



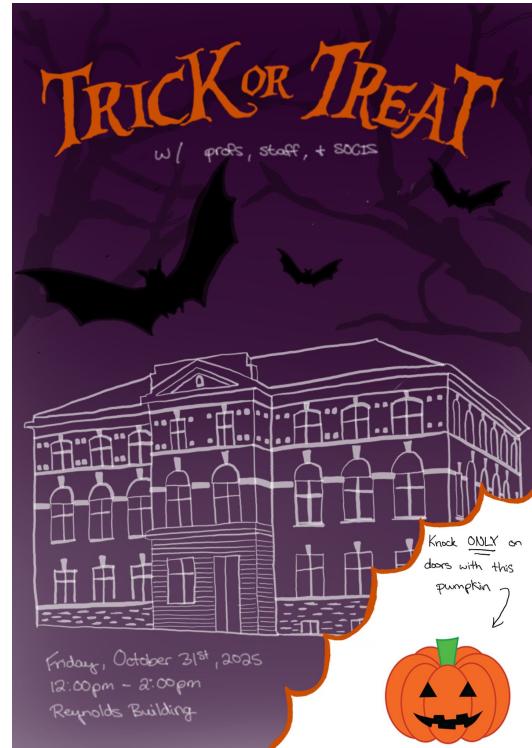
# CIS\*3750 - System Analysis and Design in Applications

Luiza Antonie, Fall 2025, University of Guelph

# Week 10 Demo (Nov 3 & 5)

- In person, during your regular lab session
- 10-minute live demo of your high-fidelity prototype
- It must showcase **2-3 key user walkthroughs** focused on the core "intelligent" learning functionality of your ITS
- Simple walkthroughs like account creation or logging in will not be considered a valid main walkthrough
- While a code-based UI is recommended, navigating a Figma prototype is also acceptable
- Provide a shareable link to your prototype (e.g., GitHub or Figma link) for review. The entire group must be present for the demo.

# Trick-or-Treat in Reynolds!



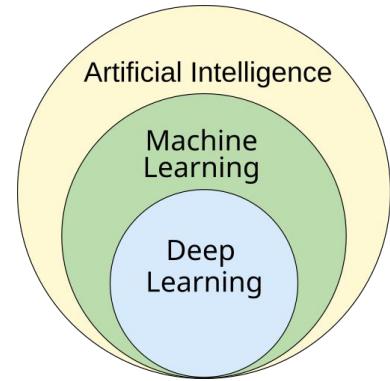
# What is Learning?

“Learning is any process by which a system improves performance from experience.”

Herbert Simon (1916-2001), American economist, political scientist and cognitive psychologist

# Machine Learning

- Machine Learning (ML)
  - A subfield of artificial intelligence
  - Development of algorithms that **learn from data** and generalize to unseen data
  - Performs tasks without explicit programmed instructions
- "A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P if its performance at tasks in T, as measured by P, improves with experience E" - Tom. Mitchell



# Types of Learning

The illustration features three anthropomorphic blue robots sitting around a round table, each with a computer monitor for a head. They are connected by a network of pipes and valves.

- Supervised (inductive) learning:** The robot on the left says: "SUPERVISED: THEY GAVE ME SO MUCH TO READ, AND TESTS!"
- Unsupervised learning:** The robot in the center says: "UNSUPERVISED: ME TOO. BUT AT LEAST THEY TOLD YOU THE ANSWERS"
- Reinforcement learning:** The robot on the right says: "REINFORCEMENT: AT LEAST Y'ALL DON'T MAKE YOUR OWN BOOK!"

**Links:**

- [https://www.reddit.com/r/TheInsaneApp/comments/rf8ytg/the\\_three\\_main\\_types\\_of\\_machine\\_learning\\_algorithms/](https://www.reddit.com/r/TheInsaneApp/comments/rf8ytg/the_three_main_types_of_machine_learning_algorithms/)



