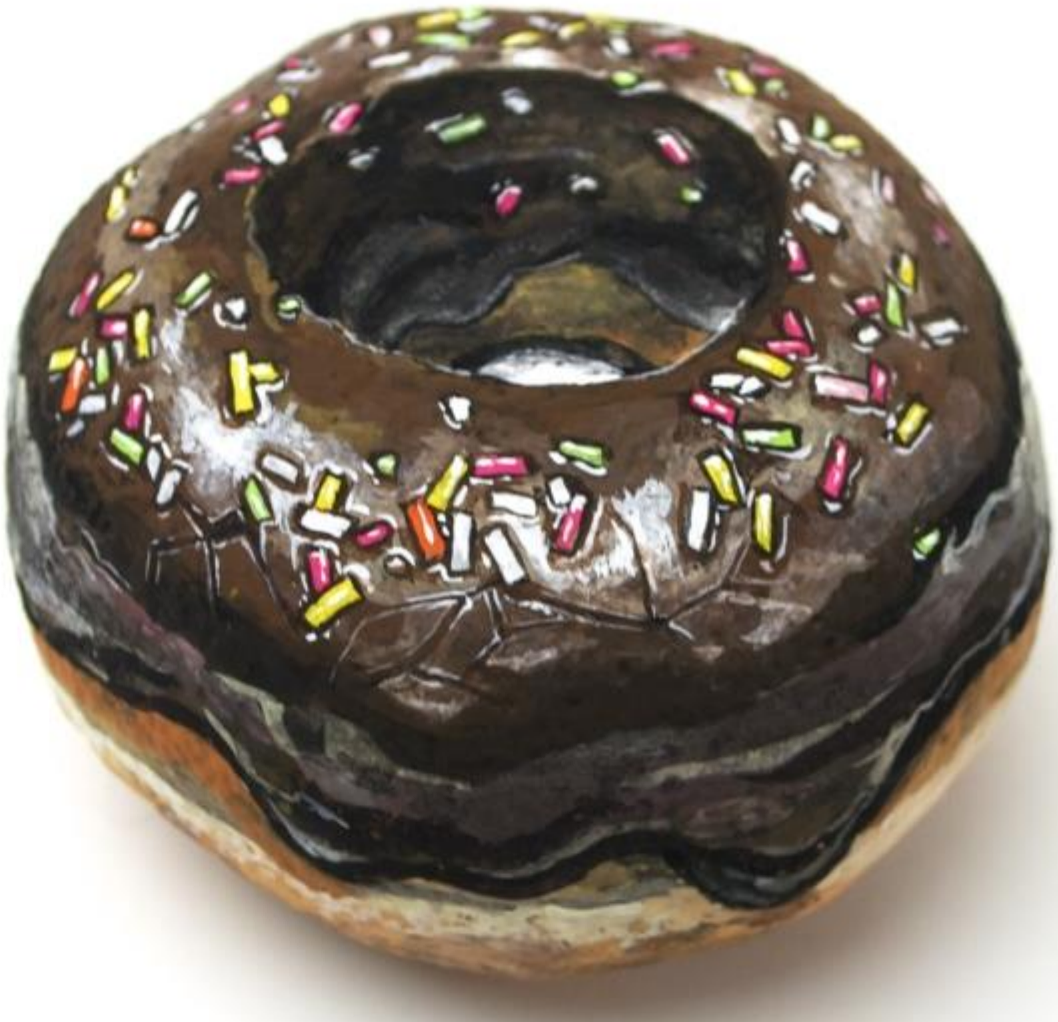
What is machine learning?

A class of techniques where the **goal** is to **describe**, **predict**, or **strategize**…

…**based on** data and past experience…

…and do so **automatically**, with minimal human intervention.

Challenges



What is this?

Image by artist Hikaru Cho

We **generalize** from past experiences

…and training data

Image: “It’s not what it seems” by artist Hikaru Cho

Challenge #1

our data must be **representative**

How about this one?

