

# Introduction to Machine Learning

CMSC 422

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# What is Learning?

- Is memorization a form of “learning”?
- One definition: Learning is the process of obtaining *expertise* from *experience*
- **Our goal:** *learning* “Machine Learning”

# What is this course about?

- Machine learning studies algorithms for learning to perform certain tasks
- By finding and exploiting patterns in data

# Machine Learning

- Paradigm: “Programming by example”
  - “human supplying data”
- Most central issue: generalization
  - How to abstract from “training” examples to “test” examples?

# What can we do with machine learning?

Google Translate

This text has been [automatically translated](#) from Arabic:

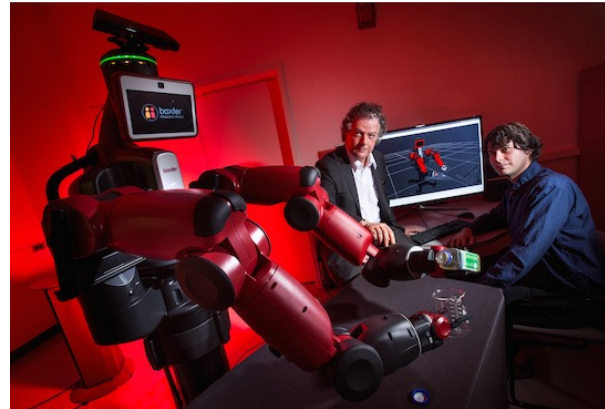
Moscow stressed tone against Iran on its nuclear program. He called Russian Foreign Minister Tehran to take concrete steps to restore confidence with the international community, to cooperate fully with the IAEA. Conversely Tehran expressed its willingness

Translate text

شدت موسكو لهجتها ضد إيران بشأن برنامجها النووي. ودعا وزير الخارجية الروسي طهران إلى اتخاذ خطوات ملموسة لاستعادة الثقة مع المجتمع الدولي والتعاون الكامل مع الوكالة الذرية. بالمقابل أبدت طهران استعدادها لاستئناف السماح بعمليات التفتيش المفاجئة بشرط إسقاط مجلس الأمن ملفها النووي.

from Arabic to English BETA Translate

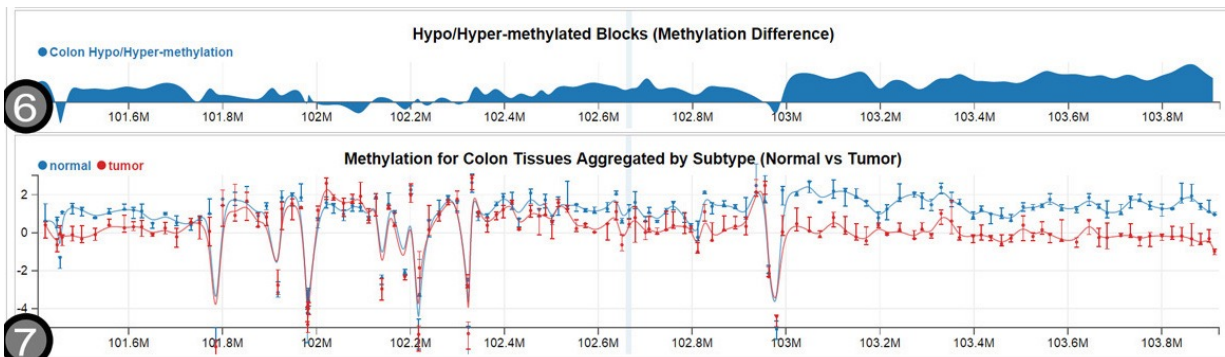
Analyze text & speech



Teach robots how to cook from youtube videos



Recognize objects in images

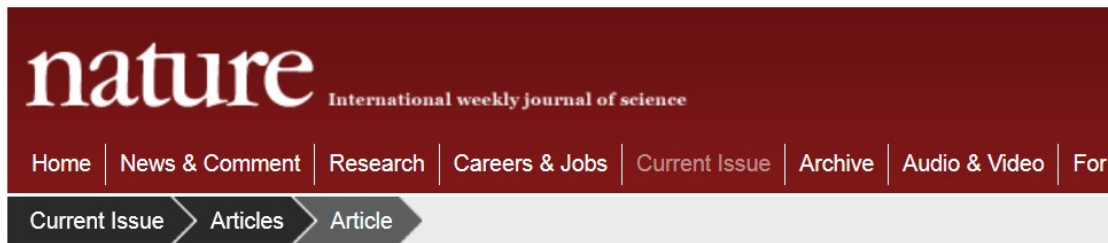


Analyze genomics data

Sometimes machines even perform better than humans!