## Reinforcement learning

Data = collected from a sequence of actions

# Supervised learning



Dangerous



Dangerous



Not dangerous



Not dangerous



Dangerous



Not dangerous

# Supervised learning



Dangerous



Dangerous



Not dangerous



Not dangerous



Dangerous



Not dangerous

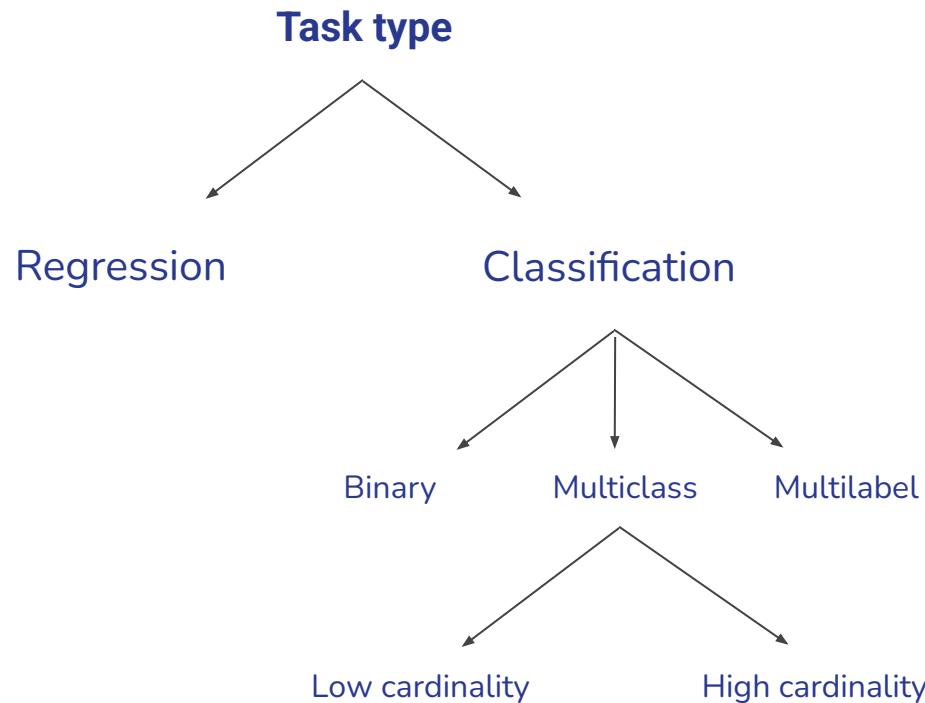


**Is this dangerous?**

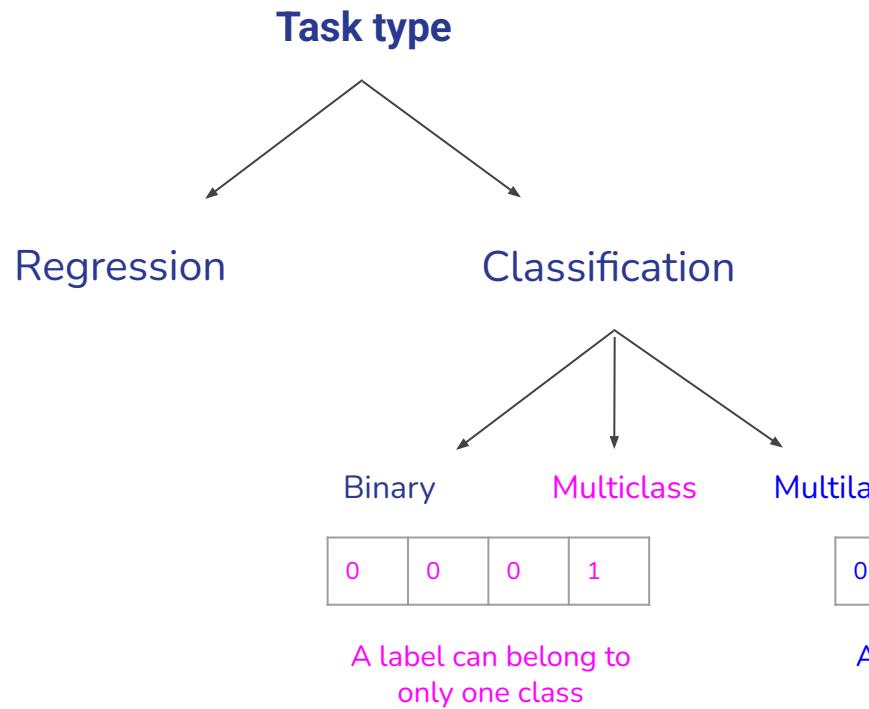


**Tasks: classify animals, decide, predict**

# Framing the problem



# Multiclass vs. multilabel



# How to handle multilabel tasks

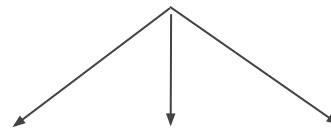
## Multilabel problem solution



A multiclass problem

A set of multiple binary  
problems

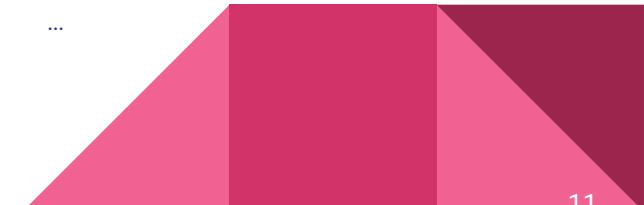
0	1	0	1
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Model 1:  
Does this  
belong to  
class 1?

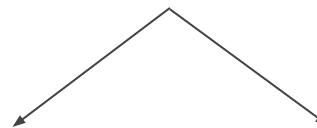
Model 2:  
Does this  
belong to  
class 2?

...



# Multilabel is harder than multiclass

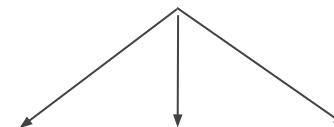
## Multilabel problem solution



A multiclass problem

0	1	0	1
---	---	---	---

A set of multiple binary problems



Model 1:  
Does this  
belong to  
class 1?

