Warming-up to Machine Learning, Data and Features

CS771: Introduction to Machine Learning

Piyush Rai

Plan for today

- Types of ML problems
- Typical workflow of ML problems
- Various perspectives of ML problems
- Data and Features
- Some basic operations of data and features

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In Machine Learning, generalization performance on the test data matters

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Plus, of course, issues such as fairness

In Machine Learning, generalization performance on the test data matters

A Loose Taxonomy of ML

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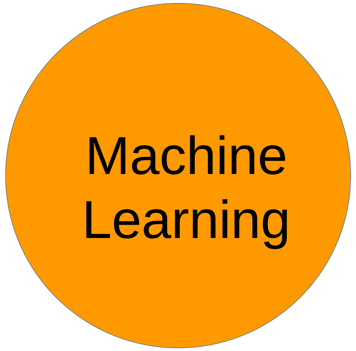

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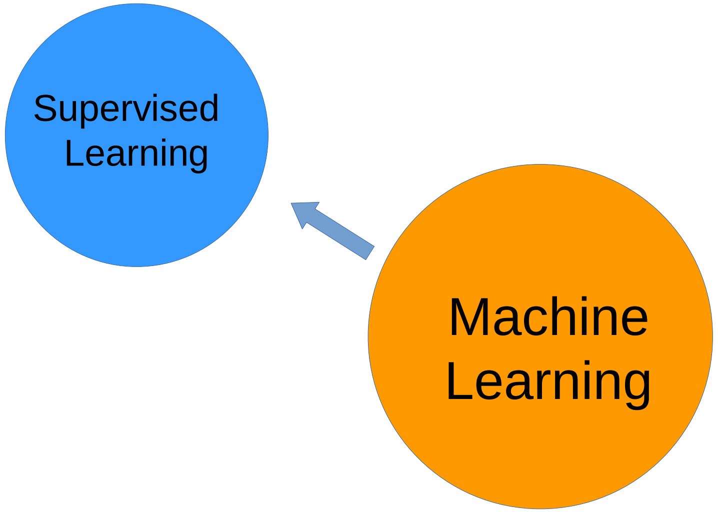

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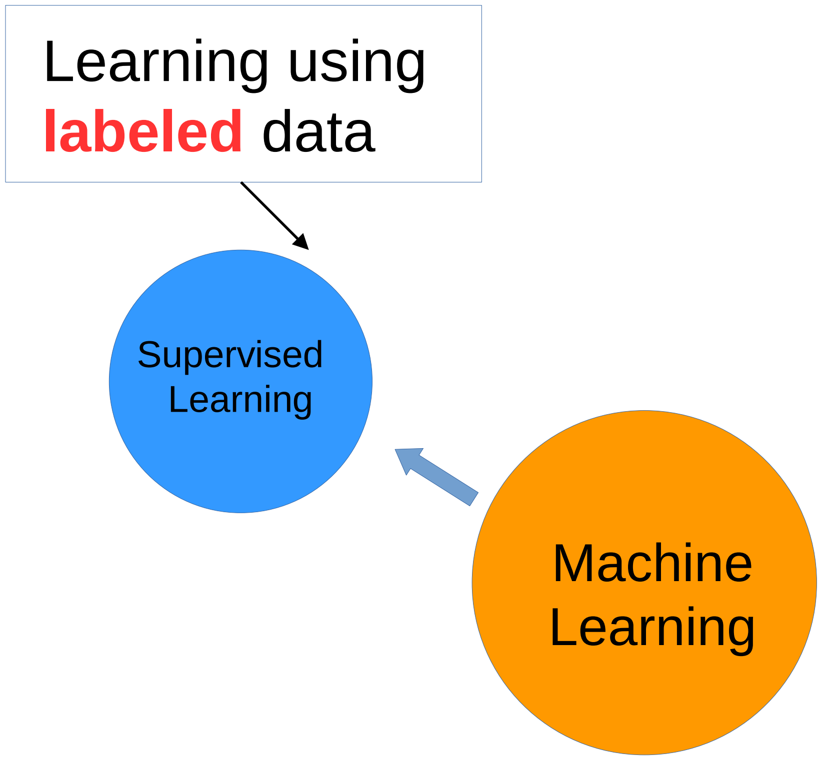

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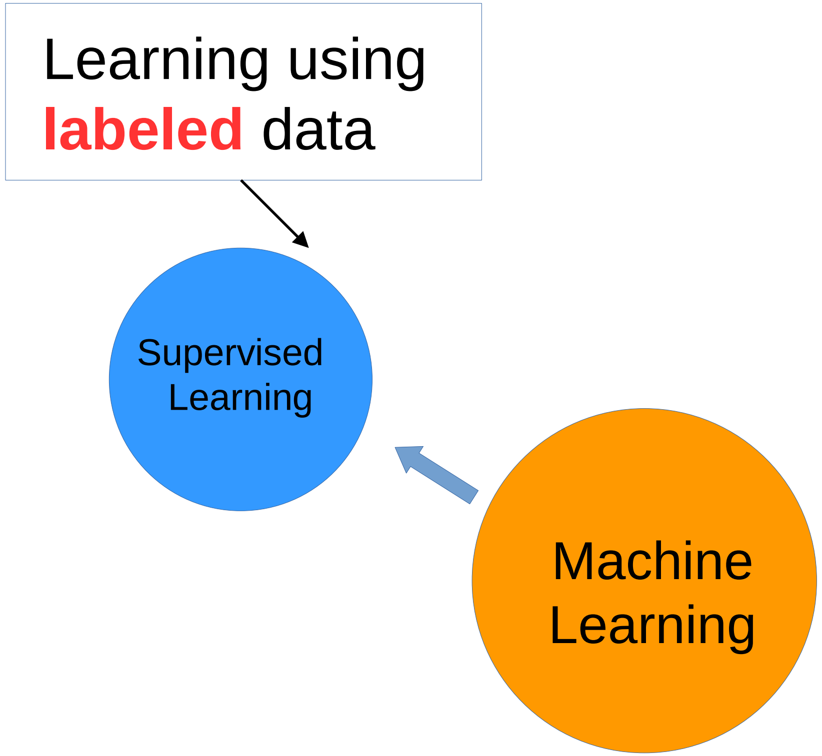

"Labeled" means, during training, for each input, the corresponding output is available (i.e., the machine learner is explicitly told that a cat image is of a cat)

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Learning using **labeled** data

Some examples of supervised learning problems

- Classification
- Regression
- Ranking

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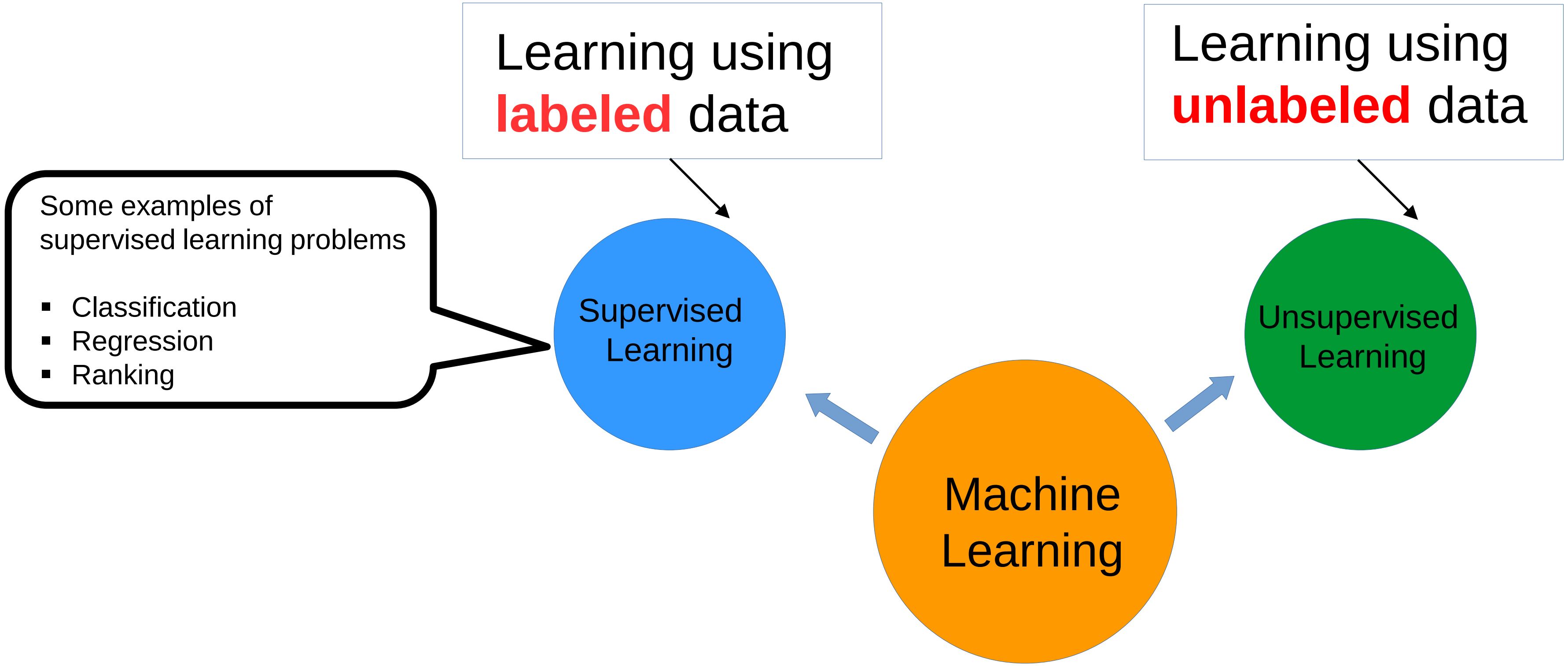

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- Dimensionality Reduction
- Unsupervised Probability Density Estimation

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RL doesn’t use “labeled” or “unlabeled” data in the traditional sense! In RL, an agent learns via its interactions with an environment

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Some examples of unsupervised learning problems

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Many other specialized flavors of ML also exist, some of which include

- Semi-supervised Learning
- Active Learning
- Transfer Learning
- Multitask Learning
- Imitation Learning (somewhat related to RL)
- Zero-Shot Learning
- Few-Shot Learning
- Continual learning

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Labeled Training Data

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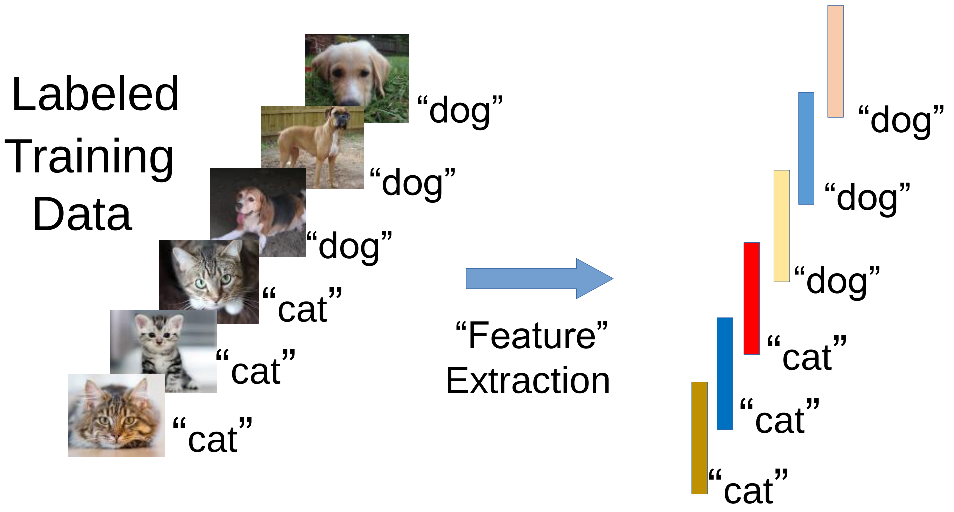

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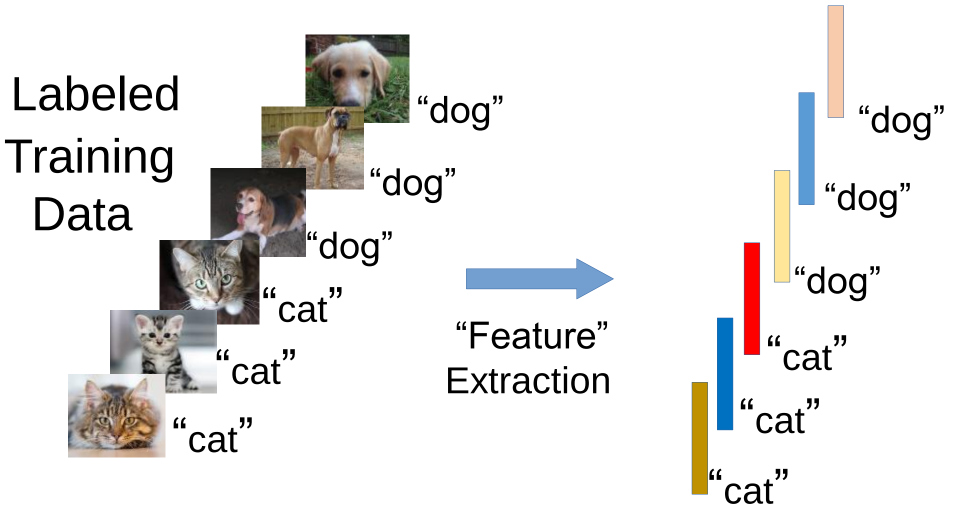

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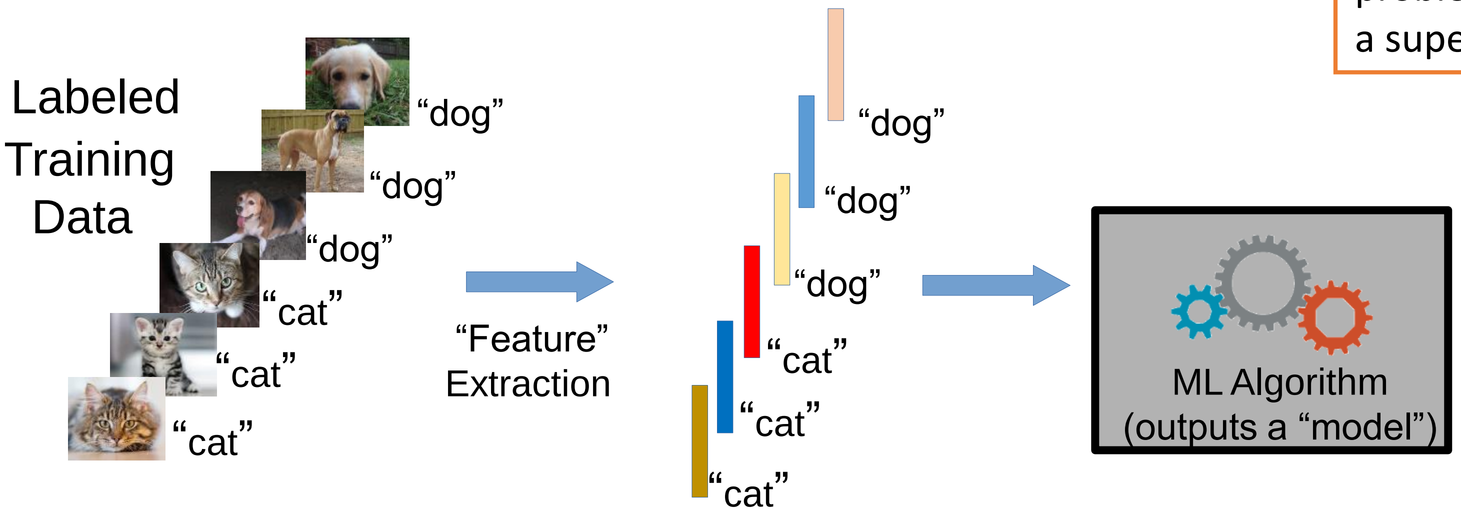