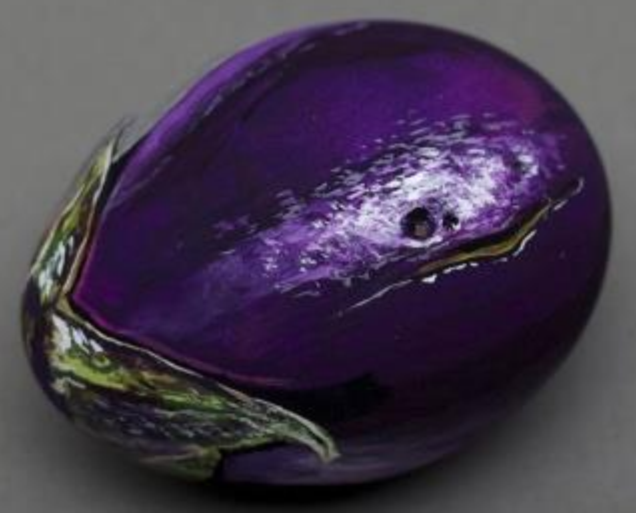


Image by artist Hikaru Cho

Image: “It’s not what it seems” by artist Hikaru Cho

Challenge #2

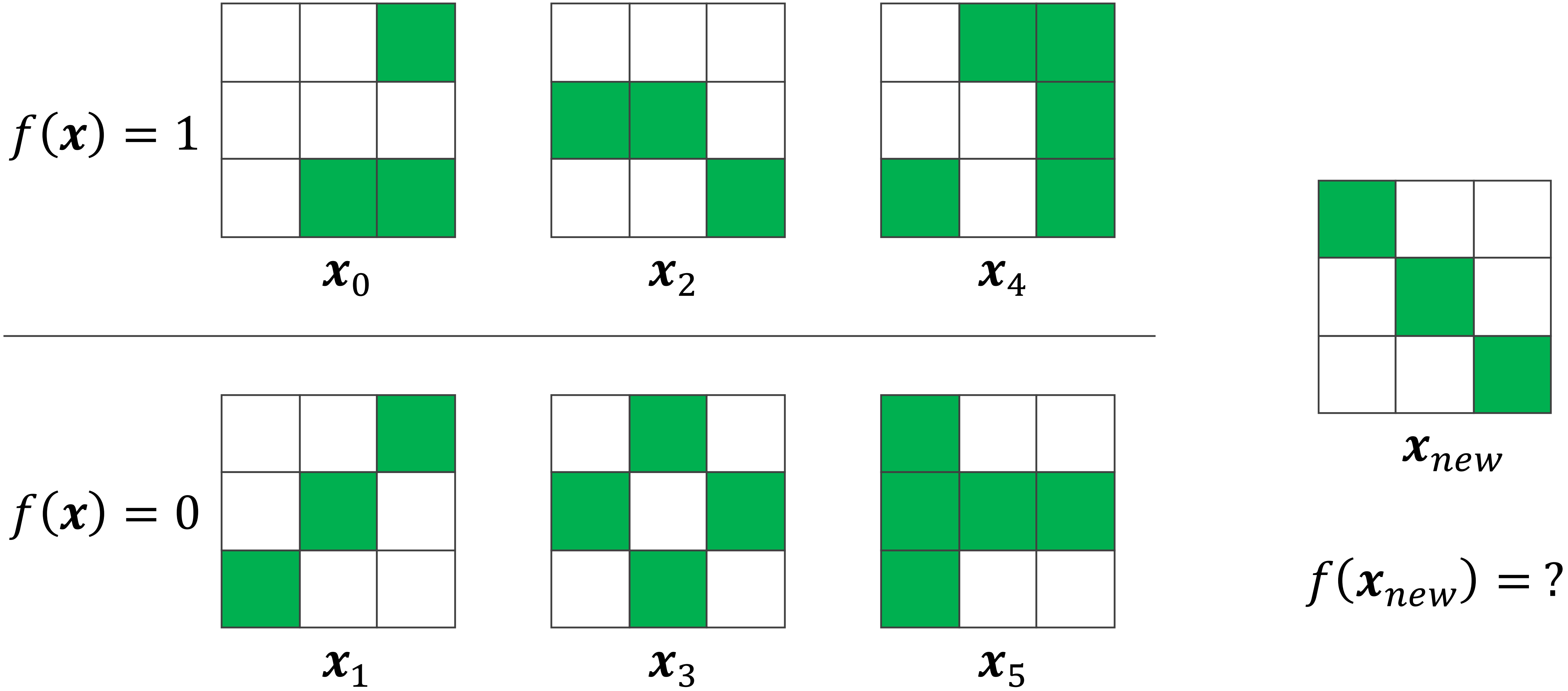
Developing representations of data to enable learning

To the poll!

bit.ly/
3LfRWfj

Responses

Predict which class x_{new} belongs to…



$f(\boldsymbol{x}_{new}) = ?$

Example credit: Yaser Abu-Mostafa, 2012

Challenge #3

Machine learning is an **ill-posed problem**

There are often **many** models that fit your **training data** similarly well

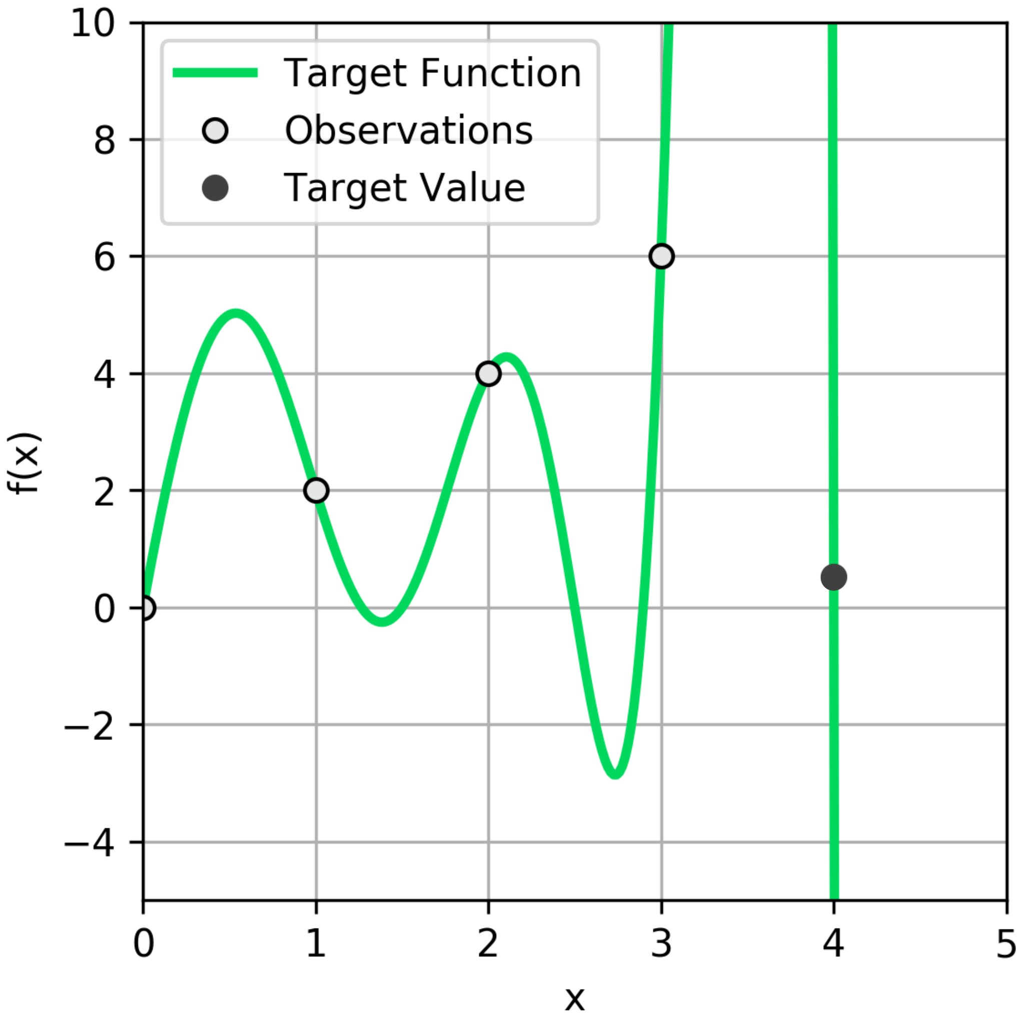
So how do we choose which model to use?

