

# Course Overview

Nimisha Roy

Lecturer, College of Computing

# Your Instructor

## Instructor: Dr. Nimisha Roy

- 1<sup>st</sup> time teaching this course
- Lecturer in the College of Computing (SCI/OMSA)
- PhD in Computational Science & Engineering from Georgia Tech
- Research Interests: Computing Education, Gen AI and Sustainability Integrations, Software Development
- Hobbies: singing (jamming), interior designing, admiring my plants





# Your TAs



We have an army of ~45 TAs who help make this class successful



Check out the class website to know about them

Refer to:

# Class Website

For anything (updates, lectures, logistics, and so on) related to this class

# Office hours

## Notes:

- 1) Each student may fill in their name and create a BlueJeans Meeting for the office hour
- 2) The signup policy is first come, first serve. **Please, DO NOT override others' sign-ups without their permissions.**
- 3) Because of the time limit, each student will have a maximum time of 10 minutes to work with the TA
- 4) Please come prepared with specific questions so we can help you more effectively

The slots were cleared on Nov 15th. Please add your name again if you had filled it for this week. Apologies for the inconvenience.

Time Slots	Student Name	Question of Interest (Please be more specific about the question you want to ask)	BlueJeans Address	Label
Jayanta's OH				
12:00--12:10				
12:10--12:20				
12:20--12:30				
12:30--12:40				
12:40--12:50				
12:50--13:00				
Waitlist				
	1			
	2			
	3			
Huili's OH				
14:30--14:40				
14:40--14:50				
14:50--15:00				
15:00--15:10				
15:10--15:20				
15:20--15:30				
Waitlist				
	1			
	2			

- You have just 10 minutes for each slot.
- Please mindful of other students (you can't block multiple office hours, just one and we have the waitlist!)
- Make sure you pinpoint your problem exactly before joining the office hour.
- Office hour is not for general code debugging. You need to be specific about your question.

# Some important notes:

- All communication must be via Ed (Chat and Threads). No Email please.
- Please read the website carefully. Website will be the first thing that we update if there any changes.
- Add HWs dues and Quizzes to your desired calendar.
- Please come to the class (required); it will help a lot 😊
  - Attendance is mandatory. Attendance will be taken few times in the semester. This genuinely comes from a place of care.

# Some important notes:

- ML is **NOT** a programming class.
- Lectures will be Math Heavy and HWs will be mostly programming. ML is all about Linear Algebra, Probability, Statistics and Optimization. You need to have both mathematical and programming skills to be successful in this area.
  - Please come to class and follow along.
  - Ask questions!
- HWs are substantial. Please start as early as possible. Don't procrastinate.

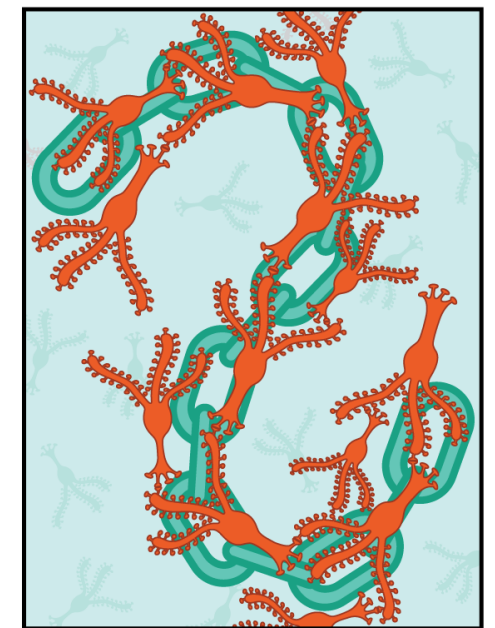
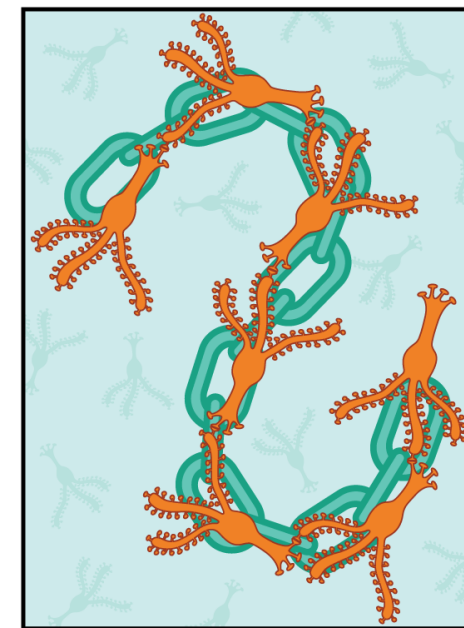
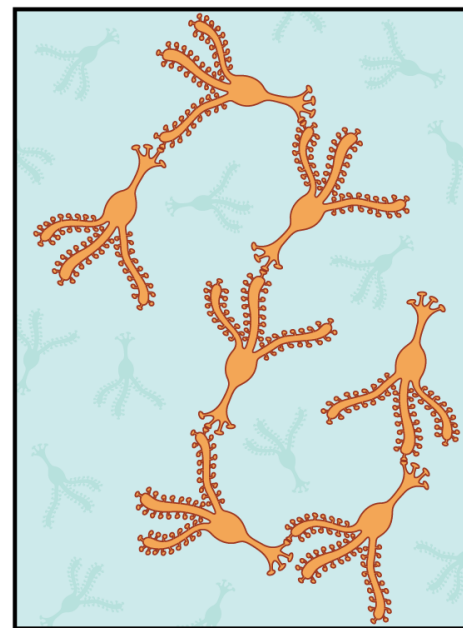
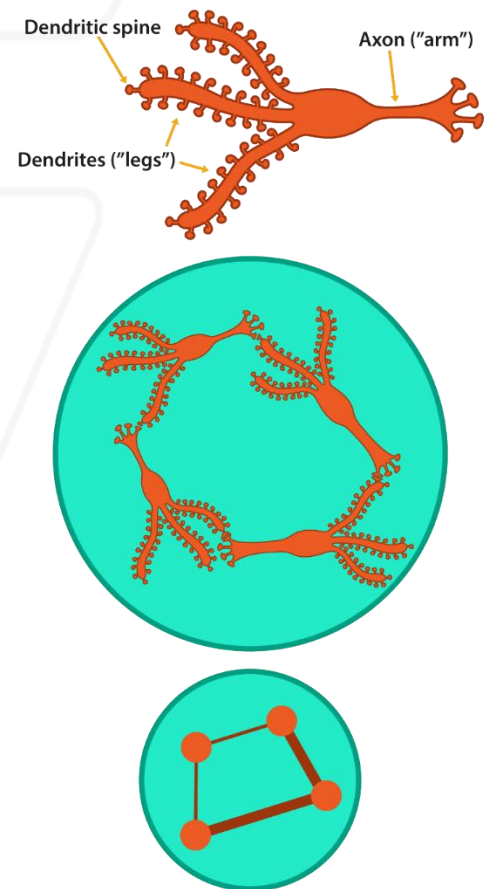
# Course Objectives

- Introduce to you the **pipeline of Machine Learning**
- Help you understand **major machine learning algorithms**
- Help you learn to **apply tools** for **real data analysis problems**
- Encourage you to **do research** in data science and machine learning



Before we talk about machine learning,  
let's talk about human learning...

