Big Data Computing

Master's Degree in Computer Science

2021-2022

SAPIENZA
UNIVERSITÀ DI ROMA

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Recap from Last Lecture(s)

2 unsupervised learning techniques to extract "structural" patterns from raw data

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- Formalized as an NP-hard optimization problem
- K-means and its variants as effective heuristics that work in practice

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Principal Component Analysis (PCA)

- Reduce data dimensionality
- Automatically extract features from raw data
- Resort to computing the eigenvectors and eigenvalues of the covariance matrix

SUPERVISED LEARNING

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- Example
  - Task/Problem: Find the maximum element of a list of 1 million unsorted numbers
  - Solution/Algorithm: Scan all the numbers in the set and keep track of the largest found "so far"
  - Code/Program: Encode the algorithm above into one specific programming language (e.g., C/C++, Java, Python)

Programming a Computer

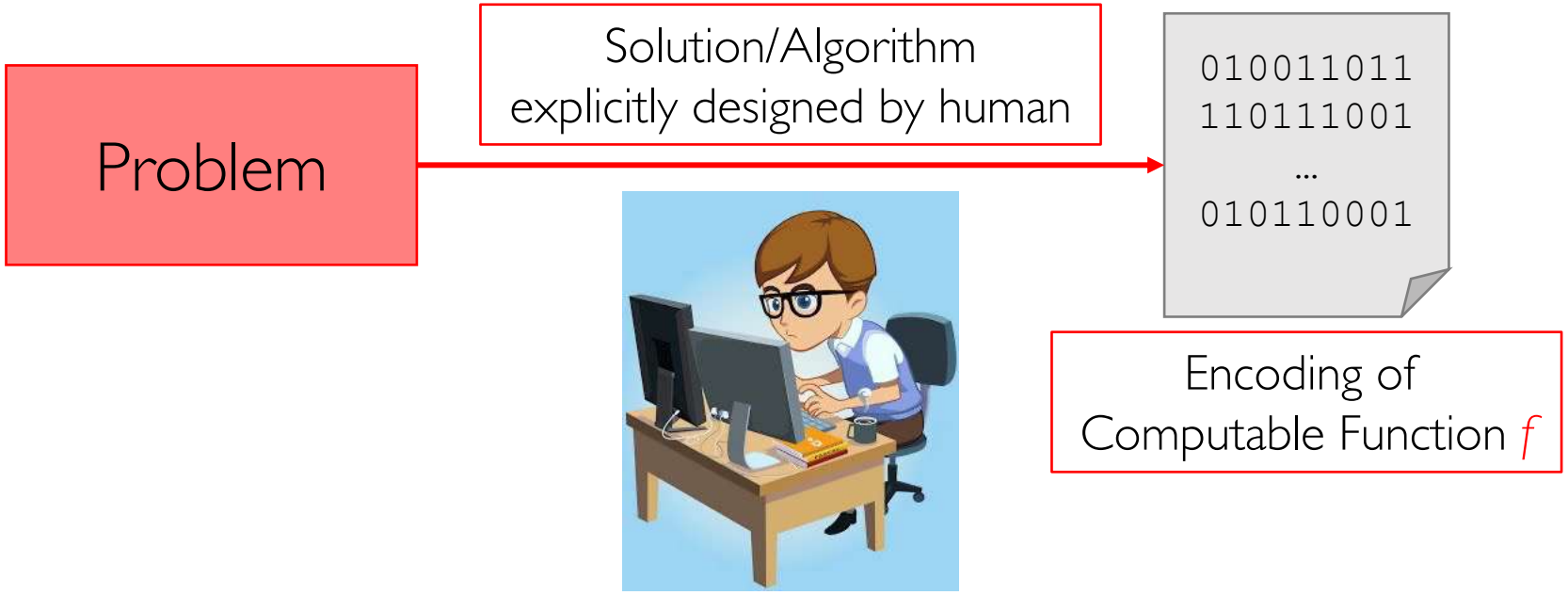
Problem

Programming a Computer

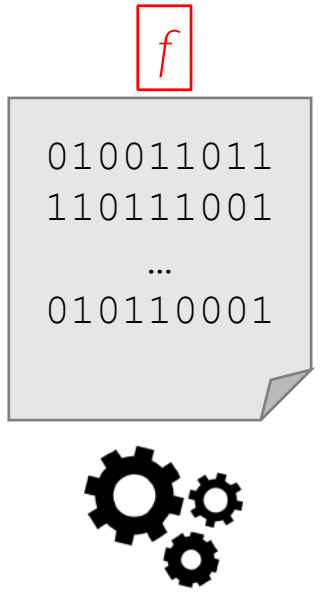
Problem

Solution/Algorithm
explicitly designed by human

Programming a Computer



Programming a Computer



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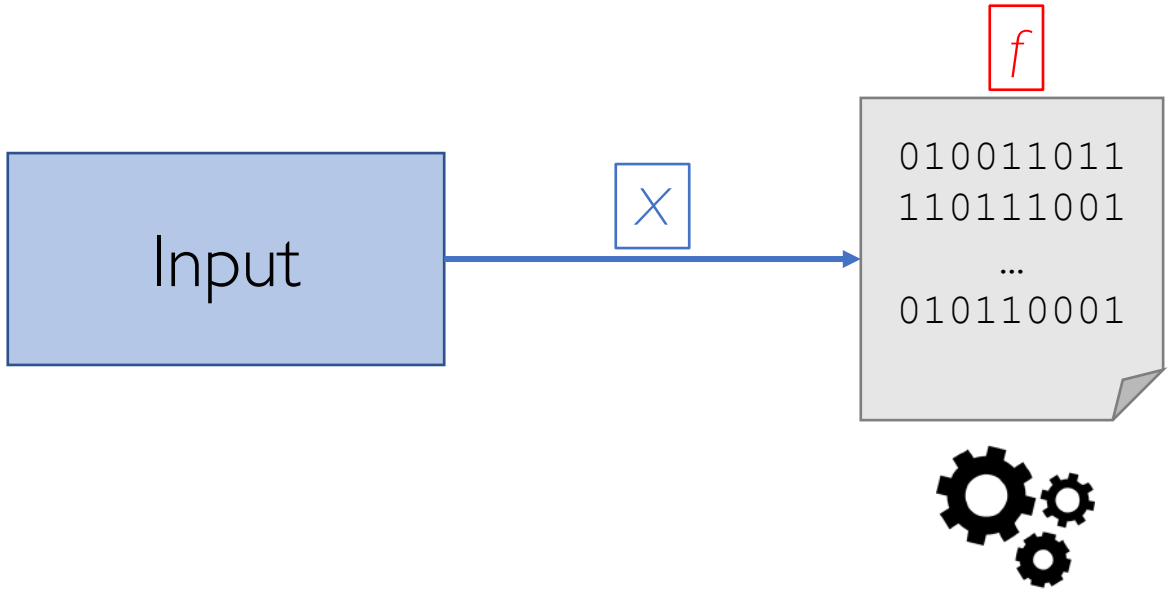