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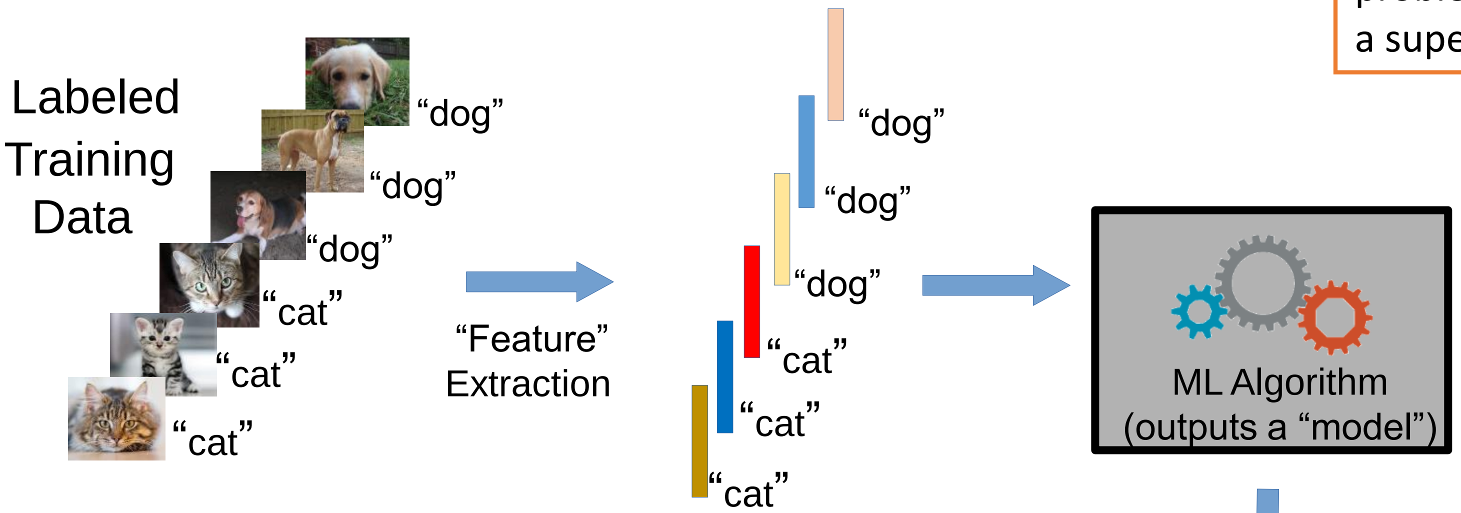

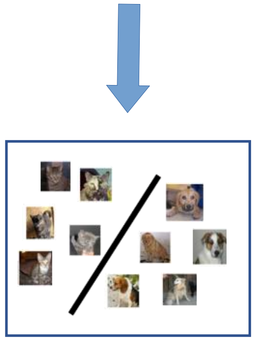

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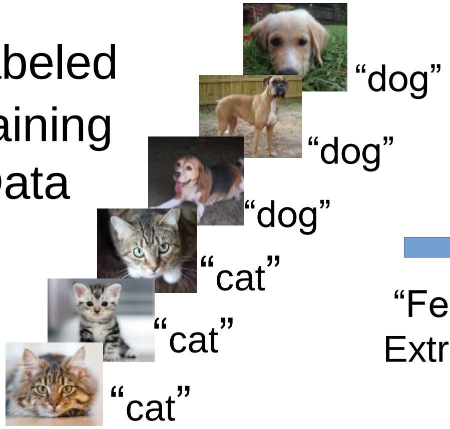
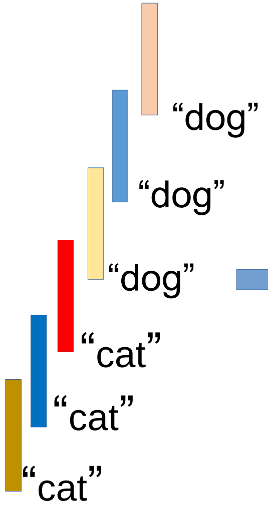


"Feature" Extraction



ML Algorithm (outputs a "model")

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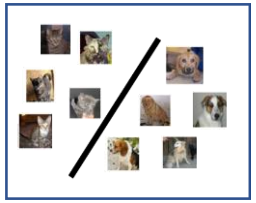
Test Image



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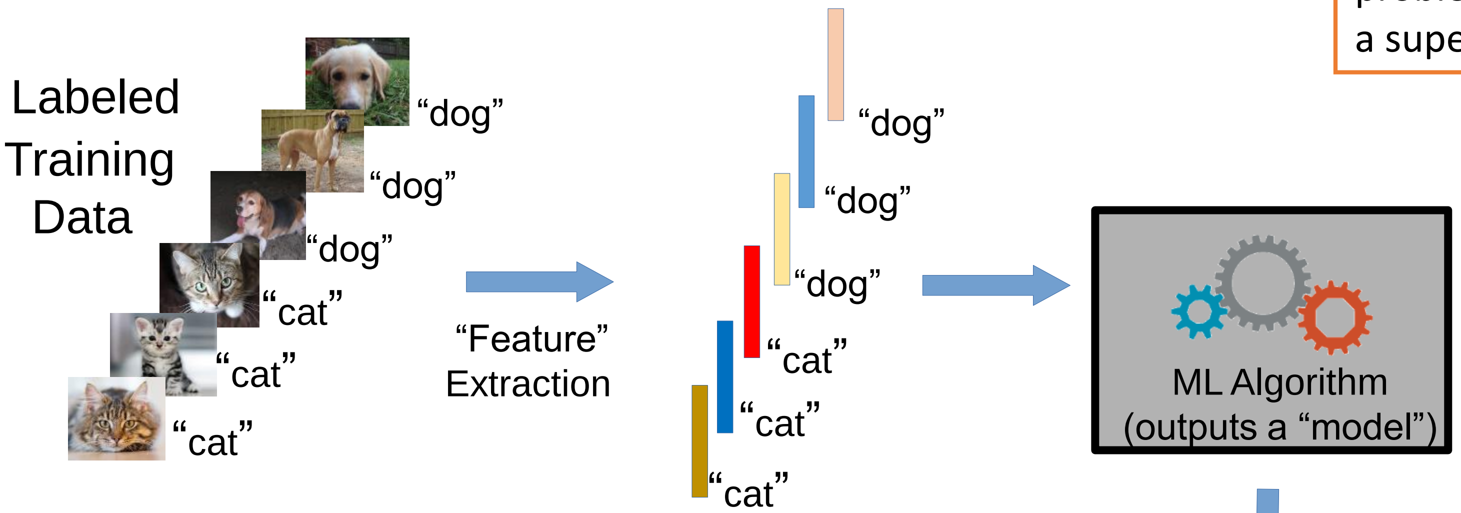

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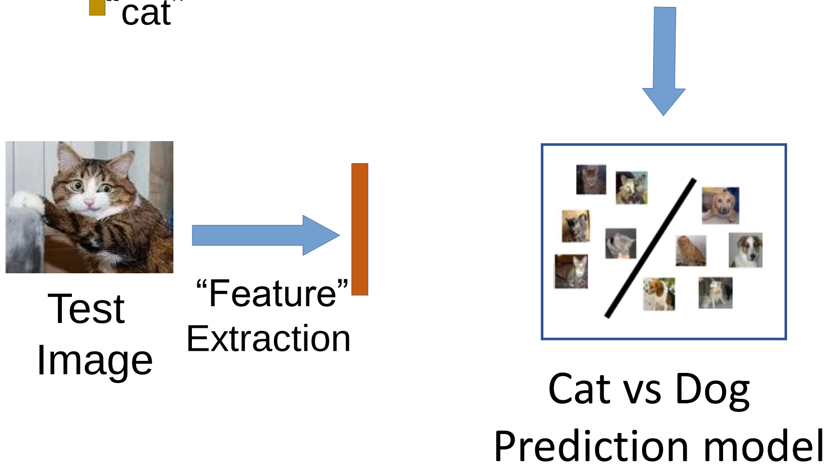

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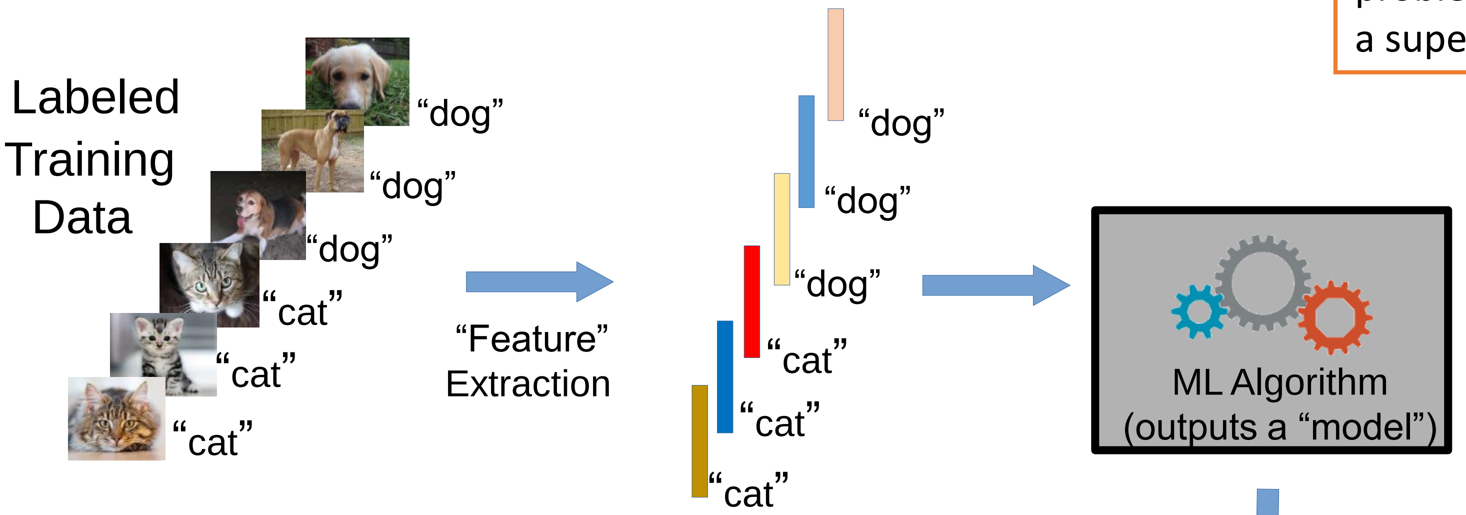

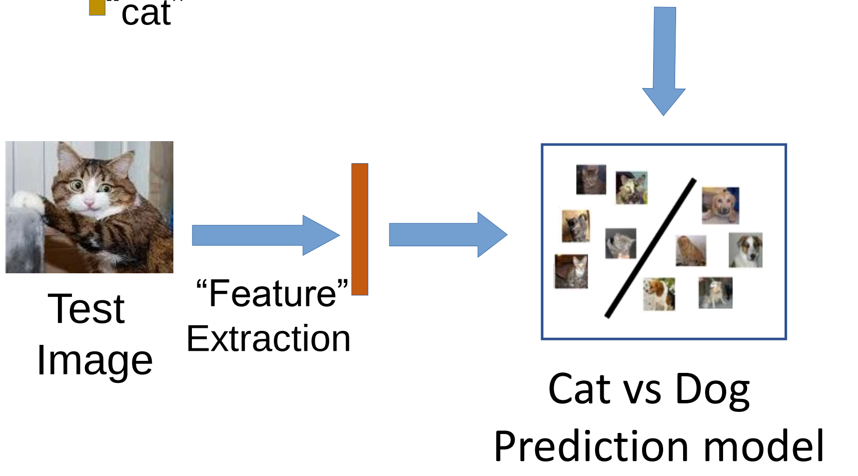

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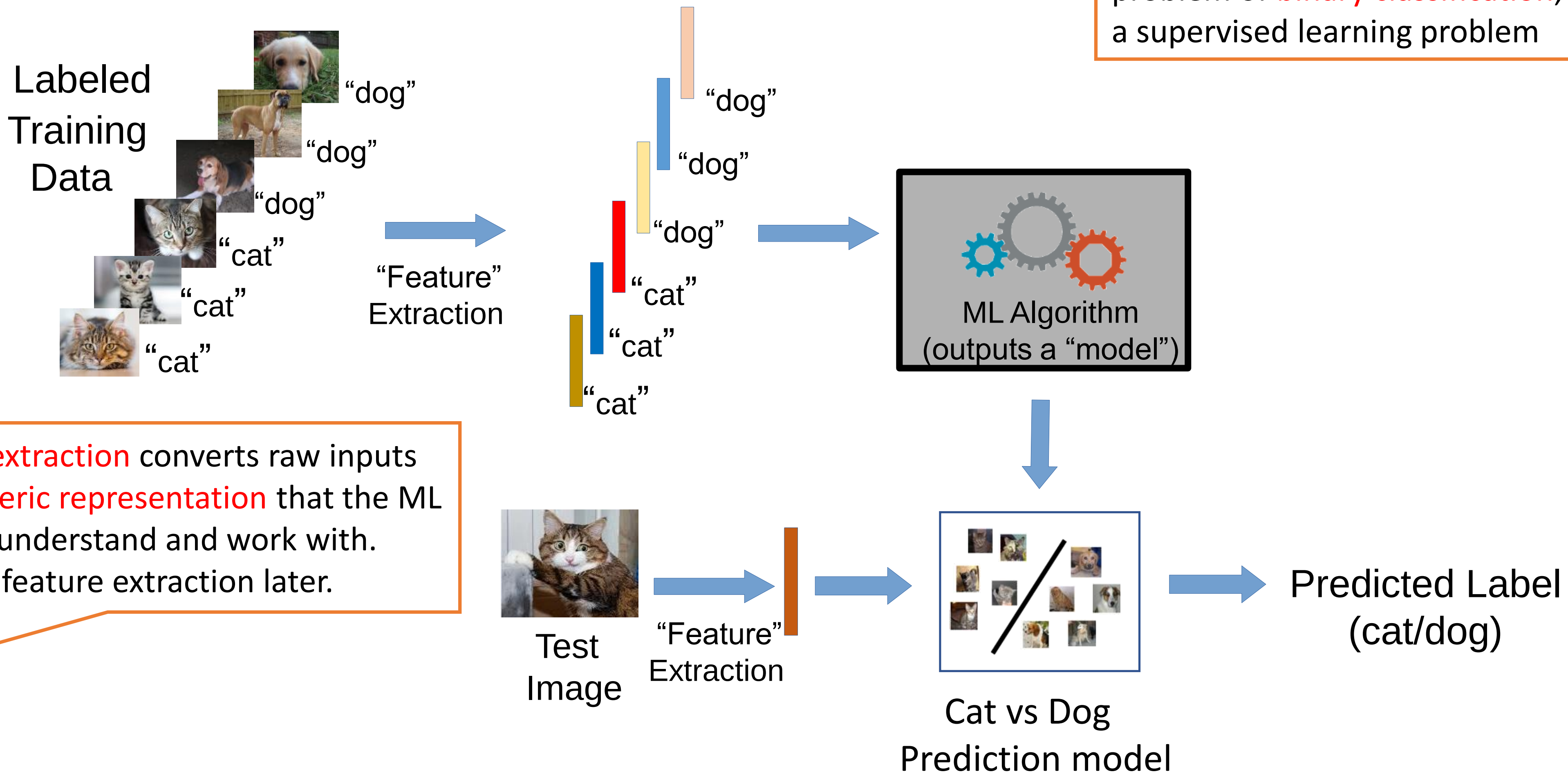

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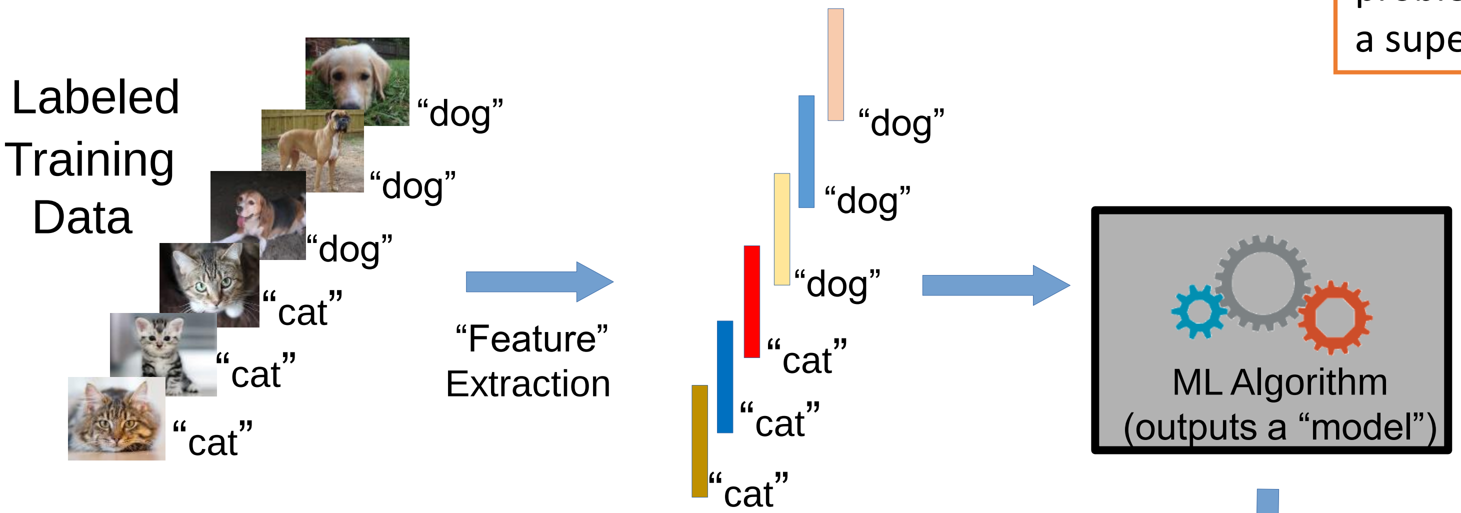

