Machine Learning Techniques

ML vs Traditional Programming

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- Task 1: Adding two numbers:

$$12 + 45 = ?$$

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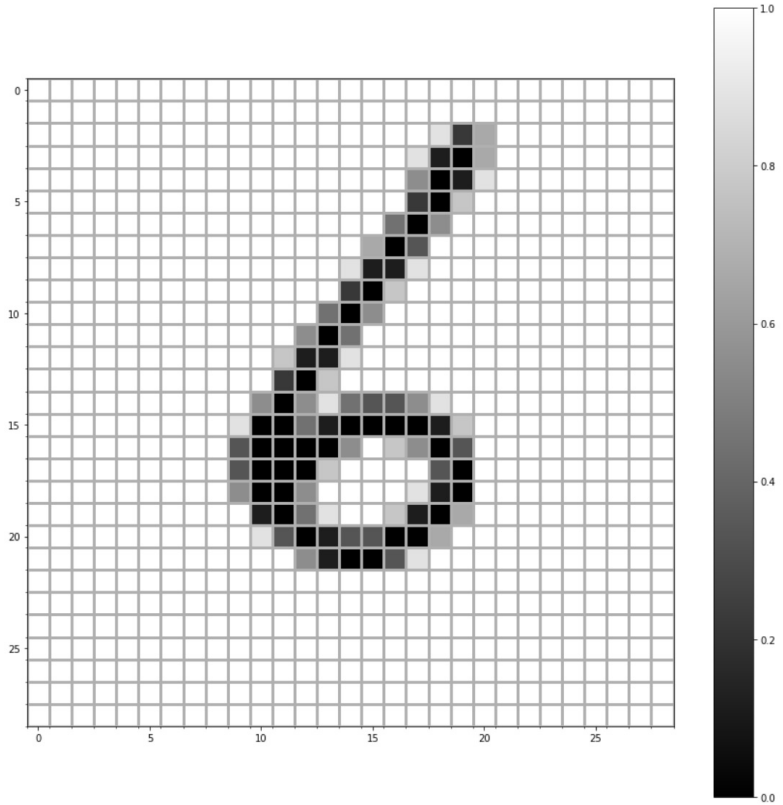

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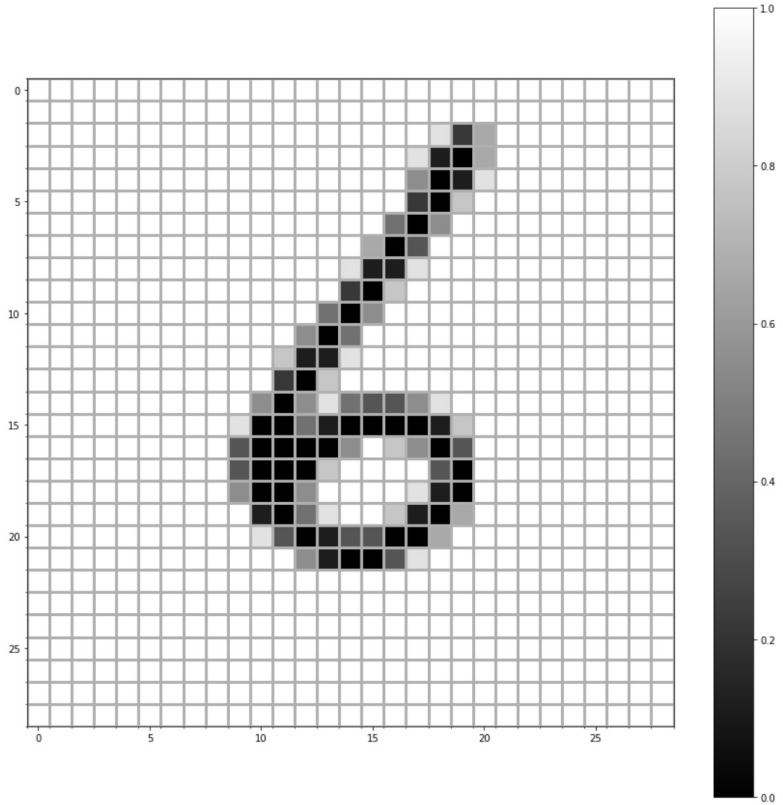

Which one is easier?

Image representation of a computer

How does a computer see an image?