# Learning involves changing your brain!

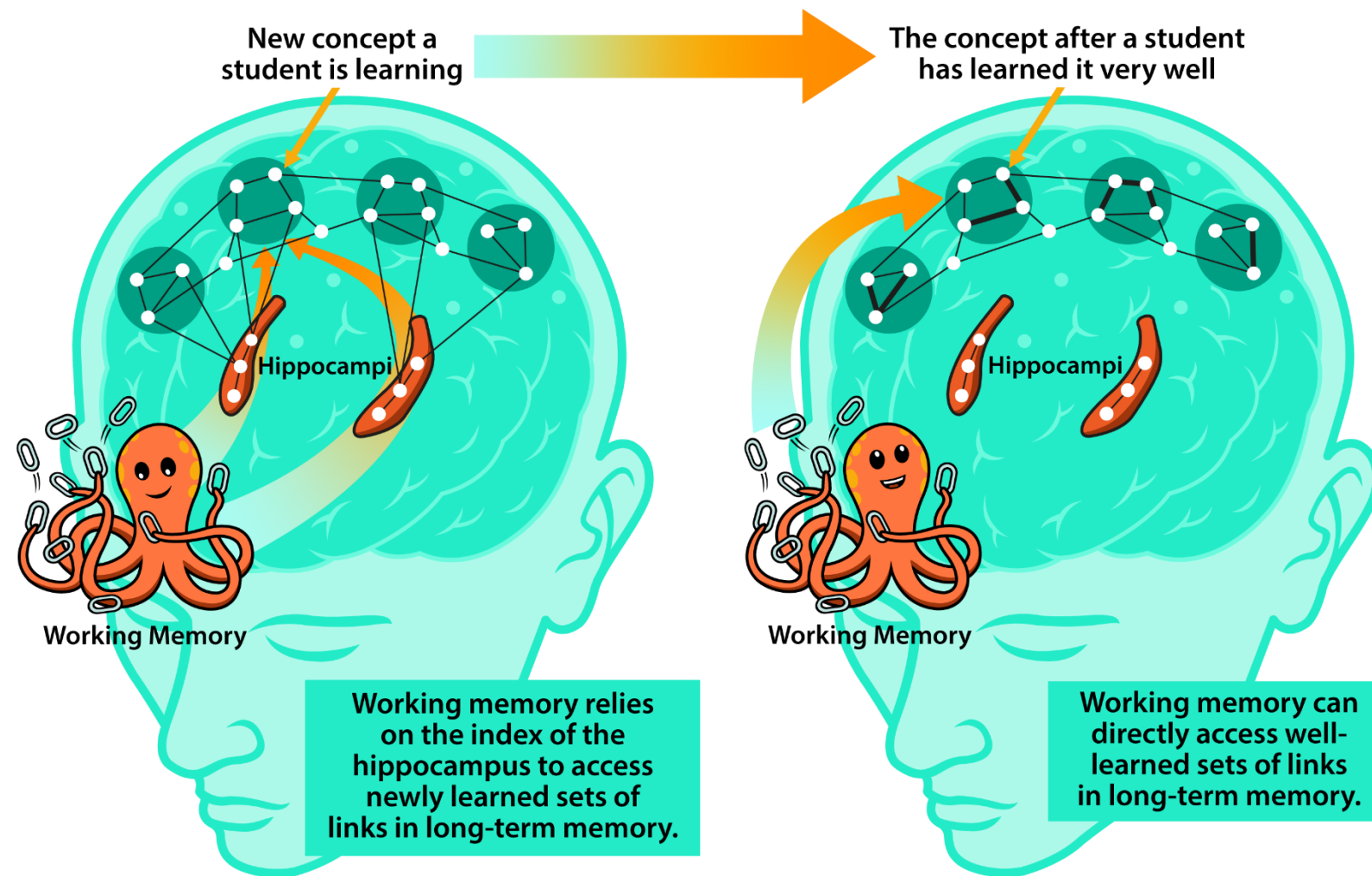


Learn it

Link it

Source: Oakley, Rogowsky & Sejnowski (2021)

# Declarative learning system



Source: Oakley, Rogowsky & Sejnowski (2021)

# Our approach to this course

- **Lectures** will introduce key theoretical concepts to enable you to understand different machine learning algorithms, maths behind them and their application
- **HWs** will help you deepen your understanding of topics covered in class and the implementation of machine learning algorithms
- **Project** will give you an opportunity to gain hands-on-experience in machine learning application to a real-world problem and expand beyond topics covered in class
- **Quizzes** will assess your understanding of the materials and motivate you to stay up to speed on topics covered in class
- 1 in class assessment in Vocareum

# Syllabus

## **Part I: Basic math** for computational data analysis

- Probability, statistics, linear algebra

## **Part II: Unsupervised learning** for data exploration

- Clustering analysis, dimensionality reduction, kernel density estimation

## **Part III: Supervised learning** for predictive analysis

- Tree-based models, linear classification/regression, neural networks



# Prerequisites

Basic knowledge in probability, statistics, and linear algebra

Basic programming skills in Python (Jupyter Notebook)

*No background in machine learning is required*

# Assignments

Four assignments (Submitted via GradeScope)  
Each can include written analysis or programming

**Start Early as soon as they are out**

**Read late policy on the class website**

**Don't copy**

Because of the large size of our class, if we observe any (even small) similarity\plagiarisms detected by GradeScope or our TAs, WE WILL DIRECTLY REPORT ALL CASES TO OSI, which may unfortunately lead to a very harsh outcome.

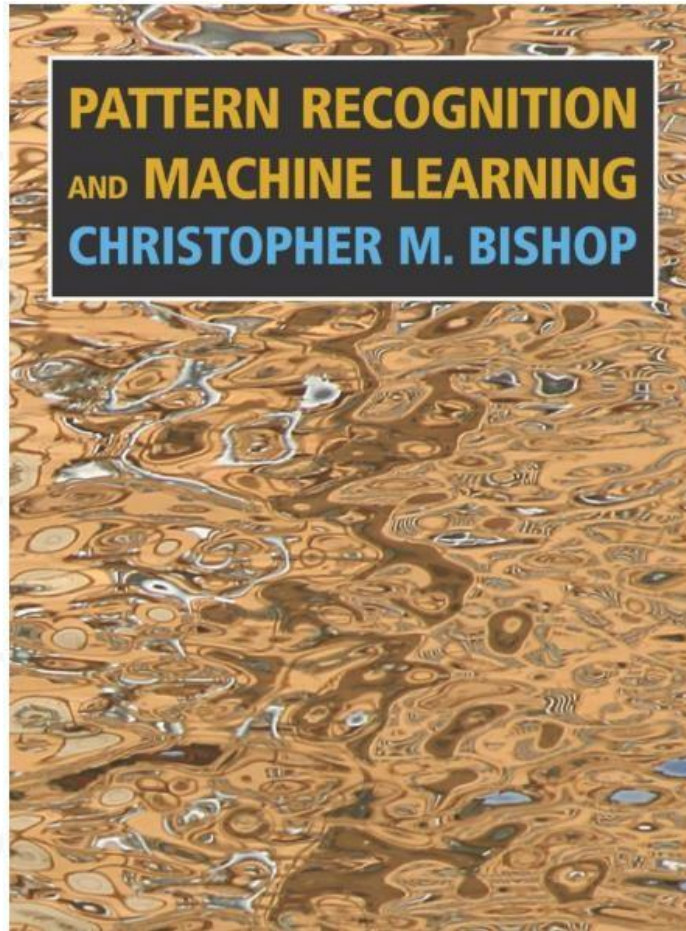
# Quizzes

- 14% of your grade
- Quiz 0 is 1% of your grade. Covers information about class website, course structure etc.
- Quiz 1 onwards covers lecture materials covered in class
- Honorlock based, open notes from canvas
- Can take from anywhere when quiz is open.