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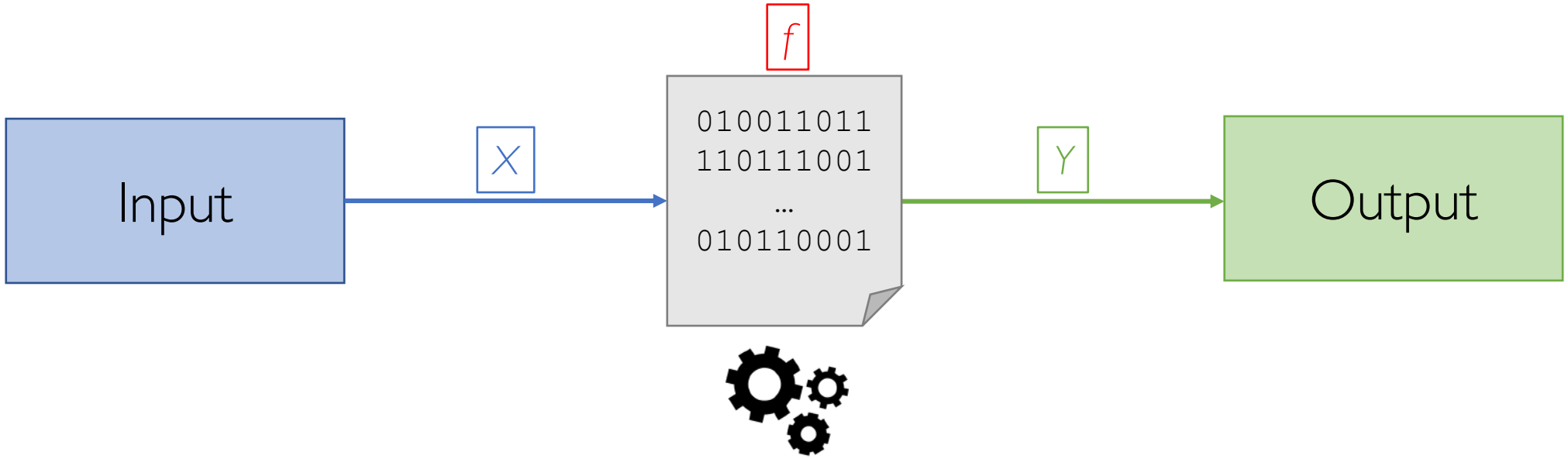

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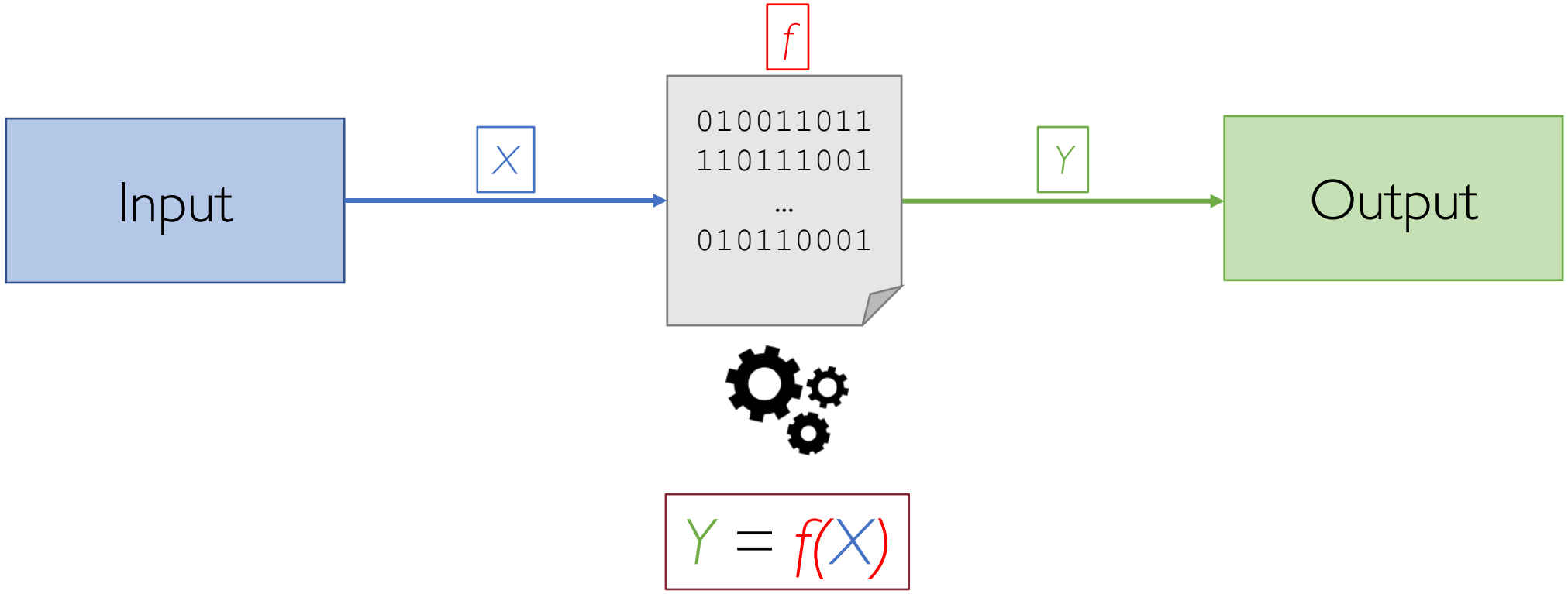


Can We Always Do That?

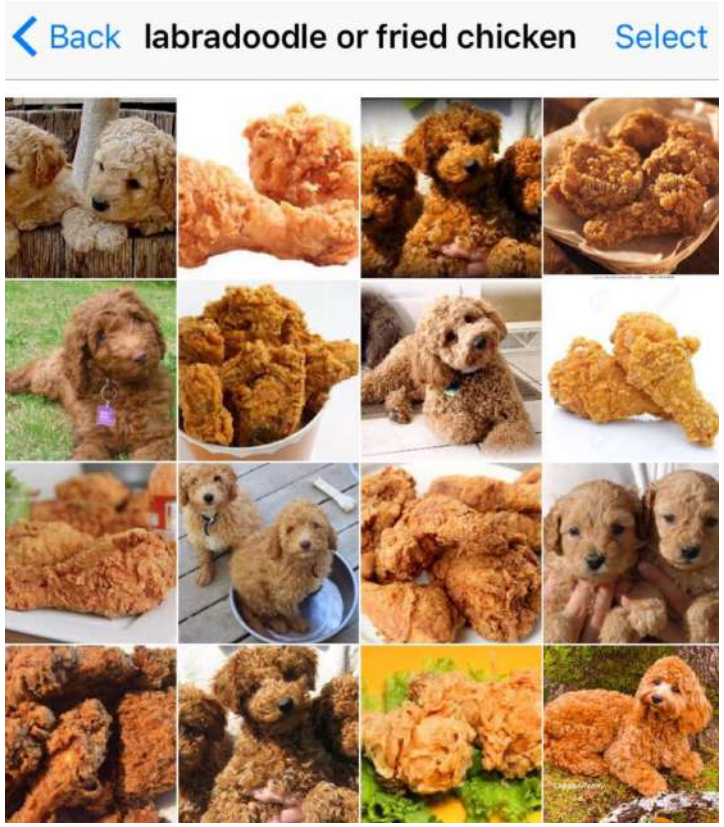
Chihuahua or Muffin?

[Copyright @teenybiscuit]

Chihuahua

Muffin

… And Lots More!



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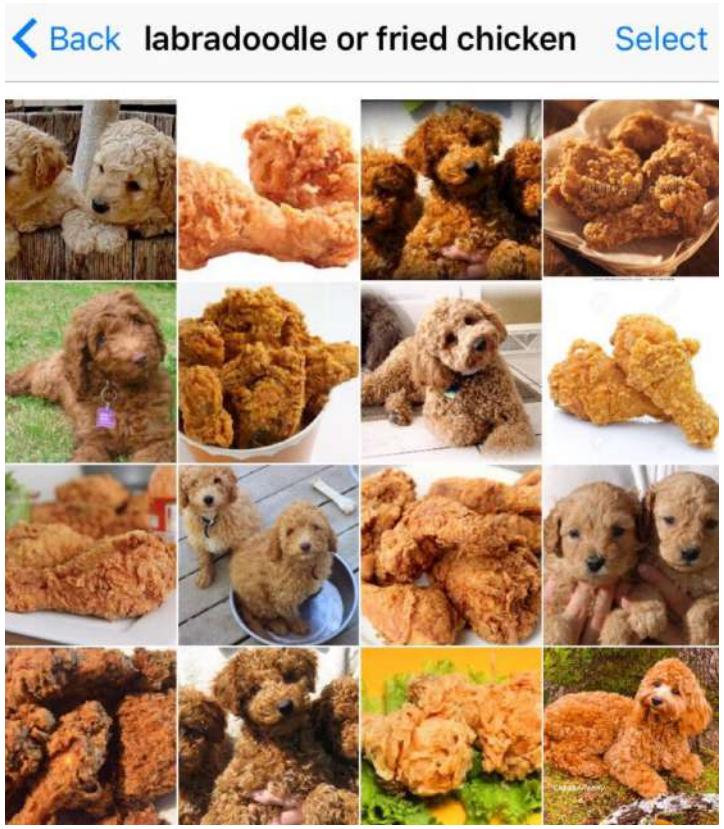