Question Answering system beats Jeopardy champion Ken Jennings at Quiz bowl!



NATURE | ARTICLE



日本語要約

## Mastering the game of Go with deep neural networks and tree search

David Silver, Aja Huang, Chris J. Maddison, Arthur Guez, Laurent Sifre, George van den Driessche, Julian Schrittwieser, Ioannis Antonoglou, Veda Panneershelvam, Marc Lanctot, Sander Dieleman, Dominik Grewe, John Nham, Nal Kalchbrenner, Ilya Sutskever, Timothy Lillicrap, Madeleine Leach, Koray Kavukcuoglu, Thore Graepel & Demis Hassabis

[Affiliations](#) | [Contributions](#) | [Corresponding authors](#)

*Nature* **529**, 484–489 (28 January 2016) | doi:10.1038/nature16961

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# Why Machine Learning?

- A growing and fast moving field with broad applicability: Finance, robotics, vision, machine translation, medicine, etc.
- Close connection between theory and practice
- Open field, lots of room for new work!

# Course Goals

- By the end of the semester, you should be able to
  - Look at a problem
  - Identify if ML is an appropriate solution
  - If so, identify what types of algorithms might be applicable
  - Apply those algorithms
- This course is **not**
  - A survey of ML algorithms
  - A tutorial on ML toolkits such as Weka, TensorFlow, ...



# Prerequisites

- MATH461: Linear Algebra for Scientists and Engineers
- MATH240: Introduction to Linear Algebra
- CMSC351: Introduction to Algorithms
- CMSC330: Organization of Programming Languages
- CMSC320: Introduction to Data Science

# What you can expect from the instructors

## 3 Teaching Assistants

- Wenxiao Wang (PhD)
- Kiarash Banihashem (PhD)
- Samyadeep Basu (PhD)

We are here to help you learn by

- Introducing concepts from multiple perspectives
  - Theory and practice
  - Readings and class time
- Providing opportunities to practice, and feedback to help you stay on track
  - Homeworks
  - Programming assignments
  - Office hours

# What I expect from you

- Work hard (this is a 3-credit class!)
  - Do a lot of math (calculus, linear algebra, probability)
  - Do a fair amount of programming
- Come to class prepared
  - Do the required readings!

# Highlights from course logistics

## Grading

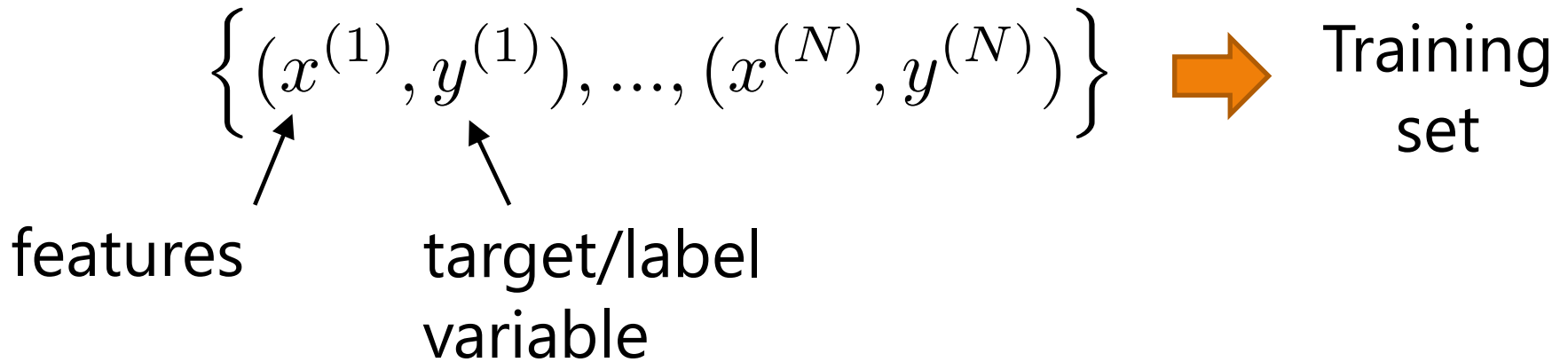
- *Homework and Programming assignments (30%)*
- *Final project (10%)*
- *Midterm exam (25%), in class on **March 14***
- *Final exam (35%)*
- HW01 posted
- No late homeworks
- Read syllabus [here](#)

