Intro to Machine Learning

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What is machine learning?

- To answer this question, I'm going to describe some computer systems that solve a problem.
- You're going to let me know whether you think I've described a machine learning solution or not.

Solving problems: example (1)

Generally speaking, to solve problems using computer systems, we program them to

- get some input from the "real world"
- produce some output which is "actionable information" for the real world.

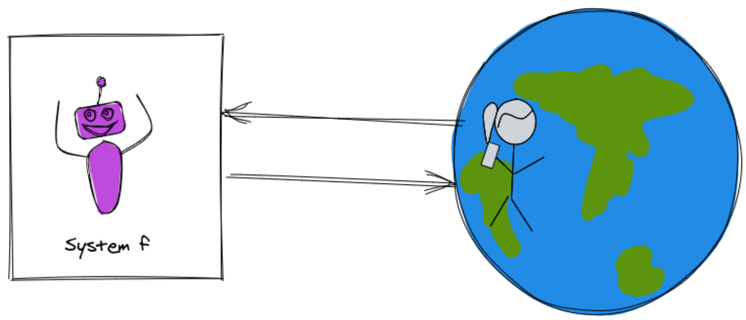


Figure 1: A system that interacts with the world.

Suppose we want a system to help students decide whether to enroll in this course or not.

- Input: grades on previous coursework
- Actionable info: predicted ML course grade

Solving problems: example (2)

Let

- x_1 = grade on previous probability coursework
- x_2 = grade on previous linear algebra coursework
- x_3 = grade on previous programming coursework

and $\hat{y}$ is predicted ML course grade.

The "hat" indicates that this is an *estimated* value.

Solving problems: example (3)

Suppose we predict your grade as

$$\hat{y} = min(x_1, x_2, x_3)$$

Is this ML?

Solving problems: example (4)

Suppose we predict your grade as

$$\hat{y} = w_1 x_1 + w_2 x_2 + w_3 x_3$$

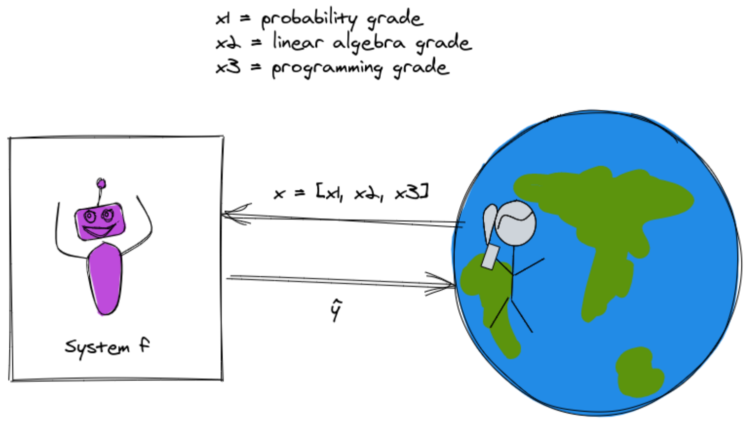


Figure 2: A system that predicts ML course grade.

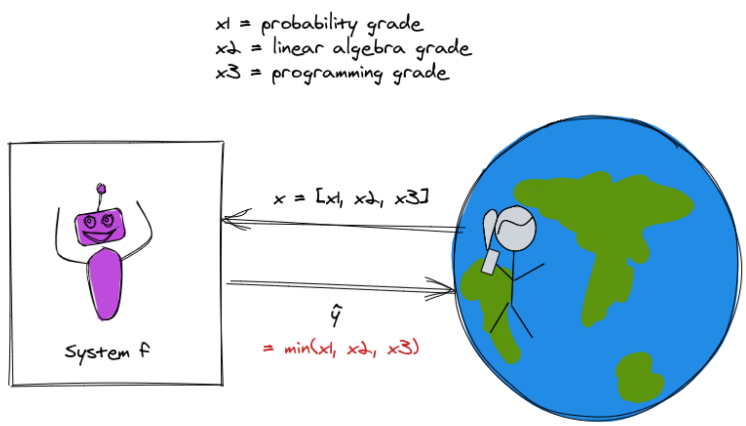


Figure 3: A system that predicts ML course grade as minimum grade from prerequisite coursework. This is a *rule-based* system.

where $w_1 = \frac{1}{4}, w_2 = \frac{1}{4}, w_3 = \frac{1}{2}$.