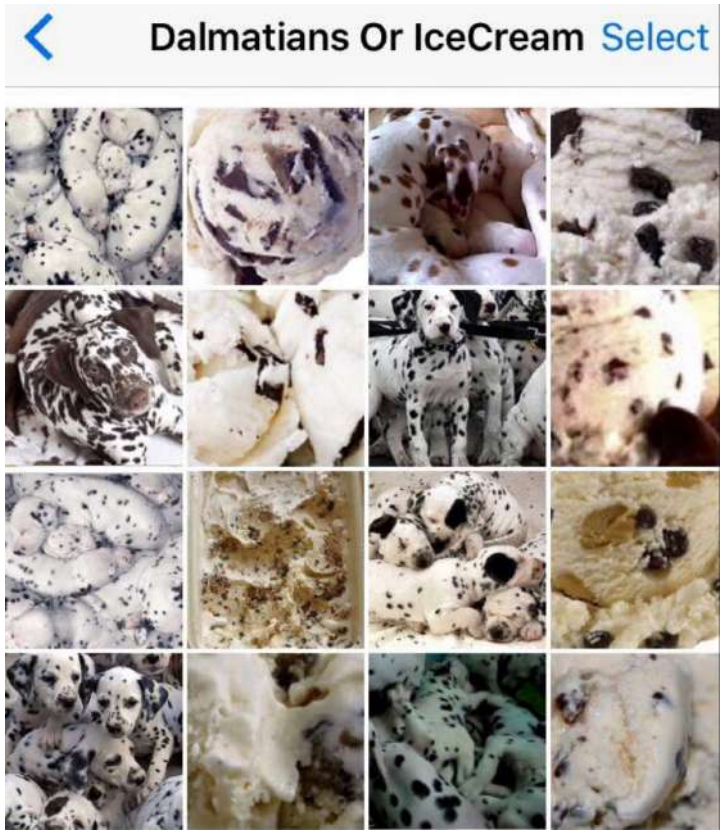

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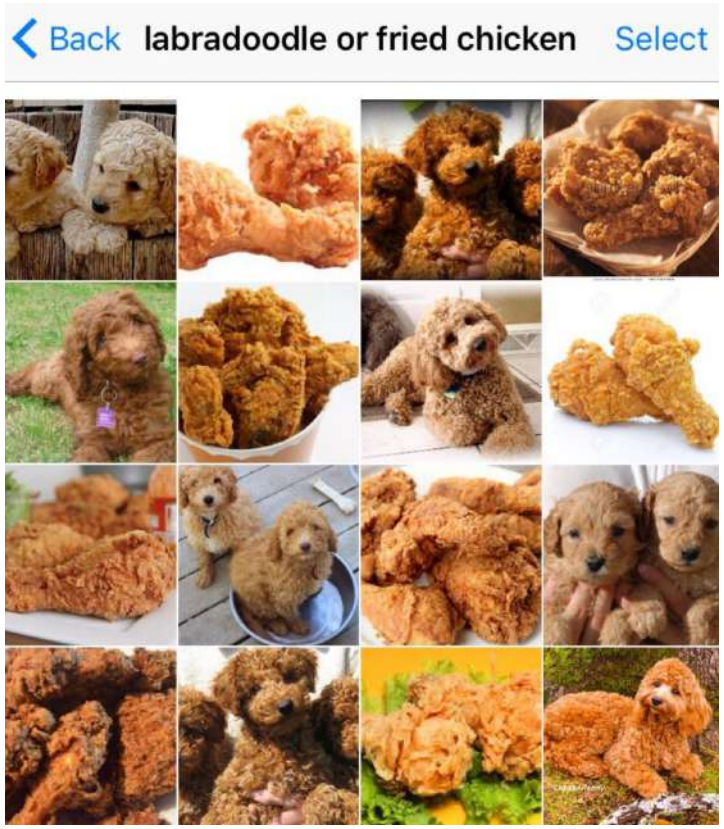

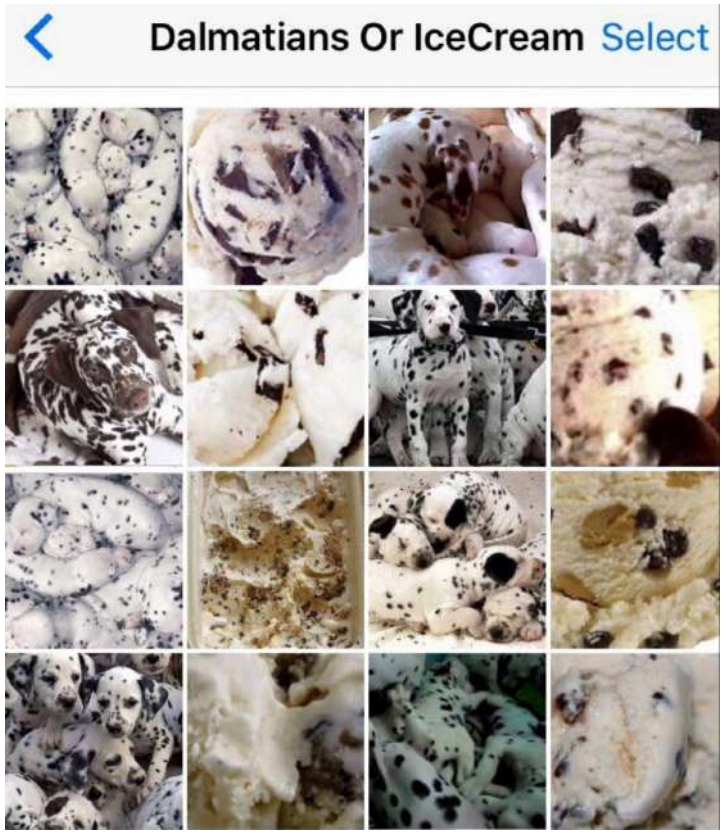

source: https://www.npr.org/sections/thesalt/2016/03/11/470084215/canine-or-cuisine-this-photo-meme-is-fetching?t=1648392960347

Programming vs. "Training" a Computer

- There exist some problems like the chihuahua vs. muffin above which are too hard to be solved directly

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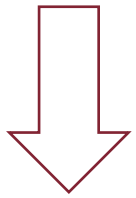