# Projects

- Work on a real-life Machine Learning problem
  - What is the problem? What is your method? How do you evaluate it?
- Exactly 5 people in a team (Grad and undergrad can't be mixed in a group)
- Deploy via GitHub Pages (index.html)
- Start your projects early
- Ask for comments and feedbacks from the teaching staff

## Text Books



### Pattern Recognition and Machine Learning, by Chris Bishop

Other recommended books:

Learning from data, by Yaser S. Abu-Mostafa

Machine learning, by Tom Mitchell

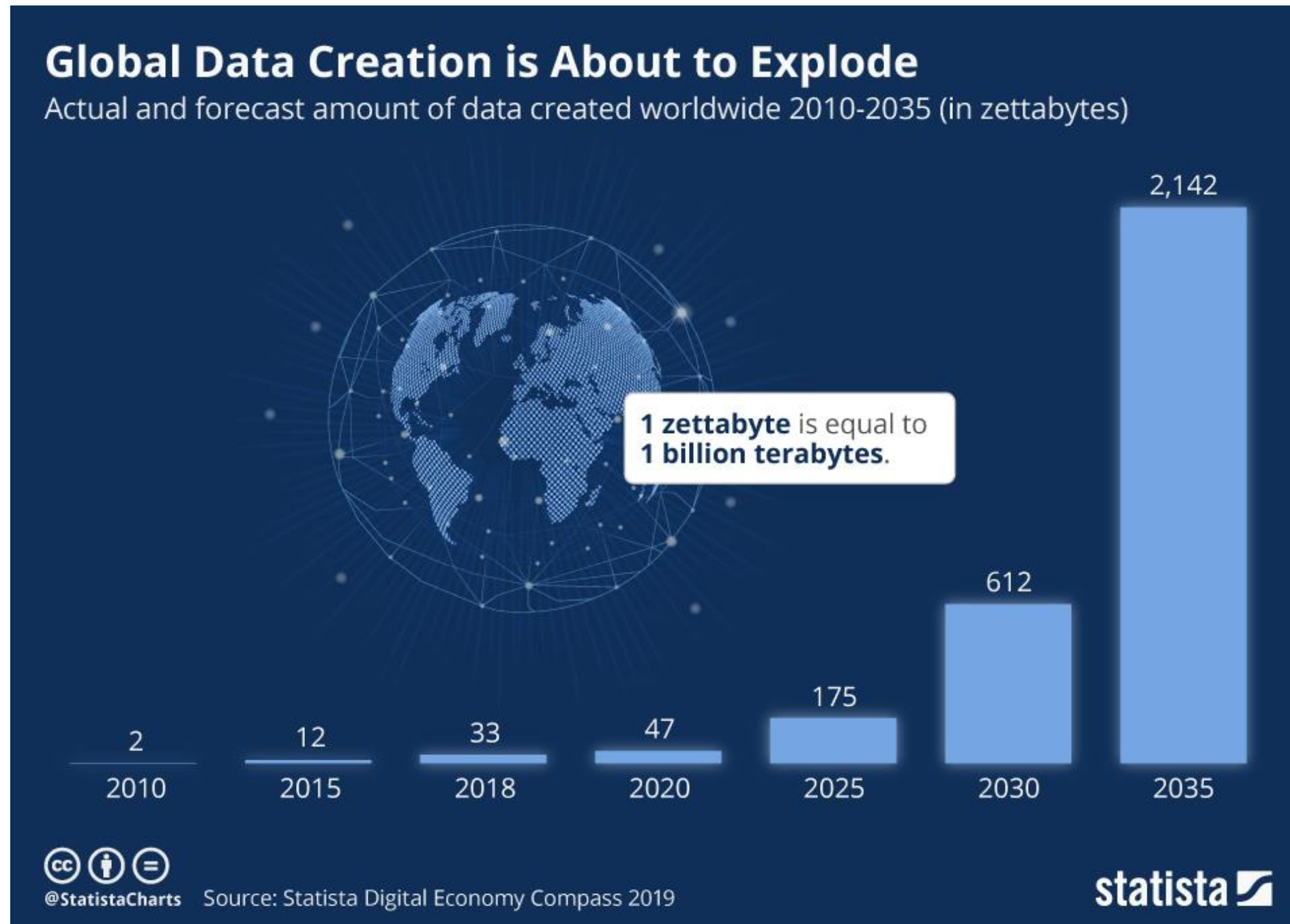
Deep Learning, by Ian Goodfellow, Yoshua Bengio, and Aaron Courville



# Questions?

# Why Machine Learning?

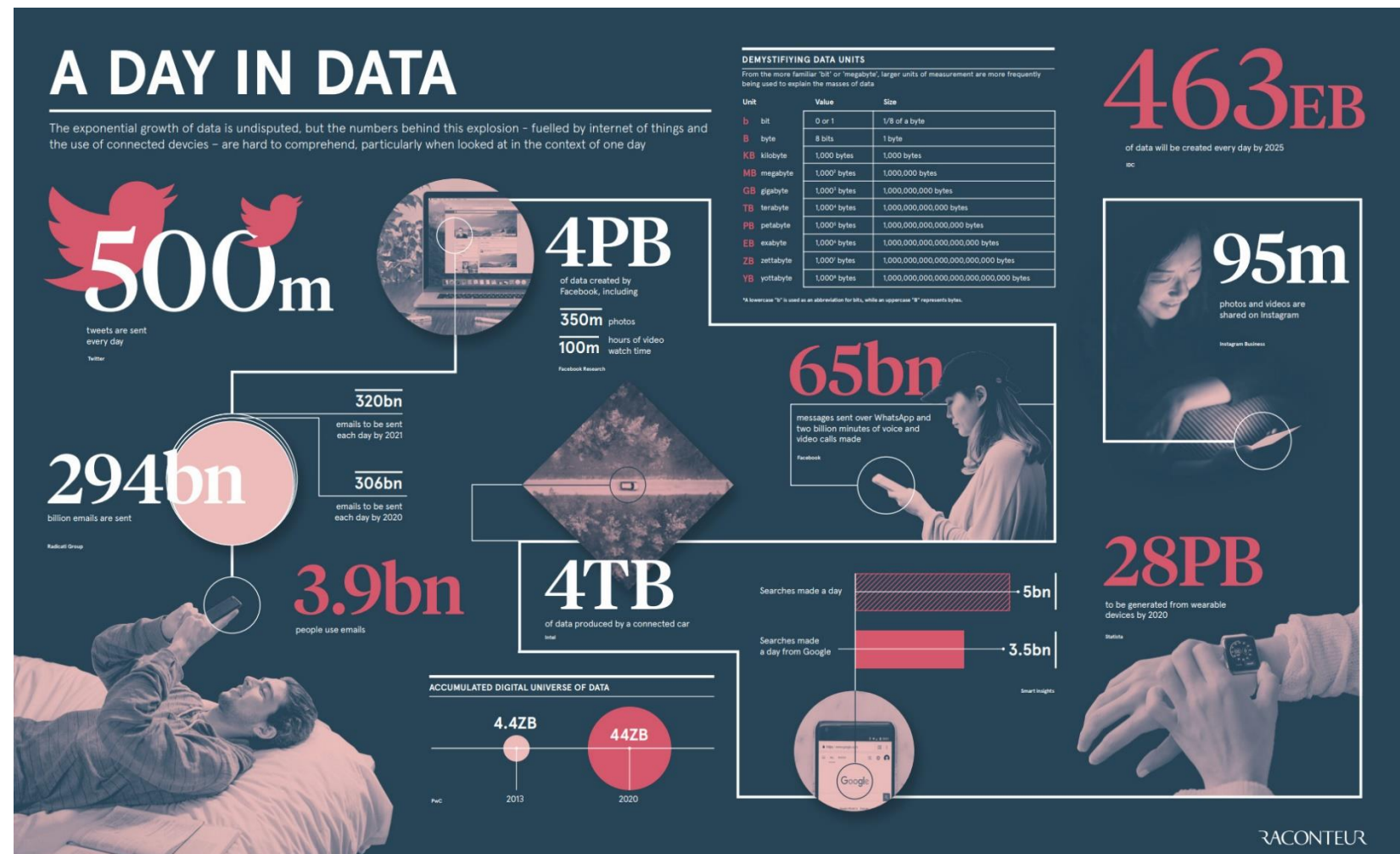
*“We are drowning in information but starved for knowledge.” — John Naisbitt*