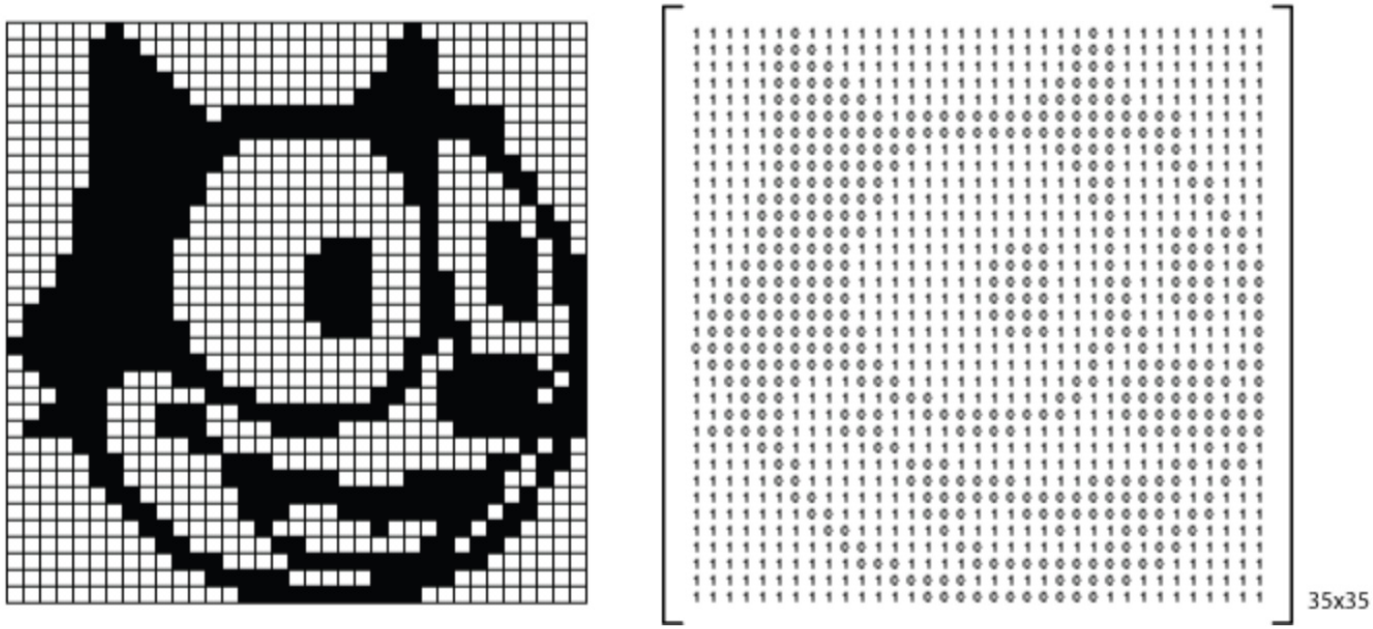

Image Source:uff.br

Adding Numbers

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$$12 + 45 = 57$$

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Solving the second task:

- Design a bunch of rules for solving this task, which seems like a reasonable approach.
- However, such rules are brittle and one can readily come up with examples that will break such a rule-based system.

What is a more robust way of solving this task?

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What makes the first task trivial and the second one tricky to program?

- Mathematical function for addition of two numbers, $c = a + b$, is ***already available!***
- In case of the second task of handwritten digit recognition, we ***do not have an exact mathematical function*** that takes an image as an input and outputs the recognized digit.
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Tasks solvable with ML

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How can we do that?

- Think, how do you recognize a digit from the image?
- You learnt this in school and since then, we have looked at many digits and have become better at the task.
- Can we replicate this process for computers?
- Can we train computers to recognize digits in this way?
- Maybe yes!