the best models **generalize** well to new data

Predict the next value in the sequence…

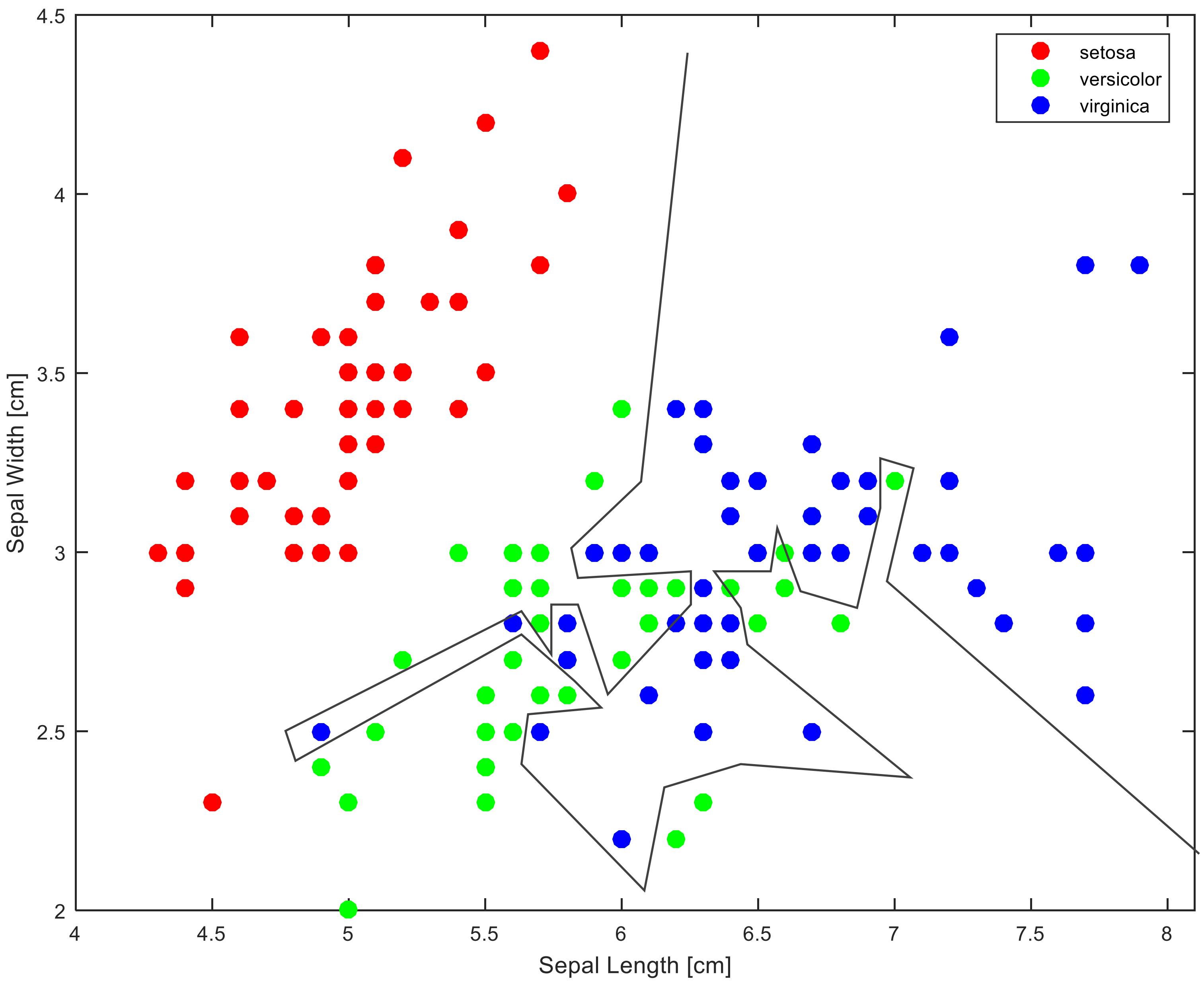
x	0	1	2	3	4
$f(x)$	**0**	**2**	**4**	**6**	**?**

$$f(4) = \boxed{\mathbf{0.530}}$$



A model:

$$f(x) = 16.2x - 6.36x^2 - 11.9x^3 - 4.77x^4 + 7.03x^5 + 8.32x^6 - 9.01x^7 + 2.75x^8 - 0.275x^9$$