33 zettabytes is equal to the storage capacity of 33 million human brains altogether

# The Booming Age of Data

- 30 trillion web pages
- 500 million tweets per day
- 2.7 billion monthly active users on Facebook
- 1.8 billion images uploaded per day
- 2.9 billion base pairs in human genome



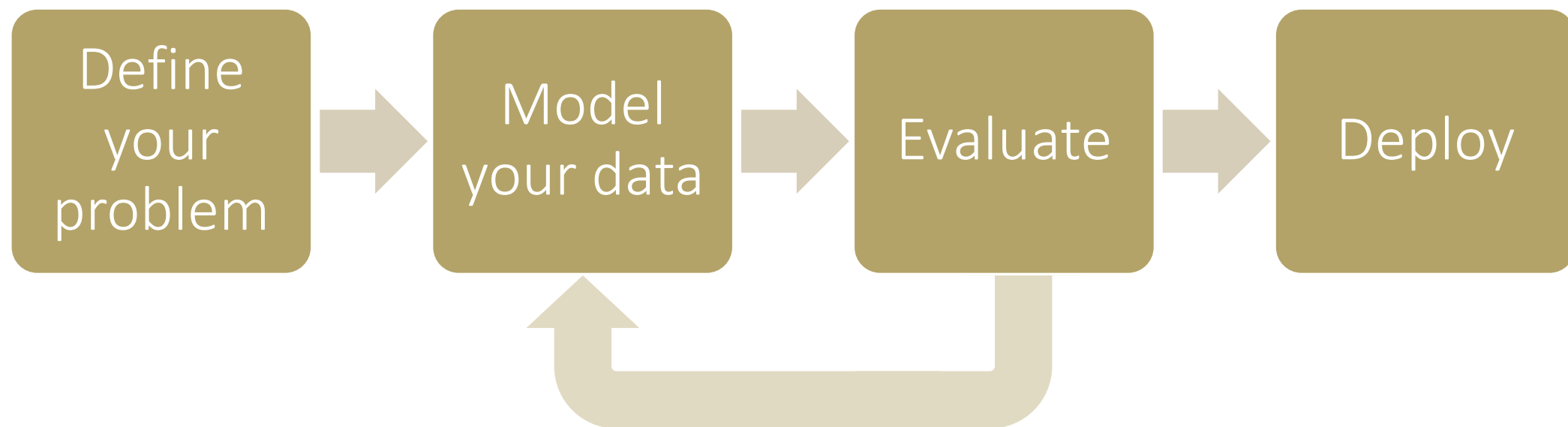
## Levels of AGI

<b>Performance</b> (rows) x <b>Generality</b> (columns)	<b>Narrow</b> <i>clearly scoped task or set of tasks</i>	<b>General</b> <i>wide range of non-physical tasks, including metacognitive abilities like learning new skills</i>
<b>Level 0: No AI</b>	<b>Narrow Non-AI</b> calculator software; compiler	<b>General Non-AI</b> human-in-the-loop computing, e.g., Amazon Mechanical Turk
<b>Level 1: Emerging</b> <i>equal to or somewhat better than an unskilled human</i>	<b>Emerging Narrow AI</b> GOFAI <sup>4</sup> ; simple rule-based systems, e.g., SHRDLU (Winograd, 1971)	<b>Emerging AGI</b> ChatGPT (OpenAI, 2023), Bard (Anil et al., 2023), Llama 2 (Touvron et al., 2023)
<b>Level 2: Competent</b> <i>at least 50th percentile of skilled adults</i>	<b>Competent Narrow AI</b> toxicity detectors such as Jigsaw (Das et al., 2022); Smart Speakers such as Siri (Apple), Alexa (Amazon), or Google Assistant (Google); VQA systems such as PaLI (Chen et al., 2023); Watson (IBM); SOTA LLMs for a subset of tasks (e.g., short essay writing, simple coding)	<b>Competent AGI</b> not yet achieved
<b>Level 3: Expert</b> <i>at least 90th percentile of skilled adults</i>	<b>Expert Narrow AI</b> spelling & grammar checkers such as Grammarly (Grammarly, 2023); generative image models such as Imagen (Saharia et al., 2022) or Dall-E 2 (Ramesh et al., 2022)	<b>Expert AGI</b> not yet achieved
<b>Level 4: Virtuoso</b> <i>at least 99th percentile of skilled adults</i>	<b>Virtuoso Narrow AI</b> Deep Blue (Campbell et al., 2002), AlphaGo (Silver et al., 2016, 2017)	<b>Virtuoso AGI</b> not yet achieved
<b>Level 5: Superhuman</b> <i>outperforms 100% of humans</i>	<b>Superhuman Narrow AI</b> AlphaFold (Jumper et al., 2021; Varadi et al., 2021), AlphaZero (Silver et al., 2018), StockFish (Stockfish, 2023)	<b>Artificial Superintelligence (ASI)</b> not yet achieved



# Machine learning in practice

Machine learning is the process of **turning data into actionable knowledge** for **task support** and **decision making**.