# Where to...

- find the schedule and slides: [Course webpage](#)
- find the readings: [A Course in Machine Learning](#)
- view and submit assignments: [Canvas](#)
- check your grades: [Canvas](#)
- For more updates on ML research, follow me on [Twitter](#)
- ask and answer questions, participate in discussions and surveys, contact the instructors, and everything else:
  - Piazza **Please use piazza instead of email**
  - Office hours

# Data

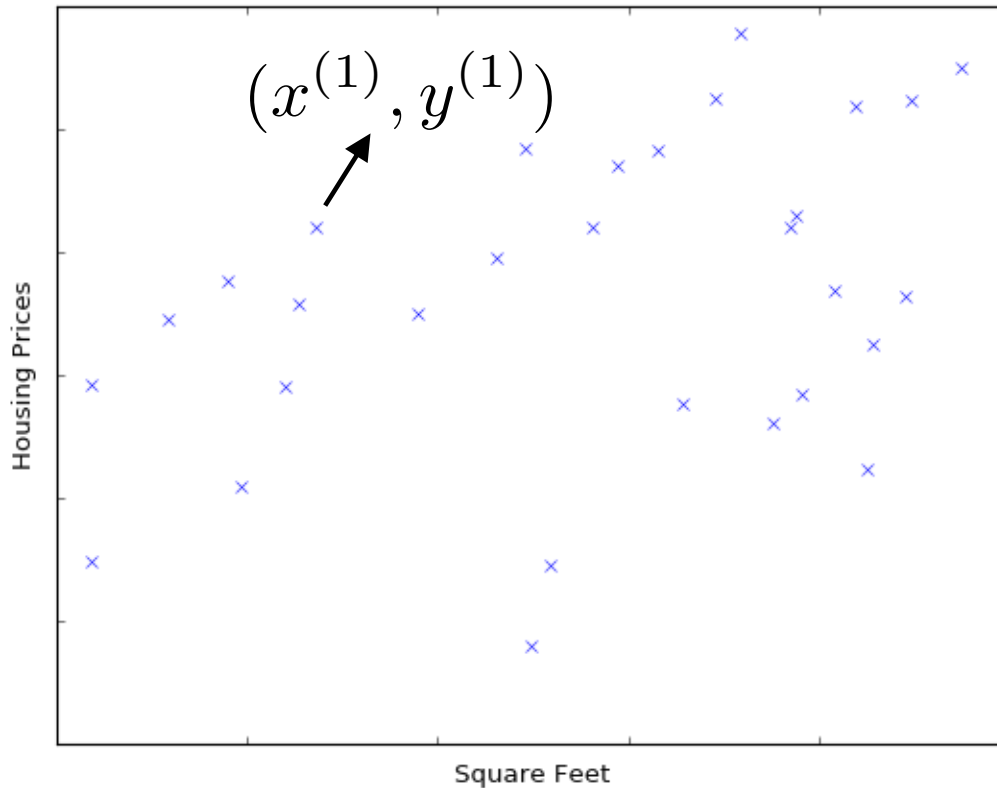
Data comes in different formats:



**Goal:** predict the label/target using features

 **Supervised** Learning

# Example

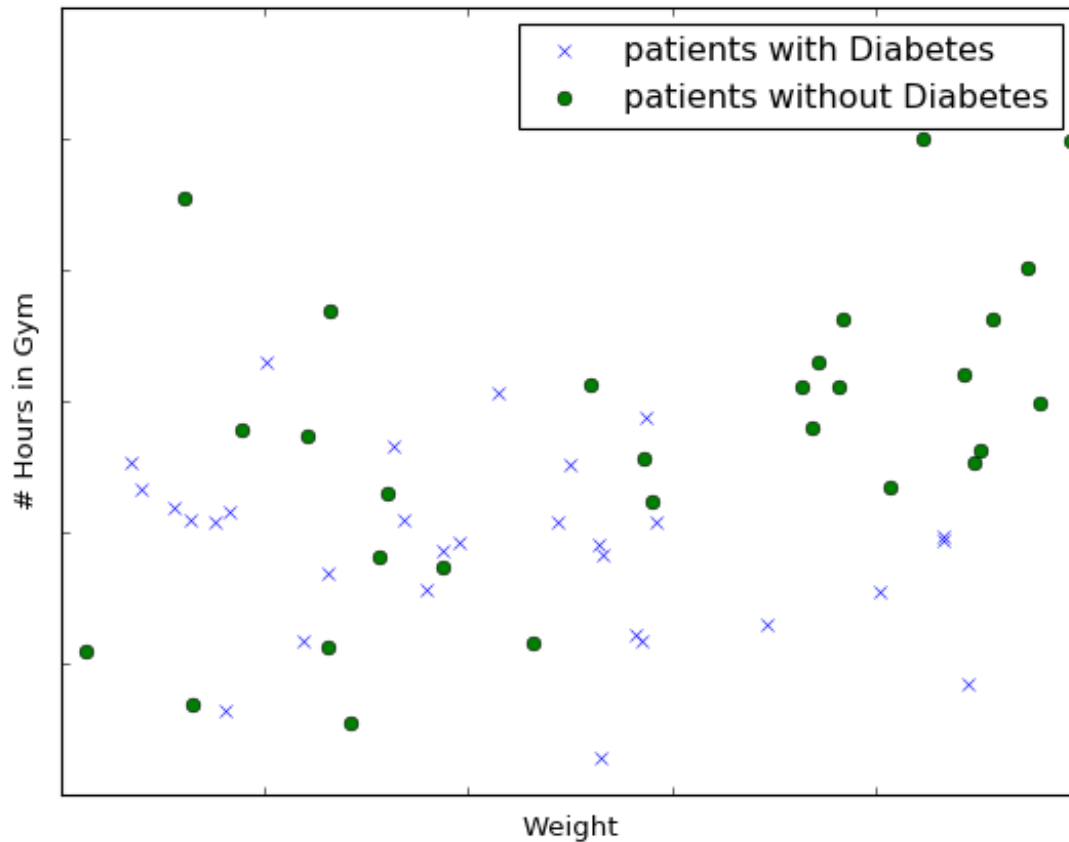


Regression  
Problem

Q1. What is the dimension of the feature var? one  $x^{(i)} \in \mathbb{R}$

Q2. What is the dimension of the target var? one  $y^{(i)} \in \mathbb{R}$

# Example



➔ **Classification Problem**

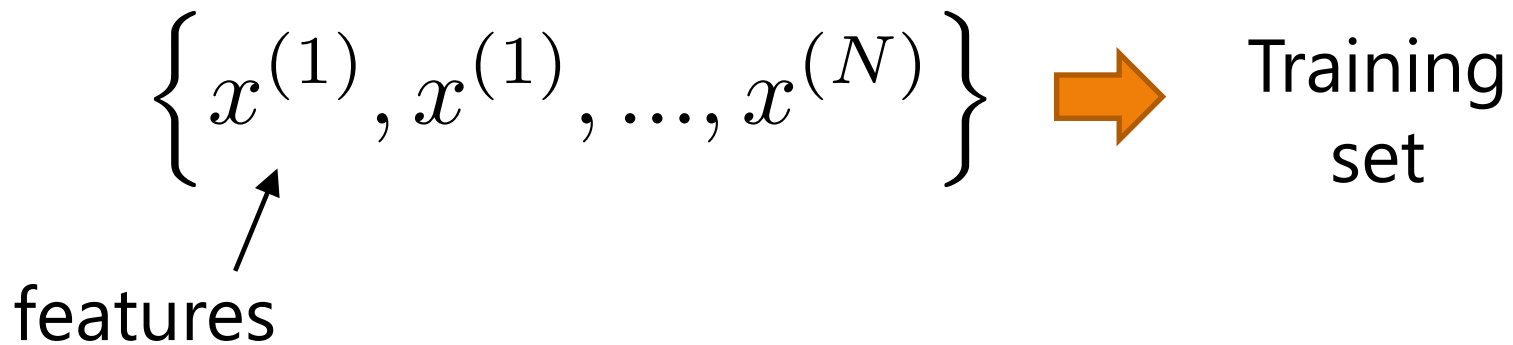
Q1. What is the dimension of the feature var? two  $x^{(i)} \in \mathbb{R}^2$