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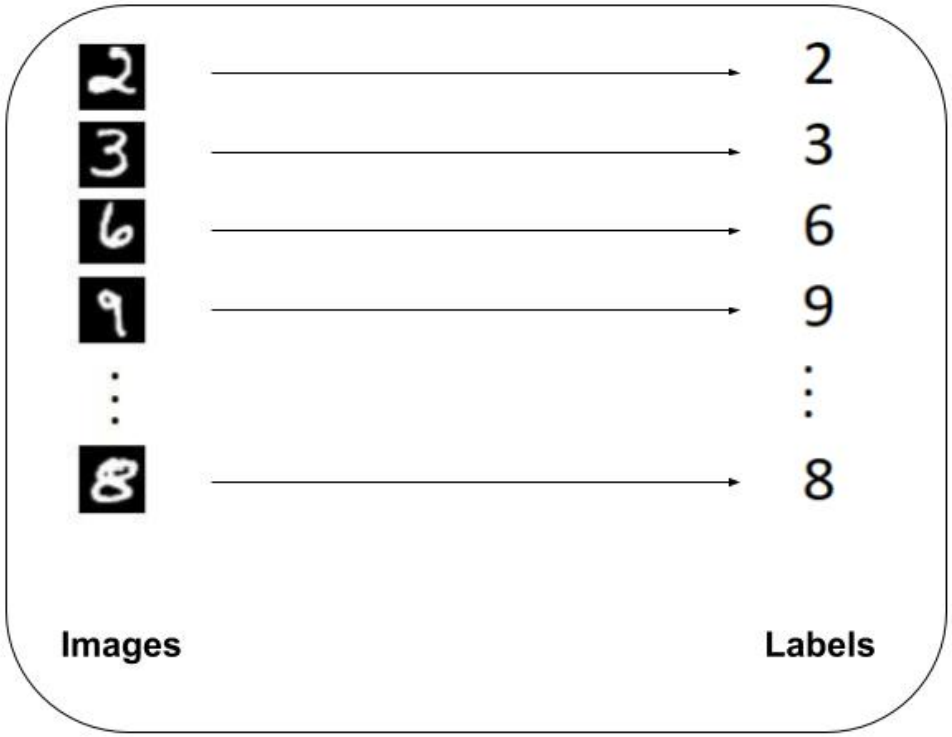
Training Data



Training Data

Model: Mathematical relationship

- Our job is to take this training data and uncover the mathematical relationship between pixels in the image and the label.
- For example, a simple linear relationship between pixels and labels is as following:

$$w_0 + w_1 \cdot pixel_1 + w_2 \cdot pixel2 + \cdots + w_m \cdot pixel_m$$

- Weights parameters: $w_0, w_1, w_2, \ldots, w_m$
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Finding parameters: Loss function

- Can these parameters be assigned some random numbers to get a model? Would that model be good enough? How do we measure it?
- **Loss function**: It measures disagreement between the actual outcome and the predicted outcome by applying the model to the input.
- The ideal set of parameters result in the minimum loss.
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Fundamental Assumption:Example of History test

- Students study history syllabus.
- Training data and test data are from the same distribution, if the teacher asks questions from this syllabus.
- If the questions are not from the syllabus - then training and test data do not come from the same distribution.
- Students perform better if the exam paper is based on the syllabus that they study or train on.
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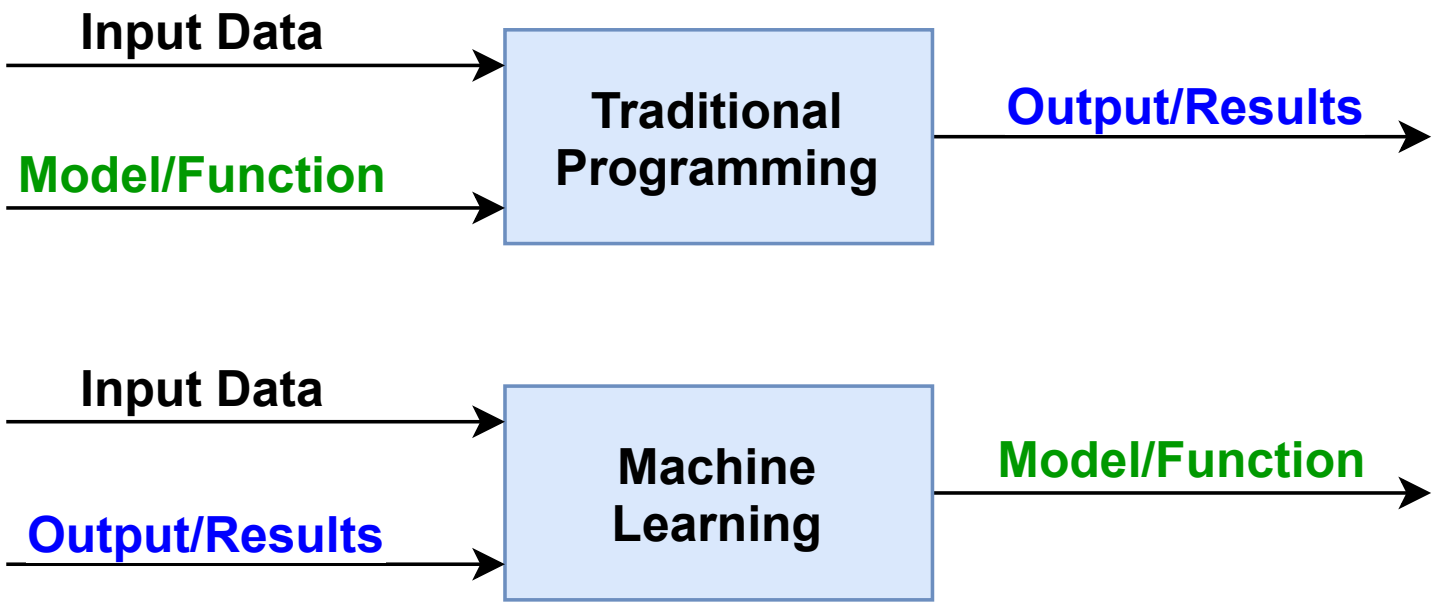