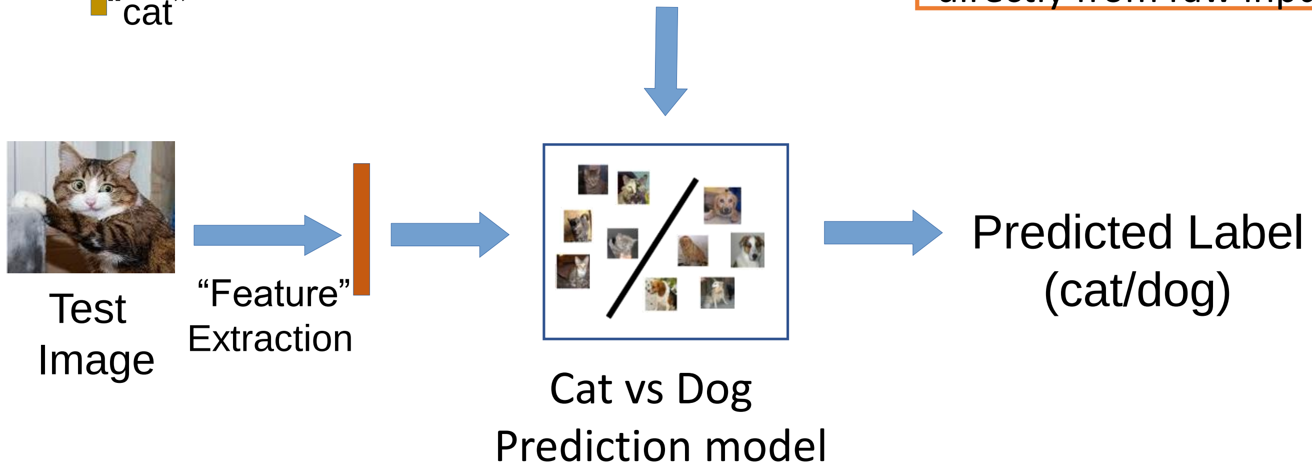

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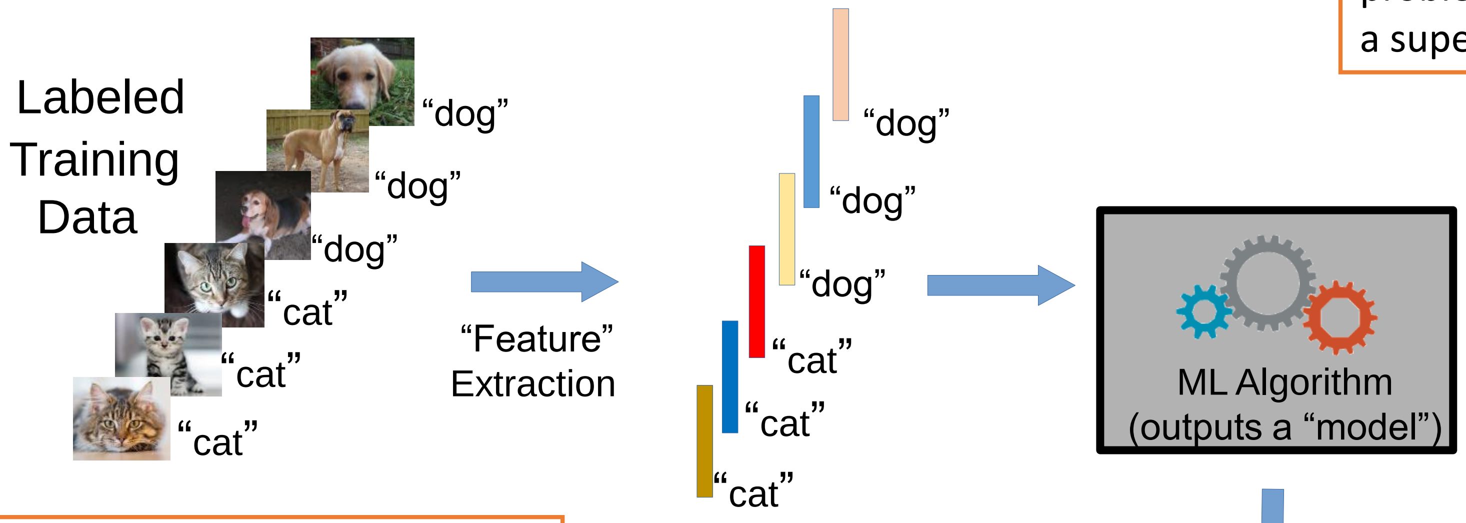

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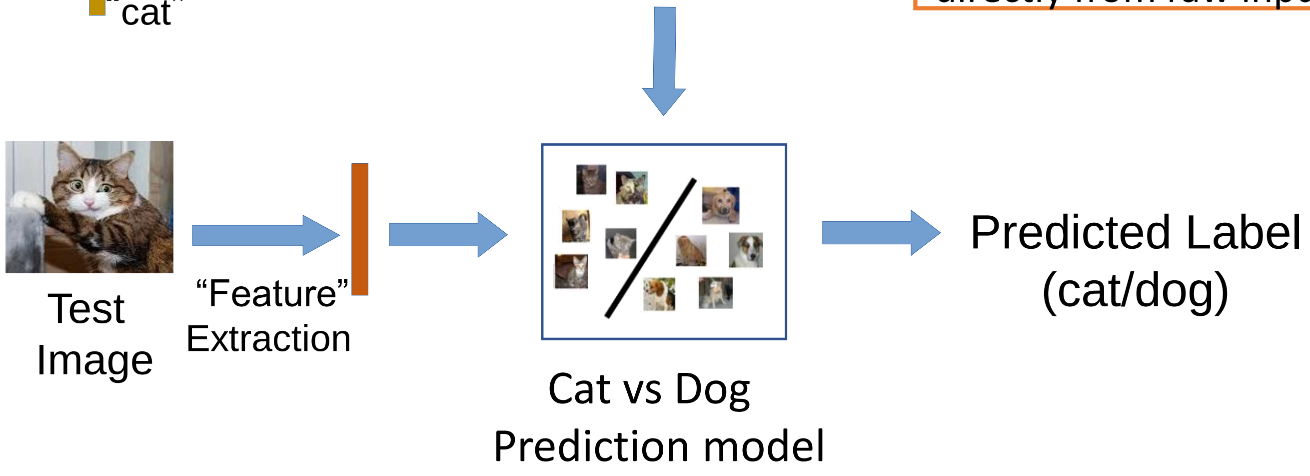

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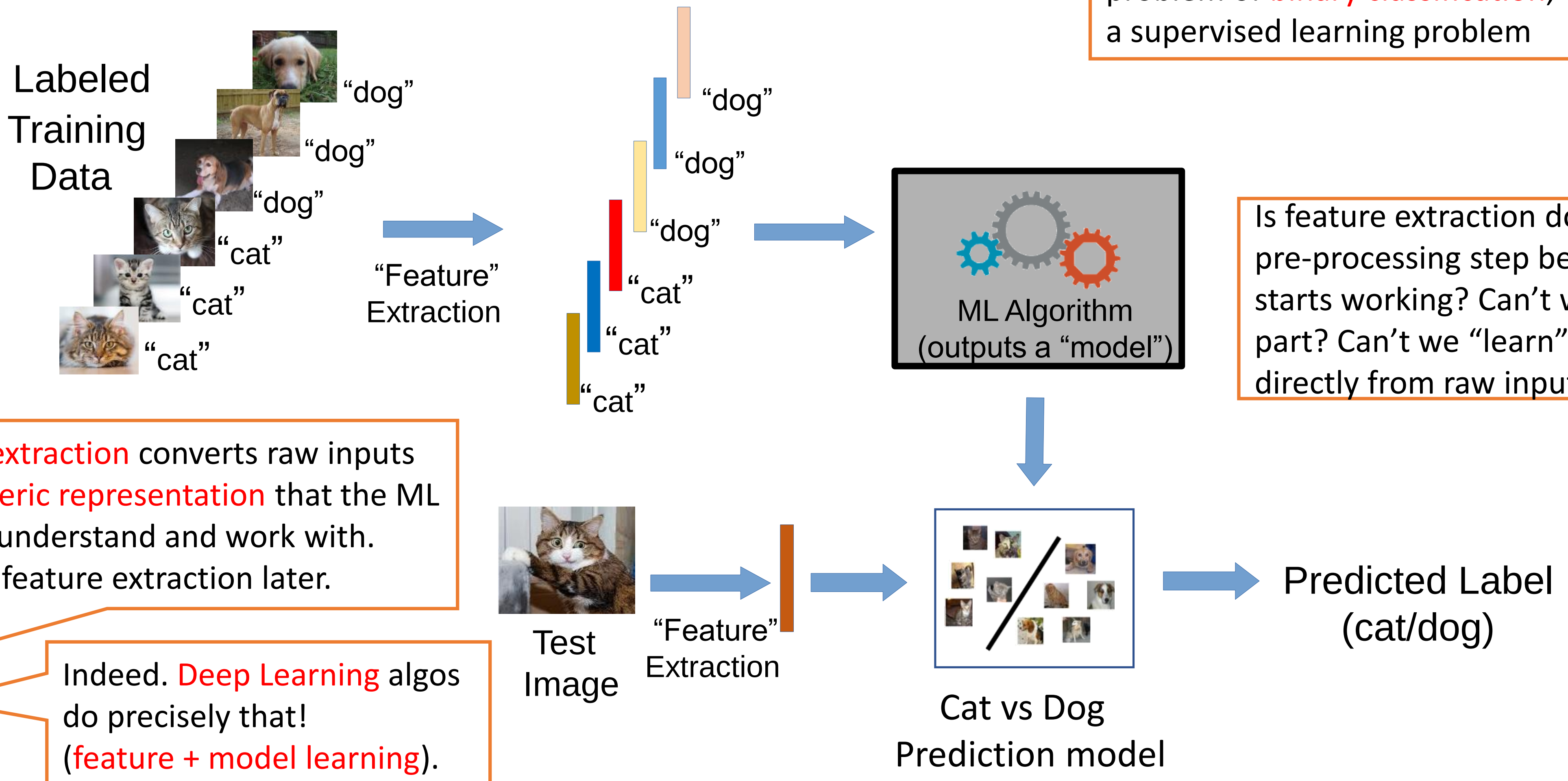

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https://www.pinclipart.com/, http://www.pngtree.com

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Unlabeled Data

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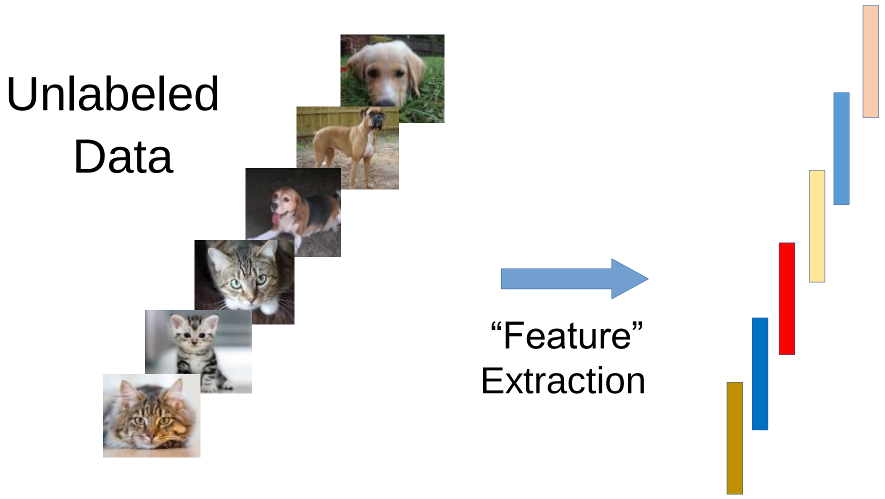

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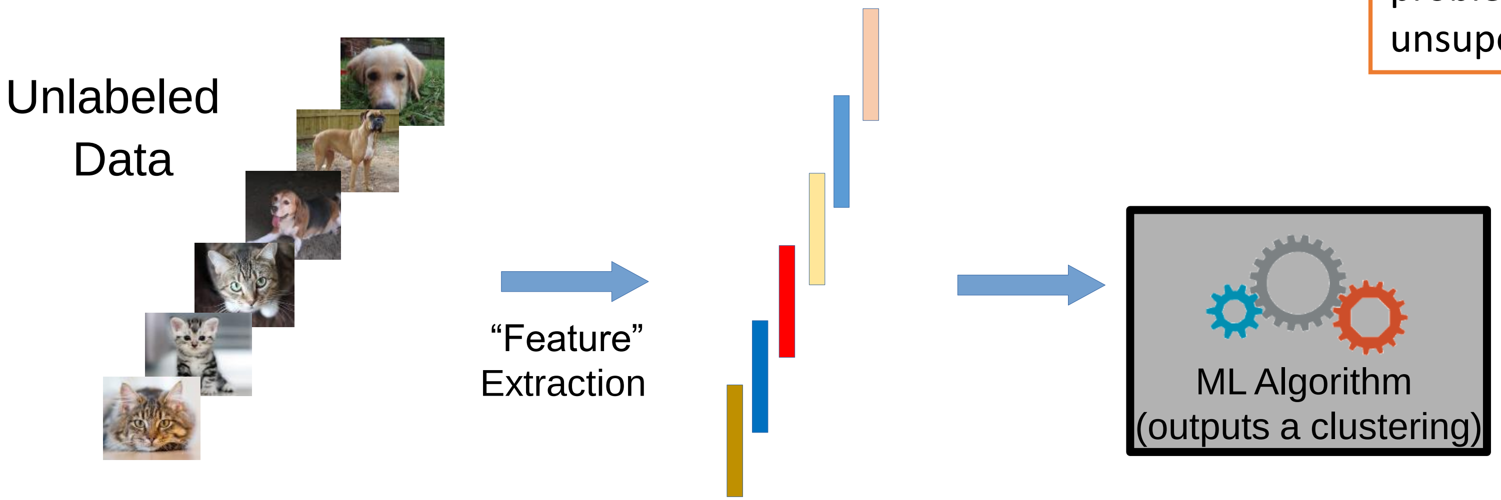

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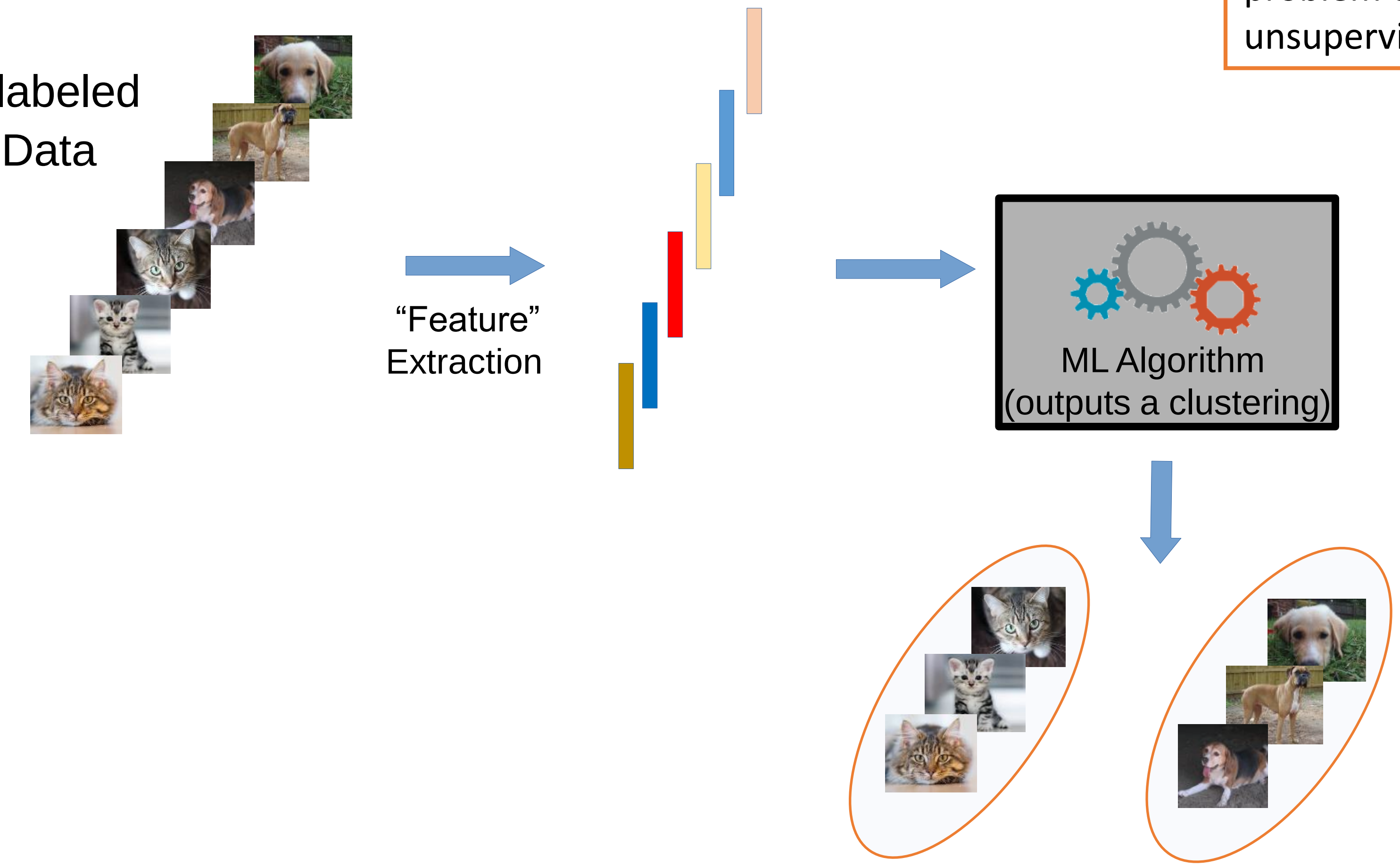

