

# COMP 135

## Introduction to Machine Learning Prof. Michael C. Hughes (“Mike”)

Fall 2020, First day of class

As you join, please check out:

\* **Website:** <https://www.cs.tufts.edu/comp/135/2020f/>

Read syllabus, skim schedule, waitlist info, etc.

\* **Piazza** forum: <https://www.piazza.com/tufts/fall2020/comp135>

Access code (today only): **validation2020**

Ask LIVE questions throughout today’s class (and every class)

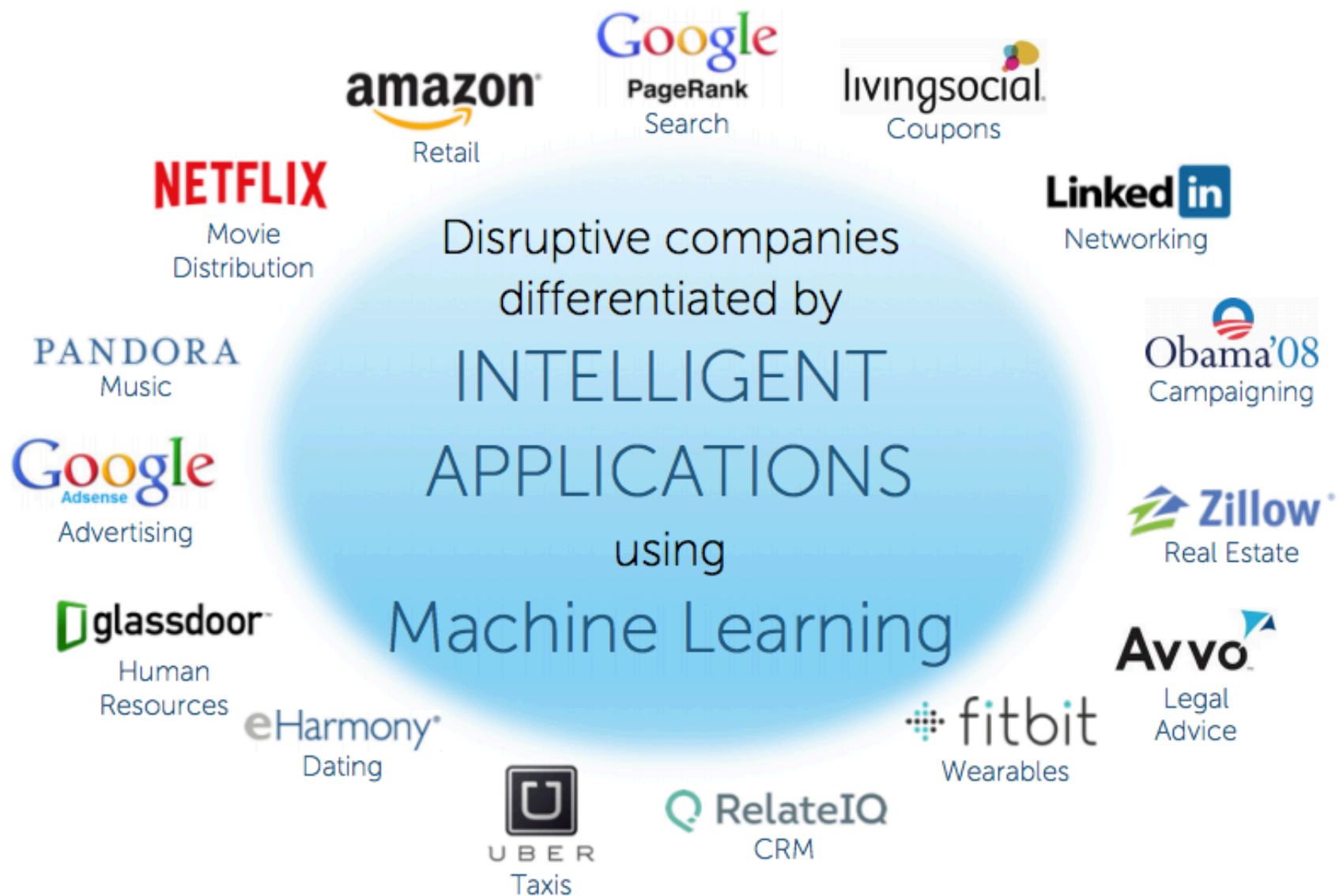
*Many slides attributable to: Emily Fox (UW), Finale Doshi-Velez (Harvard), Erik Sudderth (UCI), & Liping Liu (Tufts)*

# Today's Agenda

- Why take this course?
- What is Machine Learning?
- What skills/concepts will we learn?
- Who is teaching?
- How will we spend our time?

**Q: Why should you take this course?**

**A: Machine Learning is everywhere!** Those who know how to wield it effectively and *responsibly* can change the world.



*Image Credit: Emily Fox*

# Goals of this course

Our goal is to prepare students to effectively apply machine learning methods to problems that might arise in "the real world" -- in industry, medicine, government, education, and beyond.

Gain skills and *understanding* for a future as:

- Developer using ML “out-of-the-box”
- ML methods researcher

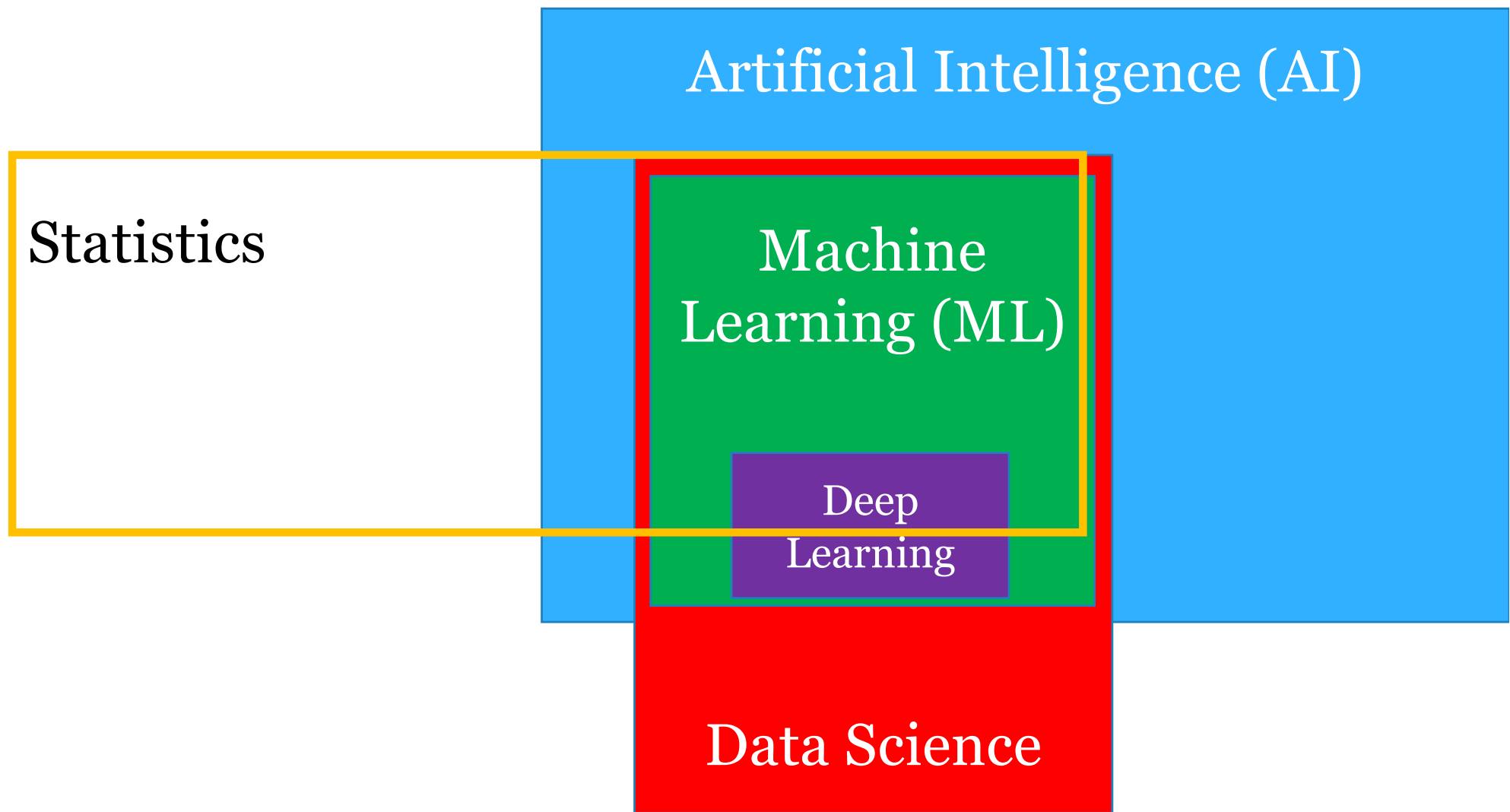
# After taking this course, you will be able to:

- *Think systematically and ethically*
  - Compare/contrast each method's strengths & limitations
  - "Can ML solve this problem?"
  - "**Should** ML solve this problem?"
- *Deploy and debug rapidly on real problems*
  - Hands-on experience with open-source libraries
  - Address issues in "real-world" data analysis
    - Numerical issues, convergence issues, class imbalance, missing values, etc.
- *Evaluate carefully and honestly*
  - Design experiments to assess generalization to never-before-seen data
  - Select task-appropriate performance metrics
  - Report confidence or uncertainty in performance numbers
- *Communicate insightfully and reproducibly*
  - Surface key insights via figures, tables, and text in a written report
  - Provide details for a peer to repeat your analysis and draw same conclusions



**Q: What is Machine Learning?**

# Venn Diagram of Knowledge





# Artificial Intelligence (AI)

Study of “intelligent” systems, with many parts:

logic, planning, search, probabilistic reasoning, **learning from experience**, interacting with other agents, etc.



## Alpha Go

Computer that can beat best human players of the game of “Go” (harder than chess)



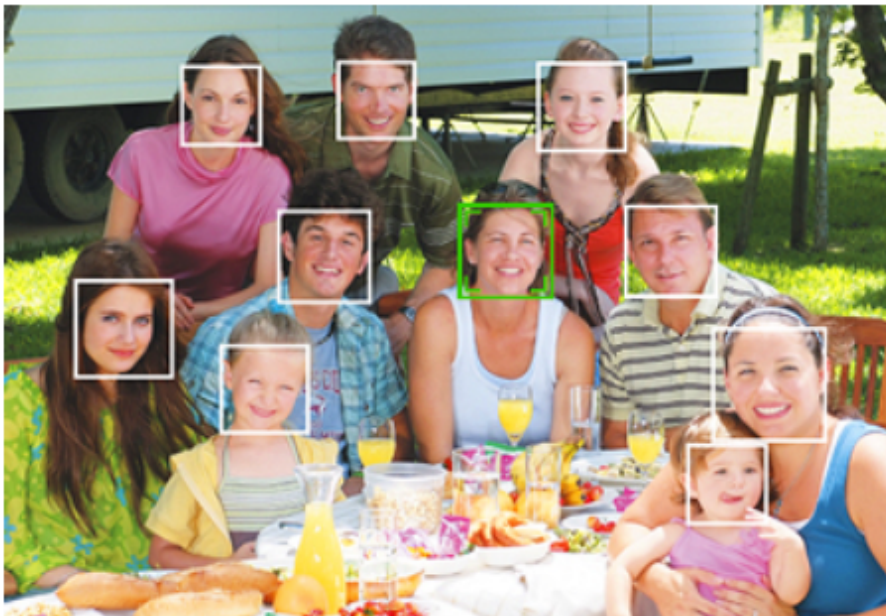
## DARPA Grand Challenge

Autonomous vehicles can navigate a real-world course without humans at the wheel

# Machine Learning (ML)

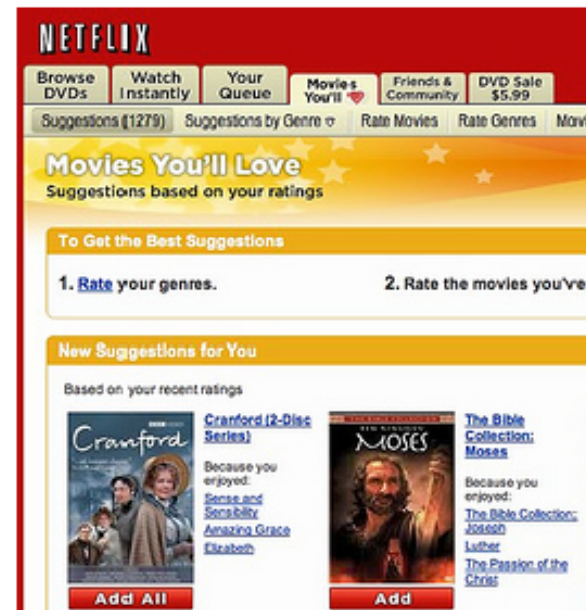
Study of computer programs that **learn from experience/data** to perform a task

- Output: a *prediction, decision, or summary*



## Face Detection

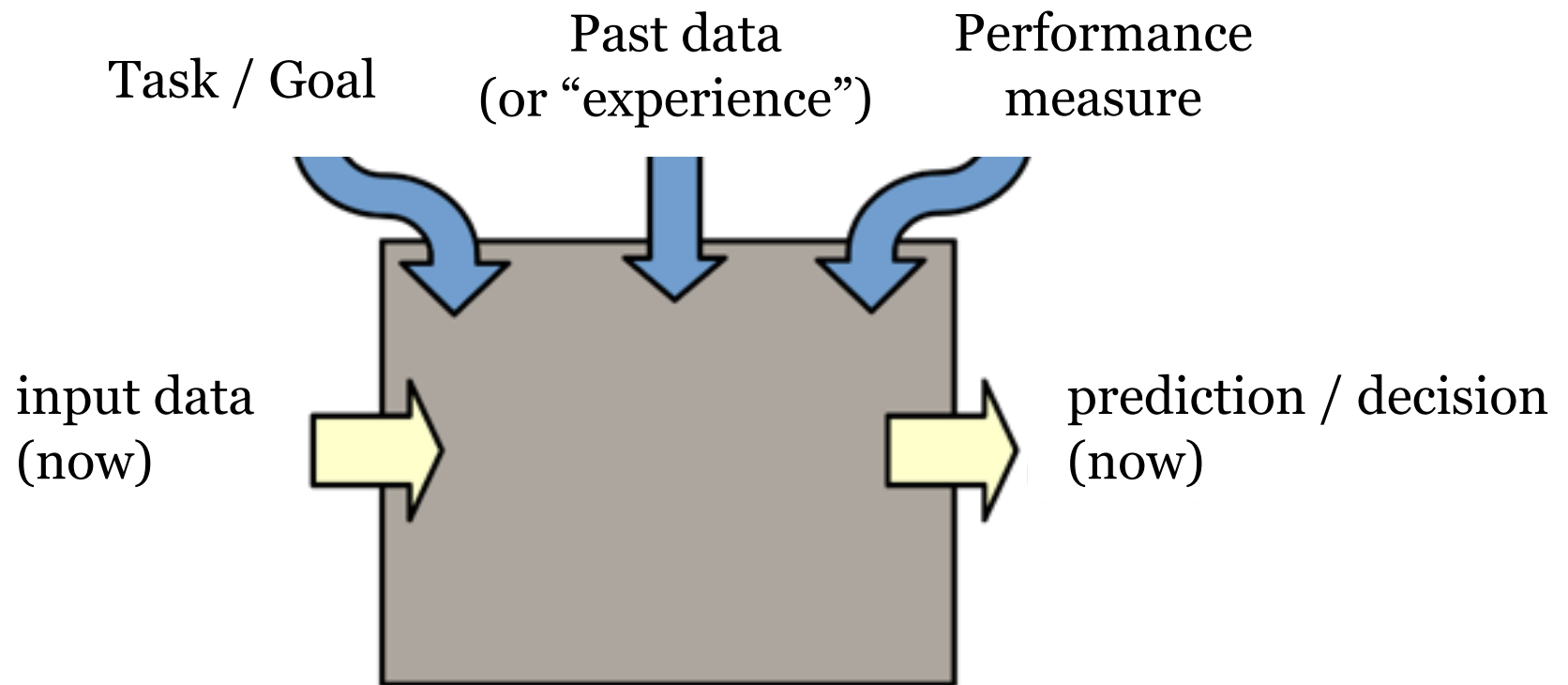
Predict location of human faces in natural images