# Brief History of Machine Learning

## 1950s

Samuel's checker player  
Selfridge's Pandemonium

## 1960s

**Neural networks: Perceptron**  
Pattern recognition  
Learning in the limit theory  
Minsky and Papert prove limitations of perceptron

## 1970s

Symbolic concept induction  
Winston's arch learner  
Expert systems and the knowledge acquisition bottleneck  
Quinlan's ID3  
Michalski's AQ and soybean diagnosis  
Scientific discovery with BACON  
**Mathematical discovery with AM (Automated Mathematician)**

# Brief History of Machine Learning

## 1980s

**Advanced decision tree and rule learning**

Explanation-based Learning (EBL)

Learning and planning and problem solving

Utility problem

Analogy

Cognitive architectures

Resurgence of neural networks  
(connectionism, backpropagation)

Valiant's PAC Learning Theory

Focus on experimental methodology

## 1990s

**Data mining**

Adaptive software agents and web  
applications

Text learning

Reinforcement learning (RL)

Inductive Logic Programming (ILP)

**Ensembles: Bagging, Boosting, and Stacking**

Bayes Net learning

# Brief History of Machine Learning

## 2000s

- Support vector machines
- Kernel methods
- Graphical models
- Statistical relational learning
- Transfer learning
- Sequence labeling
- Collective classification and structured outputs
- Computer Systems Applications
- Learning in robotics and vision

## 2010s

- Deep learning
- Reinforcement learning
- Generative models
- Adversarial learning
- Multi-task learning
- Transfer learning
- Learning in NLP, CV, Robotics, ...

## 2020s

What will your contribution be?

# Unsupervised and Supervised learning

	Weight(lb)	Height(cm)	Fur color	Eye color	Label
Point 1	10	20	$w$	$g$	$cat$
Point 2	50	100	$br$	$bl$	$dog$
Point 3	8	15	$bl$	$bl$	$dog$
Point 4	12	25	$w$	$bl$	$cat$
Point 5	14	10	$bl$	$g$	$dog$

$X_{n \times d}$   $=$   $Y_{n \times 1}$

Unsupervised just focuses on  $X_{n \times d}$

Supervised focus on  $X_{n \times d}$  and  $Y_{n \times 1}$

# We can do better than Cat and Dog

	Weight(lb)	Height(cm)	Fur color	Eye color		Label
Point 1	10	20	<i>w</i>	<i>g</i>	=	Blob Fish
Point 2	50	100	<i>br</i>	<i>bl</i>		opossum
Point 3	8	15	<i>bl</i>	<i>bl</i>		opossum
Point 4	12	25	<i>w</i>	<i>bl</i>		Blob Fish
Point 5	14	10	<i>bl</i>	<i>g</i>		opossum
$X_{n \times d}$						$Y_{n \times 1}$





# Syllabus: Unsupervised Learning

## Clustering Analysis

- K-means
- Gaussian Mixture Models
- Hierarchical clustering
- Density-based clustering
- Clustering evaluation

## Dimensionality reduction

- Principal component analysis

## Probability distributions

- Kernel density estimation
- Parametric density estimation
- Non-parametric density estimation

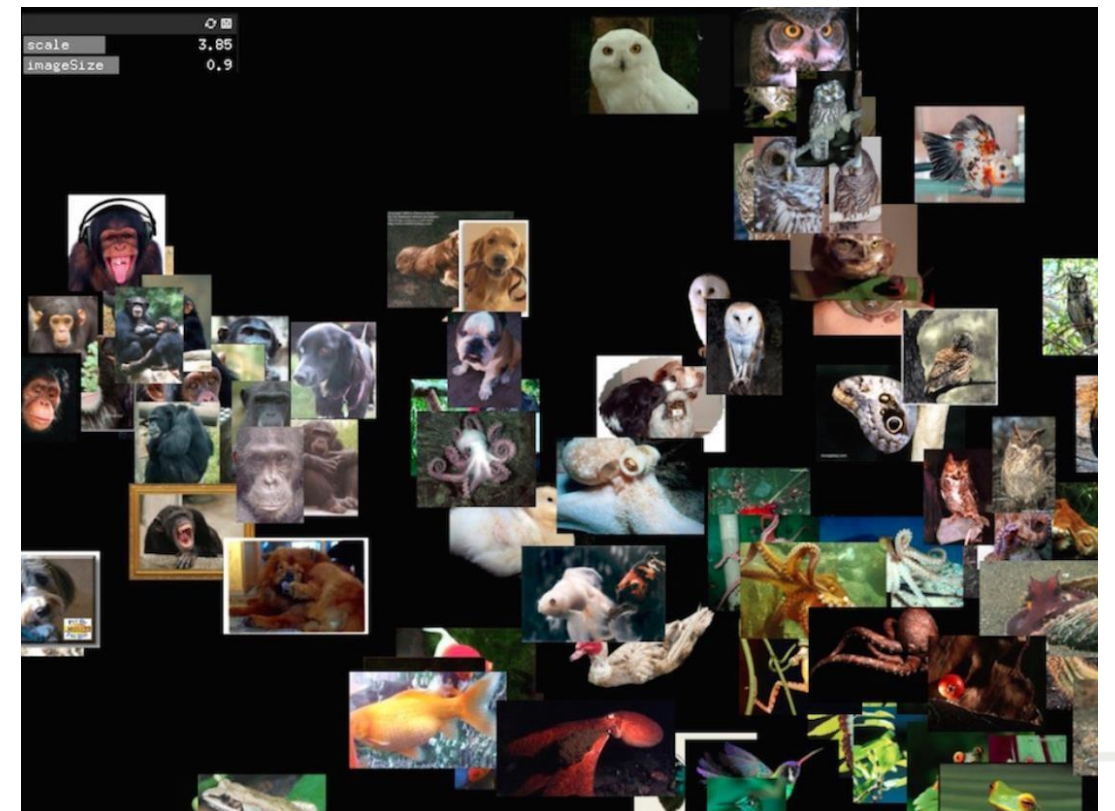
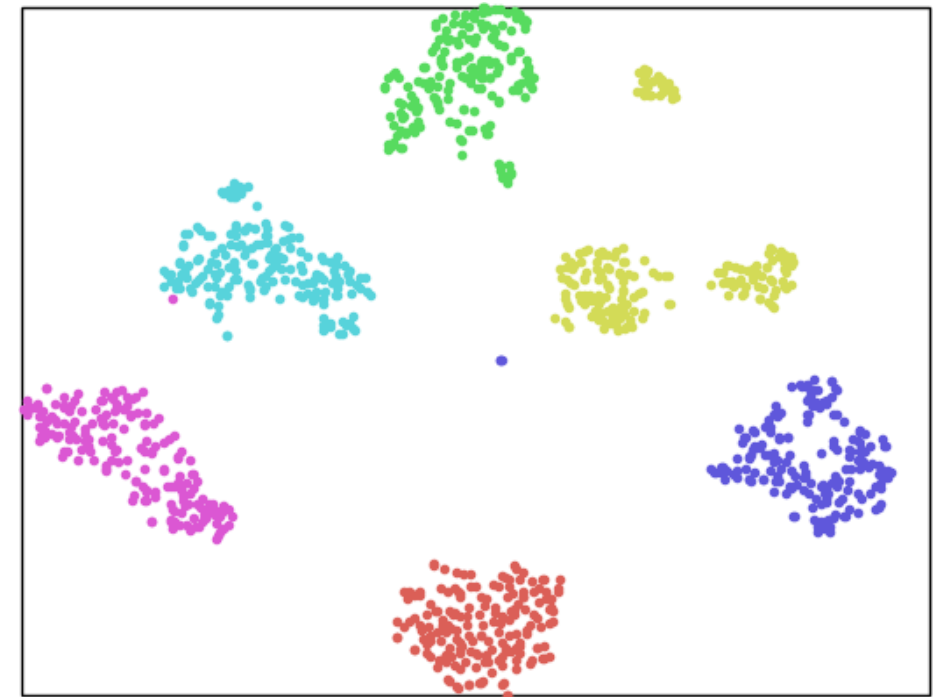
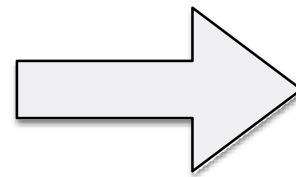
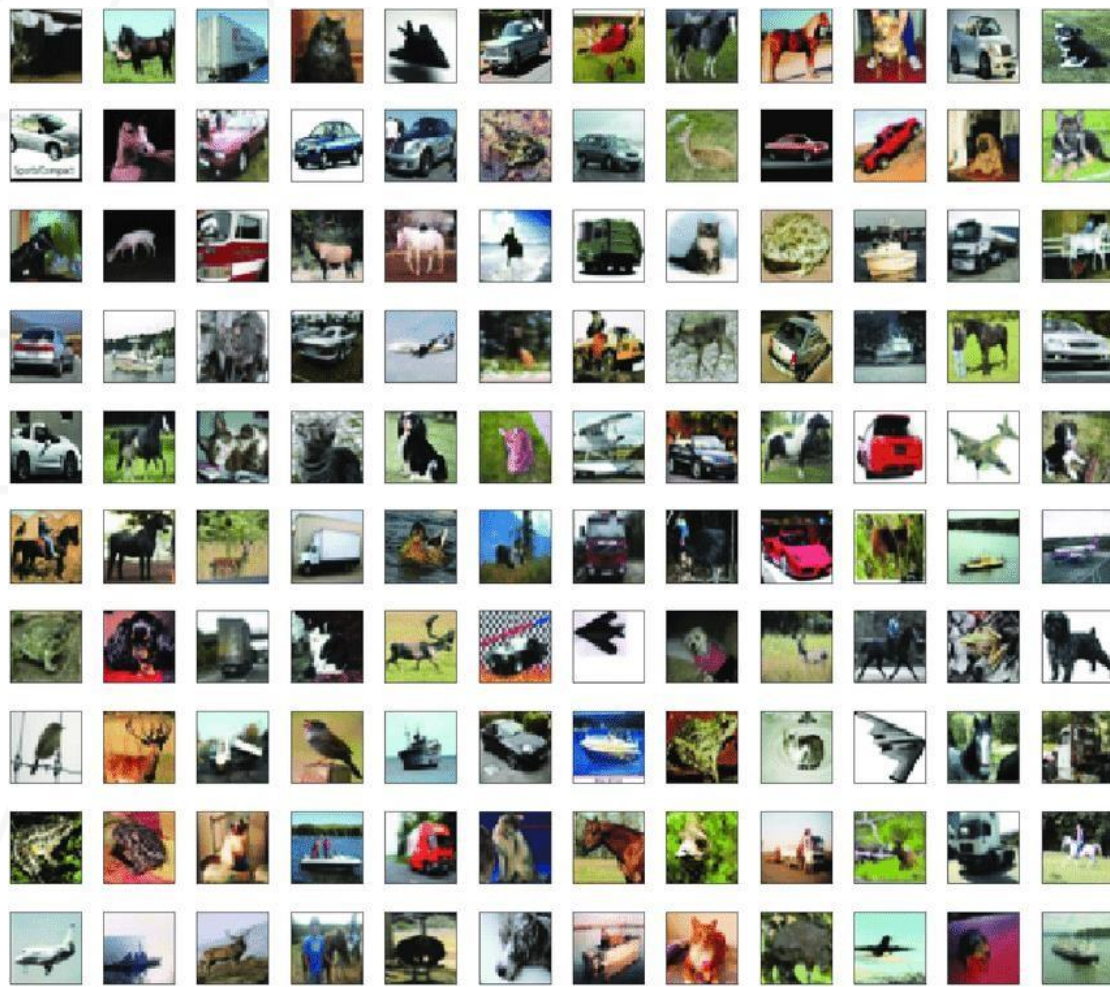
# Community Detection in Social Networks (Clustering)