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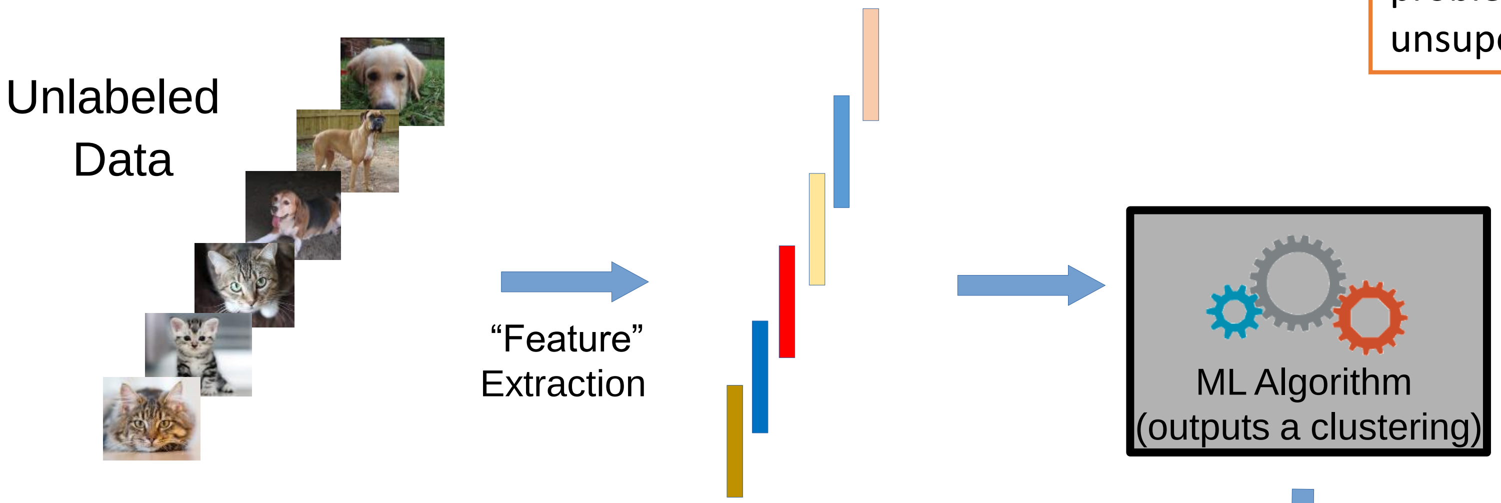

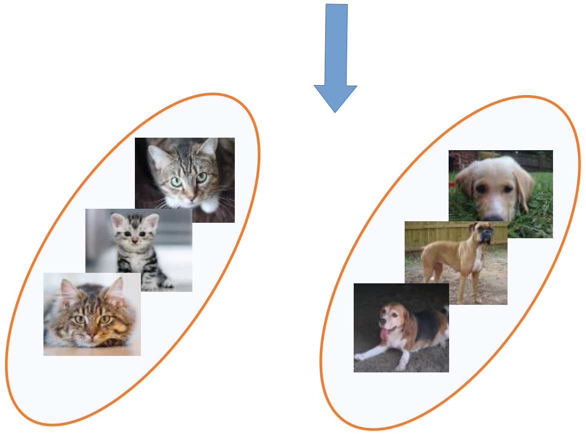

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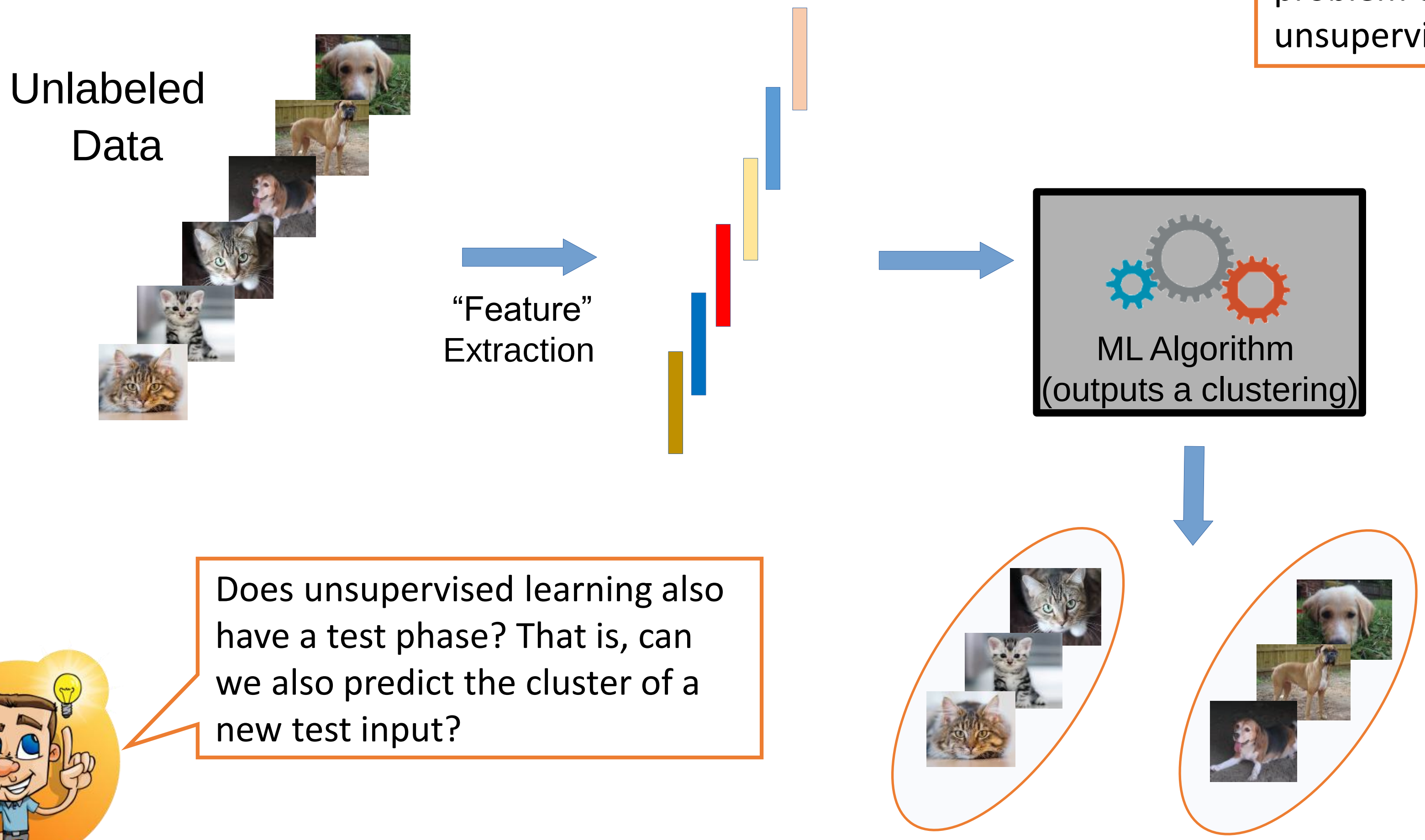

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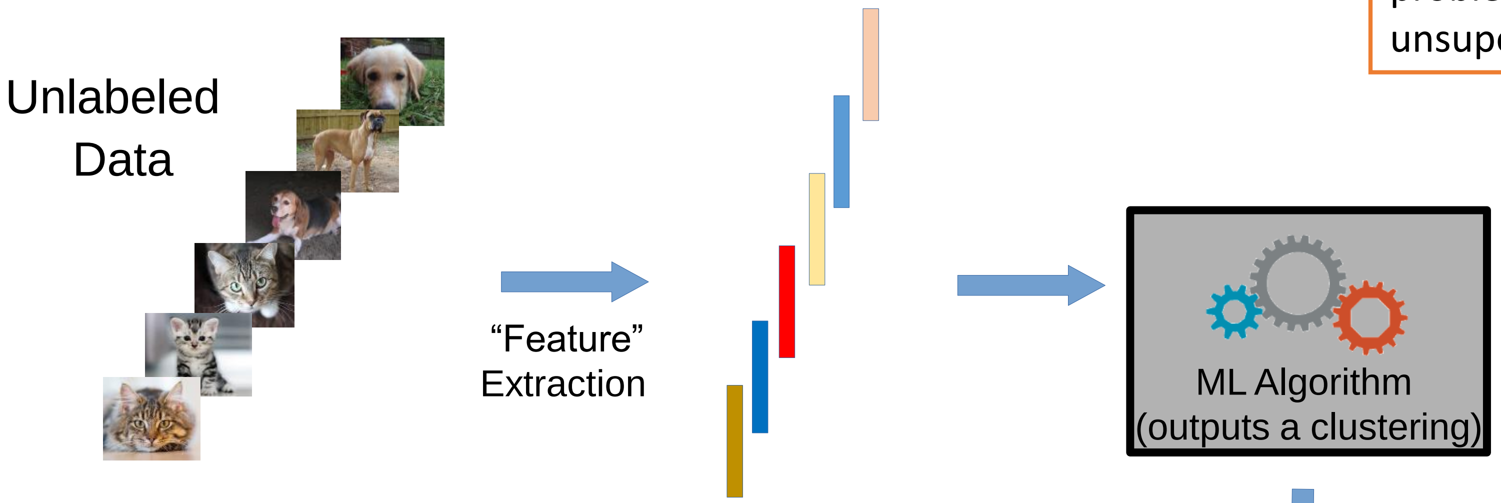

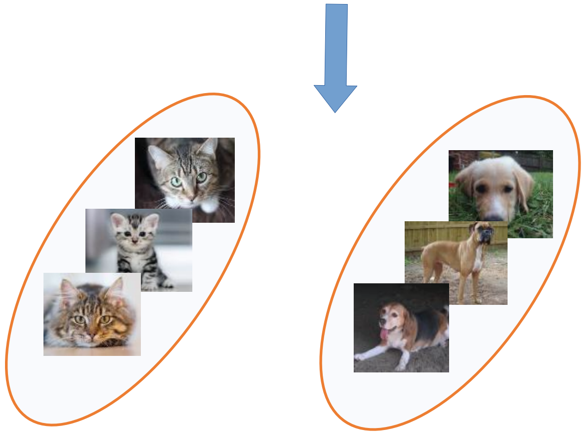

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- Senses/observes the environment
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Environment State at time t

S_t^e

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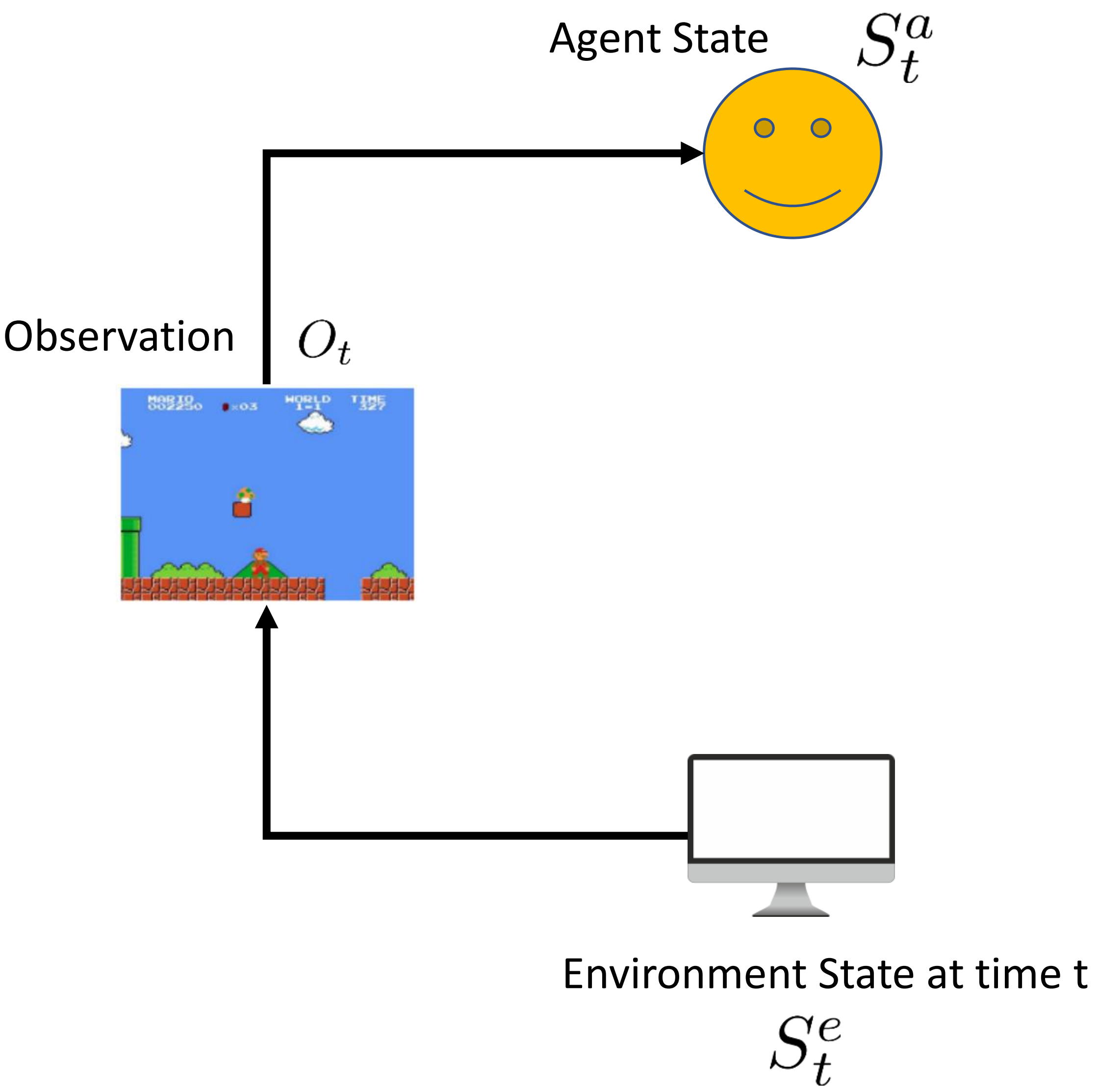