setosa

versicolor

virginica

Data Source: Fisher Iris Data

Complex models overfit to the training data

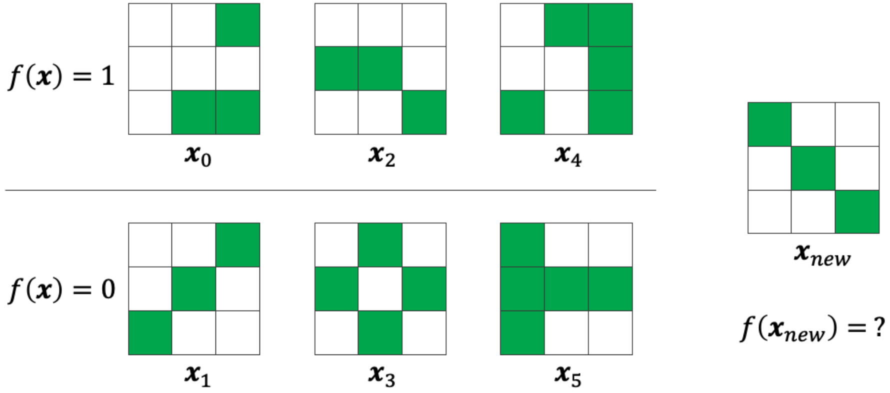
overfit works against generalization

Summary of the key challenges of ML

Image by artist Hikaru Cho

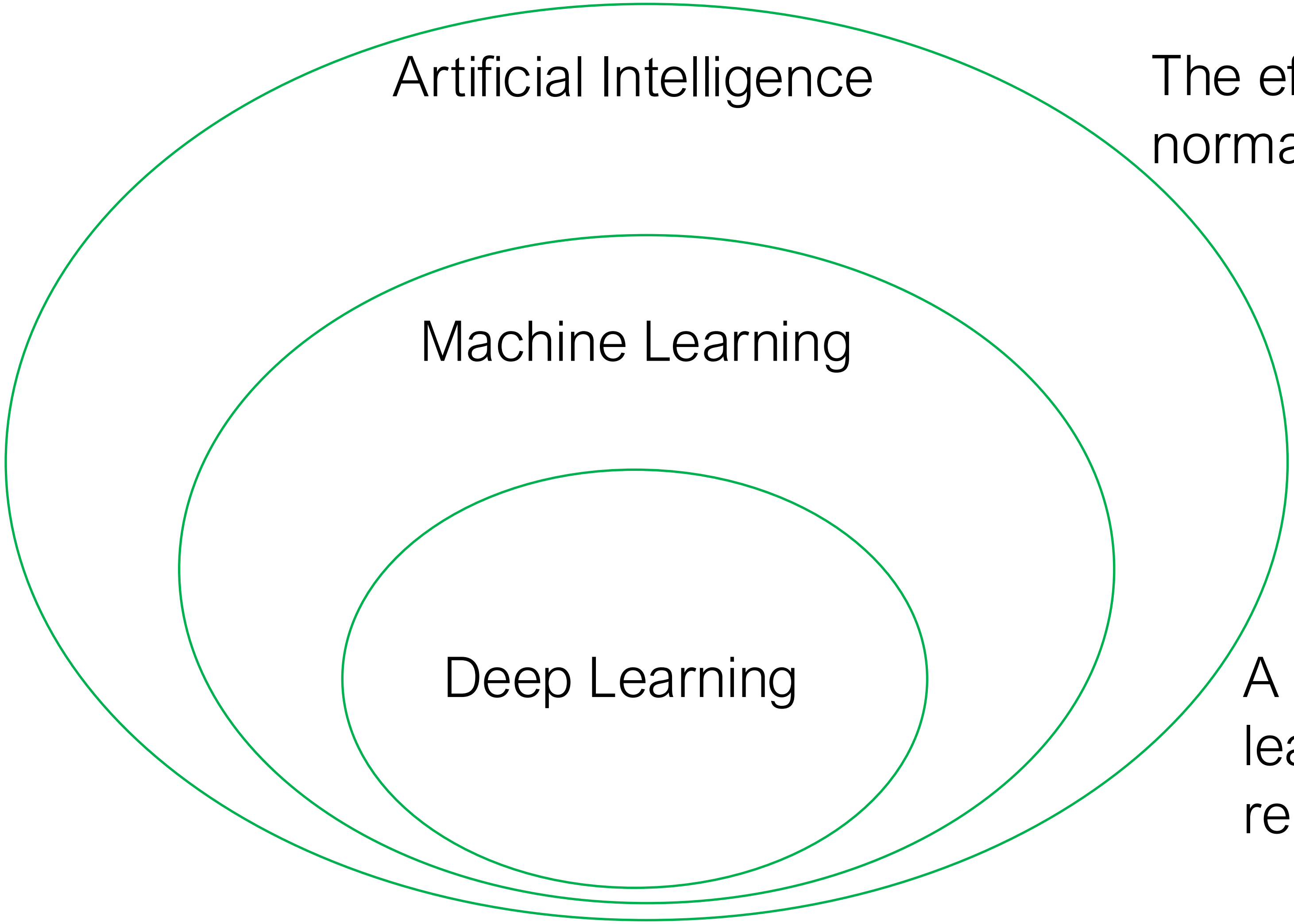
1. **Data** must be representative

2. Efficient **representations** of data are needed to enable learning
   (e.g. feature engineering or using algorithms that automatically extract features)



3. Models must **generalize** well to new data
   (pick the simplest model that achieves your goal)

What is machine learning?



Artificial Intelligence

Machine Learning

Deep Learning

The effort to automate intellectual tasks normally performed by humans

Techniques to automatically describe, predict, and strategize based on data, without being explicitly programmed with rules

A type of machine learning that learns successive layers of data representations

François Chollet, *Deep Learning with Python*, 2017

Types of machine learning tools

Types of learning	Common use case
Unsupervised learning	**Describe**
Supervised learning	**Predict**
Reinforcement learning	**Strategize** (through **trial and error** learning)

Types of machine learning

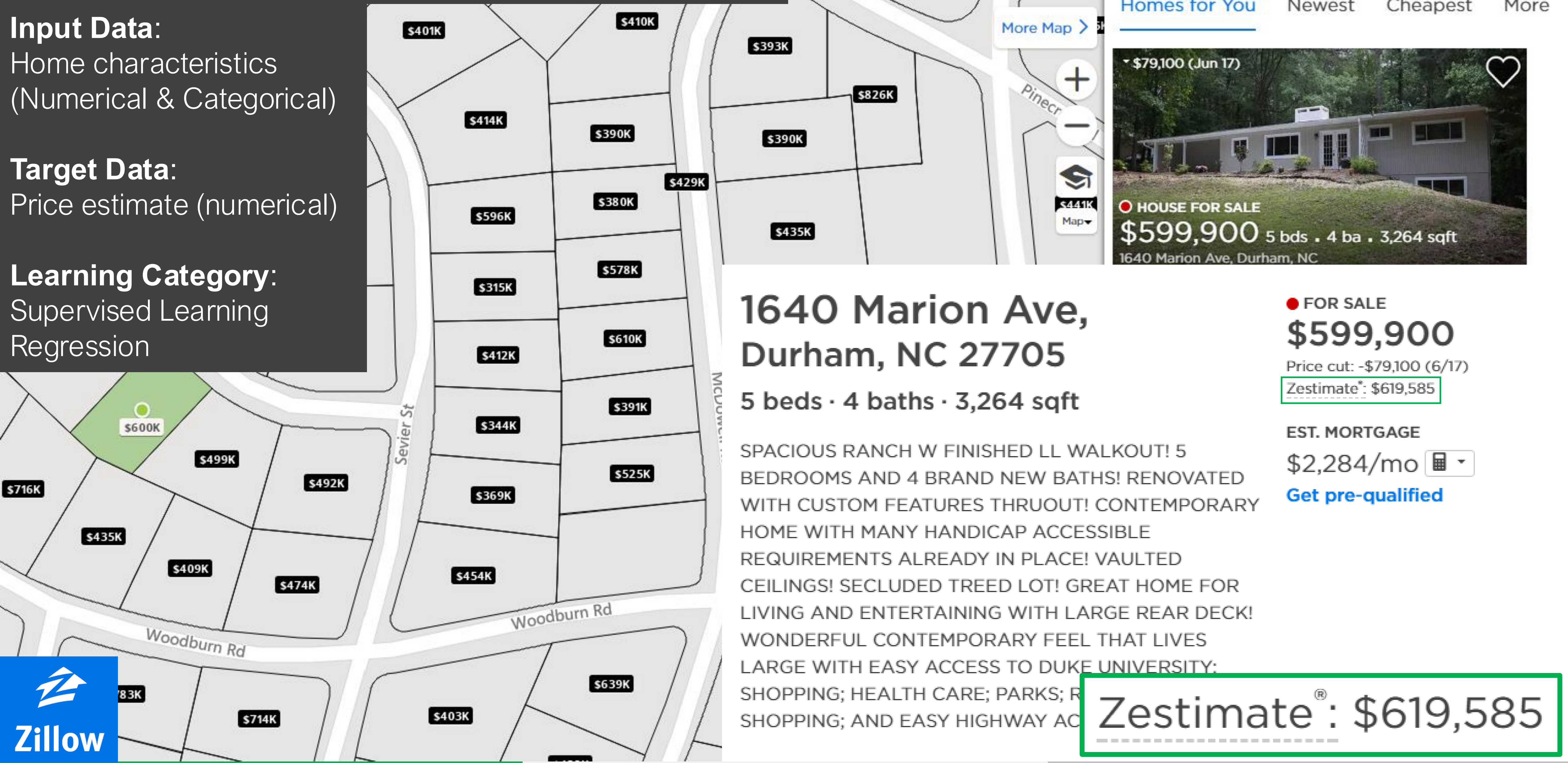
	Supervised Learning	Unsupervised Learning	Reinforcement Learning
Goal	**Predict** …from examples	**Describe** ...structure in data	**Strategize** learn by **trial and error**
Data	(x, y)	x	delayed feedback
Types	• Classification • Regression	• Density estimation • Clustering • Dimensionality reduction • Anomaly detection	• Model-free learning • Model-based learning