Model 2:  
Does this  
belong to  
class 2?

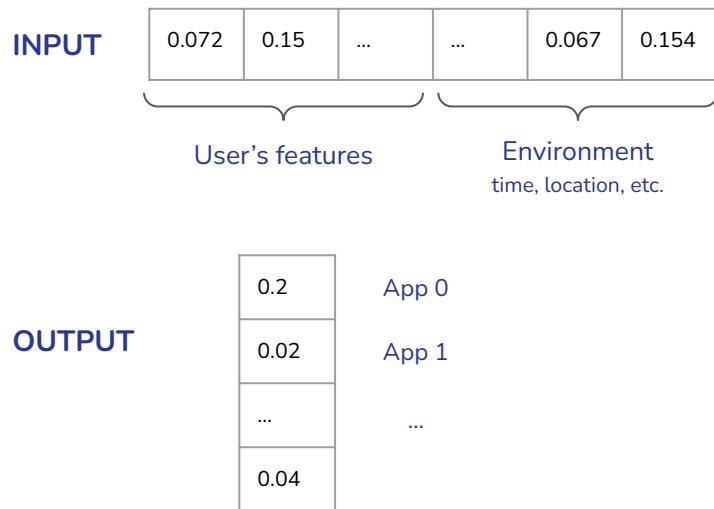
...