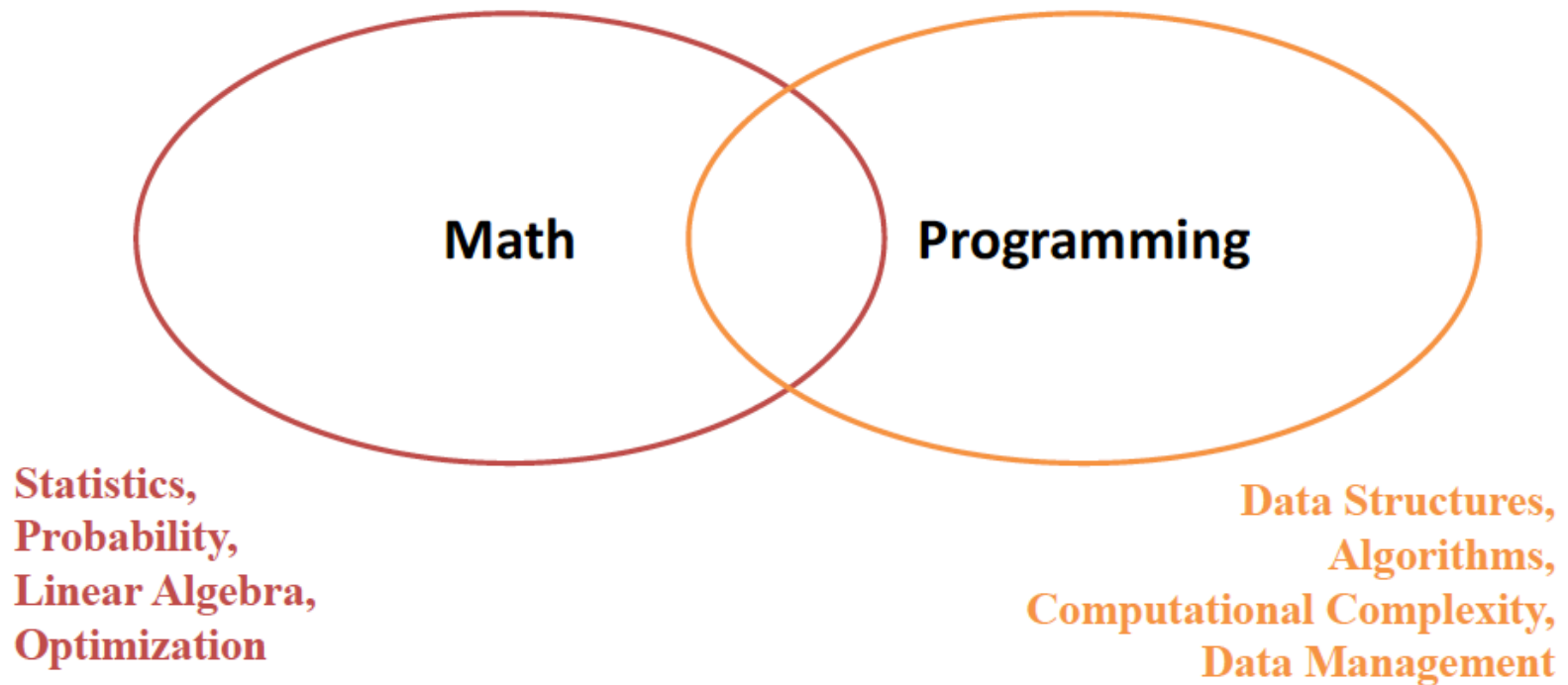
## Movie Recommendation

Predict what to watch next

# The Machine Learning Process



# Q: What concepts will we learn?

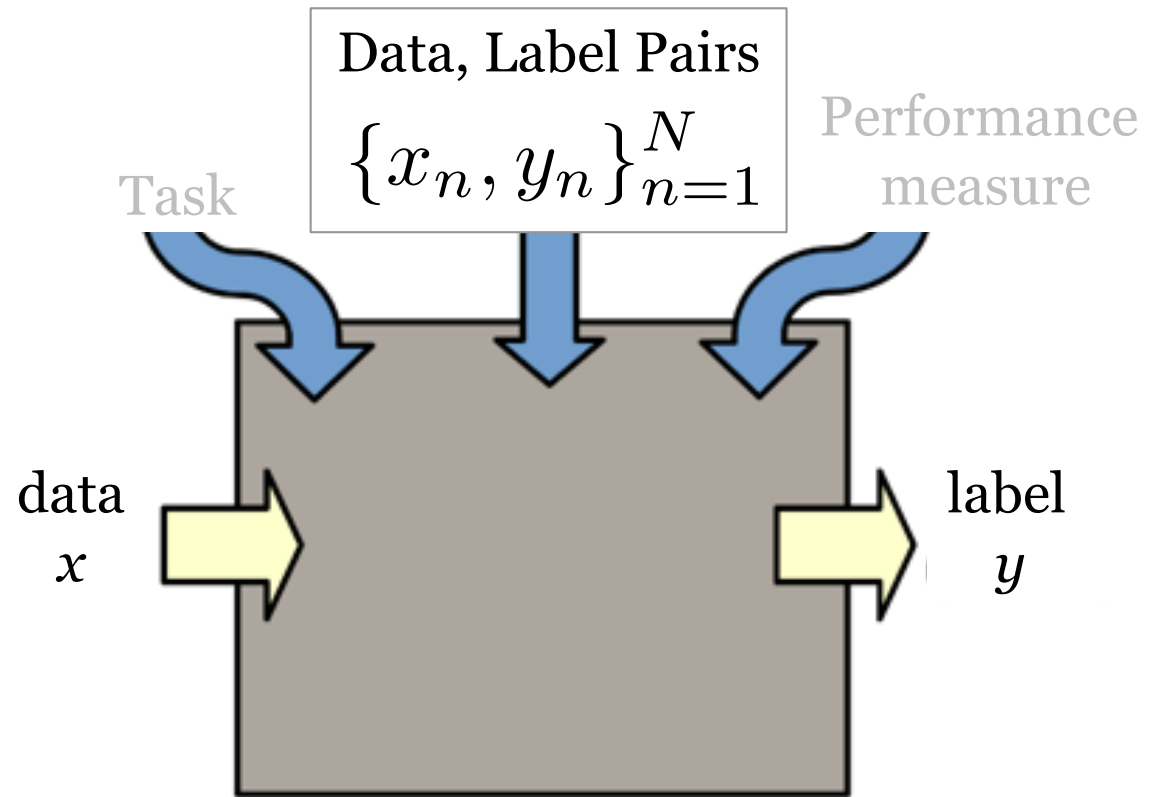


# What will we learn?

Supervised  
Learning

Unsupervised  
Learning

Reinforcement  
Learning