- What are the inputs and how to represent them?
- What are the desired outputs?
- What learning algorithms to choose?





# Dimensionality Reduction



- What are the inputs and how to represent them?
- What are the desired outputs?
- What learning algorithms to choose?

# Syllabus: Supervised Learning

## Tree-based models

- Decision tree
- Ensemble learning/Random forest

## Linear classification/regression models

- Linear regression
- Naive Bayes
- Logistic regression

## Neural networks

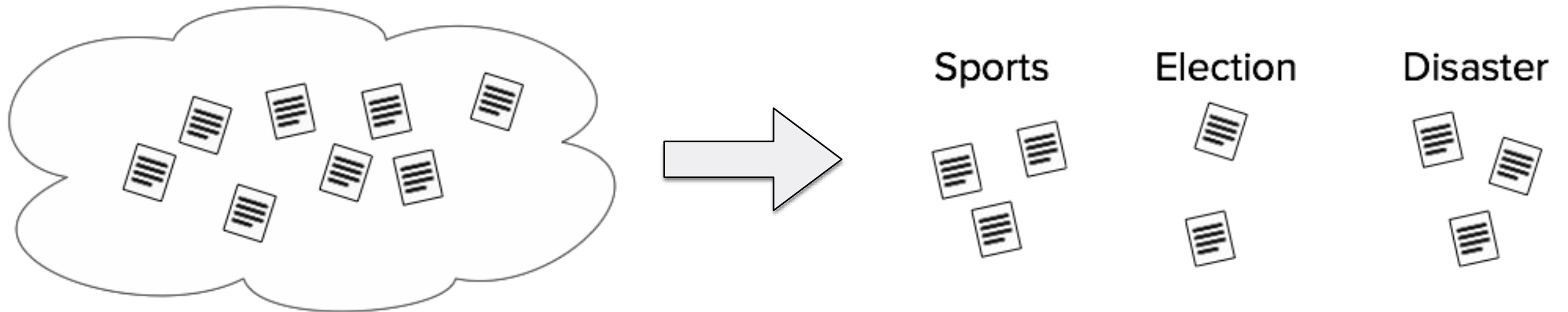
- Feedforward neural networks and backpropagation analysis
- CNN