1. How to create ground truth labels?
2. How to decide decision boundaries

# A problem can be framed as different task types

**Problem:** predict the app users will most likely open next

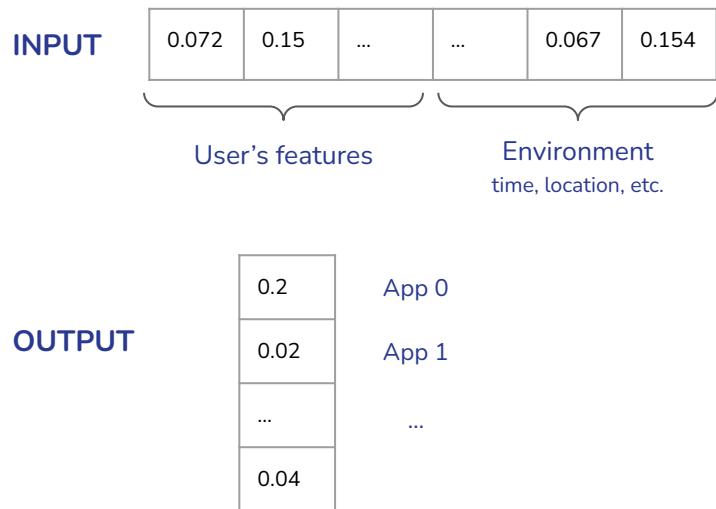
## Classification



# A problem can be framed as different task types

**Problem:** predict the app users will most likely open next

## Classification

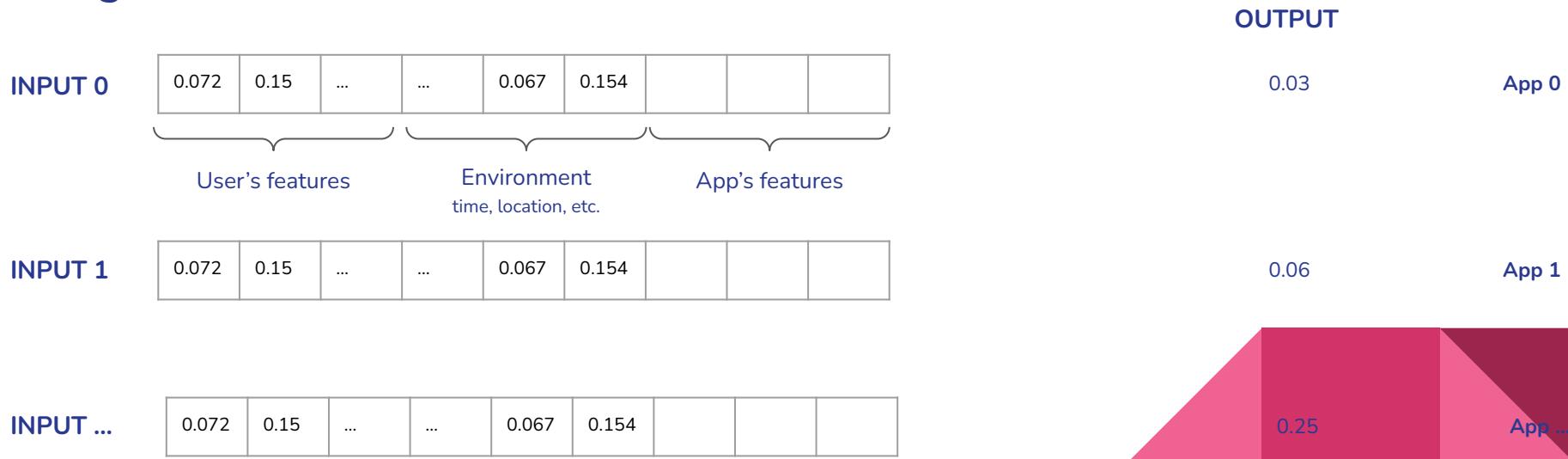


⚠️ Every time an app is added/removed, you have to retrain your model ⚠️

# Framing can make the problem easier/harder

**Problem:** predict the app users will most likely open next

## Regression



# Framing can make the problem easier/harder

**Problem:** predict the app users will most likely open next

Very common framing for recommendations

## Regression

INPUT 0	0.072	0.15	...	...	0.067	0.154			
	User's features			Environment time, location, etc.			App's features		
INPUT 1	0.072	0.15	...	...	0.067	0.154			
INPUT ...	0.072	0.15	...	...	0.067	0.154			

## OUTPUT

0.03

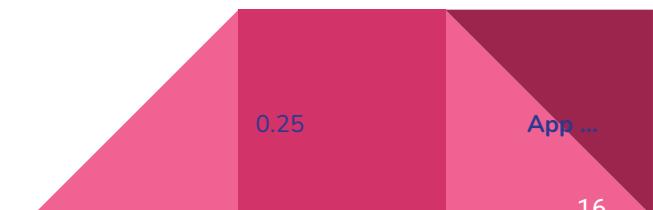
App 0

0.06

App 1

0.25

App ...



# Supervised learning tasks in an ITS

- Difficulty estimation
  - predicting difficulty of a concept/problem
- Knowledge tracing
  - estimate mastery of concepts
- Predict which type of explanation works best for a student
- Predict if the student will answer the problem correctly

# Supervised learning tasks in an ITS

- Detect/classify misconceptions or error types.
- Classify the student's state and select the most helpful hint level.
- Sentiment classification:
  - detect frustration/engagement from clicks, pauses

# Unsupervised learning

How can these pictures be grouped?

Data



# Unsupervised learning

How can these pictures be grouped?

Data



# Unsupervised learning tasks in an ITS

- Recommend what skill/concept the student should practice next
- Group students by learning behaviors (fast/slow, high/low engagement).
- Group questions/problems by difficulty/skill

# Reinforcement learning

Exploring an unknown environment

	ouch
	ouch
	yum



ouch



ouch



yum



# Reinforcement learning

Exploring an unknown environment

	ouch
	ouch
	yum



ouch



ouch



?



yum



Tasks: explore, react, remember, extrapolate

# Reinforcement learning in an ITS

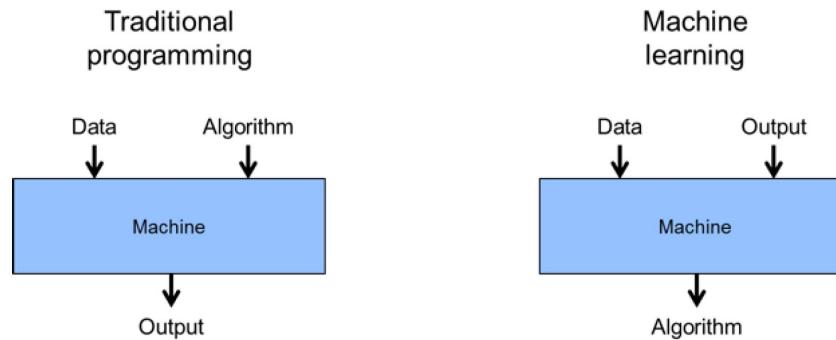
- Policy learning: Use reinforcement learning (RL) to decide the “best” next action for learning gains
- Adapting feedback: Use RL to provide feedback that is optimized for the learner

# Machine learning (ML)

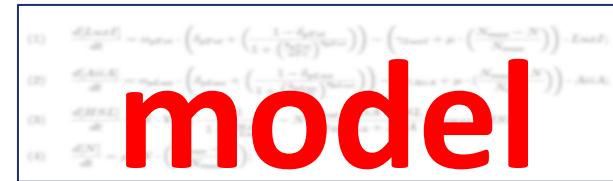
- The field of machine learning is concerned with the question of how to construct computer programs that automatically improve with experience.