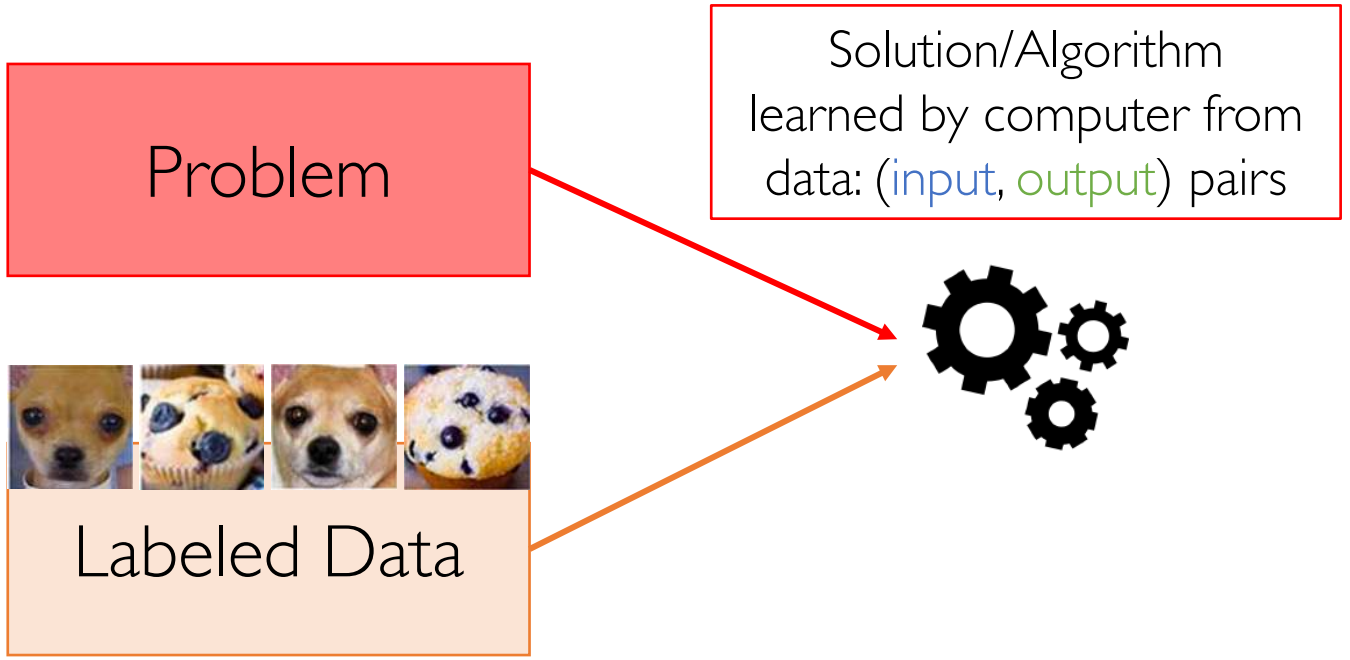
Programming vs. "Training" a Computer

"Training" a Computer

Problem

Labeled Data

"Training" a Computer



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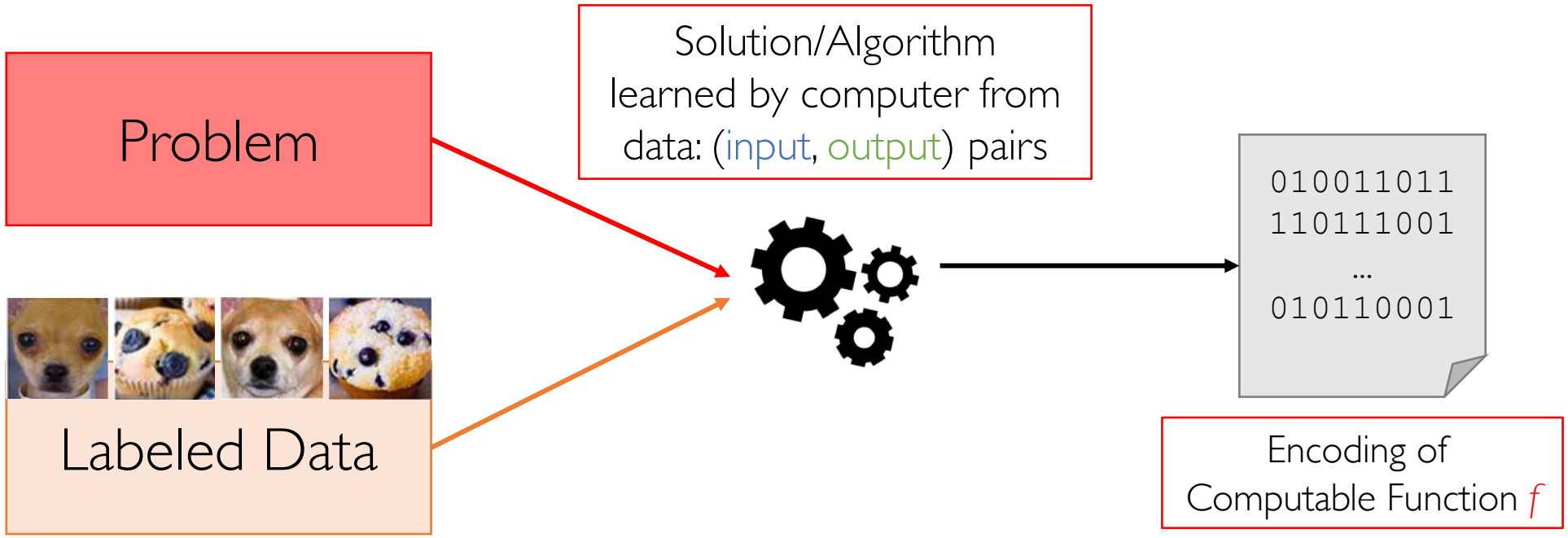

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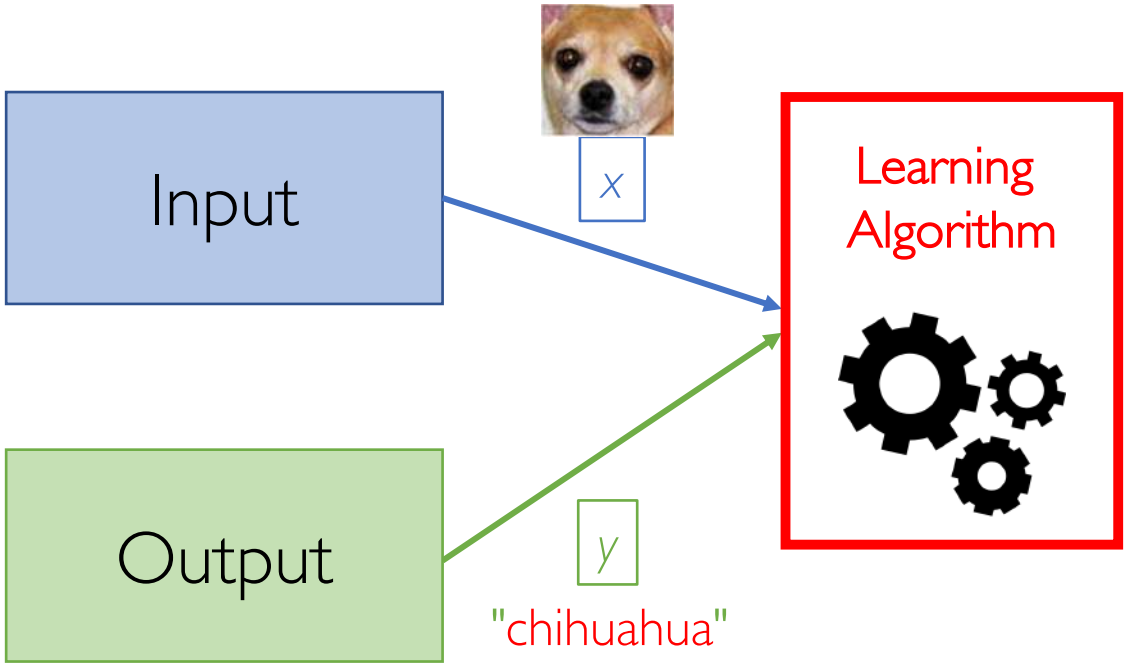