Q2. What is the dimension of the target var? one  $y^{(i)} \in \{0, 1\}$



# Data

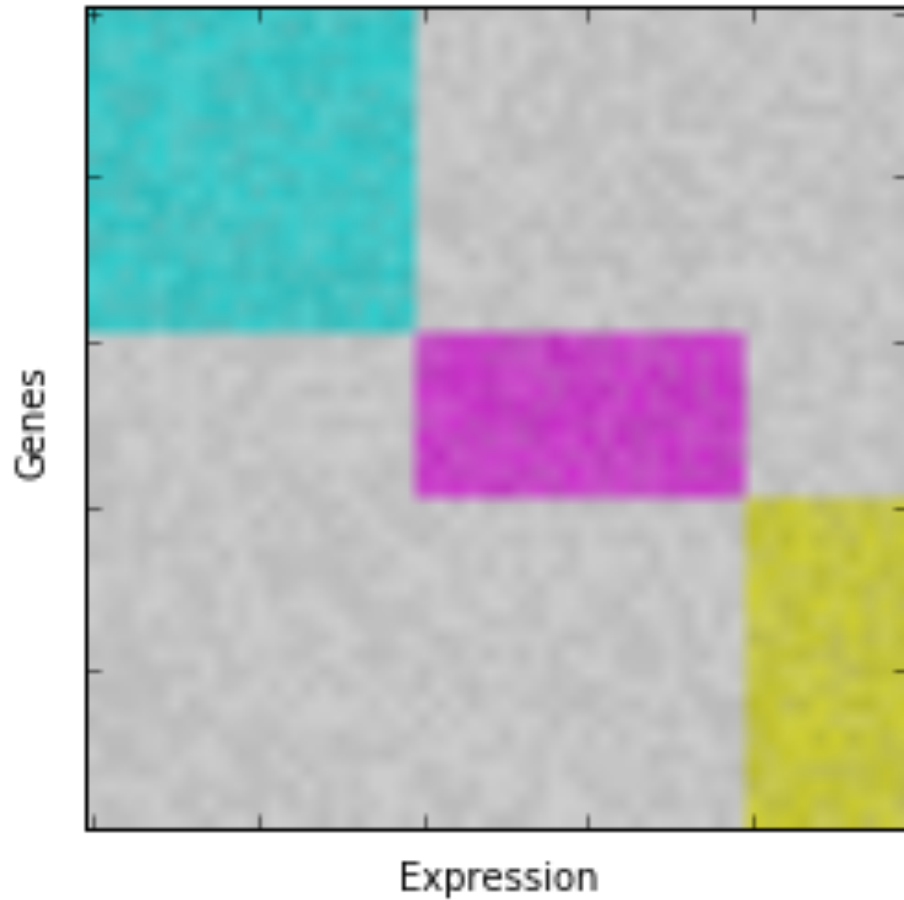
Data comes in different formats:



**Goal:** find “interesting” patterns in data

 **Unsupervised** Learning

# Example



Clustering  
Problem

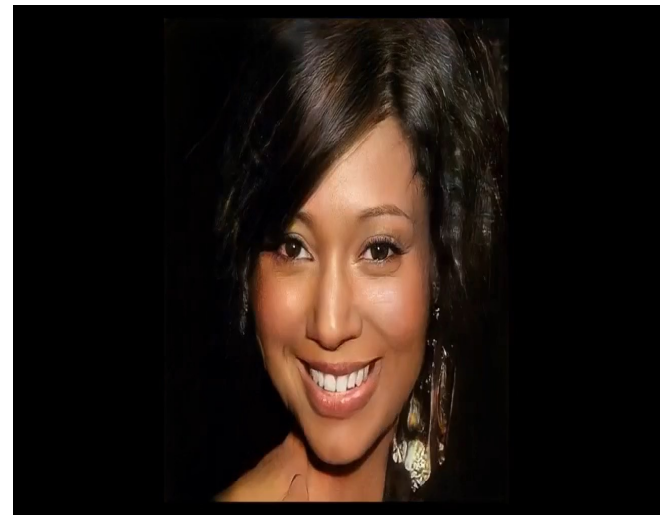
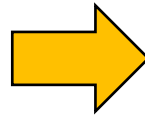
Who are these people?