Tom Mitchell, Machine Learning (1997)

i.e. get computers to program themselves



# Machine learning (ML) modelling



# Machine learning (ML) modelling

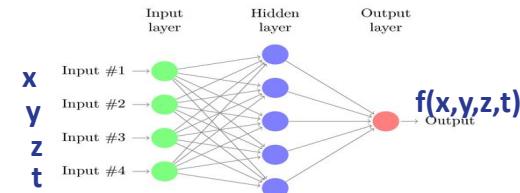
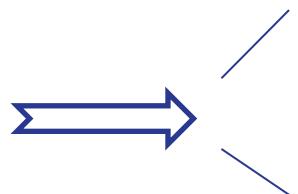


(1)  $\frac{dL_{out}}{dt} = \alpha_{out} \cdot \left( \beta_{out} + \left( \frac{1 - \delta_{out}}{1 + \left( \frac{\beta_{out}}{\delta_{out}} \right)^N} \right) - \left( \text{target} + \mu \cdot \left( \frac{N_{out} - N}{N_{out}} \right) \right) \cdot L_{out} \right)$   
(2)  $\frac{dL_{out}}{dt} = \left( \gamma_{out} - \left( \frac{1 - \delta_{out}}{1 + \left( \frac{\beta_{out}}{\delta_{out}} \right)^N} \right) \right) \cdot \left( \text{target} + \mu \cdot \left( \frac{N_{out} - N}{N_{out}} \right) \right) \cdot L_{out}$   
(3)  $\frac{dL_{out}}{dt} = \left( \gamma_{out} - \left( \frac{1 - \delta_{out}}{1 + \left( \frac{\beta_{out}}{\delta_{out}} \right)^N} \right) \right) \cdot \left( \text{target} + \mu \cdot \left( \frac{N_{out} - N}{N_{out}} \right) \right) \cdot L_{out}$   
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**model**

Example:

x	y	z	t	Output: $f(x,y,z,t)$
1	1	-10	0	-18
2	1	-9	2	-11
3	2	-8	4	5
4	2	-7	6	28
5	3	-6	8	60
6	3	-5	10	99
7	4	-5	12	145
8	4	-3	14	202
9	5	-2	16	266
10	5	-1	18	337