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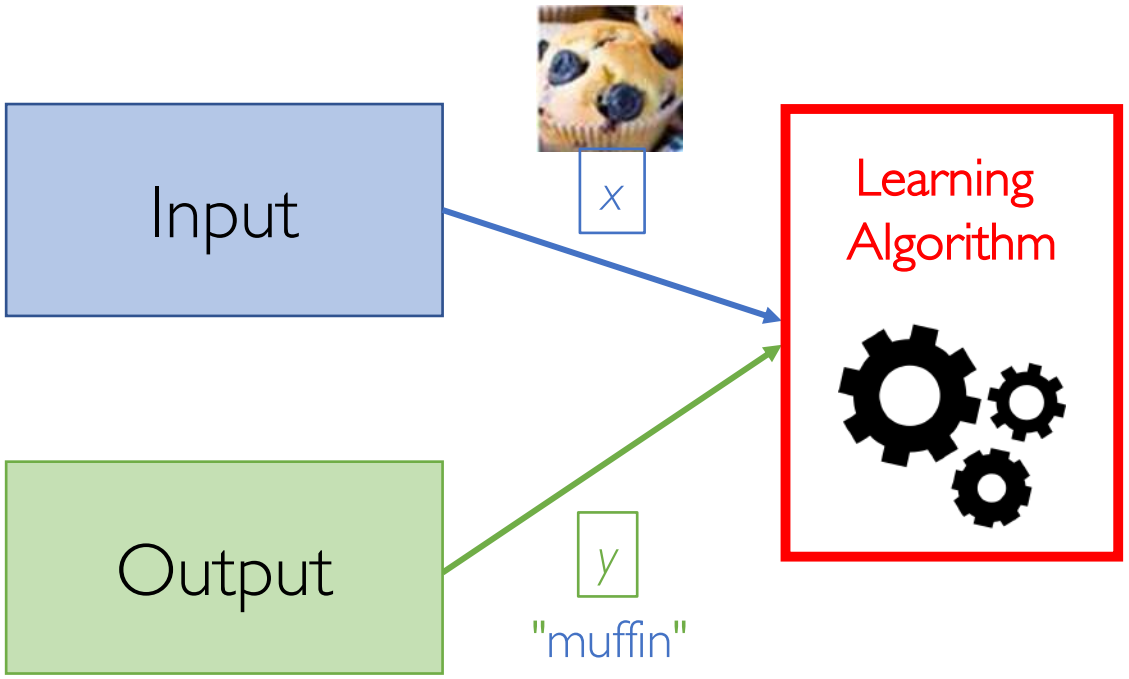

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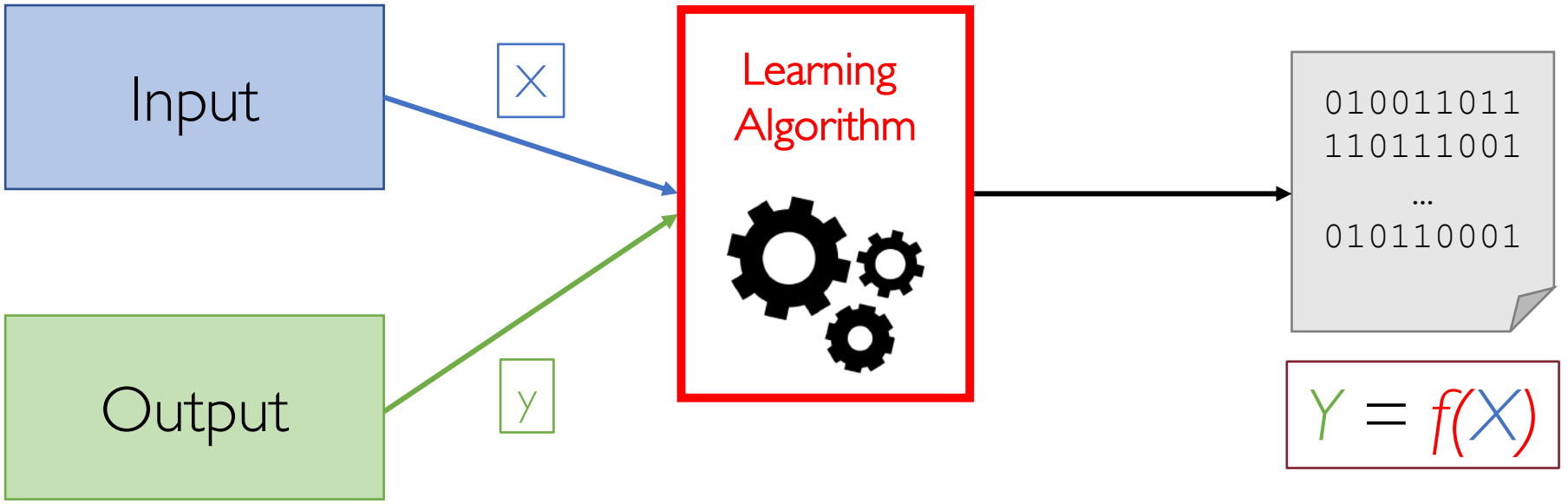

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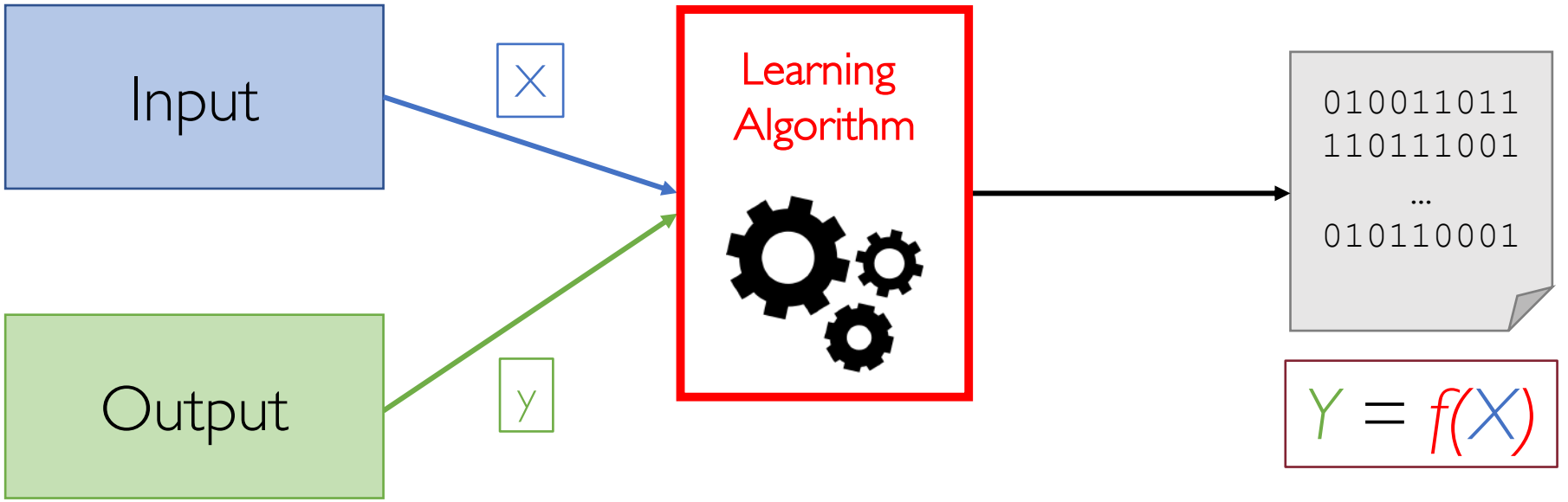

Eventually, the function *f* is learned by the learning algorithm from a (large) set of labeled data

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"*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: Taxonomy