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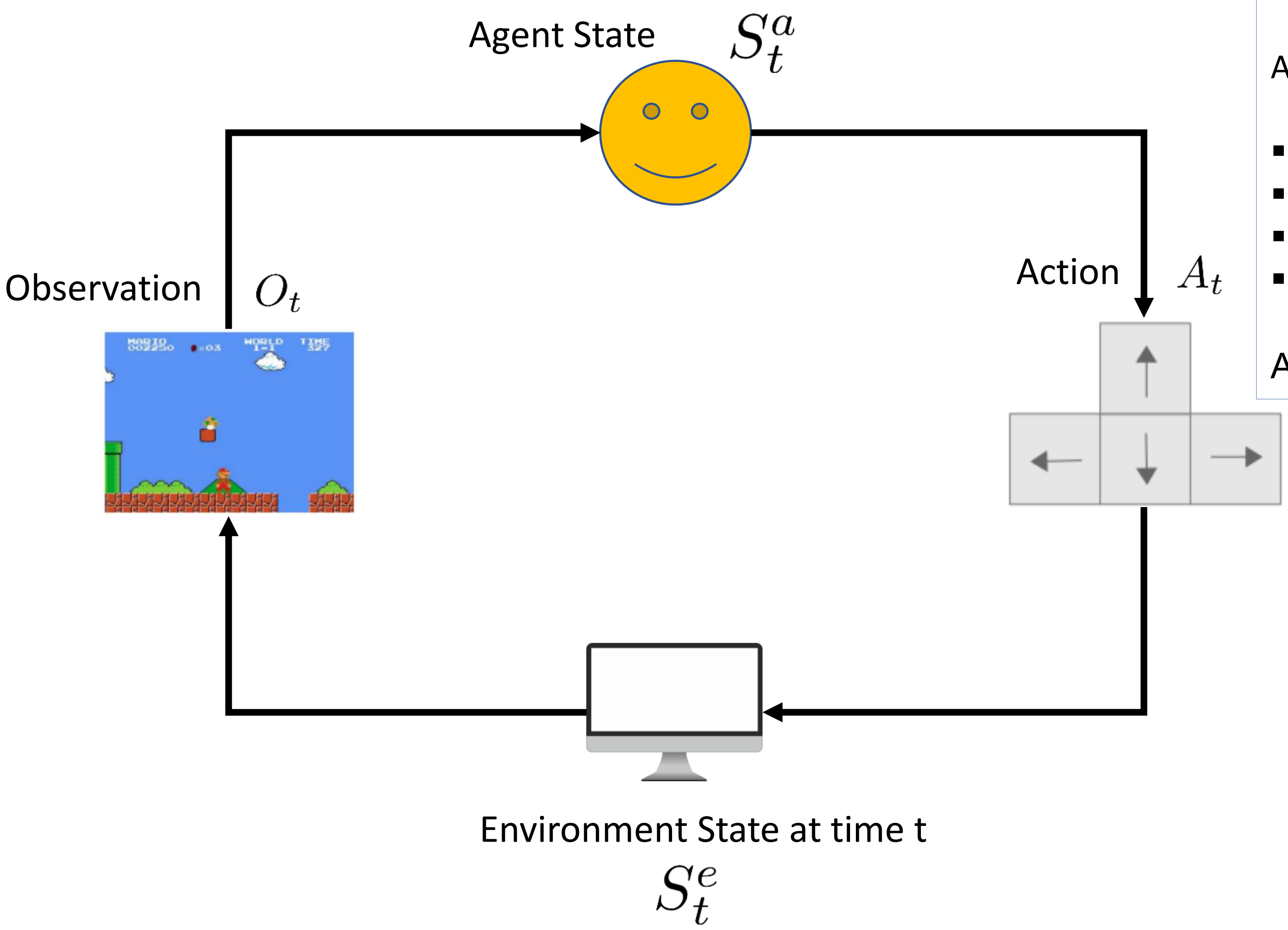

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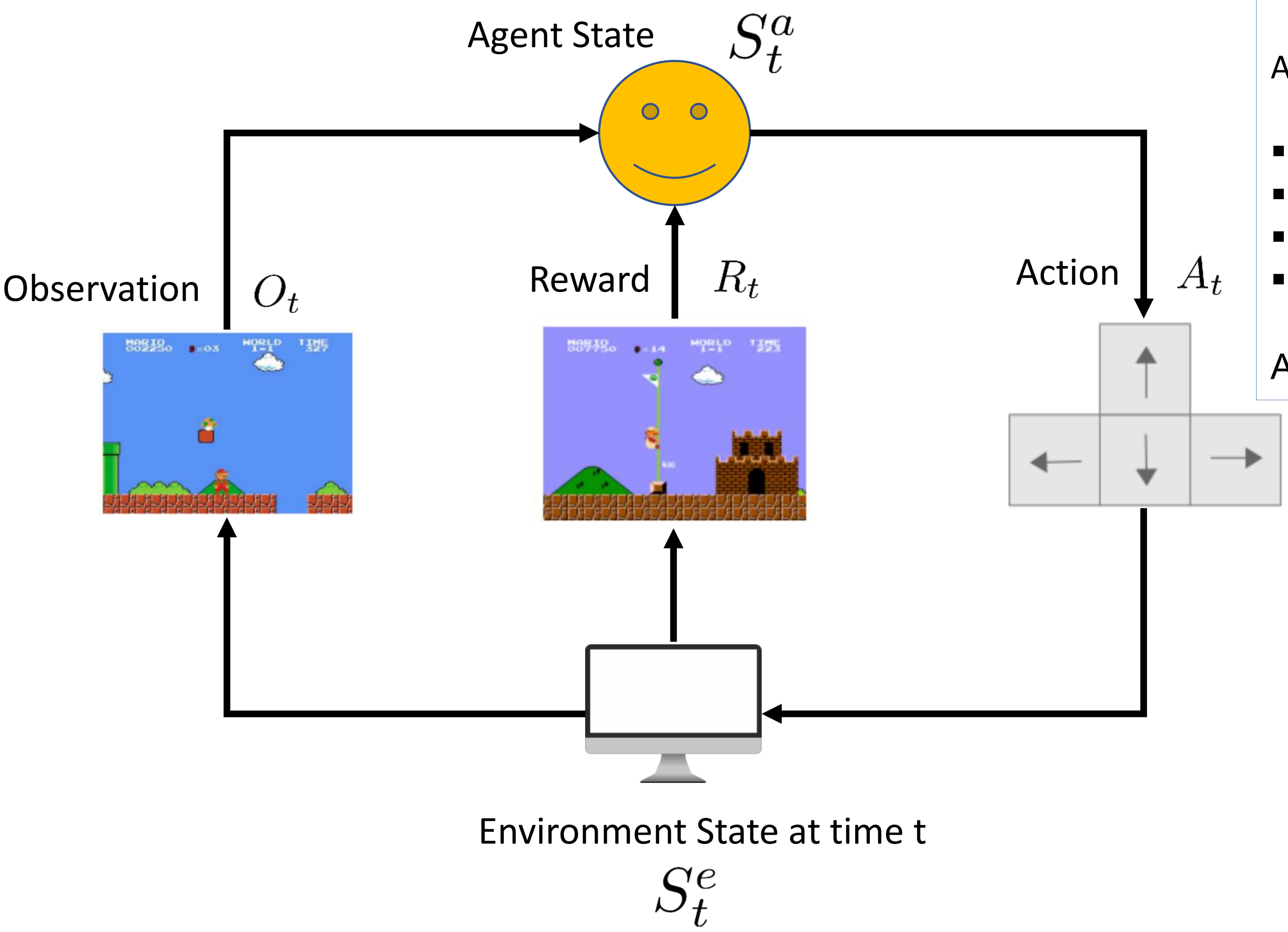

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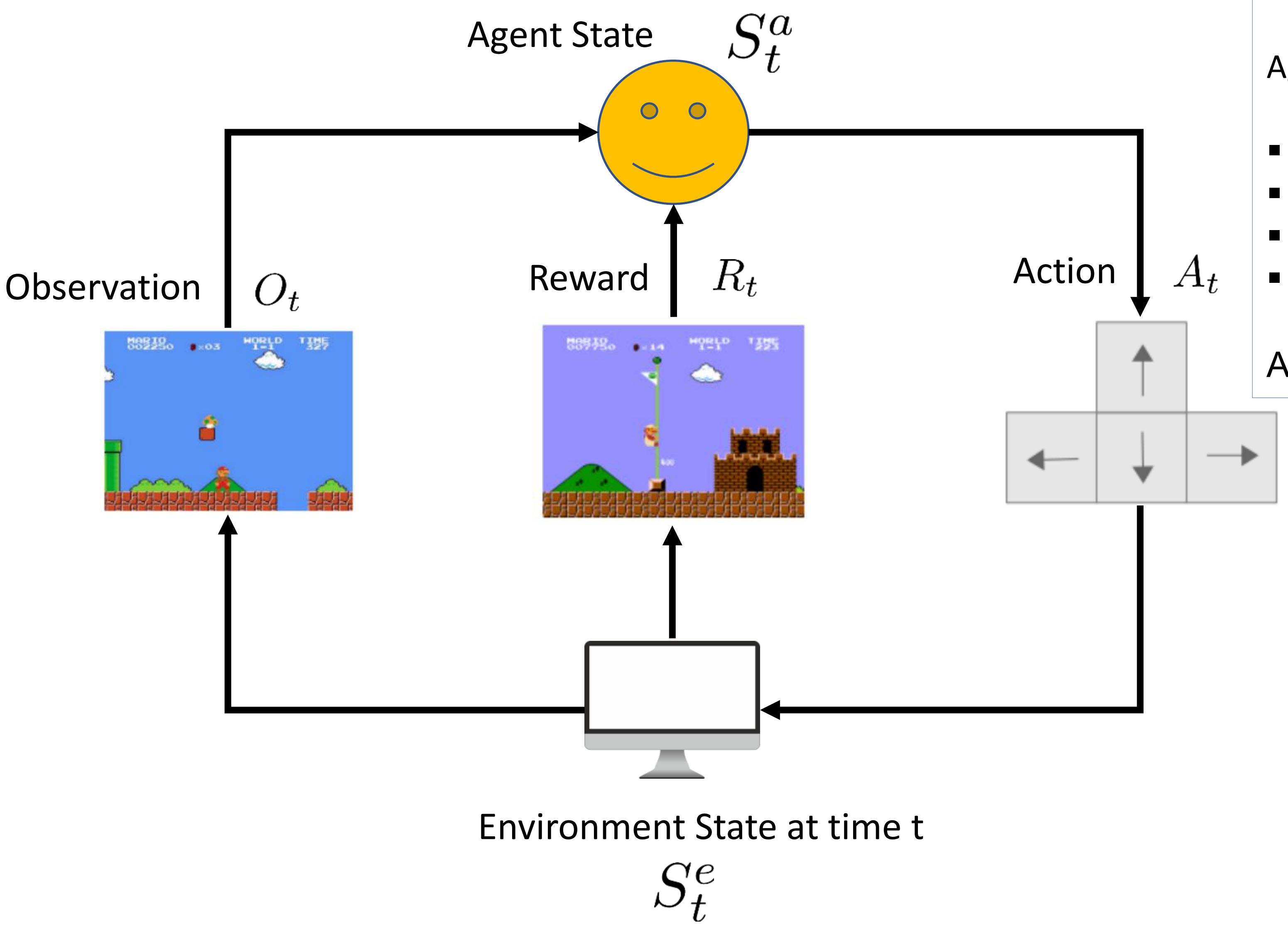

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There IS supervision, not explicit (as in Supervised Learning) but rather implicit (feedback based)

ML: Some Perspectives

Geometric Perspective

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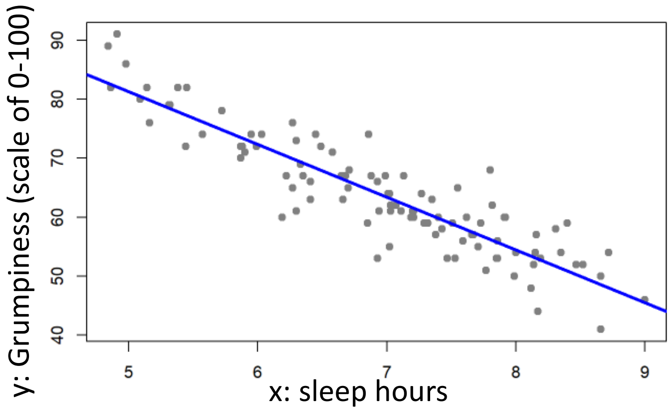

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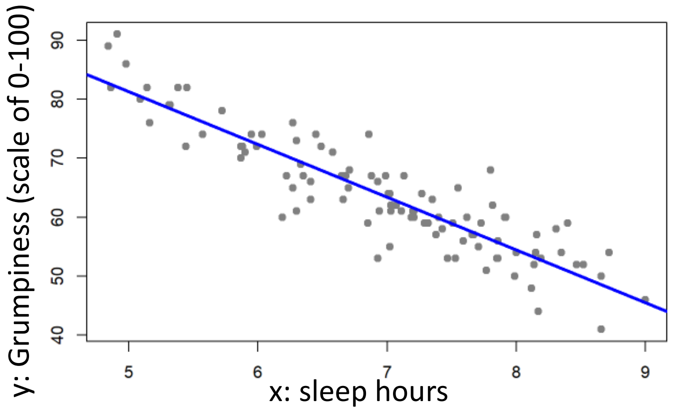

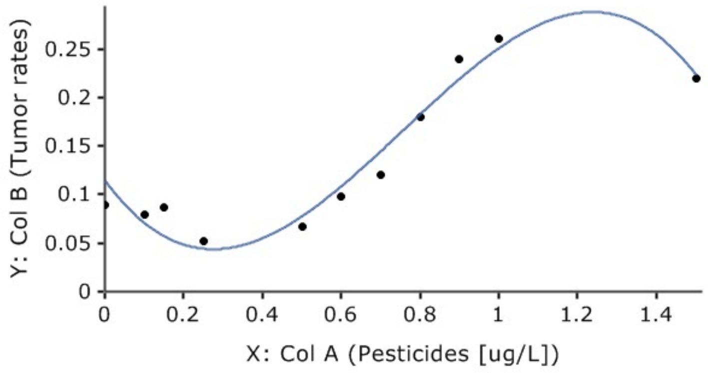

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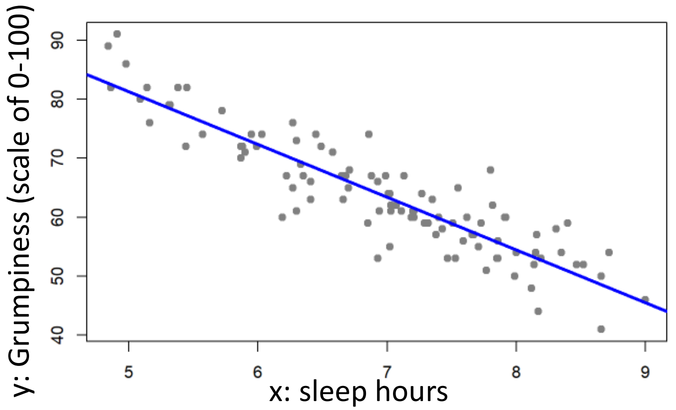

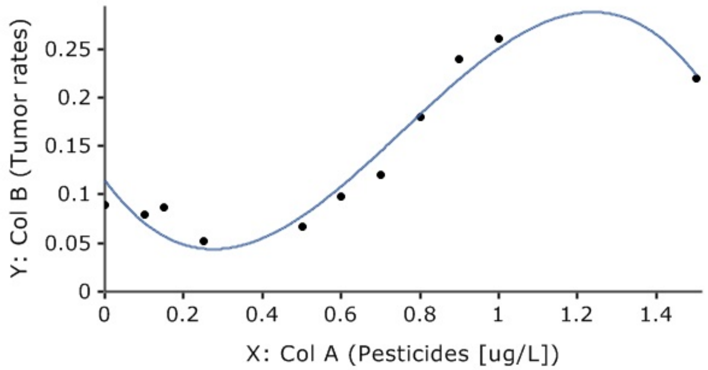

Classification: A supervised learning problem. Goal is to learn a to predict which of the two or more classes an input belongs to. Akin to learning linear/nonlinear separator for the inputs

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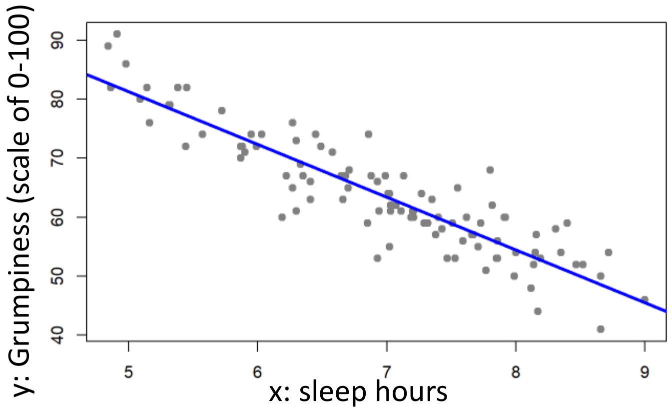
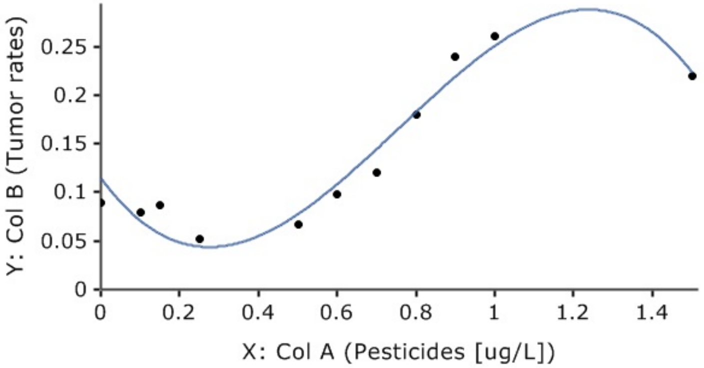
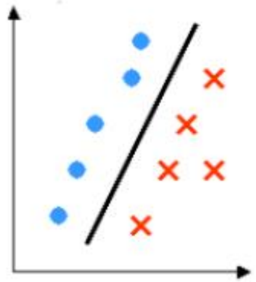
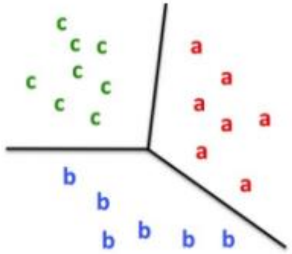
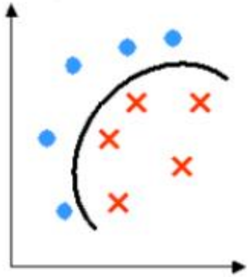