## Support vector machine

# News Classification

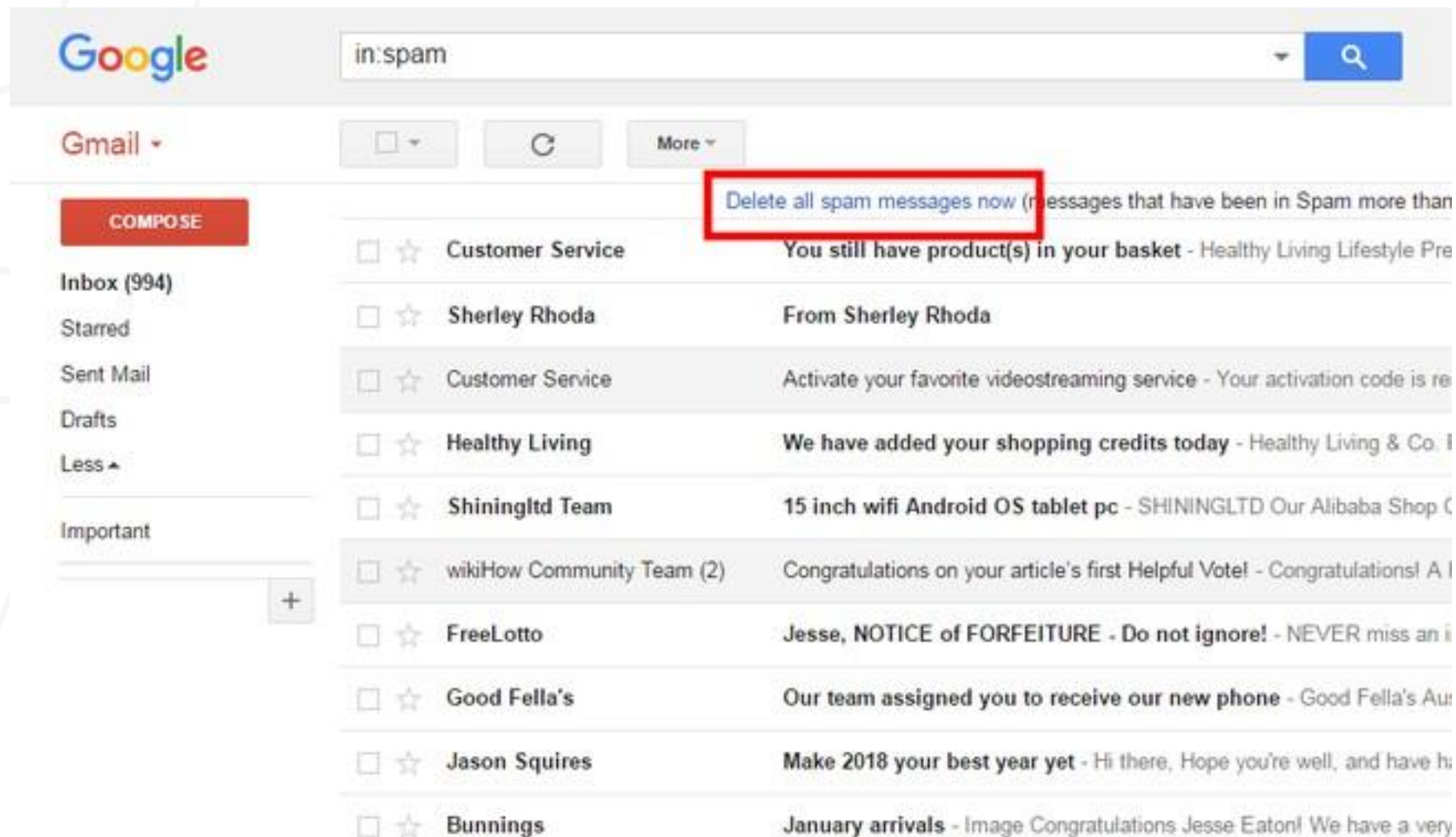


- What are the inputs and how to represent them?
- What are the desired outputs?
- What learning algorithms to choose?

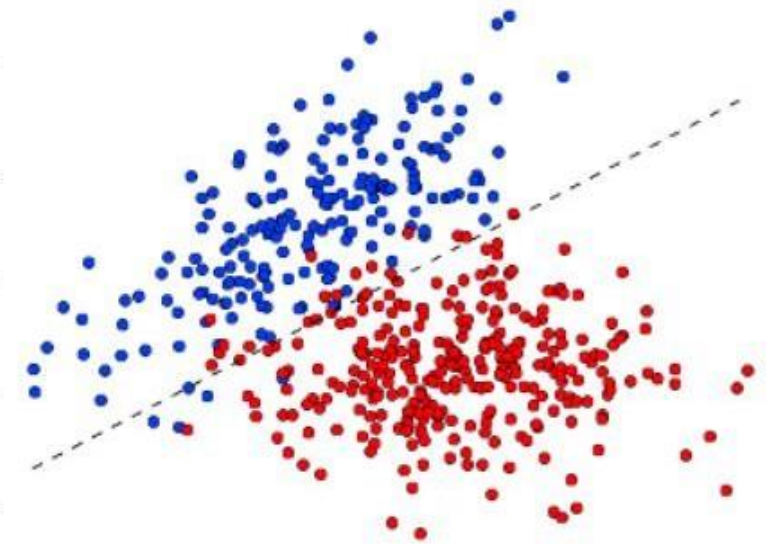




# Spam Detection



**NOT SPAM**



**SPAM**

- What are the inputs and how to represent them?
- What are the desired outputs?
- What learning algorithms to choose?



# Questions?

# Projects

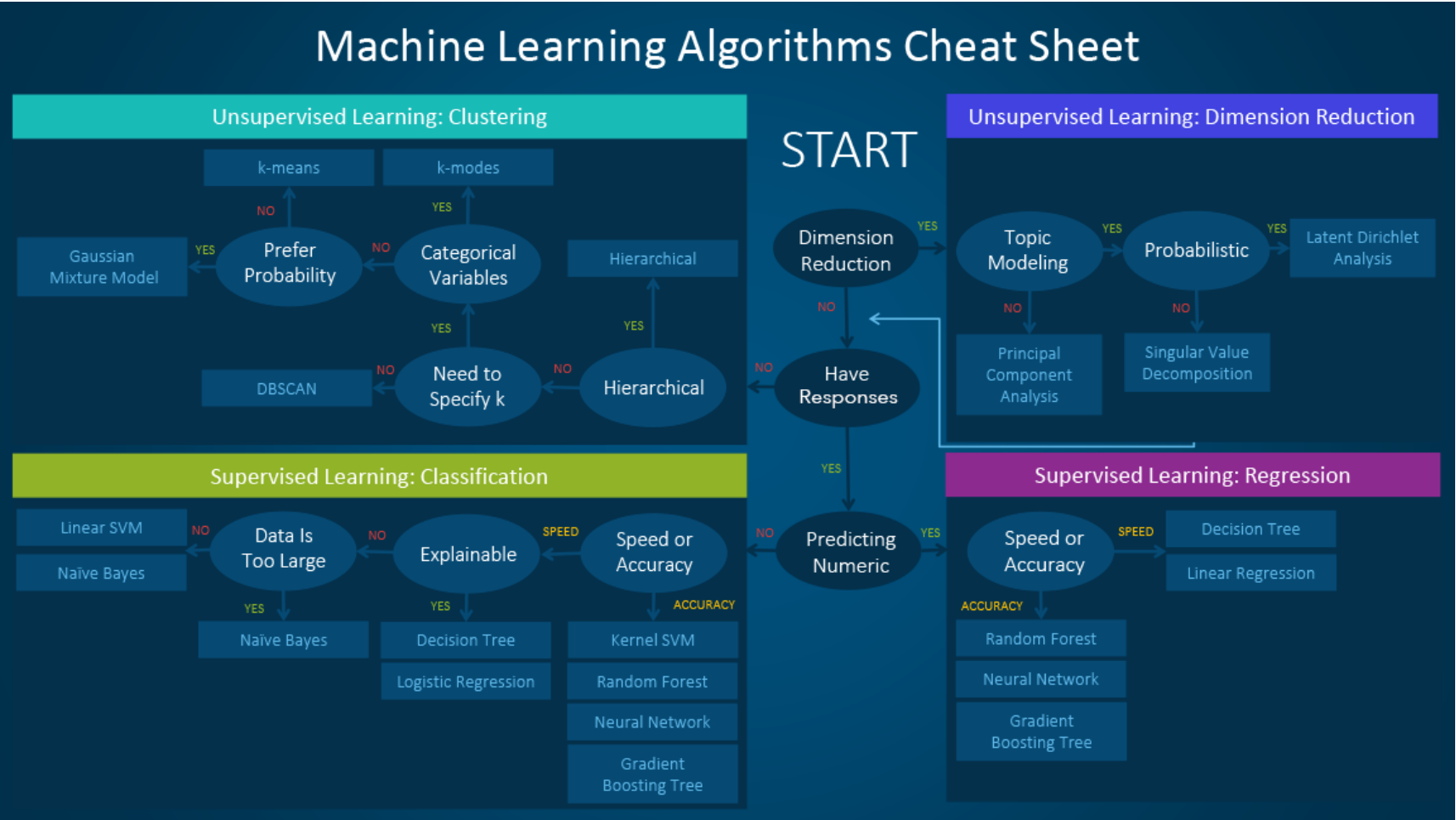
# Before you start a machine learning project