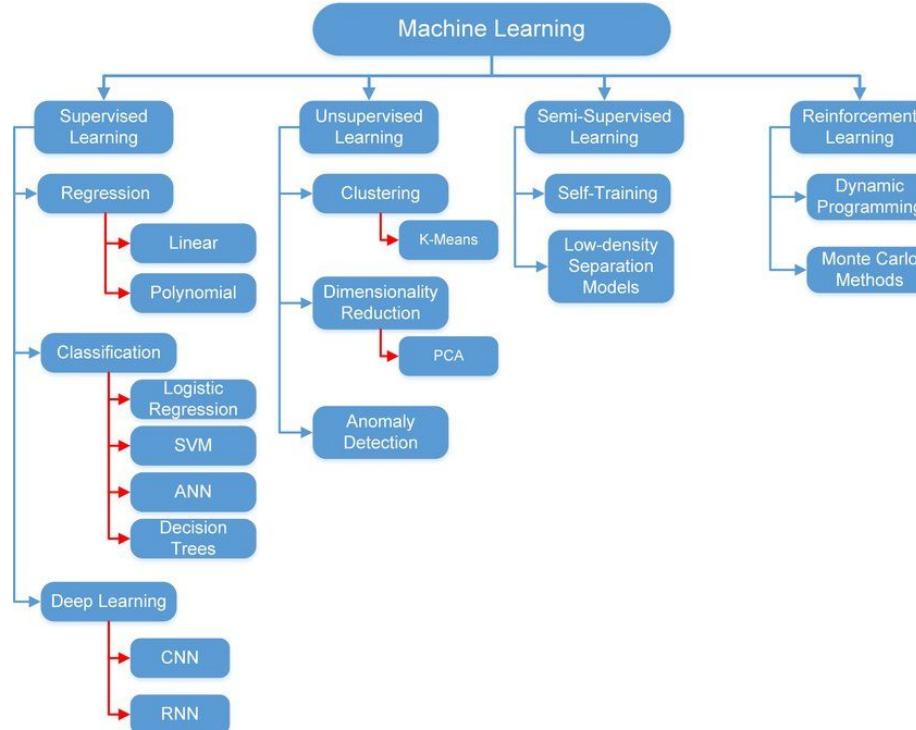


ML model

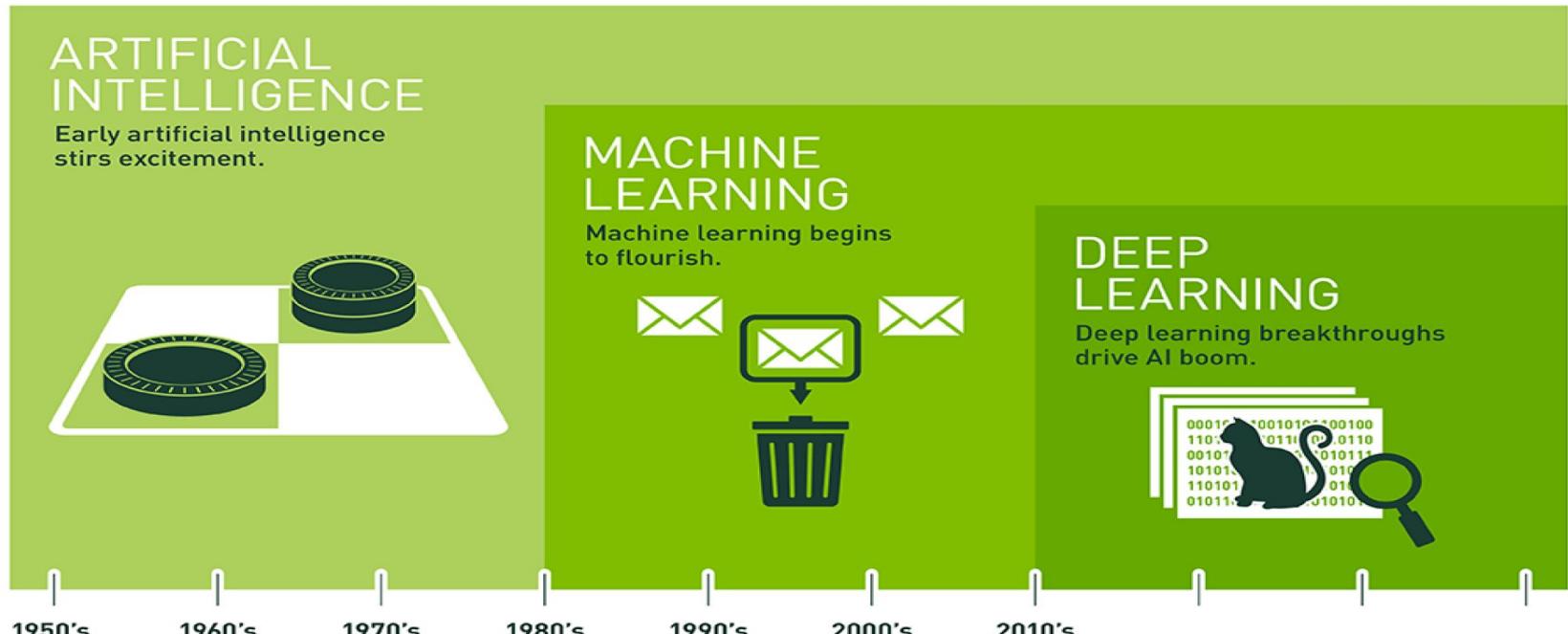
$$f(x, y, z, t) = x + y + 2z + t^2$$

traditional mathematical  
model

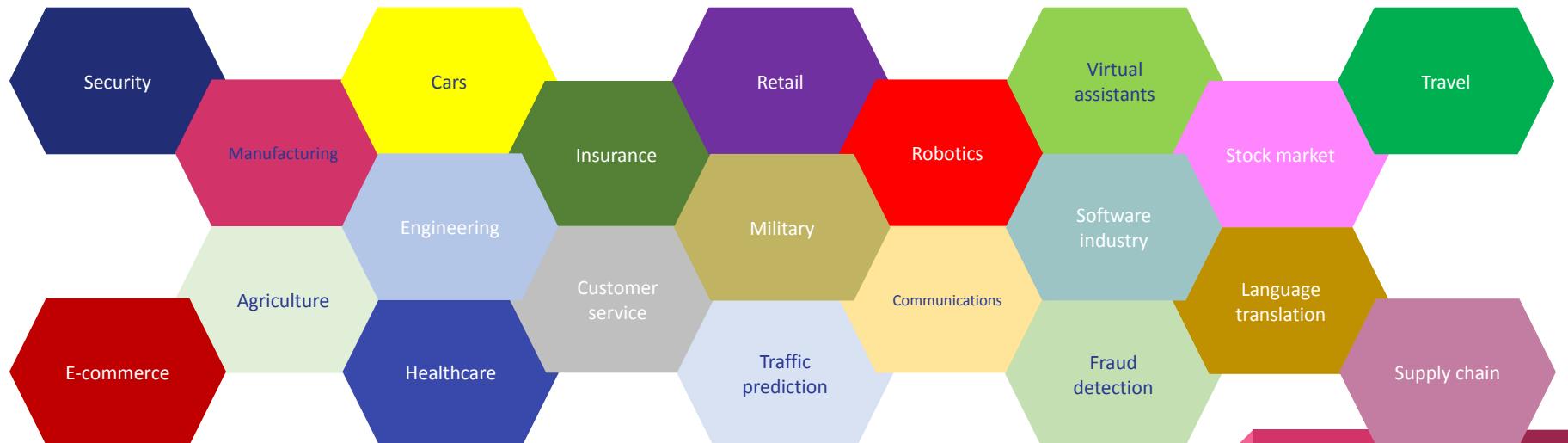
# Machine Learning Algorithms



# History of ML

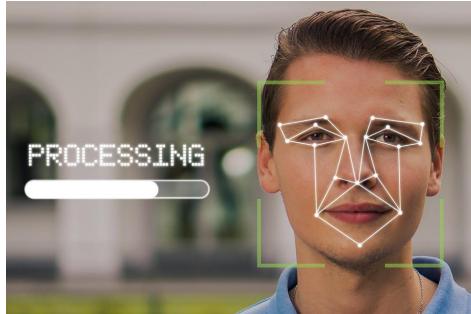


# Applications of ML



# Applications of ML

Face detection



Self driving cars



[This Photo by Unknown Author is licensed under CC BY-NC](#)