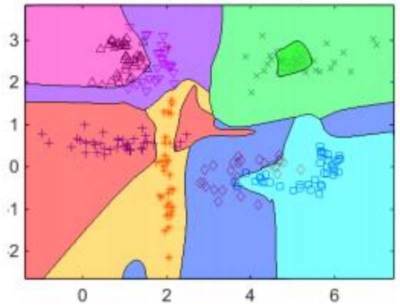


Classification: A supervised learning problem. Goal is to learn a to predict which of the two or more classes an input belongs to. Akin to learning linear/nonlinear separator for the inputs


Two-Class (binary) Linear Classification


Multi-Class Linear Classification


Two-Class (binary) Nonlinear Classification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Geometric Perspective

Recall that feature extraction converts inputs into a numeric representation

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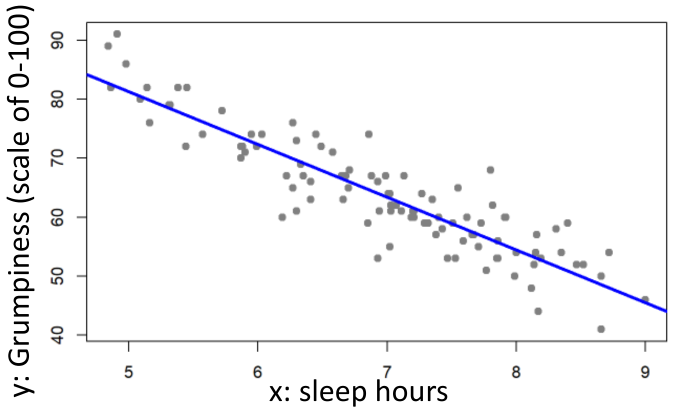

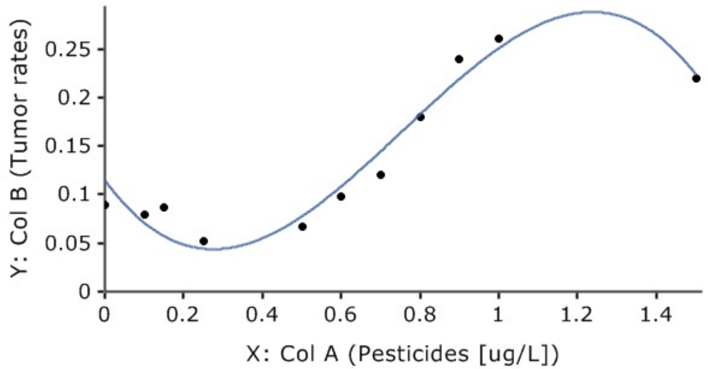

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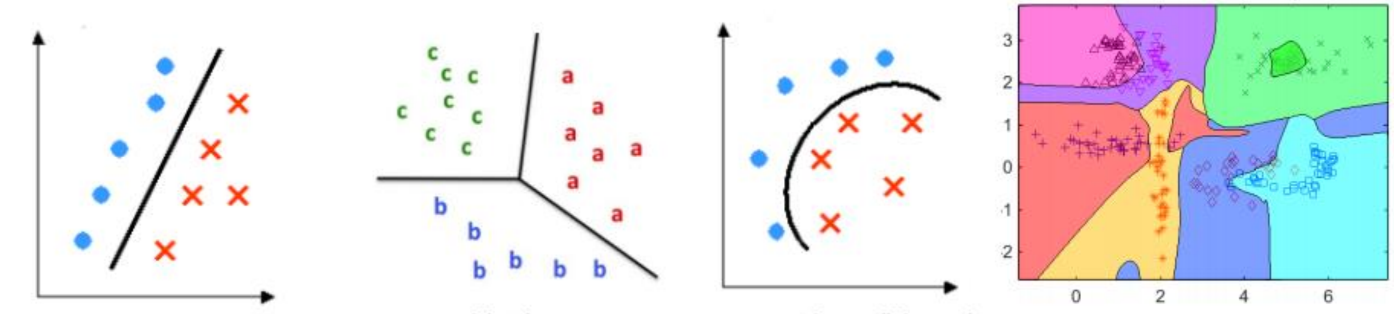

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Pic from: https://learningstatisticswithr.com/book/regression.html, https://maxstat.de/

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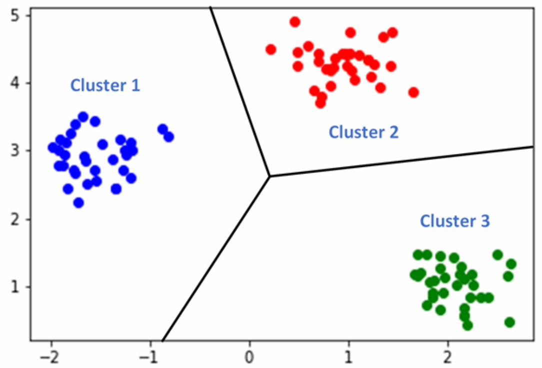

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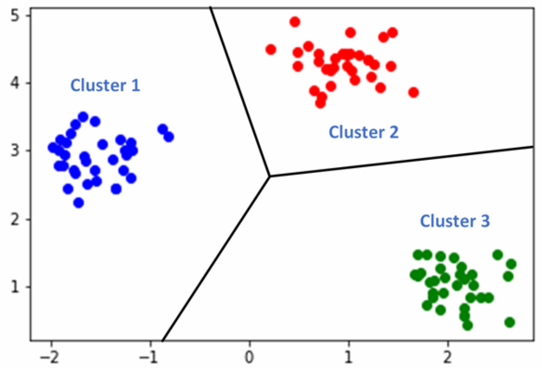

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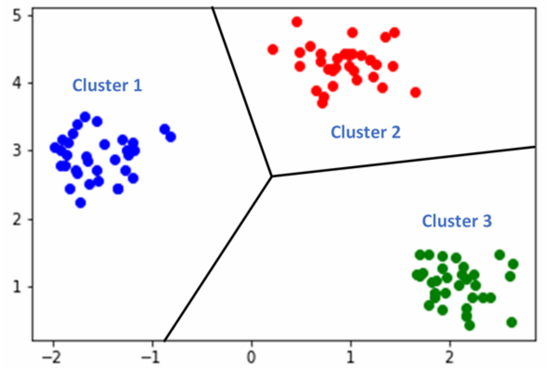

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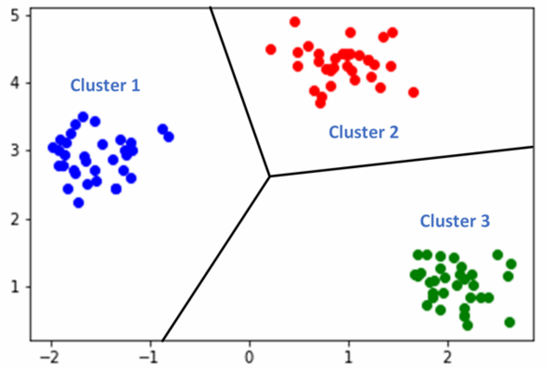

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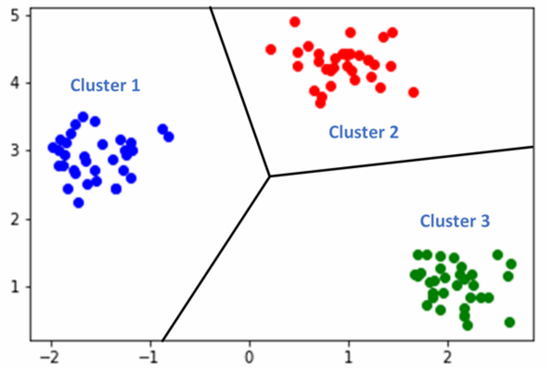

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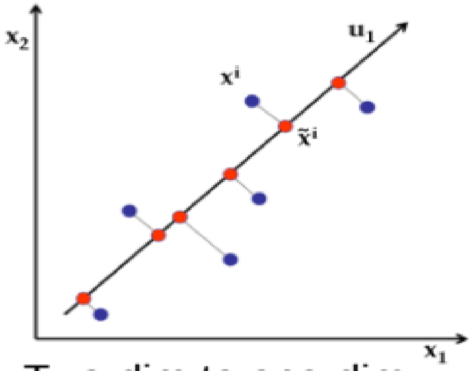

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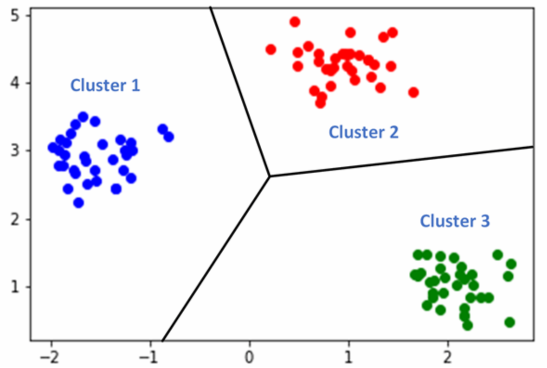

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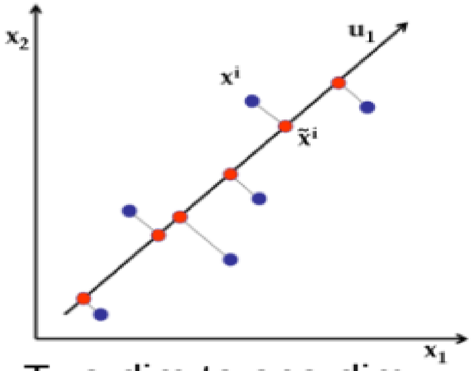

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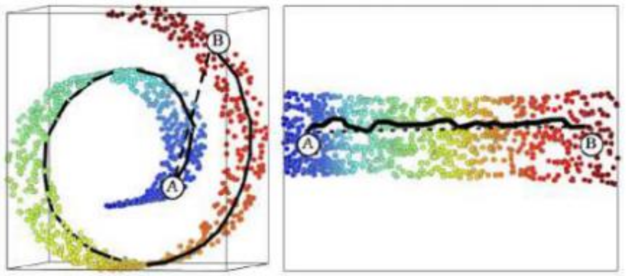

Three-dim to two-dim nonlinear projection (a.k.a. manifold learning)

Perspective as function approximation

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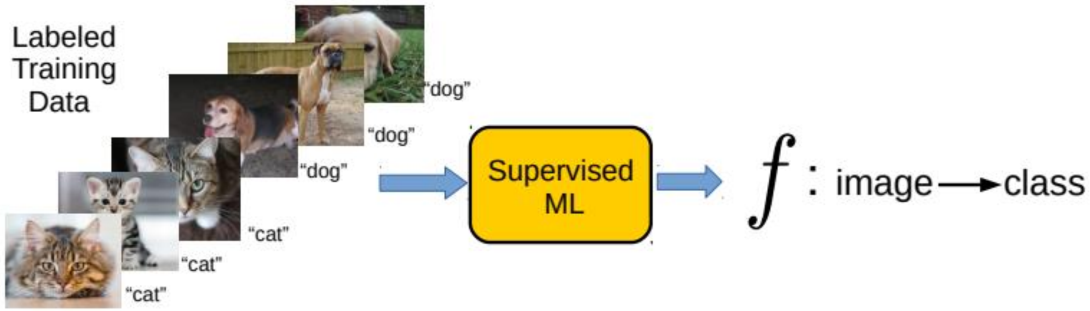

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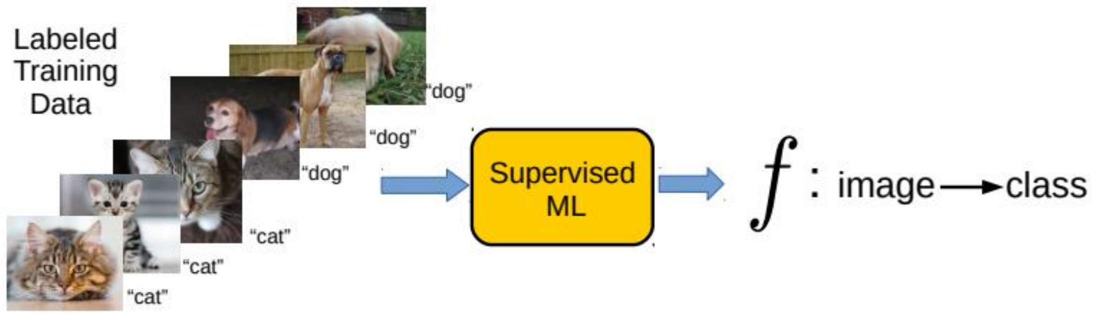

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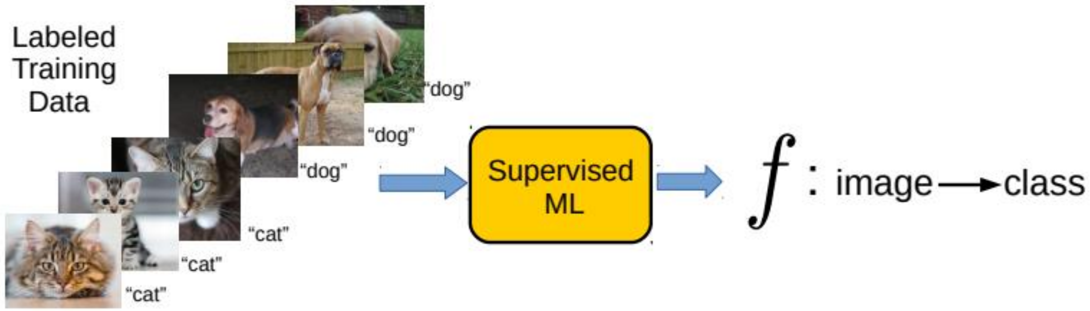

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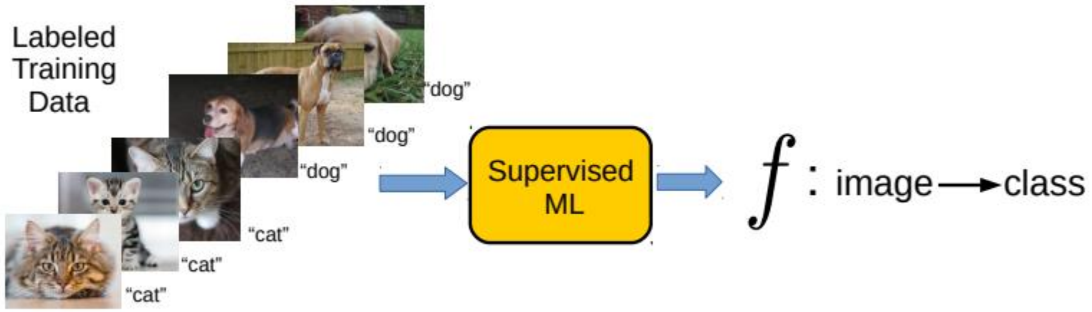

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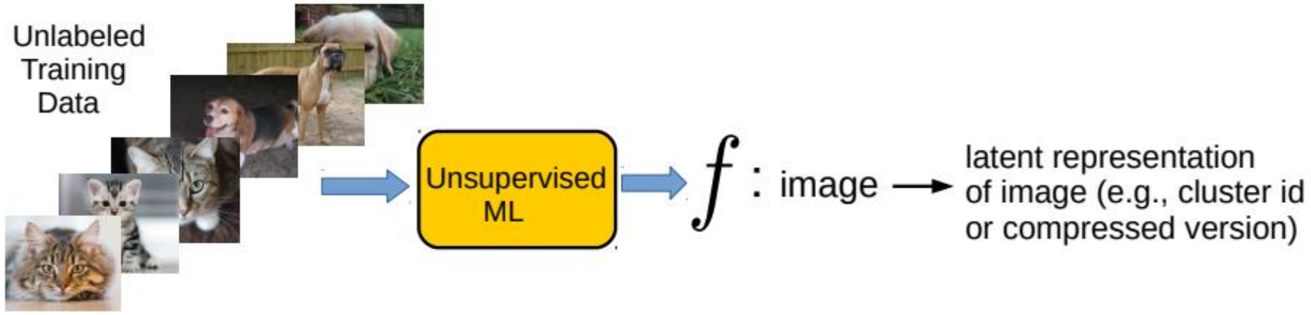