Machine Learning

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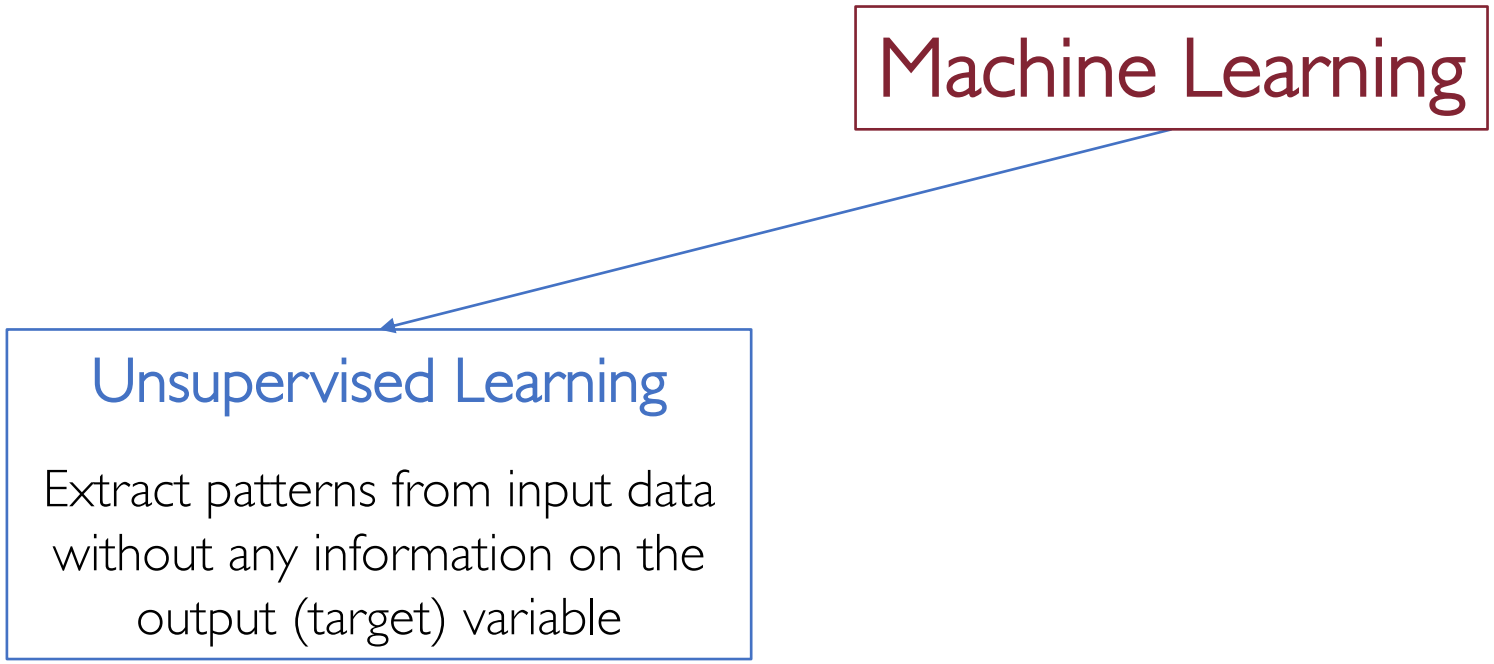

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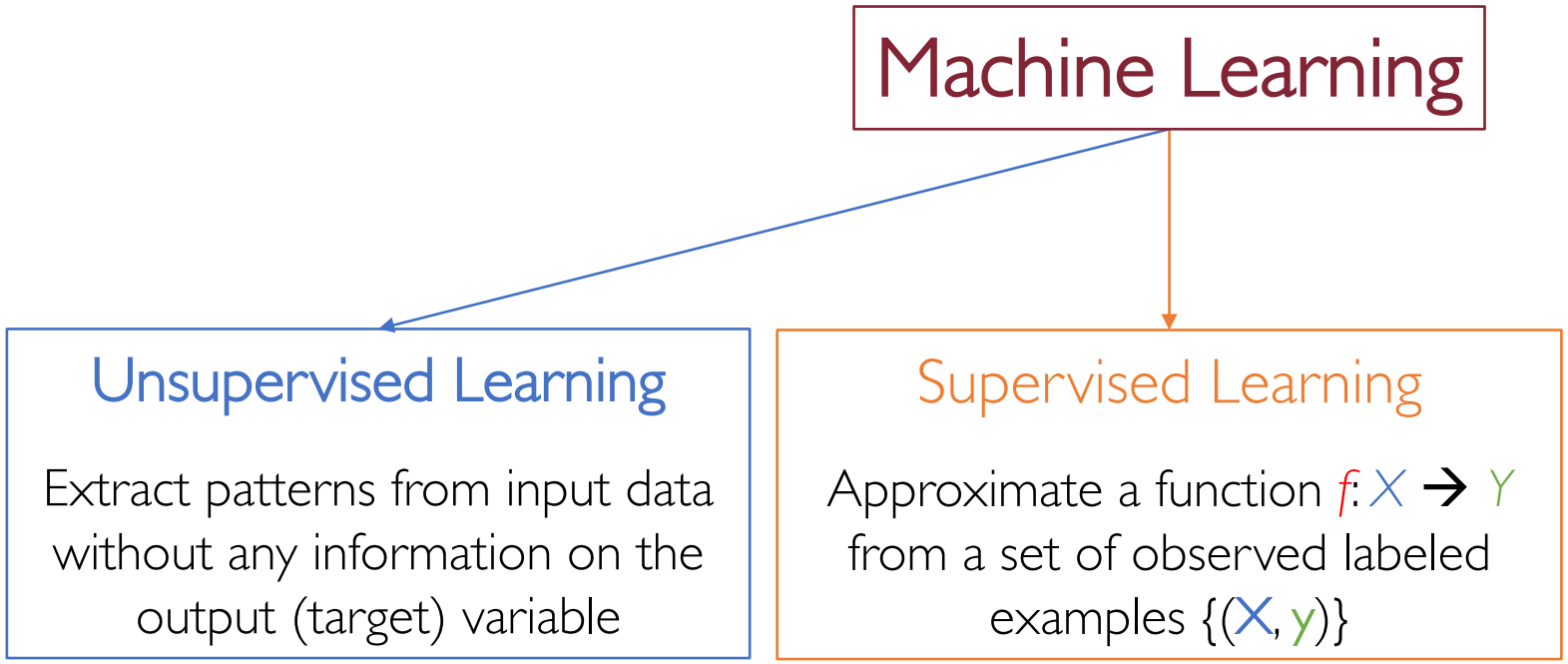

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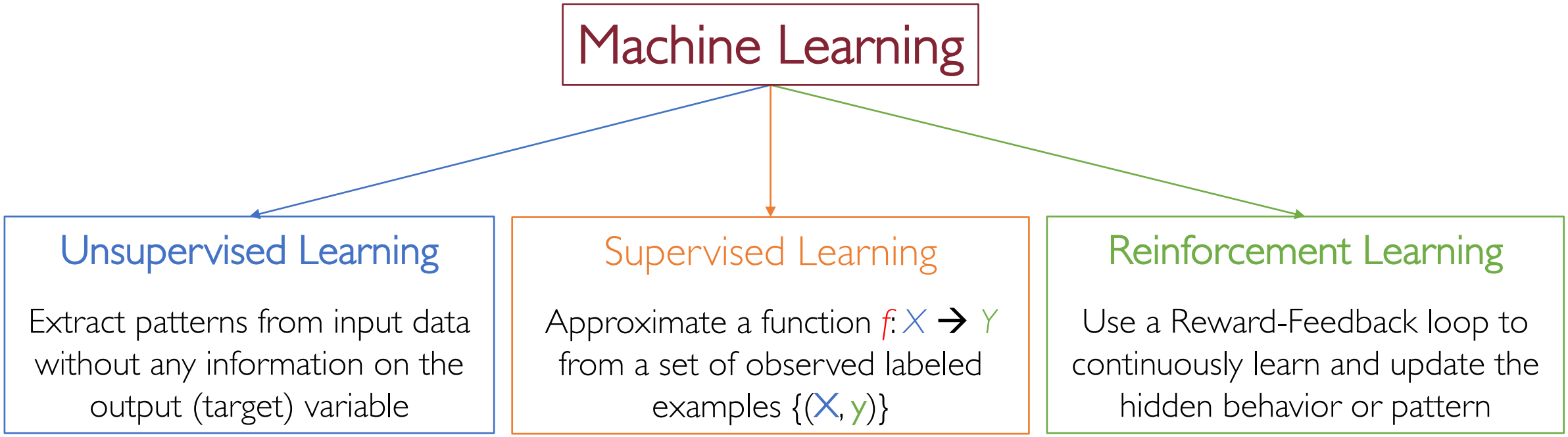