Sale Price Prediction

Input Data:
Home characteristics (Numerical & Categorical)

Target Data:
Price estimate (numerical)

Learning Category:
Supervised Learning
Regression



27708 Real Estate 1 home for sal

Homes for You Newest Cheapest More

$79,100 (Jun 17)

HOUSE FOR SALE

$599,900 5 bds . 4 ba . 3,264 sqft

1640 Marion Ave, Durham, NC

1640 Marion Ave, Durham, NC 27705

5 beds · 4 baths · 3,264 sqft

SPACIOUS RANCH W FINISHED LL WALKOUT! 5 BEDROOMS AND 4 BRAND NEW BATHS! RENOVATED WITH CUSTOM FEATURES THRUOUT! CONTEMPORARY HOME WITH MANY HANDICAP ACCESSIBLE REQUIREMENTS ALREADY IN PLACE! VAULTED CEILINGS! SECLUDED TREED LOT! GREAT HOME FOR LIVING AND ENTERTAINING WITH LARGE REAR DECK! WONDERFUL CONTEMPORARY FEEL THAT LIVES LARGE WITH EASY ACCESS TO DUKE UNIVERSITY; SHOPPING; HEALTH CARE; PARKS; R SHOPPING; AND EASY HIGHWAY AC

FOR SALE

$599,900

Price cut: -$79,100 (6/17)

Zestimate®: $619,585

EST. MORTGAGE

$2,284/mo

Get pre-qualified

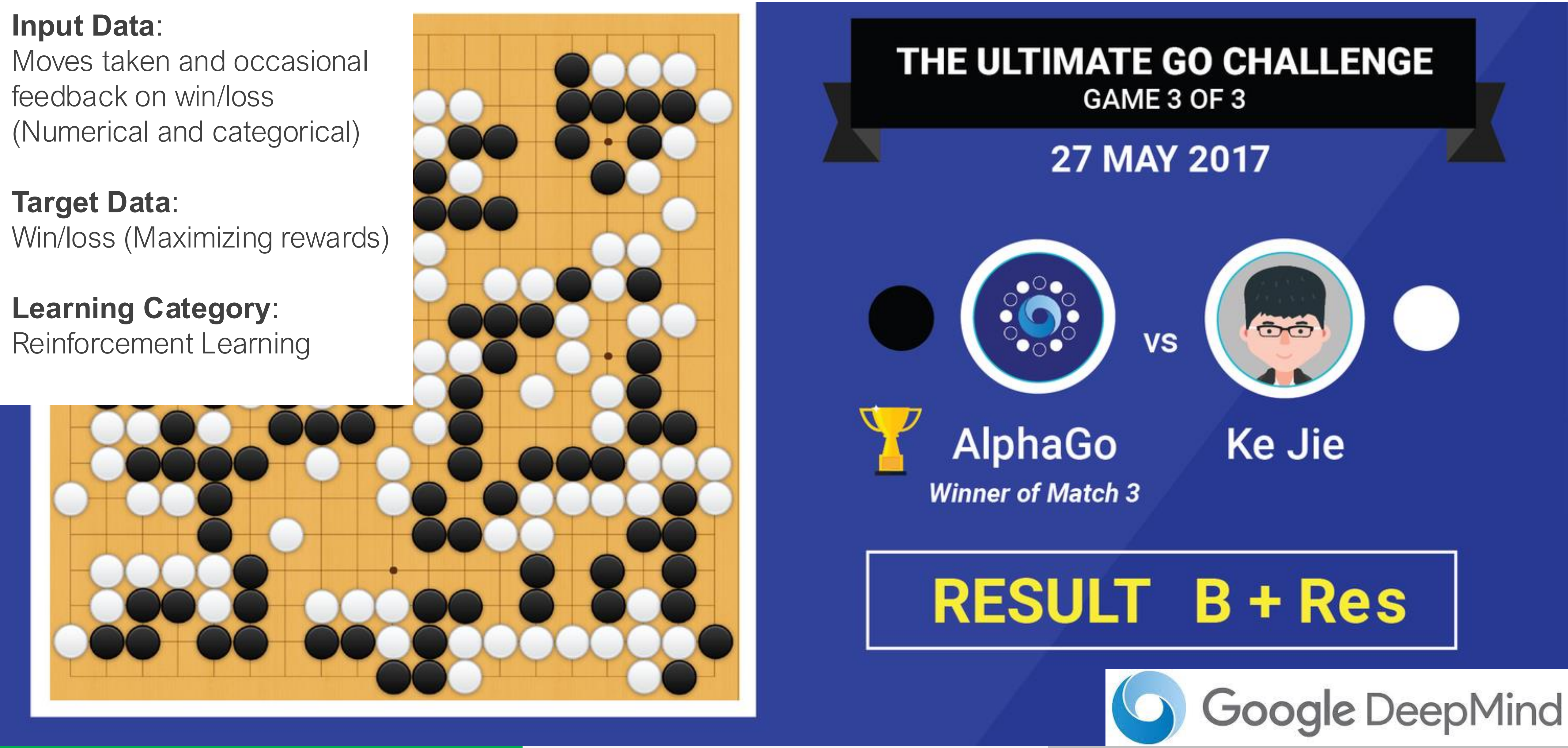
Zestimate®: $619,585

Learning a strategy to master games

Input Data:
Moves taken and occasional feedback on win/loss (Numerical and categorical)

Target Data:
Win/loss (Maximizing rewards)

Learning Category:
Reinforcement Learning



From: Internal Revenue Service [mailto:yourtaxrefund@InternalRevenueService.com]

Sent: Tuesday, July 22, 2008 9:47 AM

Subject: Get your tax refund now

Importance: High

After the last annual calculations of your account activity we have determined that you are eligible to receive a tax refund of $479.30 .

Please submit the tax refund request and allow us 2-6 days in order to process it.

A refund can be delayed for a variety of reasons. For example submitting invalid records or applying after the deadline.

To access the form for your tax refund, please click here (http://e-dlogs.rta.mi.th:84/www.irs.gov/)

Note: Deliberate wrong inputs will be prosecuted by law.