# Task: Regression

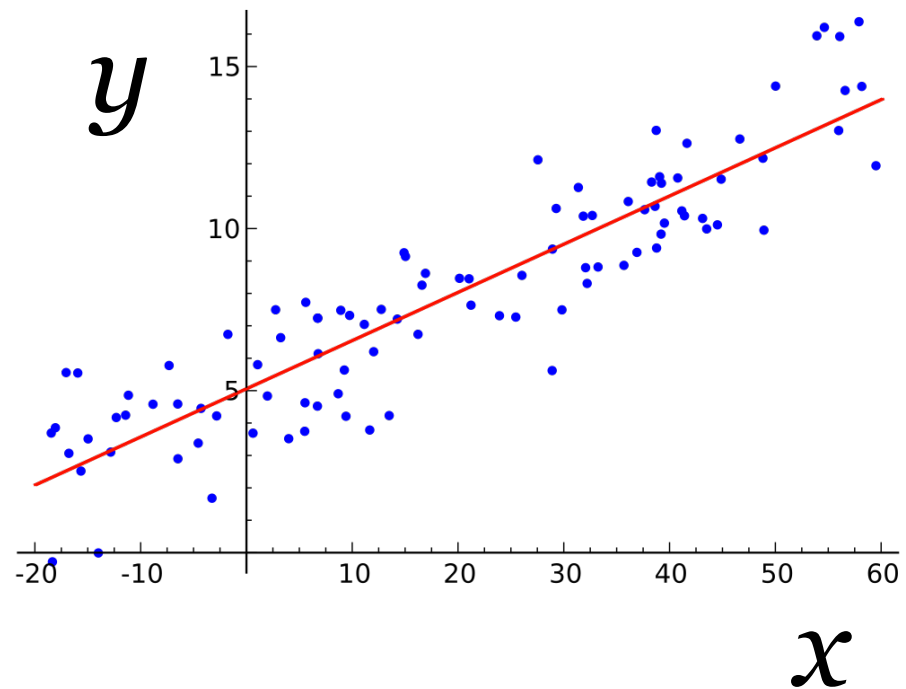
Supervised  
Learning

regression

Unsupervised  
Learning

Reinforcement  
Learning

$y$  is a continuous variable  
e.g. sales in \$\$



# Regression Example: Uber

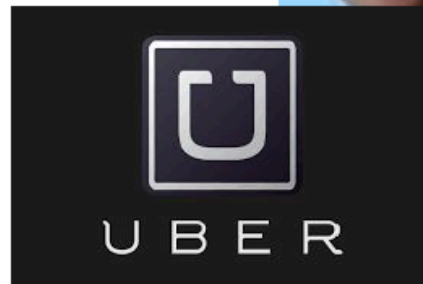
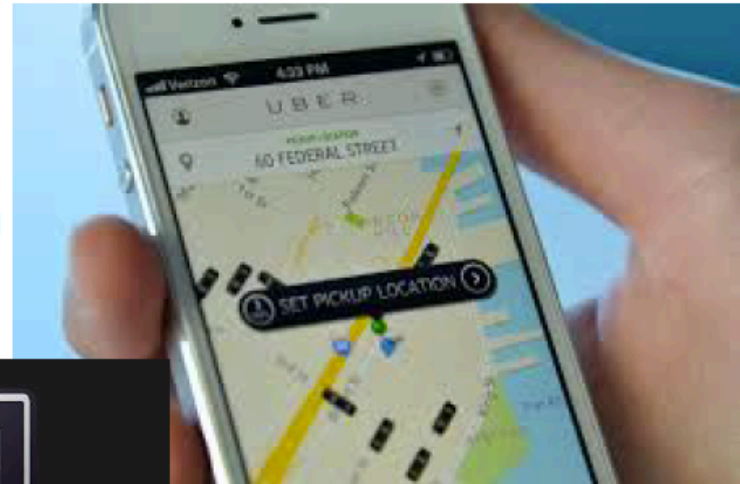
Supervised  
Learning