# Generative Models (GANs)

Generating realistic but fake samples

CelebA dataset



Karras et al. 2017

# Text to Image Models

## StableDiffusion

prompt

a gentleman otter in a 19th century portrait

num\_outputs

1

guidance\_scale

7.5

num\_inference\_steps

100

This example was created by [@bfirsh](#)

 Tweak It





# CHATGPT

A

Explain black holes to me like I am a 5 years old



Sure, I'd be happy to help explain black holes to you! A black hole is a place in space where gravity is so strong that nothing can escape from it, not even light. This means that if something were to fall into a black hole, it would be stuck there forever and we would never be able to see it again. Black holes are very interesting because they are some of the strangest and most mysterious objects in the universe. Does that help, or do you have any other questions?



A

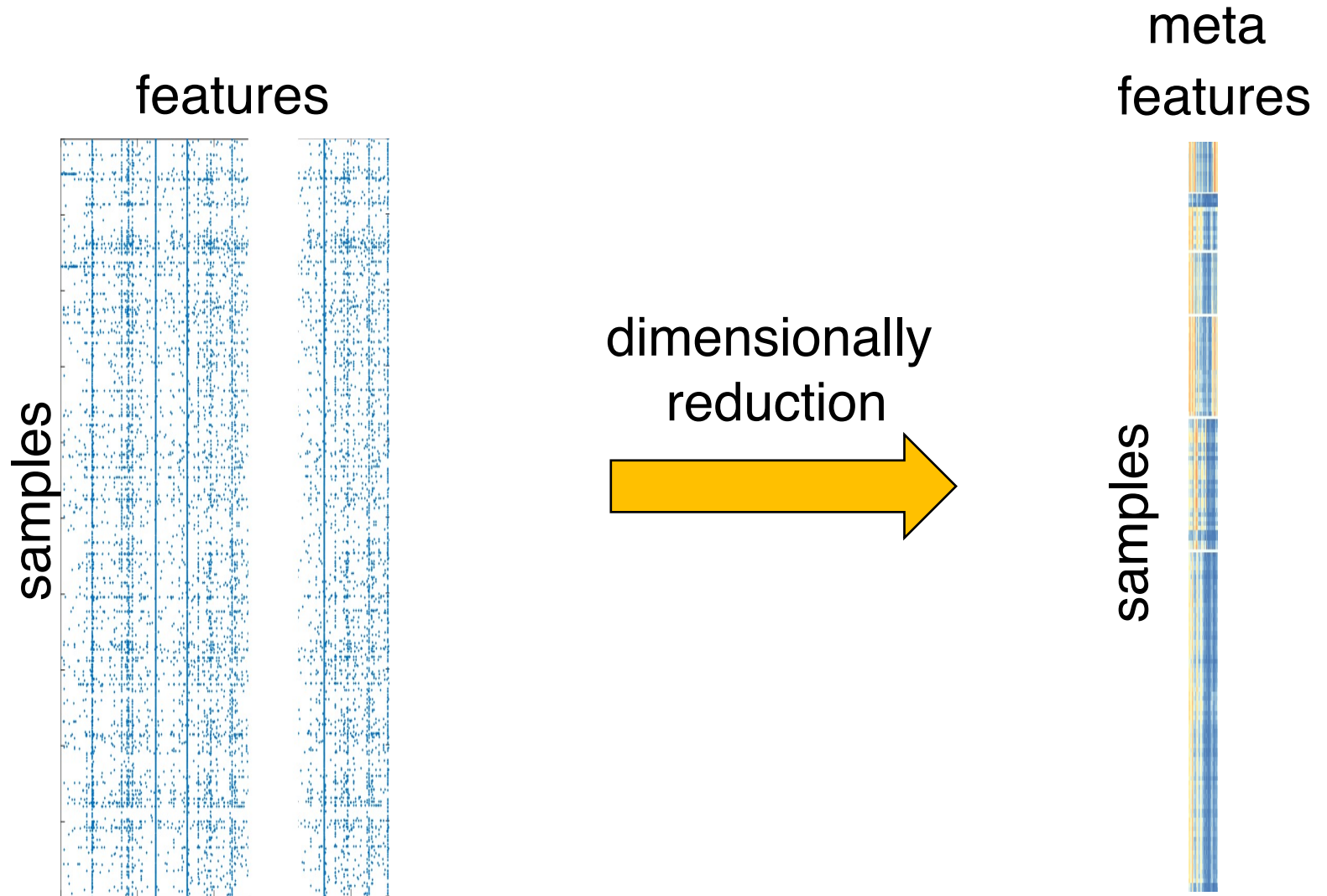
yes.. how many black holes are there in the universe ?