Regards,

Internal Revenue Service

Spam example source: itservices.uchicago.edu

Spam Filters

Input Data:
Email text (text)

Target Data :
Spam/not spam (category)

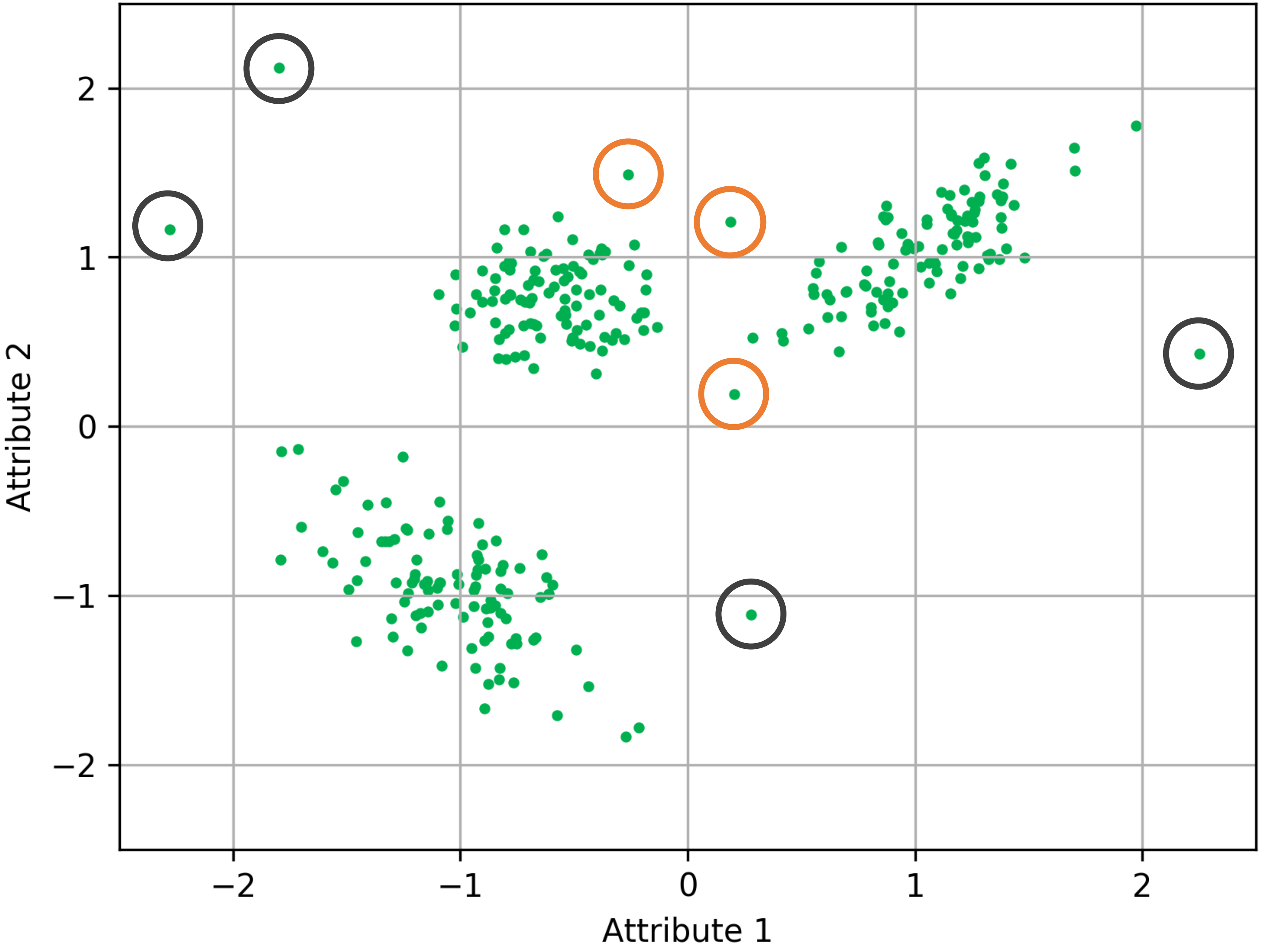
Learning Category:
Supervised Learning
Classification (binary)

Credit Fraud

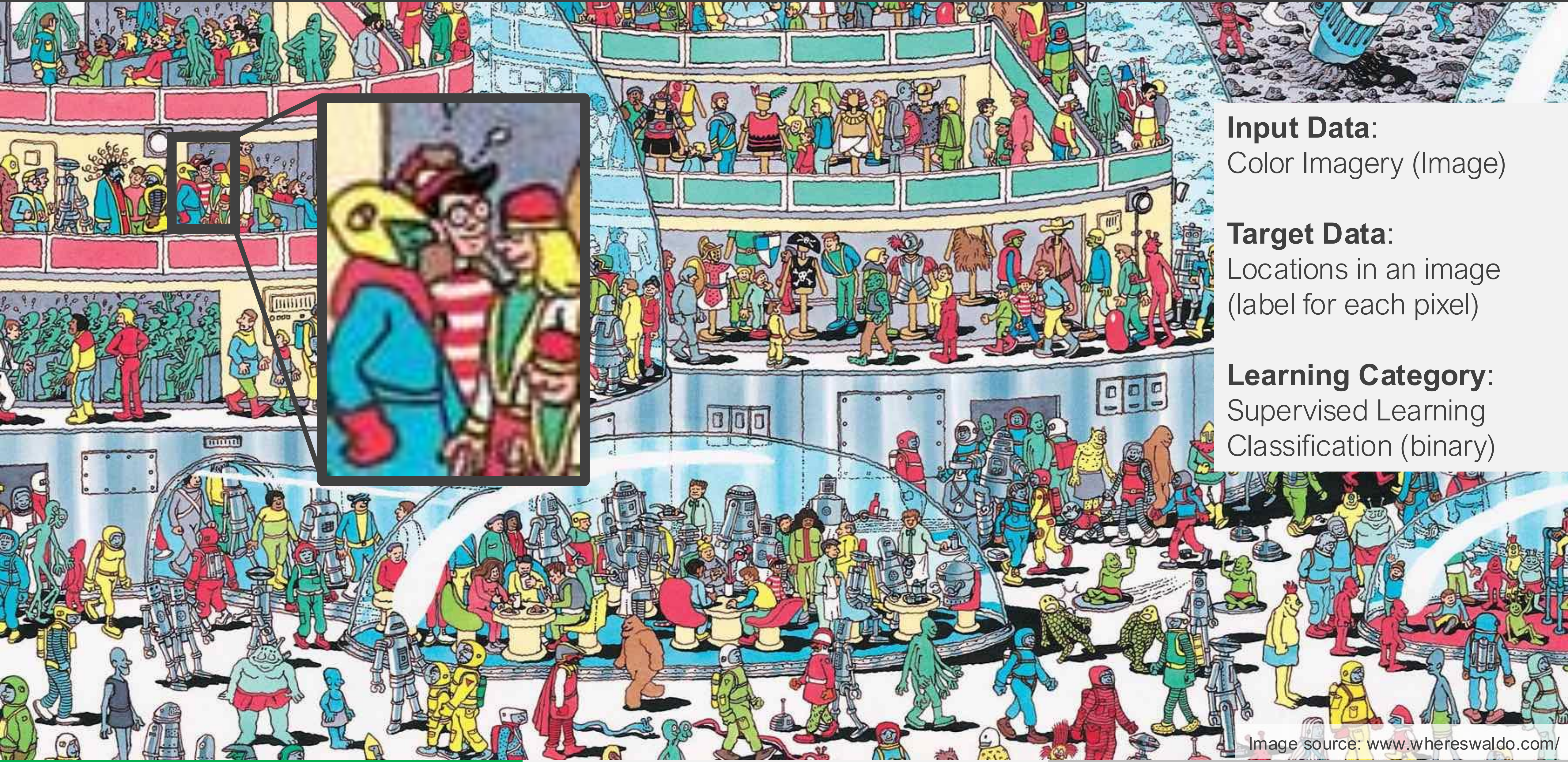
Input Data:
Account transactions, dates, locations, demographic information
(Numerical and categorical)