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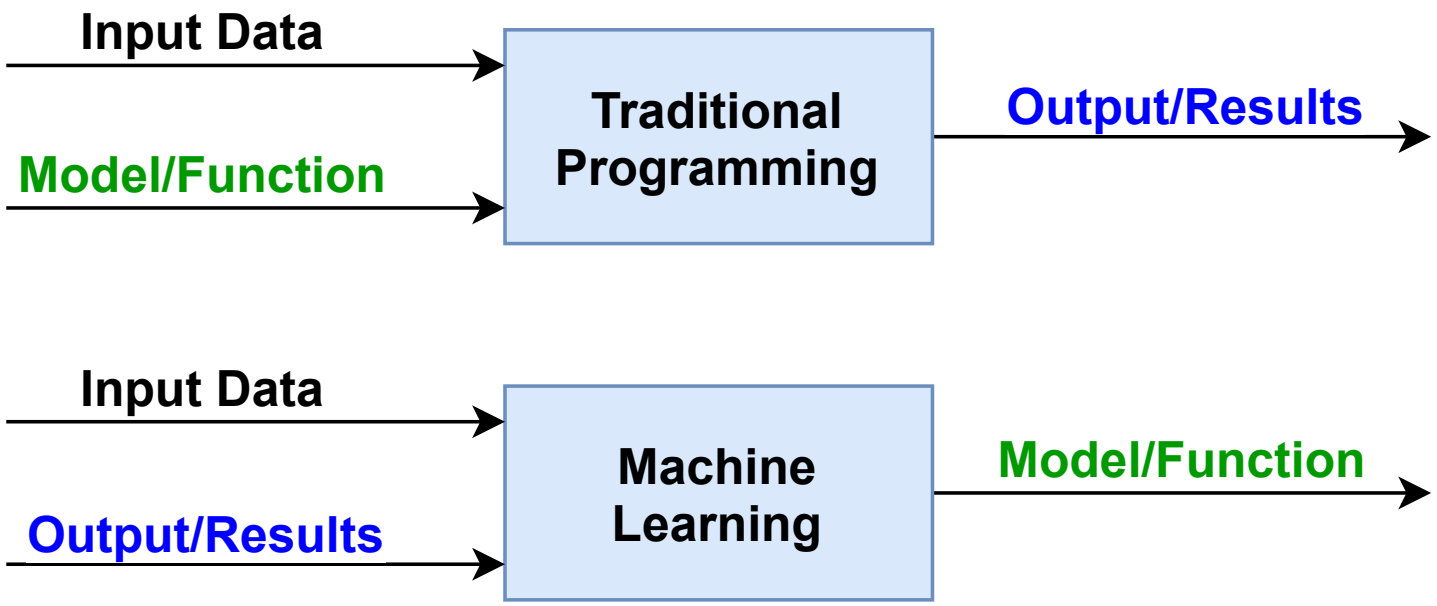

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