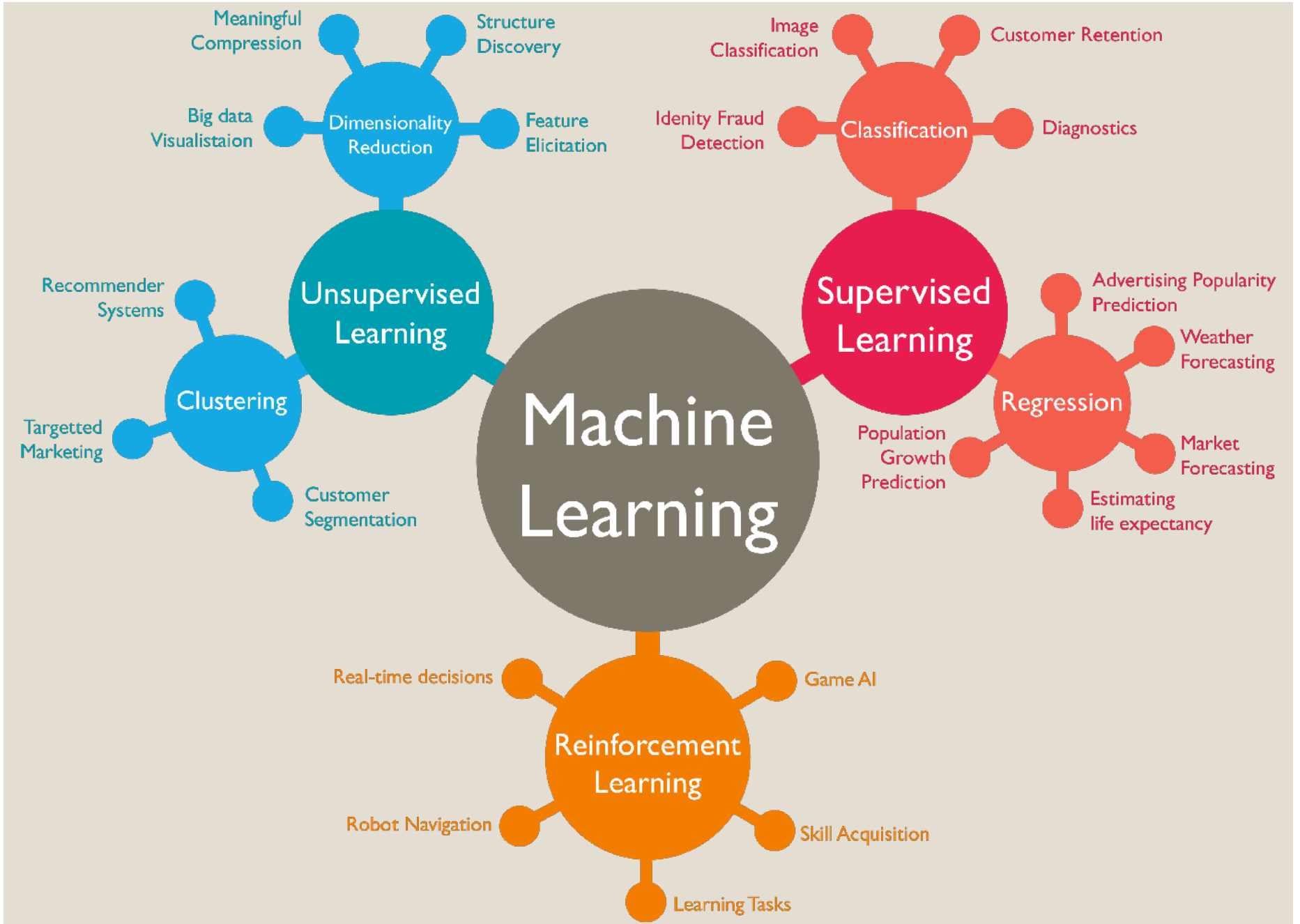


That's a great question! The truth is, we don't know for sure how many black holes there are in the universe. Black holes are extremely difficult to detect, so it's hard for scientists to know exactly how many there are. However, most scientists believe that there are many, many black holes in the universe. Some estimates suggest that there could be as many as 100 million black holes in the Milky Way galaxy alone! So there are likely to be a huge number of black holes in the universe.