**regression**

Unsupervised  
Learning

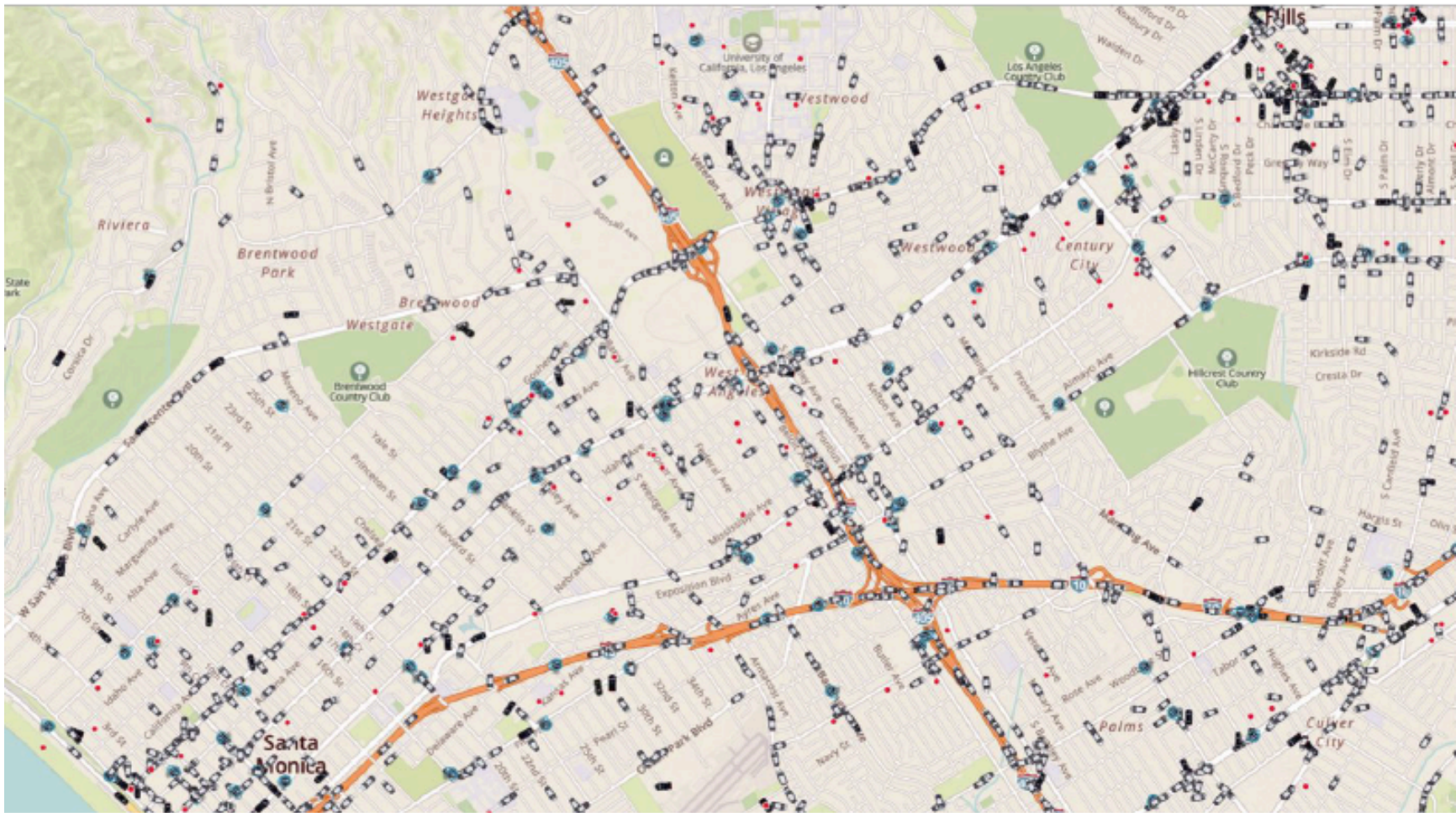
Reinforcement  
Learning

Predictions of travel  
time, price, supply,  
demand





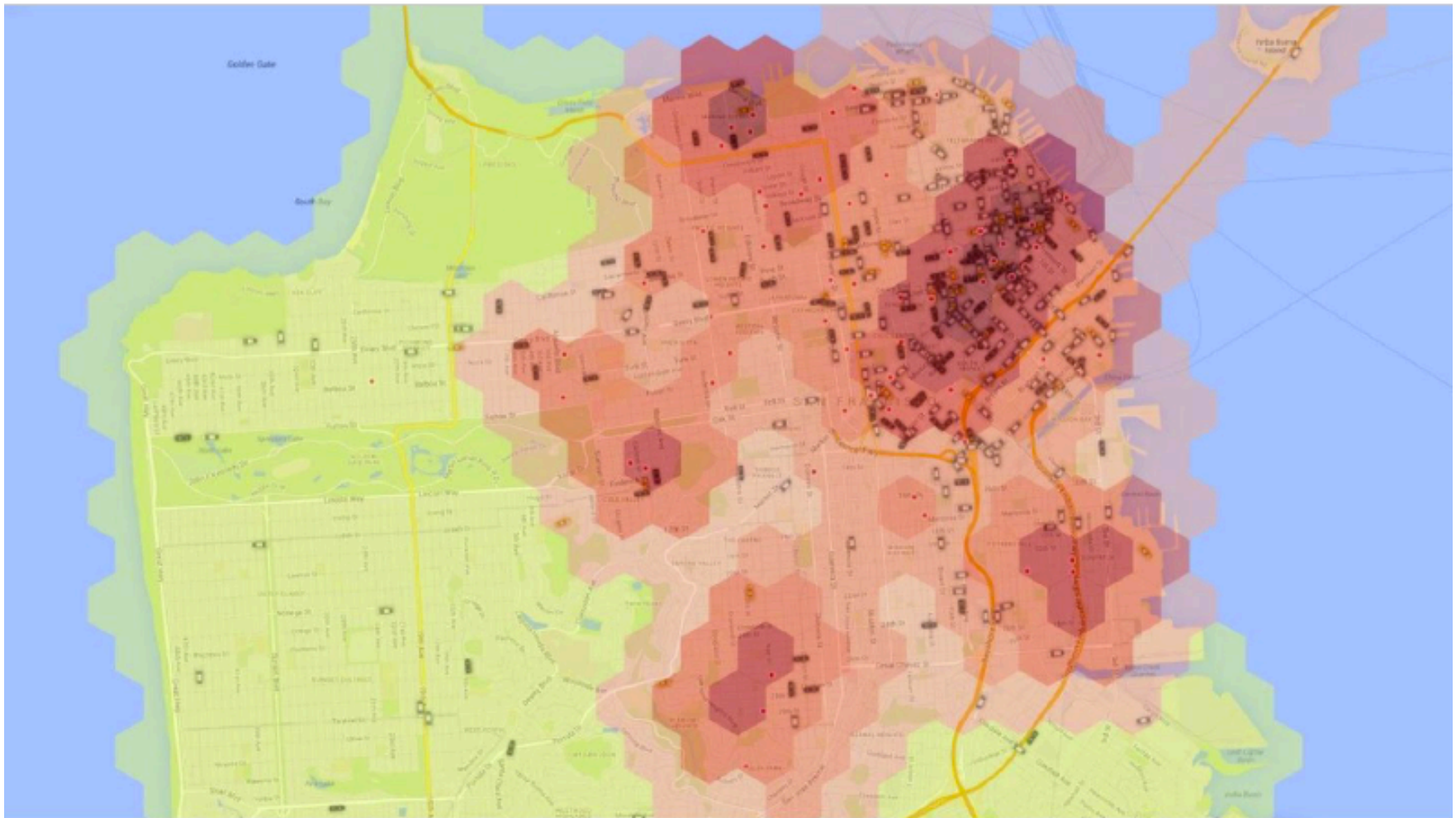
# Regression Example: Uber



(Keith Chen)



# Regression Example: Uber



(Keith Chen)

# Task: Classification

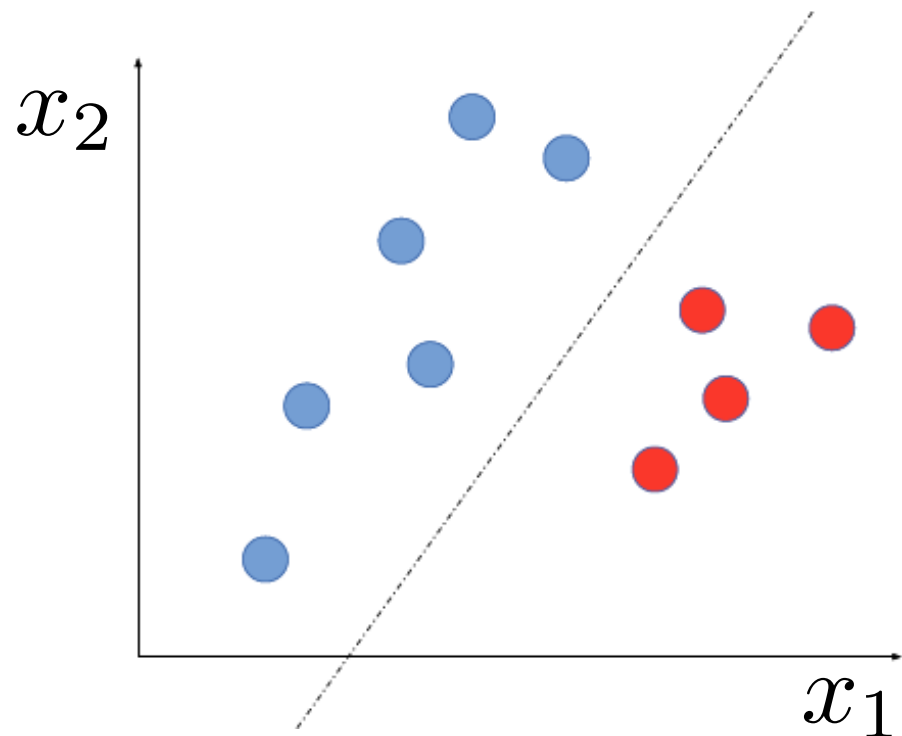
Supervised  
Learning

**classification**

Unsupervised  
Learning

Reinforcement  
Learning

$y$  is a discrete variable  
(red or blue)