Is this ML?

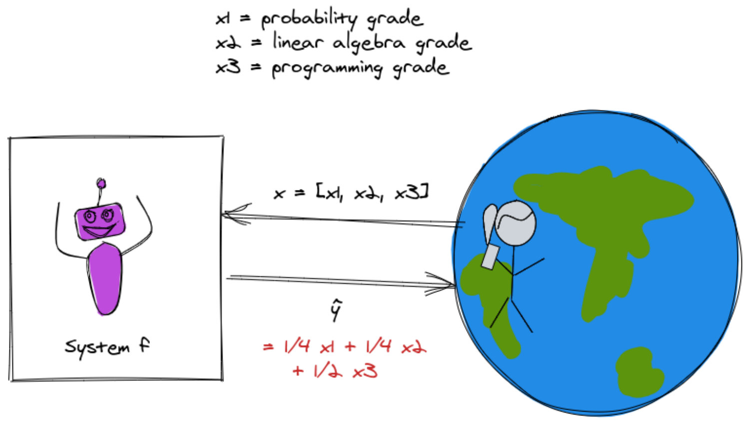


Figure 4: A system that predicts ML course grade as weighted sum of grades from prerequisite coursework, where the weights are fixed. This is a *rule-based* system.

Solving problems: example (3)

Suppose we predict your grade as the mean of last semester's grades:

$$\hat{y} = w_0$$

where $w_0 = \frac{1}{N}\sum_{i=1}^{N} y_i$.

Is this ML?

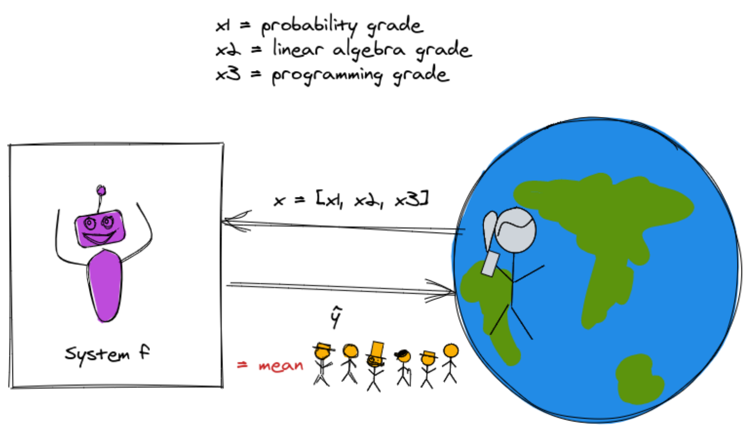


Figure 5: A system that predicts ML course grade as mean grade of previous students. This is a *data-driven* system.

Solving problems: example (4)

Suppose we predict your grade using this algorithm:

If S is the set of 3 students from last semester with a profile most similar to yours, predict your grade as the median of their grades:

$$\hat{y} = \underset{y_i \in S}{\text{median}}(y_i)$$

Is this ML?

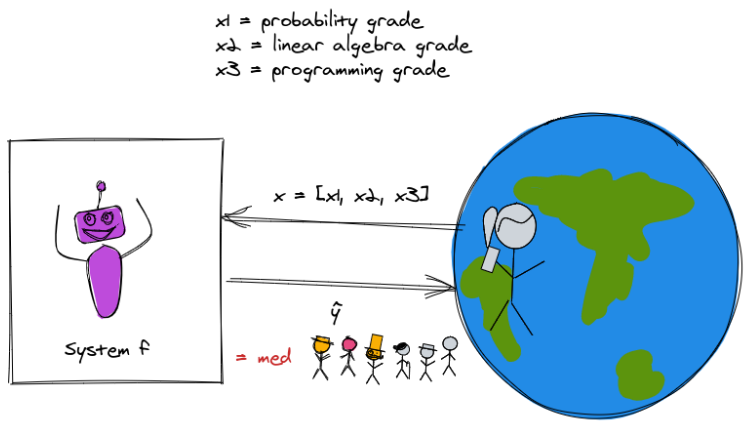


Figure 6: A system that predicts ML course grade as median of three most similar previous students. This is a *data-driven* system.