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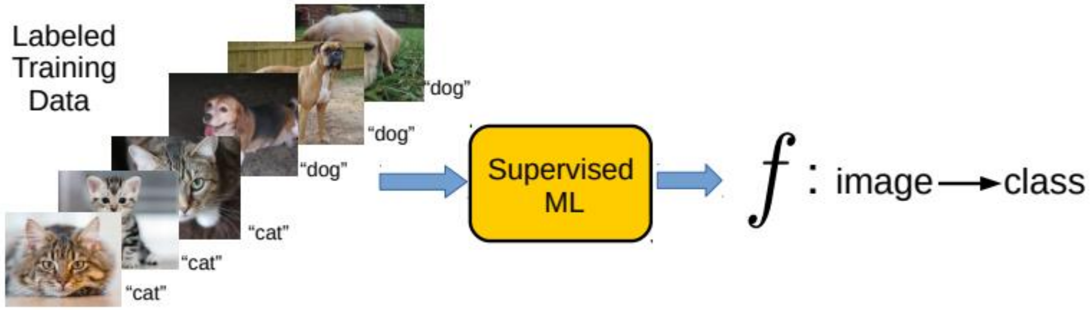

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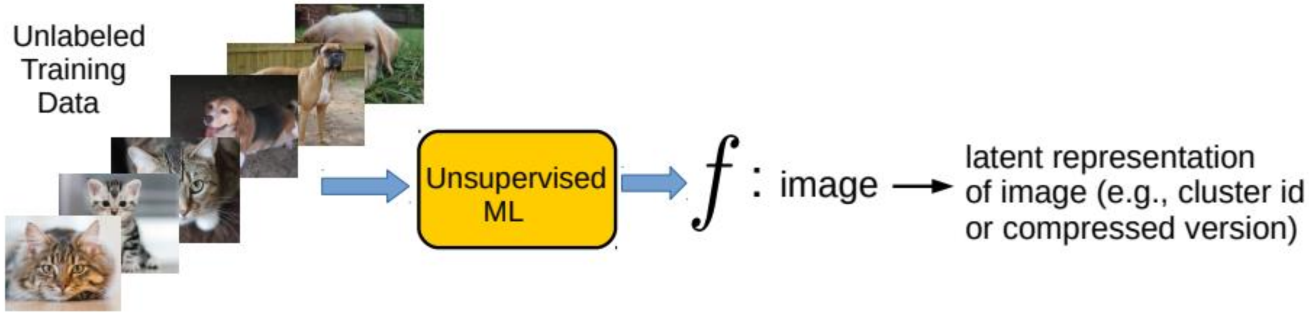

- Reinforcement Learning can also be seen as doing function approximation

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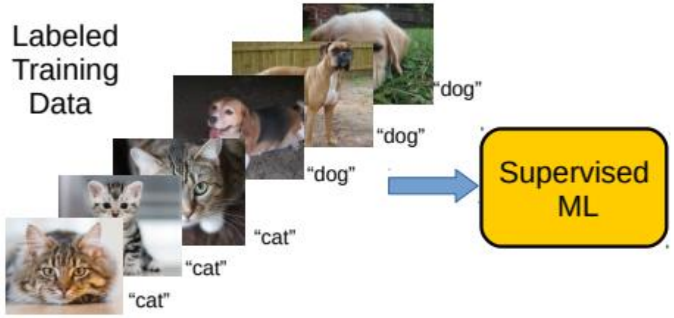

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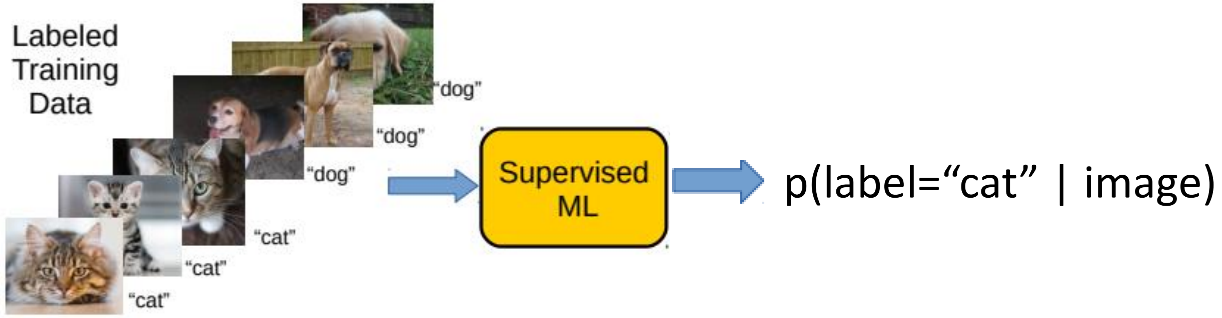

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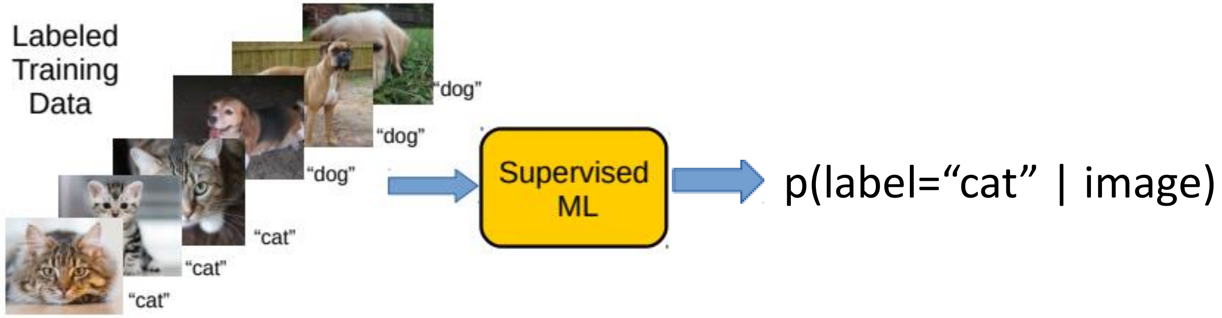

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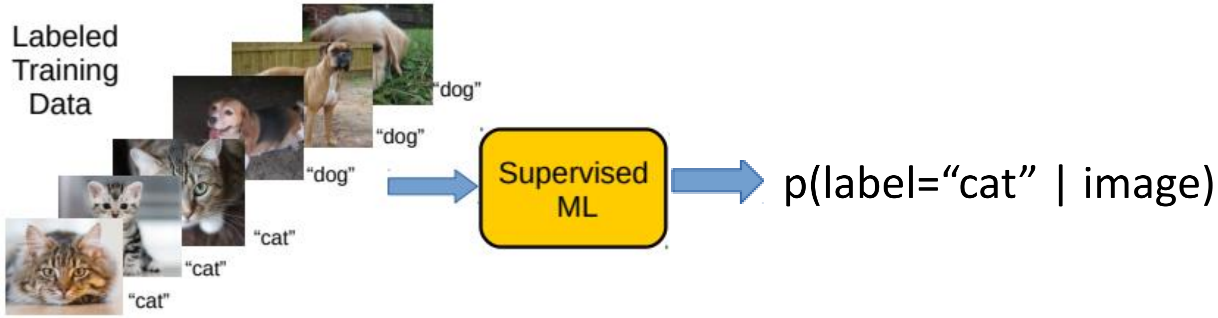

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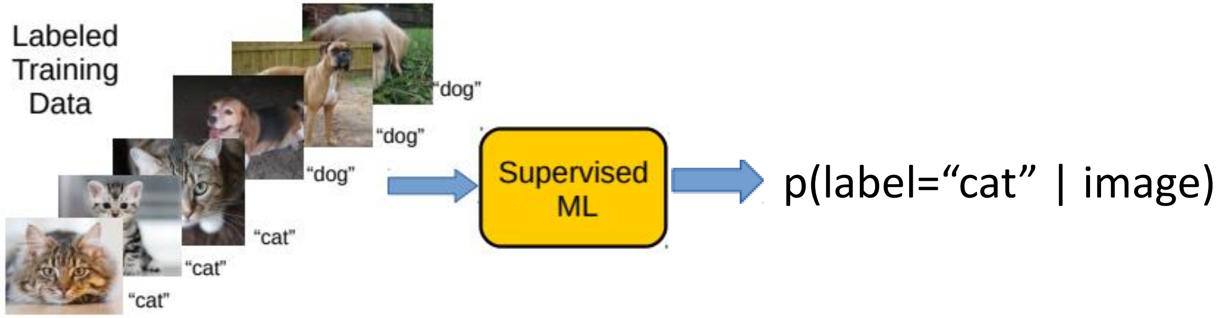

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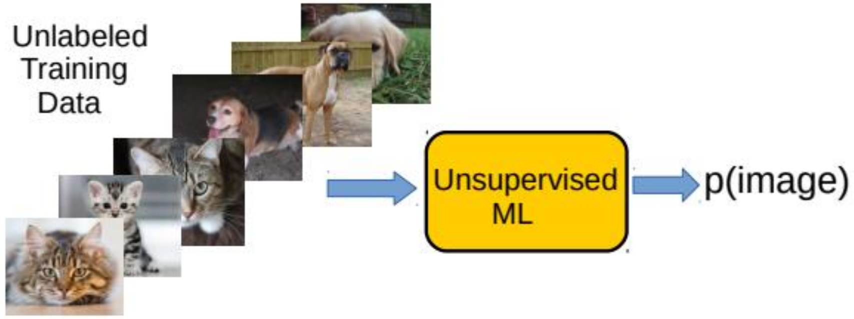

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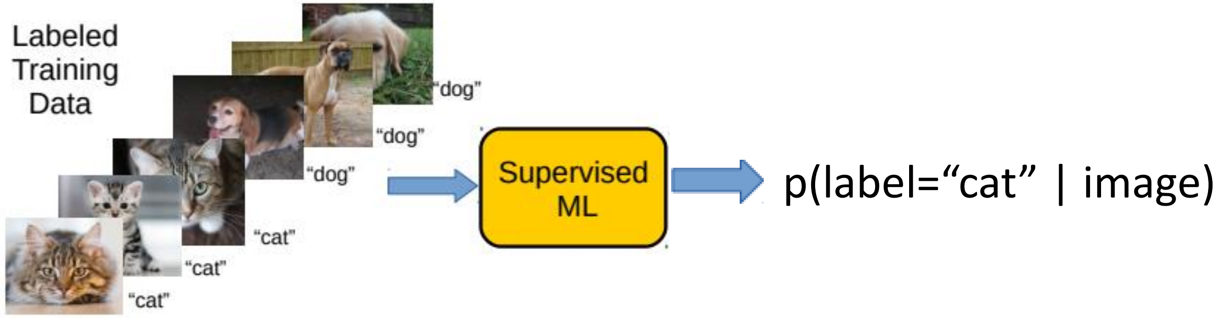

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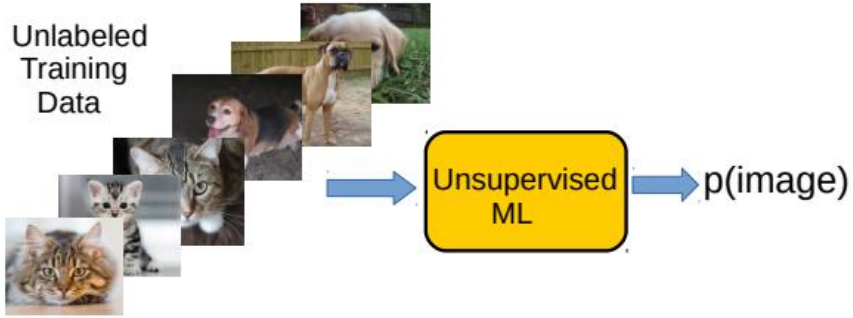

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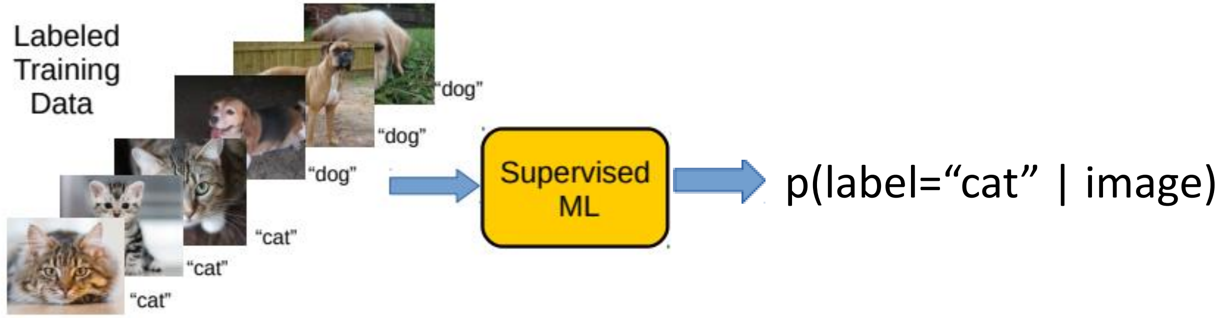

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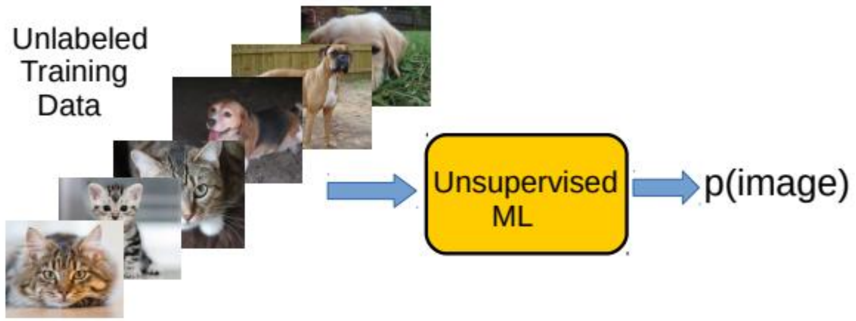

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- Reinforcement Learning can also be seen as estimating probability densities

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- Approach 1 is not as powerful as Approach 2 but still used widely

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\\
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\text{Sentence 3}
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\begin{pmatrix}
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1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 \\
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BoW is just one of the many ways of doing feature extraction for text data. Not the most optimal one, and has various flaws (can you think or some?), but often works reasonably well

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Sentence 3	1	1	0	0	0	0	0	1	1

- Each sentence is now represented as a binary vector (each feature is a binary value, denoting presence or absence of a word). BoW is also called "unigram" rep.

Example: Feature Extraction for Image Data

Pic credit: cat.uab.cat/Research/object-recognition

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- A very simple feature extraction approach for image data is flattening

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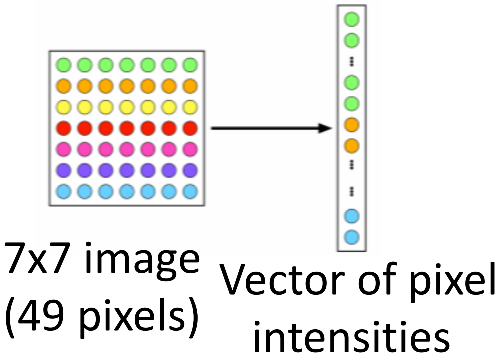

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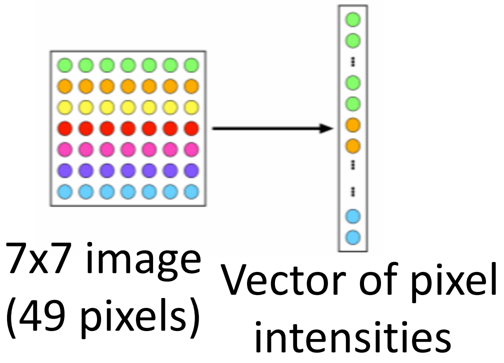

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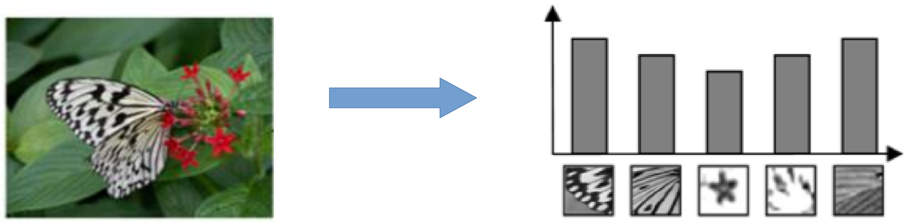

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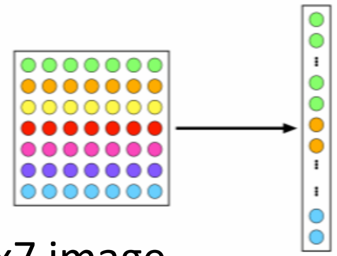

Flattening and histogram based methods destroy the spatial information in the image but often still work reasonably well

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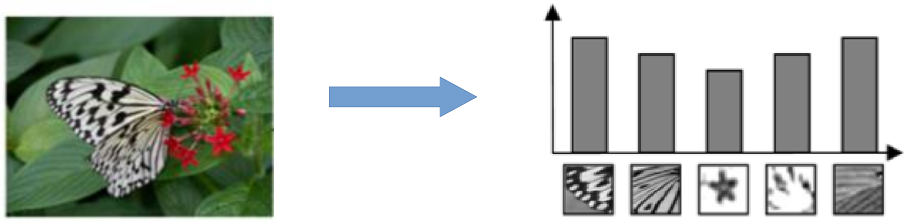