Target Data:
Anomalous transactions

Learning Category:
Unsupervised Learning
Clustering, Density Estimation



Where’s Waldo = Computer Vision Problem



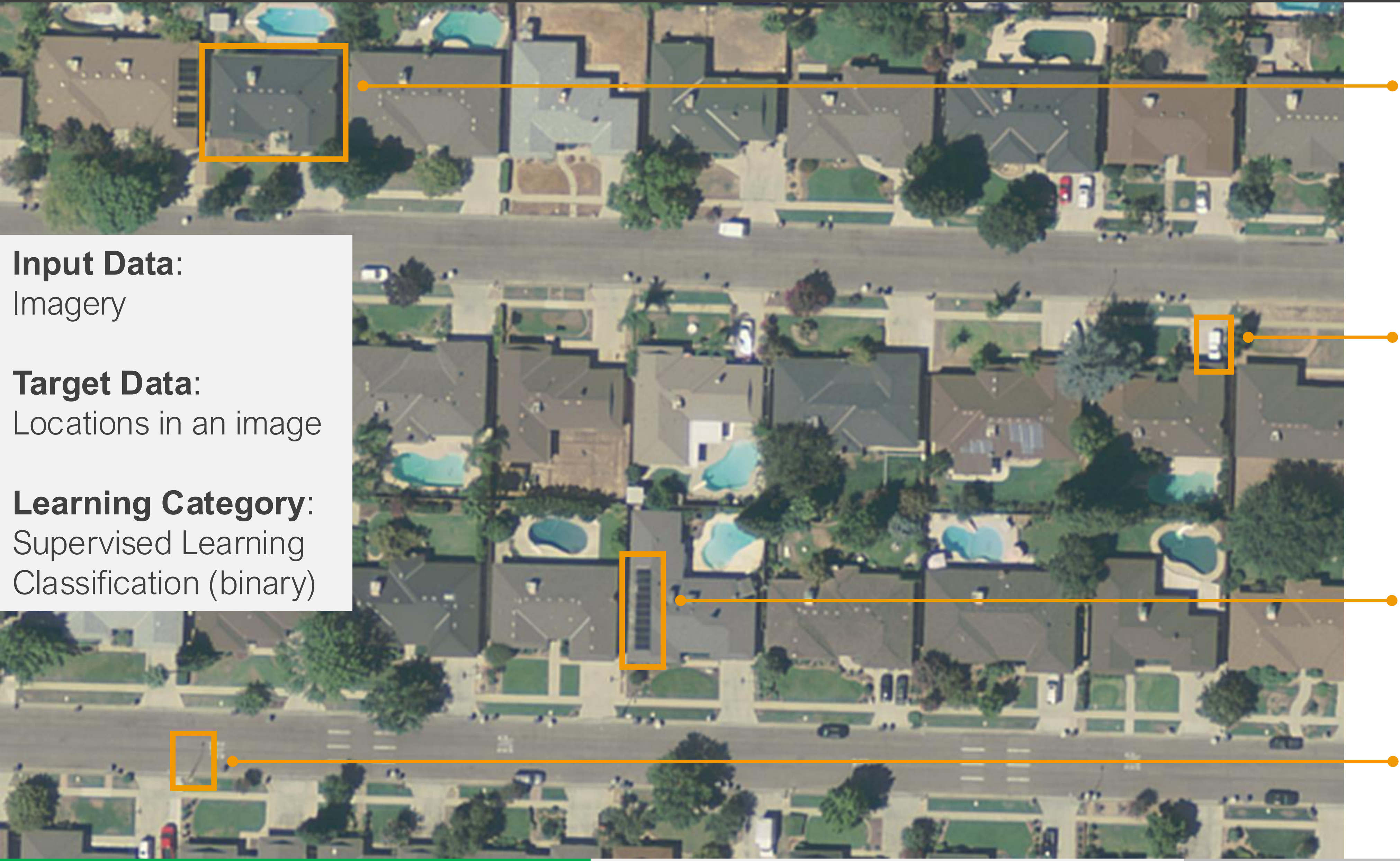
Input Data:
Color Imagery (Image)

Target Data:
Locations in an image
(label for each pixel)

Learning Category:
Supervised Learning
Classification (binary)

Image source: www.whereswaldo.com/

Object Recognition: Energy Systems



Input Data:
Imagery

Target Data:
Locations in an image

Learning Category:
Supervised Learning
Classification (binary)