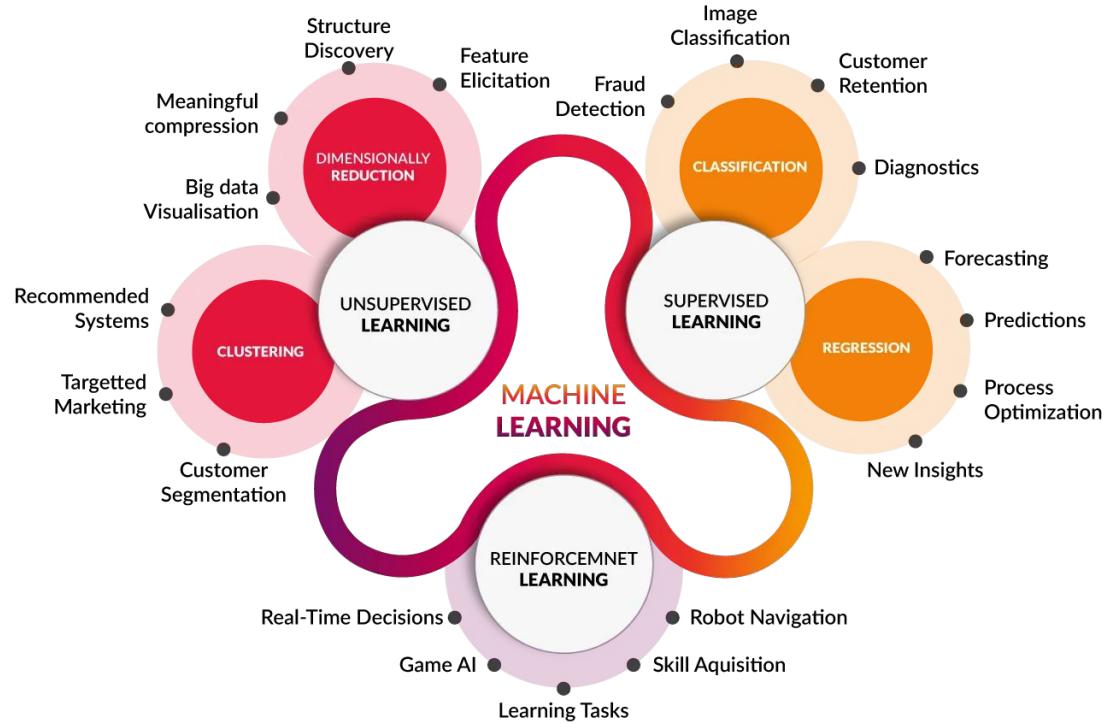
Drones



Toys ?!?



# Types of problems solved by ML



# How does ML work?

- **Step 1 [ data ]:** The user provides the learning system with **examples** of the concept to be learned or plain **data**.

DATA



# How does ML work?

- **Step 1 [ data ]:** The user provides the learning system with **examples** of the concept to be learned or plain **data**.

DATA



- **Step 2 [ training + validation ]:** The learning system algorithm **builds** a characteristic **model** from these examples.

# How does ML work?

- **Step 1 [ data ]:** The user provides the learning system with **examples** of the concept to be learned or plain **data**.

DATA



- **Step 2 [ training + validation ]:** The learning system algorithm **builds** a characteristic **model** from these examples.
- **Step 3 [ testing ]:** The **model is used to predict** quickly and with high accuracy whether or not future **novel instances** follow the model.

# How does ML work?

- **Step 1 [ data ]:** The user provides the learning system with **examples** of the concept to be learned or plain **data**.

**DATA**



- **Step 2 [ training + validation ]:** The learning system algorithm **builds** a characteristic **model** from these examples.
- **Step 3 [ testing ]:** The **model is used to predict** quickly and with high accuracy whether or not future **novel instances** follow the model.

**Golden Rule of ML: The test data cannot be used in the training process.**

# Step 1: Define the problem

## 1. What problem do I solve?

- Informal definition
- Formal definition (**tasks**, experience, performance)
- Assumptions
- Similar problems: anyone else proposed/solved this problem

## 2. Why do I want/need to solve this problem?

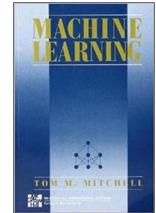
- Motivation: learning, project, ...
  - Benefits of finding a solution: to market it to others, novelty, ...
  - Use of solution: who benefits, maintenance, lifetime, write papers,
- ...

## 3. How do I solve the problem?

- Manual approach for smaller problem
- What do you need: data collection, storage, preparation, programming needs, knowledge
- Refine steps 1 and 2
- Do I need ML to solve it?

A computer program is said to **learn** from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in *T*, as measured by *P*, improves with experience *E*.