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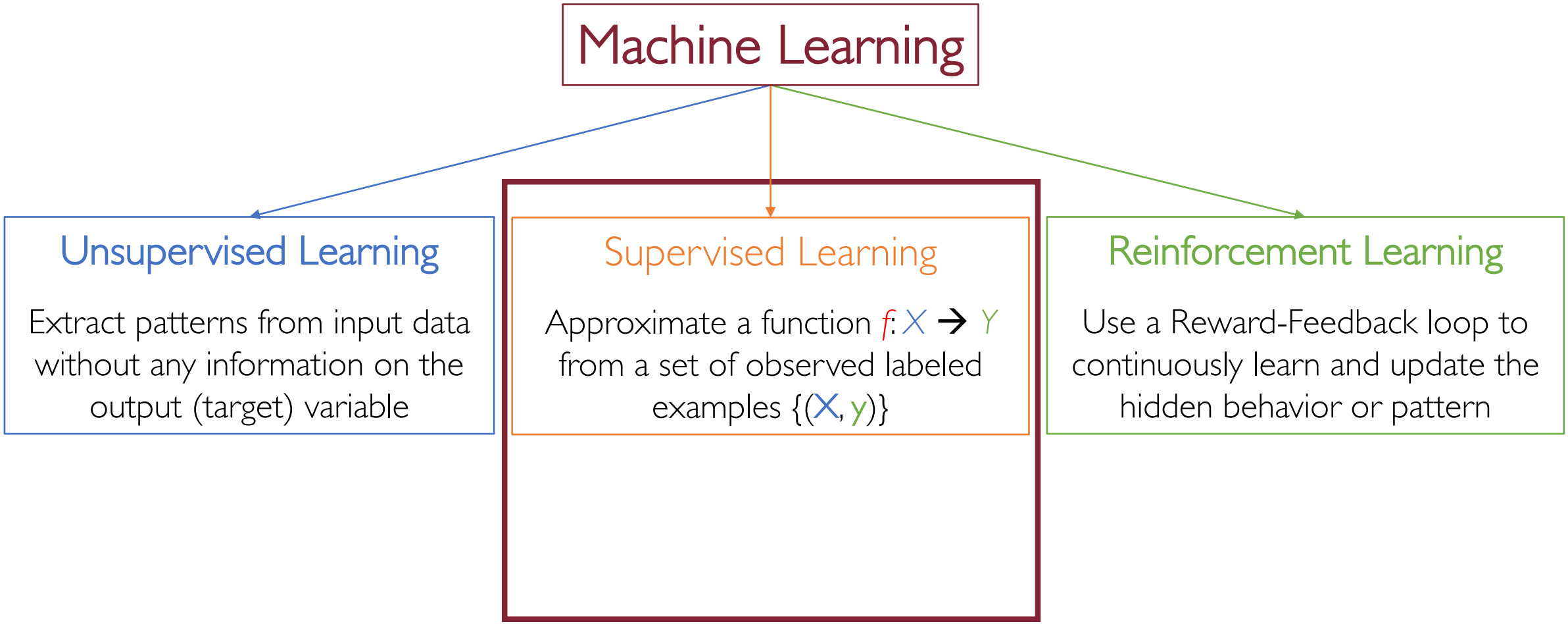

Supervised Learning: What Do We Predict?

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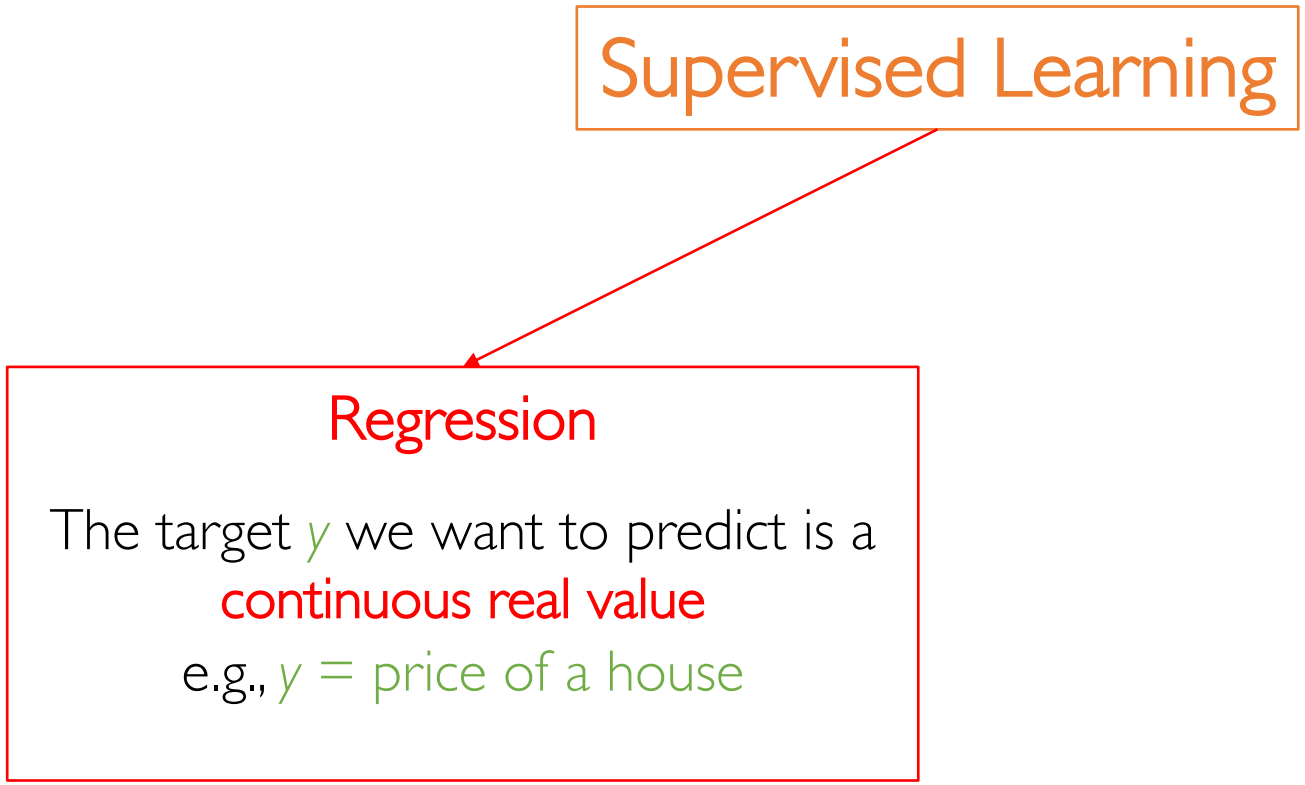

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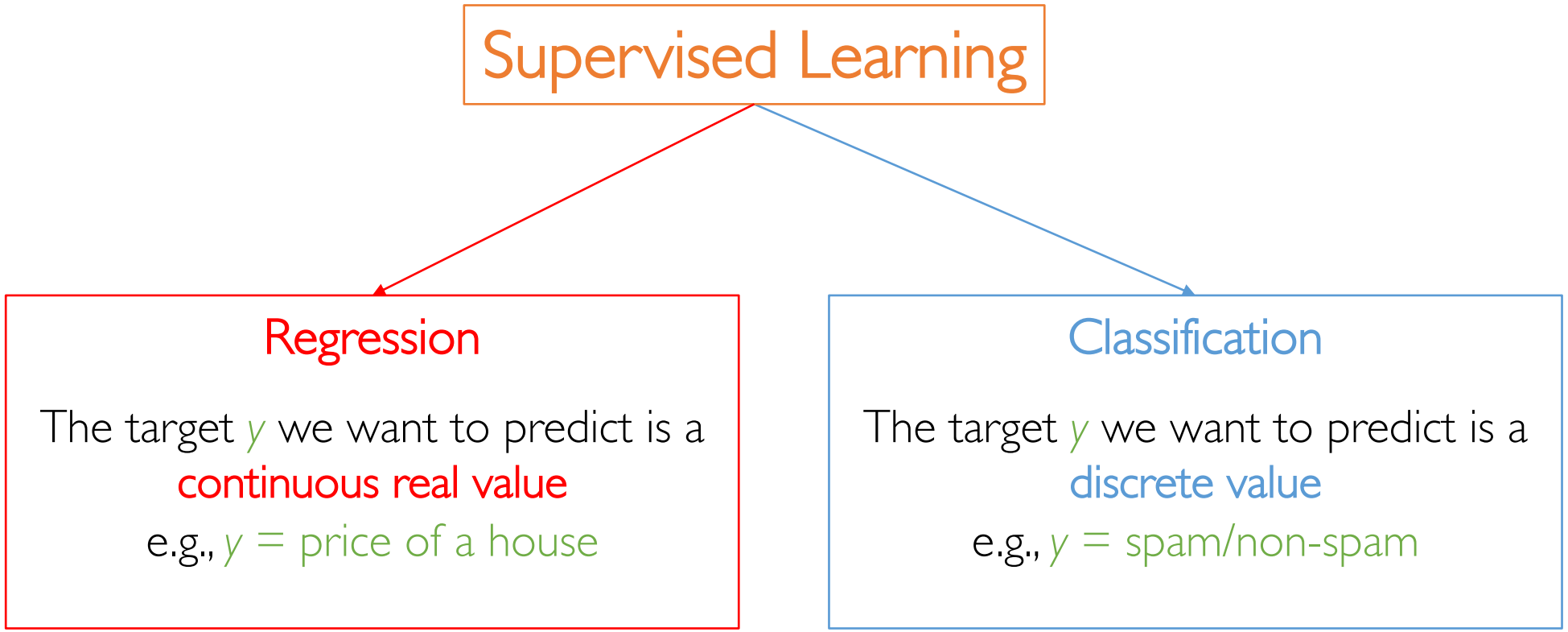