# Classification Example: Swype

Predict words from keyboard trajectories

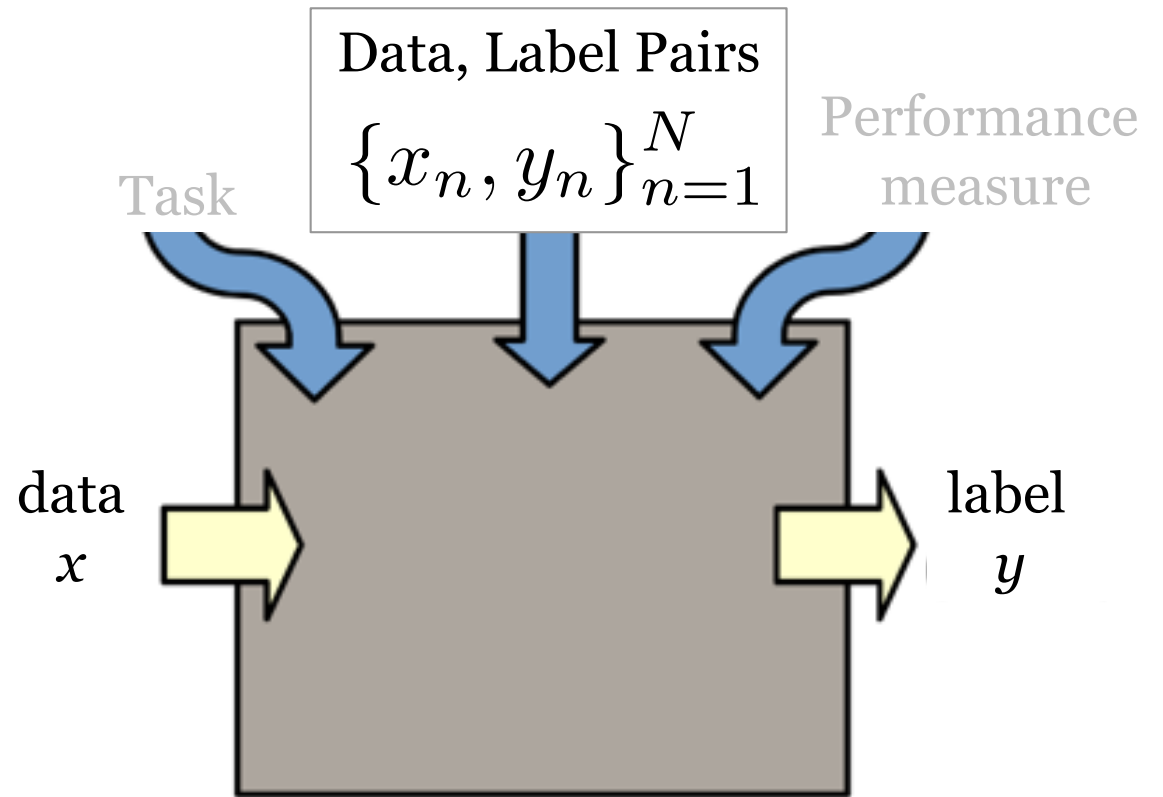


# What will we learn?

Supervised  
Learning

Unsupervised  
Learning

Reinforcement  
Learning

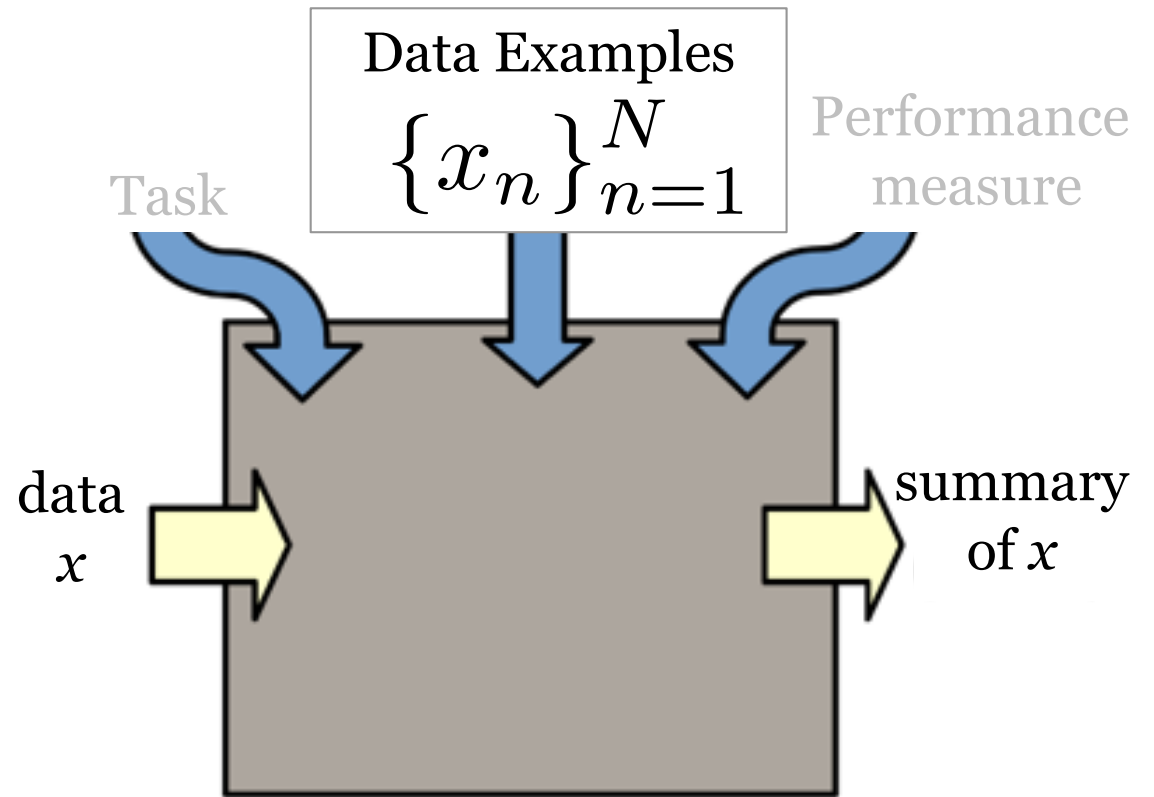


# What will we learn?

Supervised  
Learning

Unsupervised  
Learning

Reinforcement  
Learning



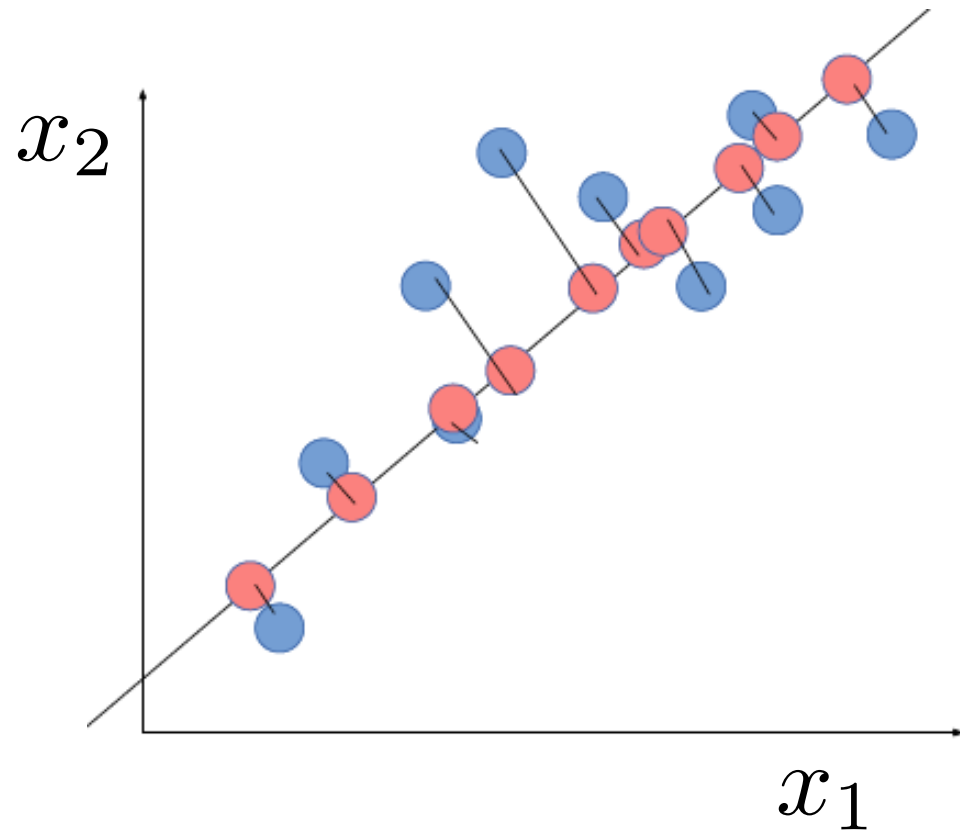
# Task: Embedding

Supervised  
Learning

Unsupervised  
Learning

**embedding**

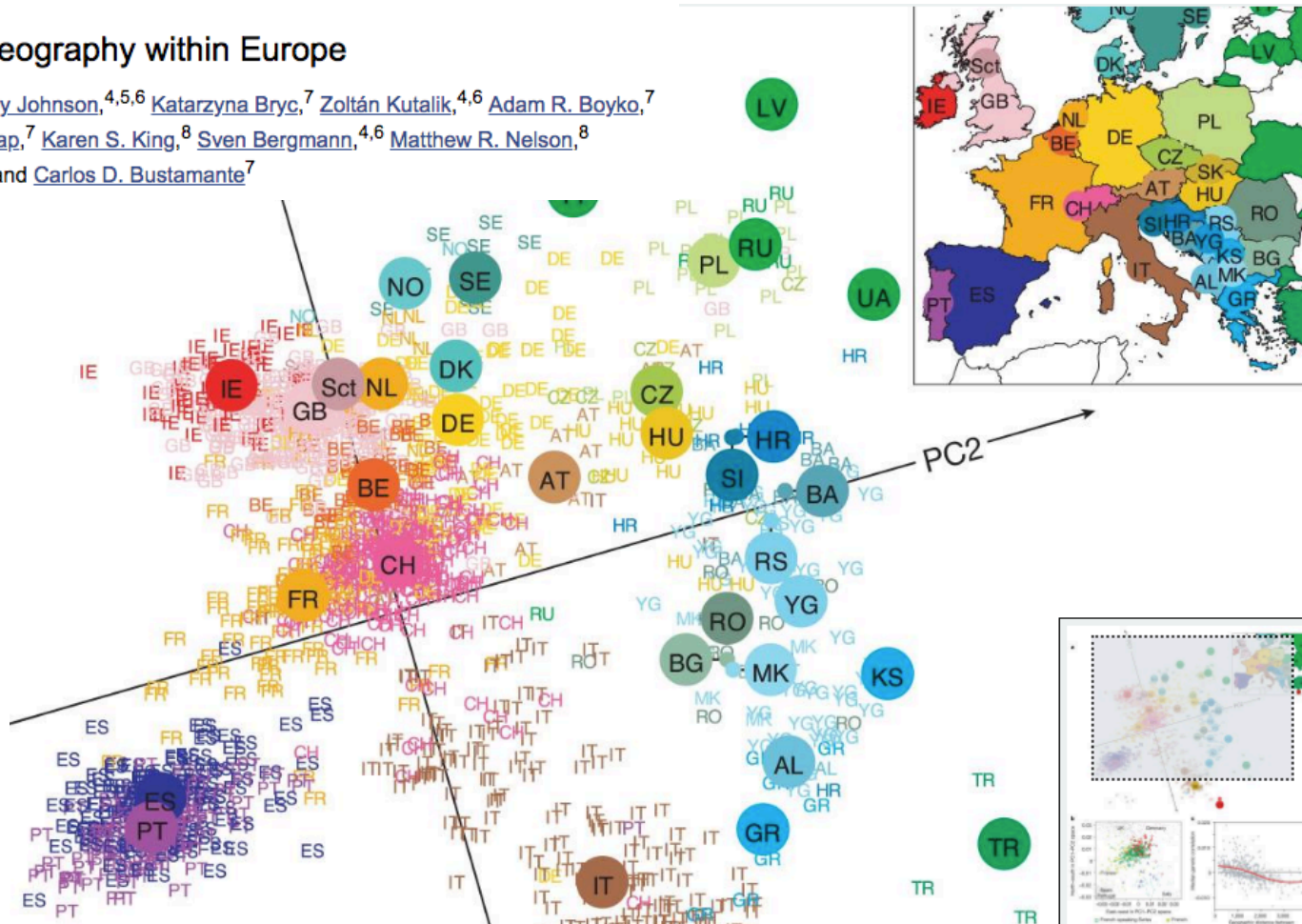
Reinforcement  
Learning



# Example: Genes vs. geography

## Genes mirror geography within Europe

[John Novembre](#),<sup>1,2</sup> [Toby Johnson](#),<sup>4,5,6</sup> [Katarzyna Bryc](#),<sup>7</sup> [Zoltán Kutalik](#),<sup>4,6</sup> [Adam R. Boyko](#),<sup>7</sup>  
[Adam Auton](#),<sup>7</sup> [Amit Indap](#),<sup>7</sup> [Karen S. King](#),<sup>8</sup> [Sven Bergmann](#),<sup>4,6</sup> [Matthew R. Nelson](#),<sup>8</sup>  
[Matthew Stephens](#),<sup>2,3</sup> and [Carlos D. Bustamante](#)<sup>7</sup>