Rule-based vs. data driven problem solving

- The first two were examples of *rule-based* problem solving. I used my domain knowledge and expertise to establish rules for solving the problem.
- The second two were examples of *data-driven* problem solving. I still used some of my own expertise to establish rules - for example, the structure of the solution - but I used *data* (and not just data from the current input) to produce the output.

"Rule-based" problem solving

1. An algorithm is developed that will produce the desired result for a given input.
2. The algorithm is implemented in code.
3. Input parameters are fed to the implemented algorithm, which outputs a result.

Problem solving with machine learning

1. Collect and prepare data.
2. Build and train a model using the prepared data.
3. Use the model on new inputs to produce a result as output.

Machine learning problems

Now that we understand the difference between rule-based problem solving and ML-based problem solving, which is data driven, we can think about *what types of problems* are best solved with each approach.

Handwritten digits (1)

Figure 7: Handwritten digits in MNIST dataset

Let's take a classic example: recognizing handwritten digits. Early solutions to this problem date back to the 1960s.

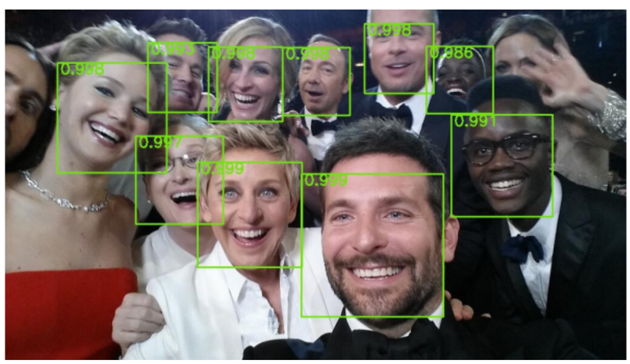


Figure 8: Face detection

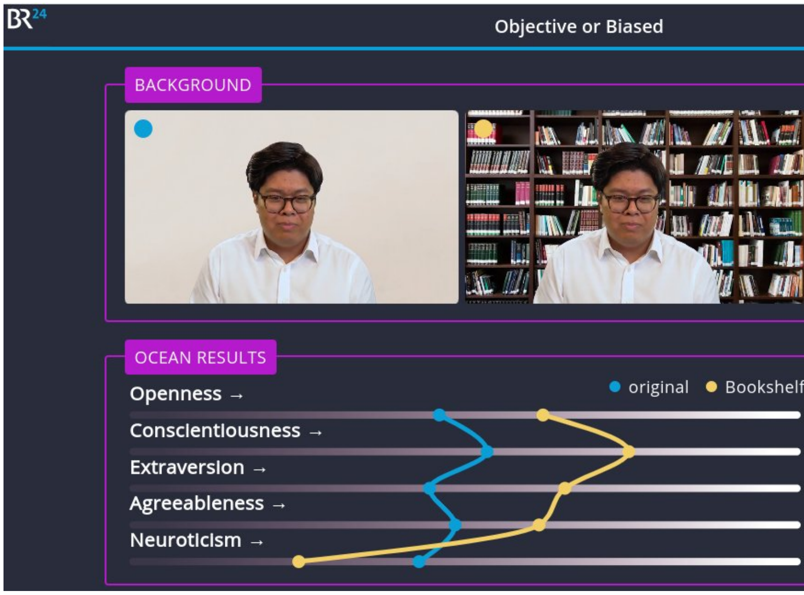
Faces

Good candidate for ML or not?

- Predict volcanic eruptions
- Recommend new products to customers based on past purchases
- Identify spam email
- Grade students' multiple choice quiz answers on NYU Classes
- Grade students' project-based homework

Score candidate's performance in a job interview (1) Is it a good candidate for ML?

- Use video recording as input to ML system
- Train using videos of past interviews + human assessment on key personality features



Score candidate's performance in a job interview (2)

Source: Bayerischer Rundfunk (German Public Broadcasting)

What characteristics of a problem make it well-suited to ML or not well-suited to ML?

Problems that are not well suited to ML

- There is an accurate and simple algorithm that will produce the desired output.
- There is no "good" data available on which to train a model.