- **Defining the problem. Is this a machine learning task?**
- **What kind of machine learning task is it?**
  - Clustering, distribution estimation, classification, regression, other?
- **Do I have the data and resources to support it?**
- **What kind of data am I working with?**
  - Spatial (map, trajectory), visual (images), text (documents, tweets, customer reviews), behavioral data (smoking habits), time-series data (stock prices)
- **How am I evaluating success?**

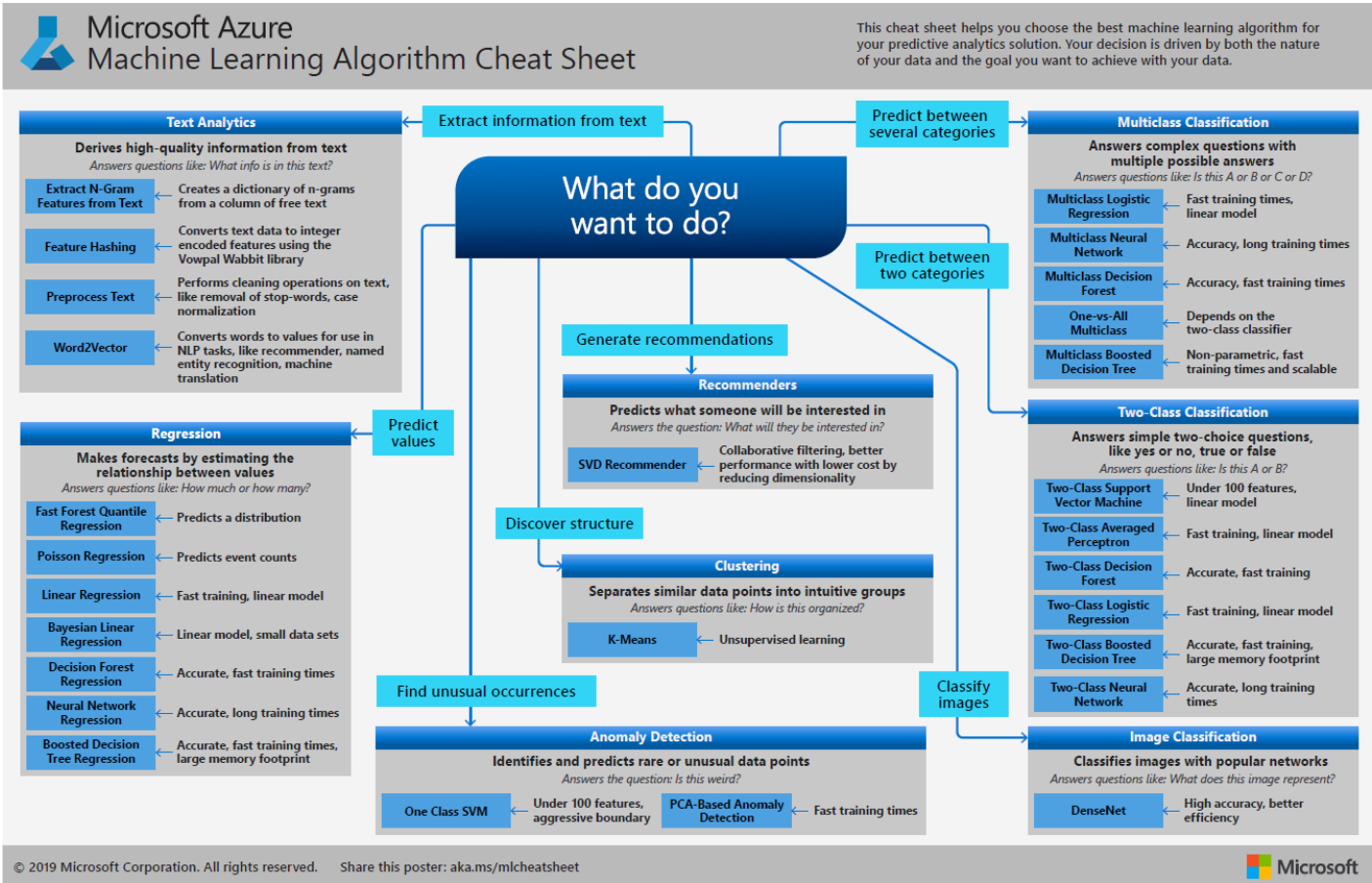
# Machine learning workflow process

- **Defining the problem:** Clearly define what you want to achieve with your model.
- **Data collection:** Gather and preprocess the data that you will use to train your model.
- **Data exploration:** Explore the data to gain insights and detect patterns, outliers, and anomalies.
- **Feature engineering:** Create features that capture relevant information from the data.
- **Model selection:** Choose a model that suits your problem, considering factors such as computational requirements and prediction accuracy.
- **Model training:** Train the model using the preprocessed data.
- **Model evaluation:** Evaluate the model's performance on a held-out test dataset.
- **Model tuning:** Fine-tune the model's hyperparameters to improve its performance.

# What algorithm should I use? (Not a comprehensive list)



Infographic by SAS Data Science Blog. Click on the figure to access the source.



# General Project Guidance on Class Website

Infographic by Microsoft Azure. Click on the figure to access the source.

# Logistics and teamwork advice

- Define clear means of communication (I strongly recommend you create a channel for your group on MS Teams)
- Listen to your teammates and be upfront about your availability
- Play to your individual strengths when tackling an activity
- Create an inclusive environment in your team and make sure all voices are heard
- Resolving conflicts within the team is part of the job
- The people you work with are part of your professional network
- Peer reviews will be used to assess your participation in the project



# Important aspects to consider

- Complex tasks demand large datasets in order to achieve satisfactory generalization. The course webpage has an extensive list of databases from which you can obtain datasets to work on your project
- The training phase of techniques involving large datasets and/or deep learning architectures are computationally intensive and require GPUs to be performed in a reasonable amount of time.
- Make sure you have the appropriate resources when dealing with such techniques. Here are some options of free GPU resources:
  - [Colab](#)
  - [Kaggle](#)
  - [AWS Educate](#)

# Example Projects applying these concepts is on our class website

- **Sample Projects**

- Sample Project from previous semester [[Undergrad Canvas Access for previous ML projects](#)]; [[Grad Canvas Access for previous ML projects](#)]; [Stanford Project Examples](#);

- **General project guidance**

- Your project will be graded based on the following criteria:

**Was the motivation clear?**

- What is the problem?
- Why is it important and why we should care?

**Were the dataset and approach used effectively?**