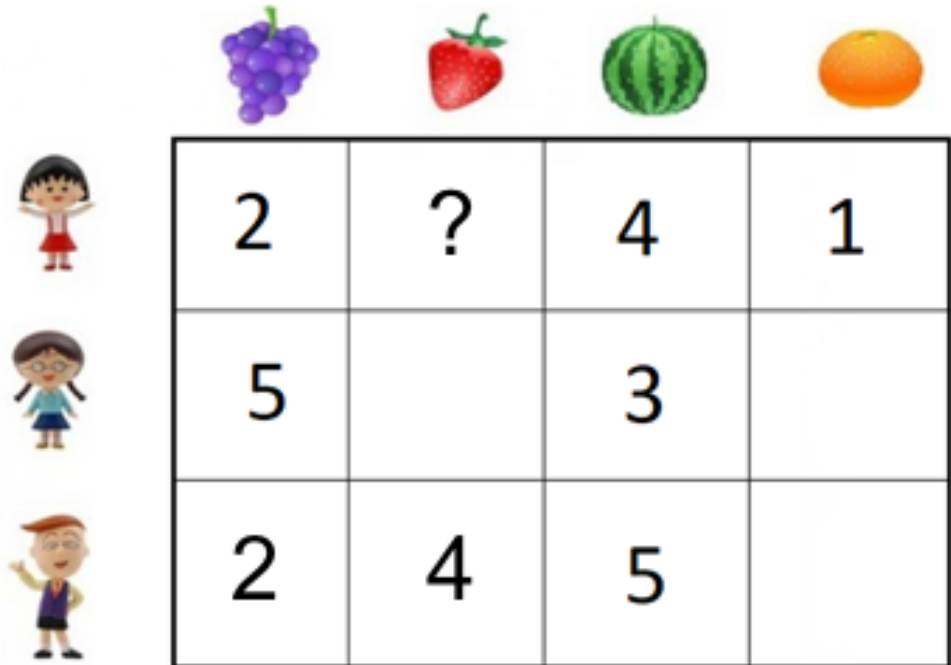
# Task: Recommendation

Supervised  
Learning








recommendation

Supervised  
Learning

Reinforcement  
Learning

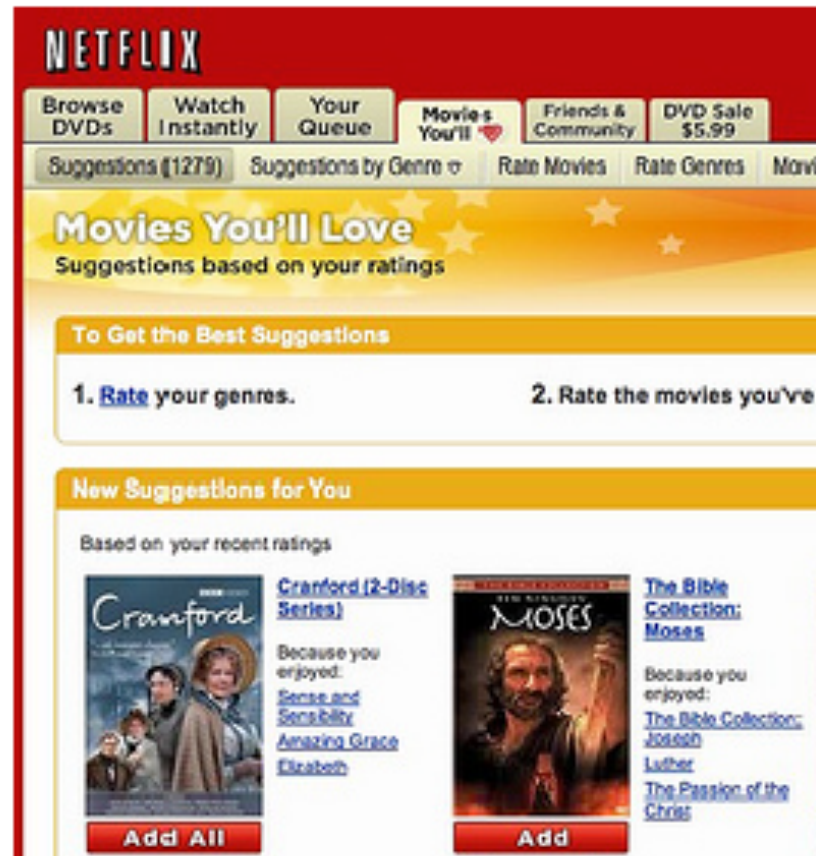


The table illustrates a recommendation system's output. The columns represent different fruit items, and the rows represent different users. The ratings are as follows:

				
	2	?	4	1
	5		3	
	2	4	5	



# Recommendation Example

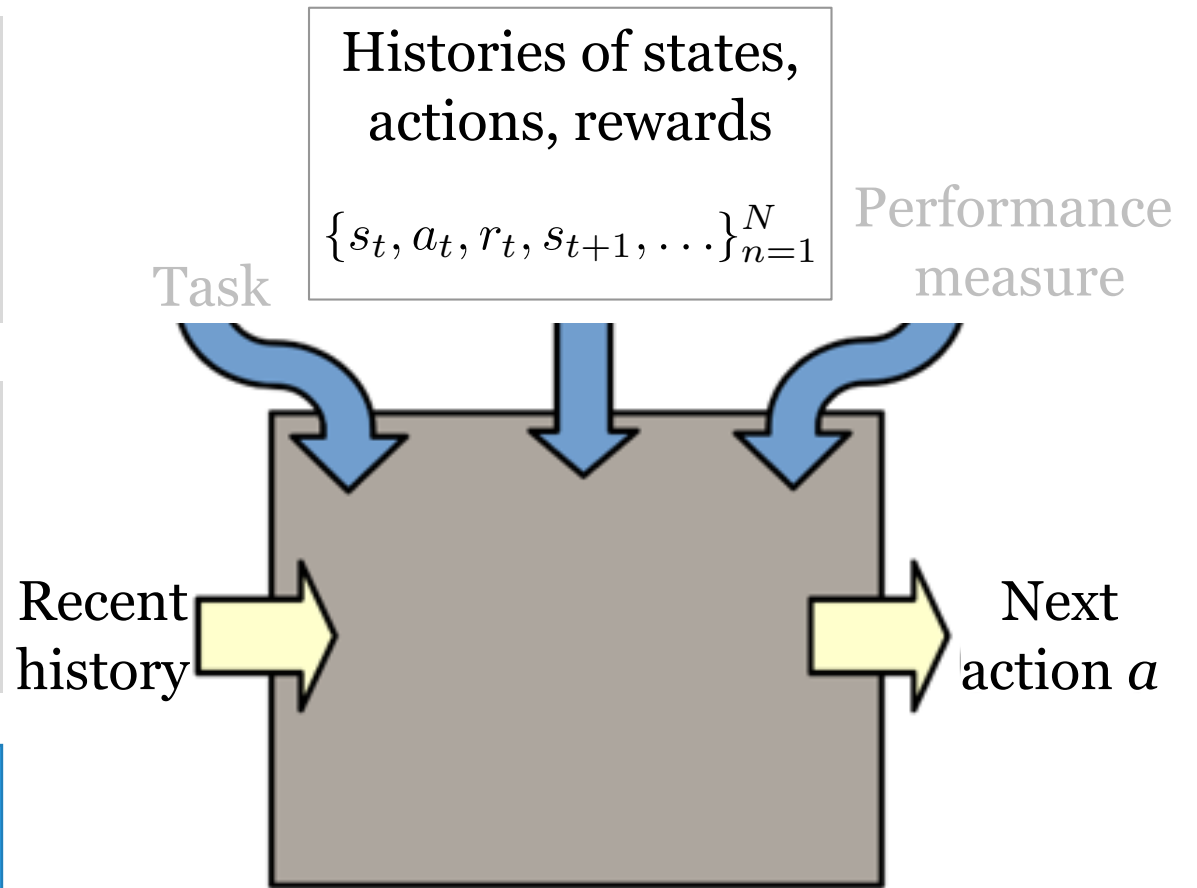


# What will we learn?

Supervised  
Learning

Unsupervised  
Learning

Reinforcement  
Learning



# RL example: Pancake robot



Peter Kornushev, Imperial College

# What **won't** we cover?

- Clustering
- Probabilistic models
- Graphical models
  
- Active learning
- Transfer learning
- Semi-supervised learning
- Learning theory
- ..... lots more