Tom Mitchell, Machine Learning, McGraw Hill, 1997  
<http://www.cs.cmu.edu/~tom/mlbook.html>



# Case study: sheep body weight prediction

## 1. What problem do I solve?

- Informal definition
- Formal definition (**tasks, experience, performance**)
- Assumptions
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# Case study: sheep body weight prediction

## 1. What problem do I solve?

- **Informal definition**
- Formal definition (tasks, experience, performance)
- Assumptions
- Similar problems: anyone else proposed/solved this problem

Need a model to predict sheep body weight from body measurements.

## 2. Why do I want/need to solve this problem?

- Motivation: learning, project, ...
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# Case study: sheep body weight prediction

## 1. What problem do I solve?

- Informal definition
- **Formal definition** (tasks, experience, performance)
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- **Task** = estimate body weight of a new sheep for which we do not know its real weight.
- **Experience** = a collection of measurements for which we have known weights
- **Performance** = the difference between the predicted and known body weight

## 2. Why do I want/need to solve this problem?

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# Case study: sheep body weight prediction

## 1. What problem do I solve?

- Informal definition
  - Formal definition (tasks, experience, performance)
  - Assumptions
  - Similar problems: anyone else proposed/solved this problem
- Measurements are performed with high accuracy (small errors)
  - Data is collected by the same person using the same tools
  - Sheep age might influence the prediction accuracy

## 2. Why do I want/need to solve this problem?

- Motivation: learning, project, ...
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- Use of solution: who benefits, maintenance, lifetime, write papers, ...

## 3. How do I solve the problem?

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## 1. What problem do I solve?

- Informal definition
- Formal definition (tasks, experience, performance)
- Assumptions
- **Similar problems: anyone else proposed/solved this problem**

Significant number of publications available:

Sowande and Sobola, 2008; Kunene et al., 2009; Chay-  
151 Canul et al., 2019; Canul-Solis et al., 2020

## 2. Why do I want/need to solve this problem?

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Associations potentially interested in this project:



1. Sheep welfare
2. Industrial automation

# Case study: sheep body weight prediction

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- Use of solution: who benefits, maintenance, lifetime, write papers, ...

- Reduce stress for both sheep and handlers
- Enable continuous growth monitoring
- Optimize time-to-market
- Appealing for agro-tech companies

## 3. How do I solve the problem?

- Manual approach for smaller problem
- What do you need: data collection, storage, preparation, programming needs, knowledge, technologies
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# Case study: sheep body weight prediction

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- Benefits of finding a solution: to market it to others, novelty, ...
- **Use of solution: who benefits, maintenance, lifetime, write papers, ...**

- Beneficiaries: researchers, industry, breeders, farmers
- Maintenance: medium to long-term
- Lifetime value: 5-10 years (until new tech arrives)
- Publications: articles or patents
- Used on mobile devices and computers

## 3. How do I solve the problem?

- Manual approach for smaller problem
- What do you need: data collection, storage, preparation, programming needs, knowledge, technologies
- Refine steps 1 and 2
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## 3. How do I solve the problem?

- **Manual approach for smaller problem**
- **What do you need:** data collection, storage, preparation, programming needs, knowledge, technologies
- Refine steps 1 and 2
- Do I need ML to solve it?

- Collect 5 measurements from 100 sheep (manual + images).
- Store data as text and images.
- Remove/impute missing data
- Programming in Python (OpenCV,...) and later for mobile platforms

# Case study: sheep body weight prediction

## 1. What problem do I solve?

- Informal definition
- Formal definition (tasks, experience, performance)
- Assumptions
- Similar problems: anyone else proposed/solved this problem

## 2. Why do I want/need to solve this problem?

- Motivation: learning, project, ...
- Benefits of finding a solution: to market it to others, novelty, ...
- Use of solution: who benefits, maintenance, lifetime, write papers, ...

- Might need more data (more sheep, more measurements).
- Results could be influenced by sheep color  breed  adjust assumptions
- Might be able to apply the same process for cows and pigs.
- **Shocking realization:** sheep have a lot of hair  overestimations  adjust assumptions

## 3. How do I solve the problem?

- Manual approach for smaller problem
- What do you need: data collection, storage, preparation, programming needs, knowledge, technologies
- **Refine steps 1 and 2**
- Do I need ML to solve it?

# Case study: sheep body weight prediction

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## 3. How do I solve the problem?

- Manual approach for smaller problem
- What do you need: data collection, storage,
- Refine steps 1 and 2
- **Do I need ML to solve it?**

YES

- Can be formulated as a regression problem
- Unknown relation (linear, non-linear) between measurements and body weight
- Output (weight) is known  supervised learning

# In-class exercise

Use these questions to explore one of the problems you want to solve with ML for your project

## 1. What problem do I solve?

- Informal definition
- Formal definition (tasks, experience, performance)
- Assumptions
- Similar problems: anyone else proposed/solved this problem

## 2. Why do I want/need to solve this problem?

- Motivation: learning, project, ...
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