The Supervised Learning Pipeline

The Stages of Supervised Learning

0. Be sure your problem needs actually to be tackled using Machine Learning techniques

(i.e., there is no point in adopting any fancy ML solution if it can be solved "directly"!)

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4. **Model selection/evaluation:** pick the best-performing model according to some quality metrics

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- Supervised Learning requires labeled data which may be even harder to get
  - e.g., emails + spam/non-spam tags
- Might involve combining multiple and heterogeneous data sources

Feature Engineering

Domain Objects

Feature Engineering

Collected data need to be encoded with a machine-readable format

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Domain Objects

i-th object

0.27	3.8	1.12	…	4.75	…	…	56.9
0.0	3.65	0.04	…	6.81	…	…	1.0
…							
6.94	5.4	0.9	…	3.92	…	…	8.2

Each domain object is translated into a *n*-dimensional vector of features

Feature Engineering

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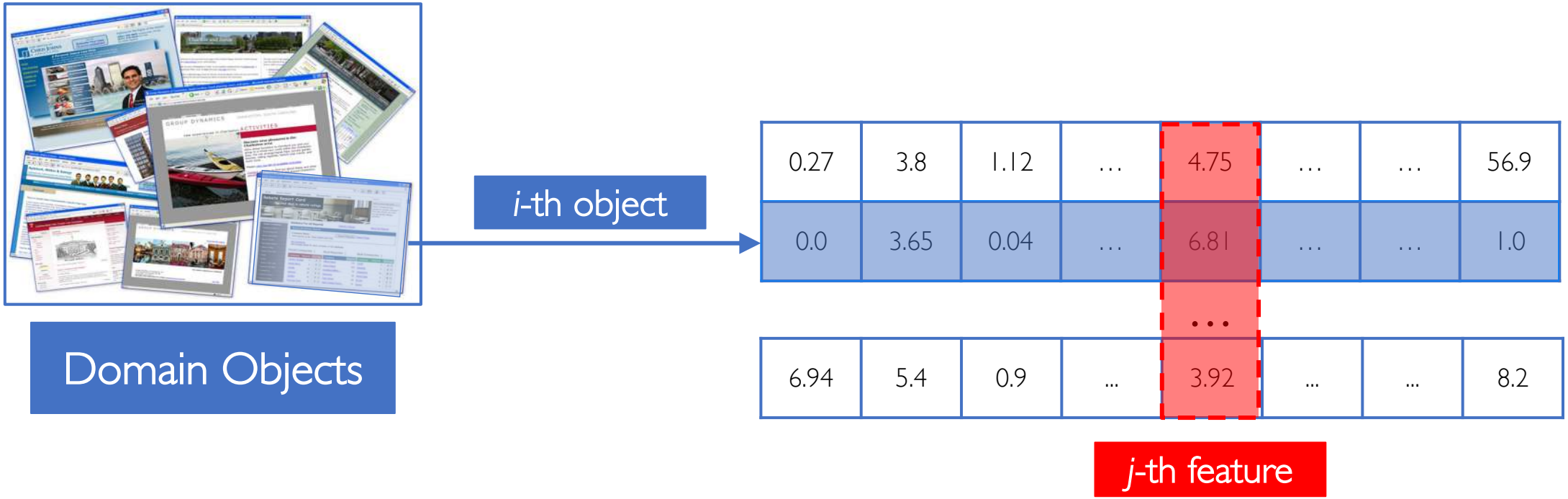

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  - e.g., **`number_of_bedrooms`** in the case our domain objects are "houses"
- Each feature can be either derived locally from an instance
  - e.g., **`annual_income`** of a person
- Or it can be the result of more complex computation involving the whole data collection
  - e.g., **`tf-idf`** of a word of a document w.r.t. a corpus

Feature Engineering

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- Require in-depth knowledge of the specific domain of application
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- Tedious and time-consuming process
- Techniques to **automatically** learn data representation (i.e., features):
  - K-means clustering, PCA, autoencoders (**unsupervised**)
  - Neural Networks (**supervised**)

Feature Engineering: Challenges and Solutions

Collected (raw) data is far from being perfect!

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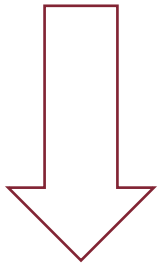

Data Preprocessing

Feature Engineering: Challenges and Solutions

Challenge	Description	
Missing values	A feature value may not be available for one or more instances	

Feature Engineering: Challenges and Solutions

Challenge	Description	Solution
Missing values	A feature value may not be available for one or more instances	Replace missing values with the **median** (continuous) or the **mode** (categorical) of the existing values

Feature Engineering: Challenges and Solutions

Challenge	Description	
Sparsity	Most of the instances contain just a small subset of the features	

Feature Engineering: Challenges and Solutions

Challenge	Description	Solution
Sparsity	Most of the instances contain just a small subset of the features	Use "sparse-friendly" data structures (e.g., DOK)

Feature Engineering: Challenges and Solutions

Challenge	Description	
Outliers	One or more instances have out-of-range values for one or more features	

Feature Engineering: Challenges and Solutions

Challenge	Description	Solution
Outliers	One or more instances have out-of-range values for one or more features	Retention vs. Exclusion (*trimming* or *winsorising*)

Feature Engineering: Challenges and Solutions

Challenge	Description	
Mix of continuous and discrete values	Feature set contains both numerical and categorical values	

Feature Engineering: Challenges and Solutions

Challenge	Description	Solution
Mix of continuous and discrete values	Feature set contains both numerical and categorical values	Transform categorical features using *one-hot encoding*

Feature Engineering: Challenges and Solutions

Challenge	Description	
Multiple feature magnitudes	Feature set contains very wide range of values	

Feature Engineering: Challenges and Solutions

Challenge	Description	Solution
Multiple feature magnitudes	Feature set contains very wide range of values	Standardization (min-max, z-scores)

Feature Engineering: Challenges and Solutions

Challenge	Description	
Class imbalance	Instances labeled with the class of interest represents a tiny fraction of the total	

Feature Engineering: Challenges and Solutions

Challenge	Description	Solution
Class imbalance	Instances labeled with the class of interest represents a tiny fraction of the total	Over-/Under-sampling, cost-sensitive learning

Feature Engineering: Challenges and Solutions

Challenge	Description	
Strong multicollinearity	Linear relationship between one or more features	

Feature Engineering: Challenges and Solutions

Challenge	Description	Solution
Strong multicollinearity	Linear relationship between one or more features	Dimensionality reduction (PCA)