# Dimensionality Reduction







# A Closer Look: the classification problem

What does it mean to “learn by example”?

- Classification tasks
- Inductive bias
- Formalizing learning

# Classification tasks

- How would you write a program to distinguish a picture of a cat from a picture of a dog?
- Provide examples pictures of cats and pictures of dogs and let a **classifier** learn to distinguish the two.

# Classification tasks

- How would you write a program to distinguish a **sentence** is **grammatical** or **not**?
- Provide examples of **grammatical** and **ungrammatical sentences** and let a **classifier** learn to distinguish the two.

# Classification tasks

- How would you write a program to distinguish **cancerous cells** from **normal cells**?
- Provide examples of **cancerous** and **normal cells** and let a **classifier** learn to distinguish the two.

Let's try it out...

- Your task: learn a classifier to distinguish class A from class B from examples

- Examples of class A:



- Examples of class B



# Let's try it out...

- ✓ learn a classifier from examples
- Now: predict class on new examples using what you've learned













# Key ingredients needed for learning

- Training vs. test examples
  - Memorizing the training examples is not enough!
  - Need to generalize to make good predictions on test examples
- Inductive bias
  - Many classifier hypotheses are plausible
  - Need assumptions about the nature of the relation between examples and classes

# Machine Learning as Function Approximation

## Problem setting

- Set of possible instances  $X$
- Unknown target function  $f: X \rightarrow Y$
- Set of function hypotheses  $H = \{h \mid h: X \rightarrow Y\}$

## Input

- Training examples  $\{(x^{(1)}, y^{(1)}), \dots, (x^{(N)}, y^{(N)})\}$  of unknown target function  $f$

## Output

- Hypothesis  $h \in H$  that best approximates target function  $f$

# Formalizing induction: Loss Function

$l(y, f(x))$  where  $y$  is the truth and  $f(x)$  is the system's prediction

$$\text{e.g. } l(y, f(x)) = \begin{cases} 0 & \text{if } y = f(x) \\ 1 & \text{otherwise} \end{cases}$$

Captures our notion of what is important to learn

# Formalizing induction: Data generating distribution

- Where does the data come from?
  - Data generating distribution
    - A probability distribution  $D$  over  $(x, y)$  pairs
  - We don't know what  $D$  is!
    - We only get a sample from it: our training data



# Formalizing induction: Expected loss

- $f$  should make good predictions
  - as measured by loss  $l$
  - on **future** examples that are also drawn from  $D$
- Formally
  - $\varepsilon$ , the expected loss of  $f$  over  $D$  should be small

$$\varepsilon \triangleq \mathbb{E}_{(x,y) \sim D} \{l(y, f(x))\} = \sum_{(x,y)} D(x, y) l(y, f(x))$$

# Formalizing induction: Training error

- We can't compute expected loss because we don't know what  $D$  is
- We only have a sample of  $D$ 
  - training examples  $\{(x^{(1)}, y^{(1)}), \dots, (x^{(N)}, y^{(N)})\}$
- All we can compute is the training error

$$\hat{\varepsilon} \triangleq \sum_{n=1}^N \frac{1}{N} l(y^{(n)}, f(x^{(n)}))$$

# Formalizing Induction

- Given
  - a loss function  $l$
  - a sample from some **unknown** data distribution  $D$
- Our task is to compute a function  $f$  that has low expected error over  $D$  with respect to  $l$ .

$$\mathbb{E}_{(x,y) \sim D} \{l(y, f(x))\} = \sum_{(x,y)} D(x, y) l(y, f(x))$$

# Recap: introducing machine learning

What does “learning by example” mean?

- Classification tasks
- Learning requires examples + inductive bias
- Generalization vs. memorization
- Formalizing the learning problem
  - Function approximation
  - Learning as minimizing expected loss

# Your tasks before next class

- Check out course webpage, Canvas, Piazza
- Start reading the reviews on probability and linear algebra (posted on course webpage)
- Get started on HW01