Problems that are good candidates for ML

- Human expertise does not exist or is insufficient (for example, complex medical process that is not fully understood)
- Humans cannot easily explain their expertise (for example, handwritten digit recognition)
- The solution is very specific to particular cases (for example, recommendation systems)

Why now?

- Statistical foundations have been around for decades
- What's new:
  - Storage
  - Connectivity
  - Computational power

Machine learning terminology

Machine learning paradigms (1)

Supervised learning: learn from labeled data, make predictions

- Continuous target variable: **regression**
- Categorical target variable: **classification**

Machine learning paradigms (2)

Unsupervised learning: learn from unlabeled data, find structure

- Group similar instances: **clustering**
- Compress data while retaining relevant information: **dimensionality reduction**

Machine learning paradigms (3)

Reinforcement learning: learn from how the environment responds to your actions, solve interactive problems

Simple example, revisited

Earlier, we described four systems to predict a student's grade in the course.

The basic supervised learning problem

Given a **sample** with a vector of **features**

$$\mathbf{x} = (x_1, x_2, ...)$$

There is some (unknown) relationship between $\mathbf{x}$ and a **target** variable, y, whose value is unknown.

We want to find $\hat{y}$, our **prediction** for the value of y.

A supervised machine learning "recipe"

- Get **data** in some usable **representation**
- For supervised learning, we need **labeled** examples: $(\mathbf{x_i}, y_i), i = 1, 2, \cdots, N$
- Select a **model** f: $\hat{y} \approx f(x)$
- Select a **loss function** that will measure how good the model is
- If your model has **parameters**, find the parameter values that minimize the loss function (use a **training algorithm**)
- Use model to **predict** $\hat{y}$ for new, unlabeled samples (**inference**)

Your role in the ML process

ML system via XKCD

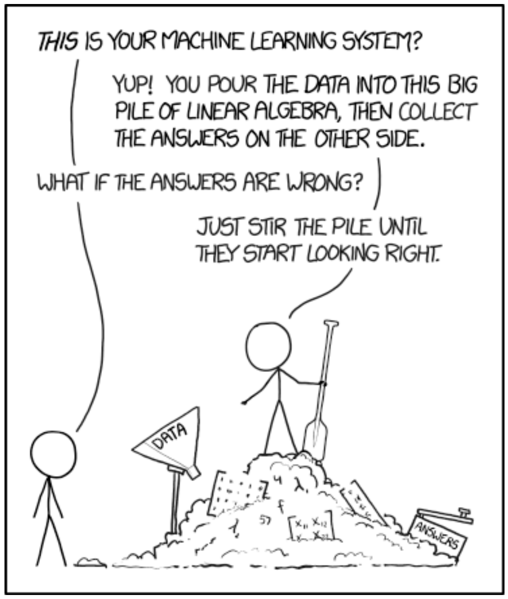


Figure 9: Image via XKCD

The machine learning process

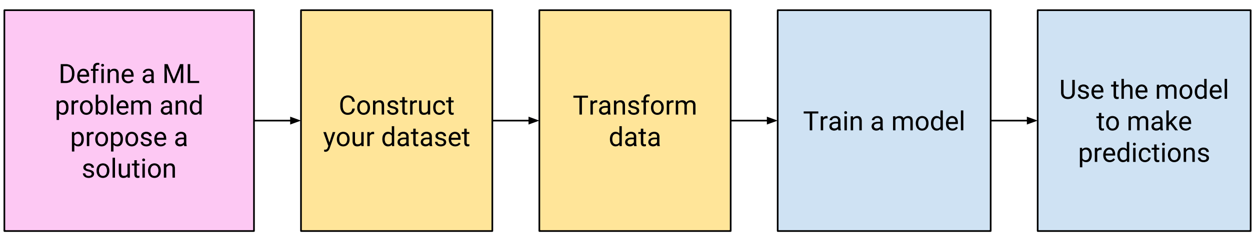


Figure 10: Image based on https://developers.google.com/machine-learning/

Challenges in ML design

- Acquiring and preparing data
- Choosing an appropriate model, and “hyperparameters”
- Designing a system that will *generalize* (not only to “test” data, but also in production)

Model gap, metric gap, algorithm gap

The model

The metric

- Example: how would you train an ML system to develop new recipes?

The algorithm