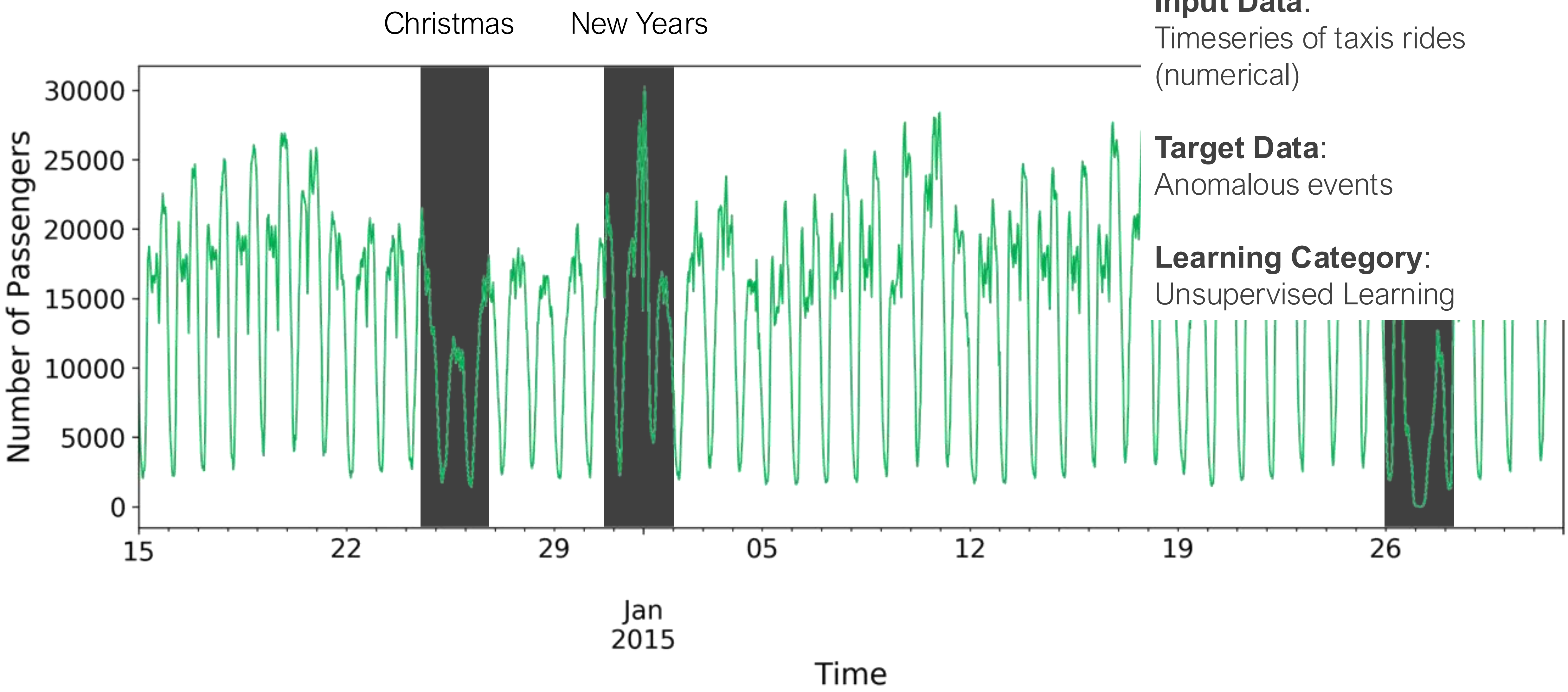
Building
behind-the-meter
energy consumption

Car
transportation
energy consumption

Solar Array
distributed energy
resources

Light Pole
access to electricity

Anomalous Event Detection: NYC Taxis



Input Data:
Timeseries of taxis rides (numerical)

Target Data:
Anomalous events

Learning Category:
Unsupervised Learning

Data source: Numenta Anomaly Benchmark (NAB), from kaggle.com

Manufacturing – learn to pick up iron cylinders

Input Data:
Actions taken and occasional feedback on success/failure (Numerical and categorical)

Target Data:
Success/failure (Maximizing rewards)

Learning Category:
Reinforcement Learning

Source: MIT Technology Review; Company: FANUC

Types of machine learning

	Supervised Learning	Unsupervised Learning	Reinforcement Learning
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Cautionary advice for aspiring data scientists on machine learning

1

Machine Learning should **NOT** be the first tool you reach for in **all** cases

When NOT to use machine learning

Your objective doesn’t require machine learning

(e.g. it can be solved with simpler methods like a heuristic or a data visualization – know physical rules, tax calculations)

Don’t have sufficient training data and can’t get it

(e.g. unique/new cases, nonstationary problems, poor data quality)

High-risk problems that require guarantees

(e.g. safety-critical systems, cryptography, financial transaction validation)

2

Communicating your findings effectively is often **more important** than squeezing out a tiny bit more performance

Pitch 1

Includes superfluous information that can be easily summarized

Mod_conf_covid	Pred	GT
0.9385243634	1	1
0.6457346346	1	0
0.3184929258	0	0
0.0282716155	0	0
0.8332211769	1	1
0.7290847238	1	1
0.7239875235	1	1
0.3495938237	0	1
0.1929357283	0	0
0.6399959583	1	0

Jumps into the methods without mentioning context

Our deep neural network has a precision of 0.67 and recall of 0.8

Uses metrics that people outside the field may not understand

*Note all data/facts on this slide are invented for illustration and not valid

Pitch 2

Conveys the meaning of the metrics in easy-to-understand language

Our COVID detection model **successfully detects 4 out of 5** instances of COVID-19.

False COVID diagnoses in patients without COVID occur in only **2 of every 6 patients**.

This technique is 30% cheaper than the alternative rapid test and equally effective

Provides context as to why this approach is better than the alternatives

Course logistics

Learning objectives

Through this course you will learn…

- To describe fundamental concepts in **machine learning**
- How to **structure experiments** to address a machine learning problem
- To automatically make **decisions** from data
- Understand how ML algorithms work and when/how to use them
- To communicate and effectively **interpret** machine learning output
- To implement your own **end-to-end machine learning project**

Pedagogy

- **Good learning is active learning**
  - Our instructional team provides guidance and structure through the material
  - Most learning is through your work on the assignments, quizzes, and project

- **Desirable difficulty leads to meaningful learning**
  - Creates reusable mental models for independent, lifelong learning
  - Enhances abilities to interpret machine learning results effectively

- **Reading, reflection, and recall is a pattern for effective learning**
  - True learning happens in long-term memory → time is required
  - You'll typically interact with each concept **4 times**
    (lectures, readings, quizzes, and assignments)
  - We will work to avoid the illusion of knowledge

Course website

kylebradbury.github.io/ids705

Course communications

https://edstem.org/us/courses/90514/

(A link is available on the course website)

Graded Components

Quizzes (Individual - no Collaboration)	20%	(One before each class, ~1% each)
Assignments (Some collaboration)	50%	(5 assignments, 10% each)
Exam (Individual – closed book)	15%	
Final project (Fully team-based project)	15%	

Action items

1. Complete the first set of readings and **watch** the next lecture
2. Take Lecture 2 Quiz on Gradescope **before** the start of our next class (quizzes are always due **before** the start of each class)
3. Log into each of the course sites (Canvas, Ed Discussions, and Gradescope) and verify you can access each of them. Read the syllabus on the course website for course policies.
4. Begin working on Assignment #1, posted on the syllabus
5. Come ready for an in-class exercise next THURSDAY!

No class Tuesday 1/13, this will be made-up Friday (1/30) at 10:05 in Gross Hall 270