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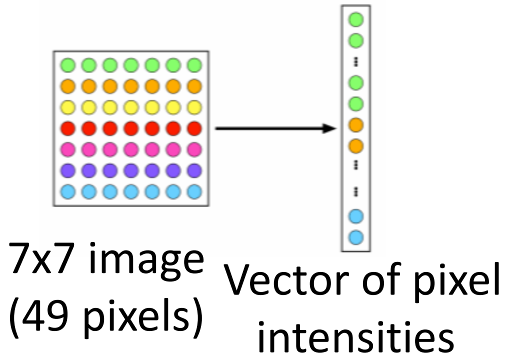
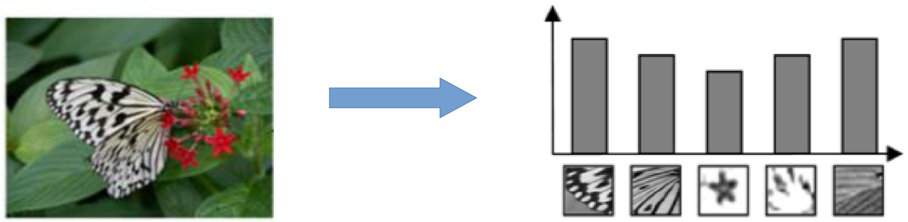
Example: Feature Extraction for Image Data

- A very simple feature extraction approach for image data is flattening



Flattening and histogram based methods destroy the spatial information in the image but often still work reasonably well

- Histogram of visual patterns is another popular feature extr. method for images



- Many other manual feature extraction techniques developed in computer vision and image processing communities (SIFT, HoG, and others)

Pic credit: cat.uab.cat/Research/object-recognition

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- More common in supervised learning but can also be done for unsup. learning

Some More Postprocessing: Feature Scaling

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Pic credit: https://becominghuman.ai/demystifying-feature-scaling-baff53e9b3fd, https://stackoverflow.com/

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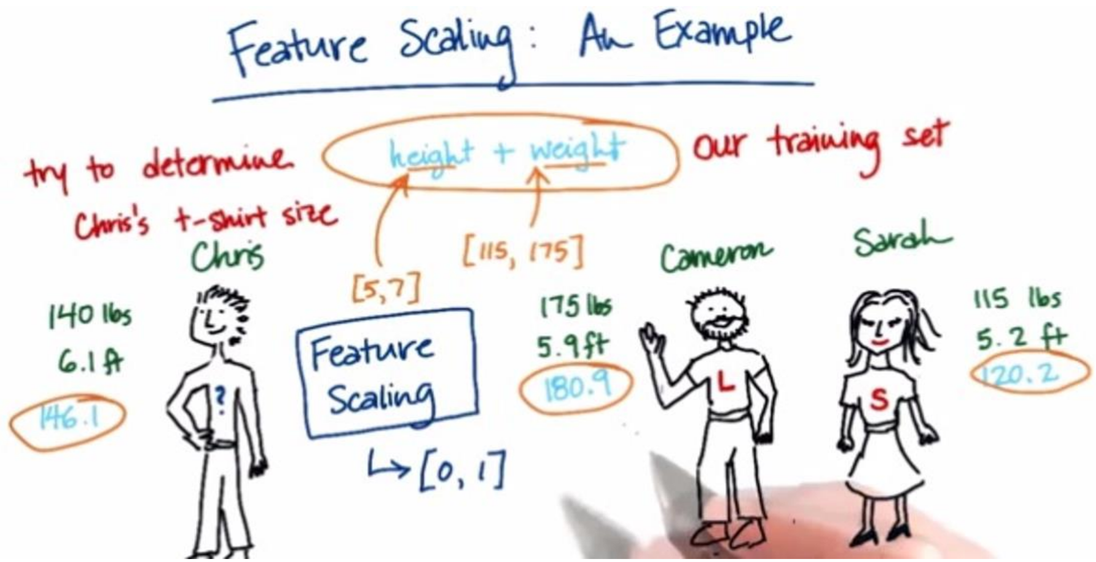

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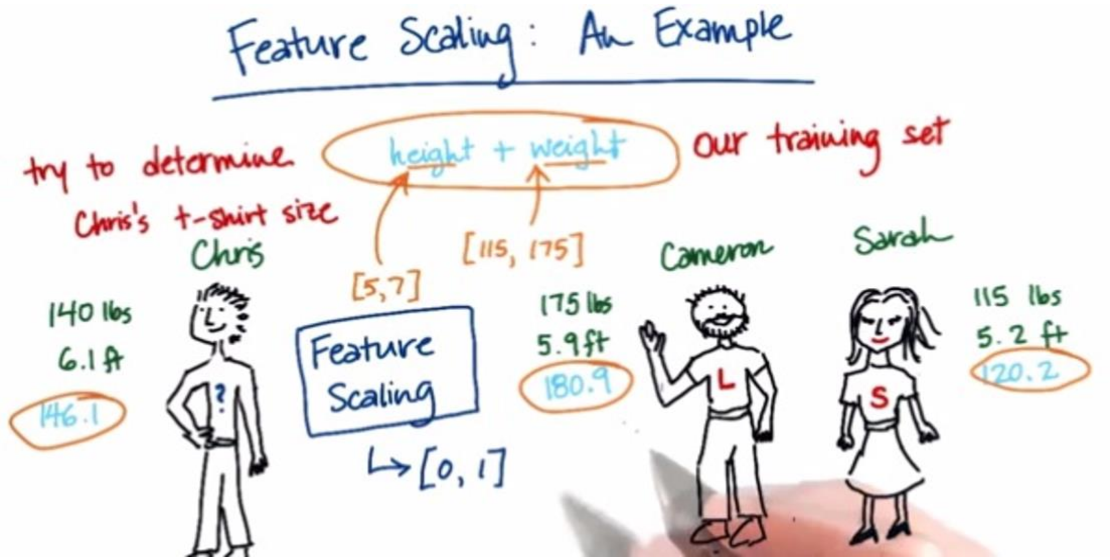

- Also helpful for stabilizing the optimization techniques used in ML algos

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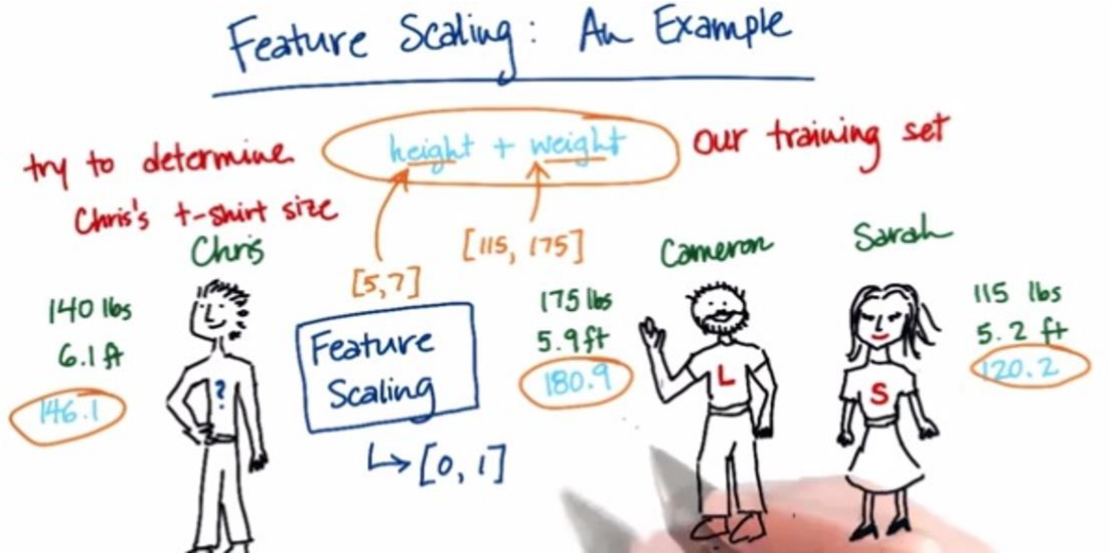

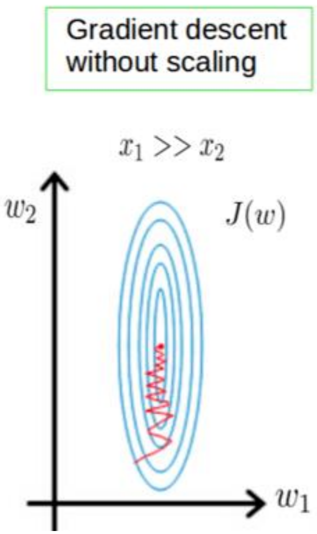

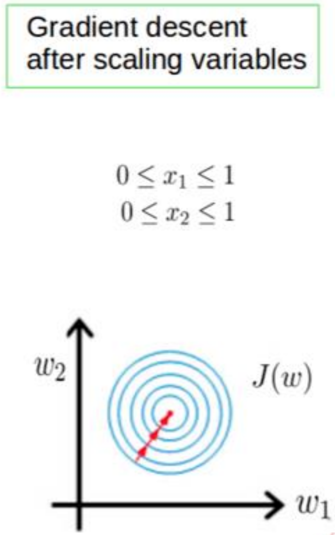

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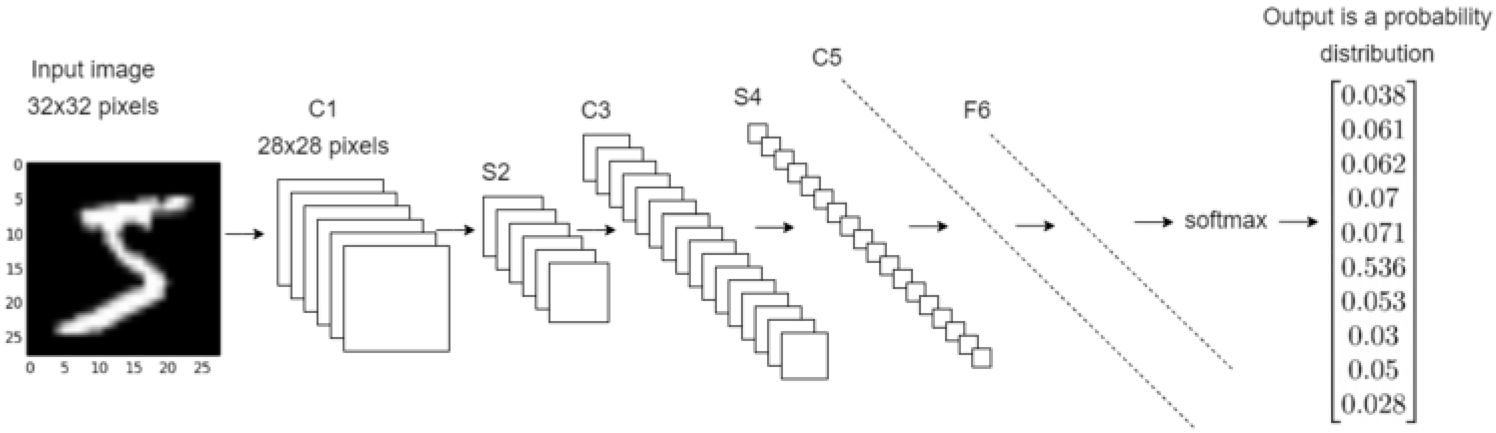

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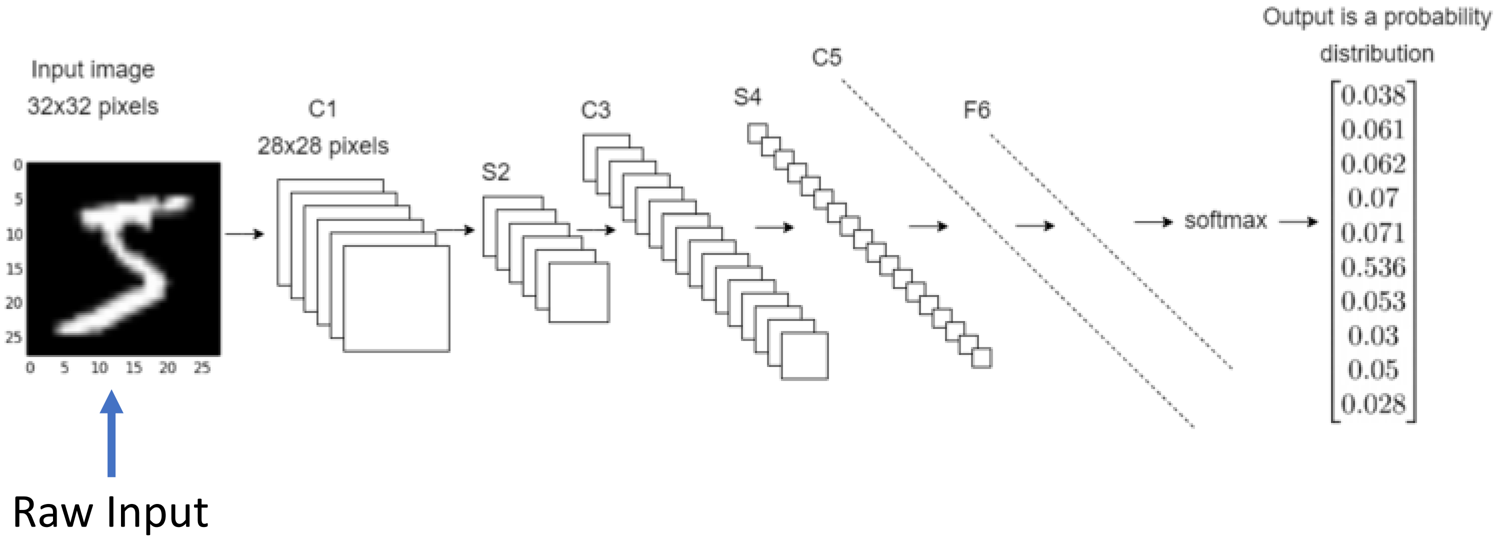

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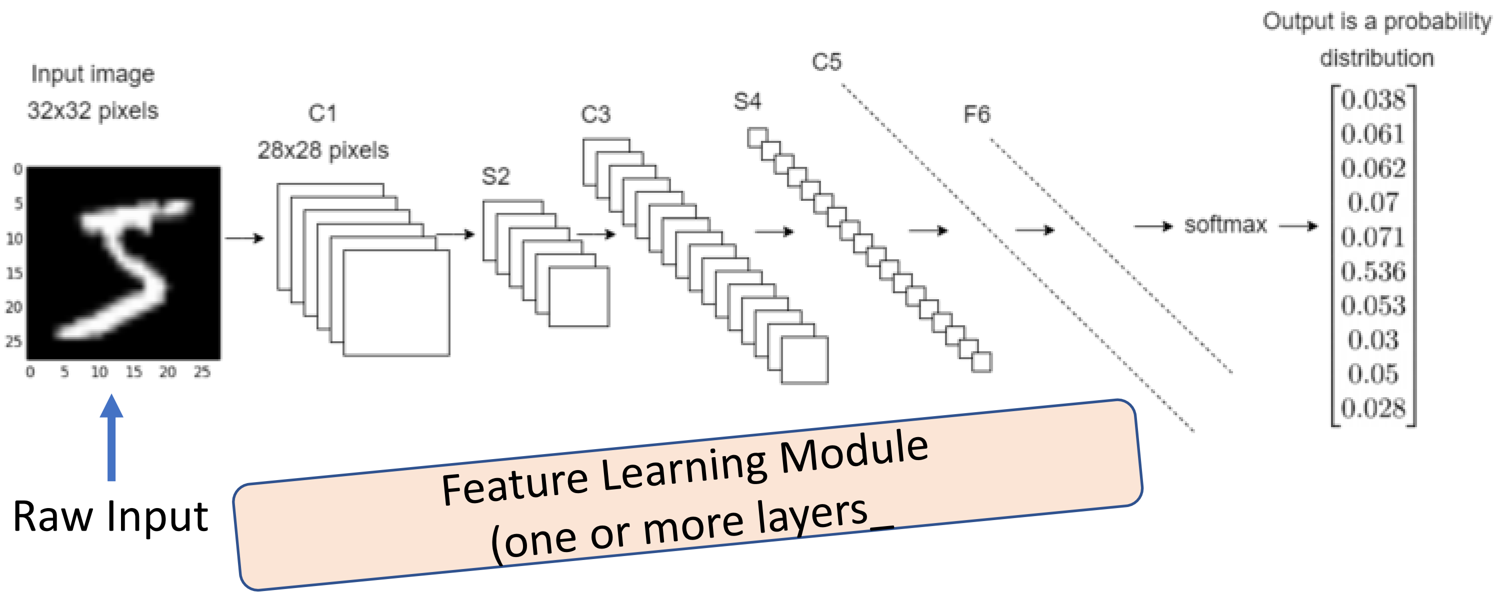

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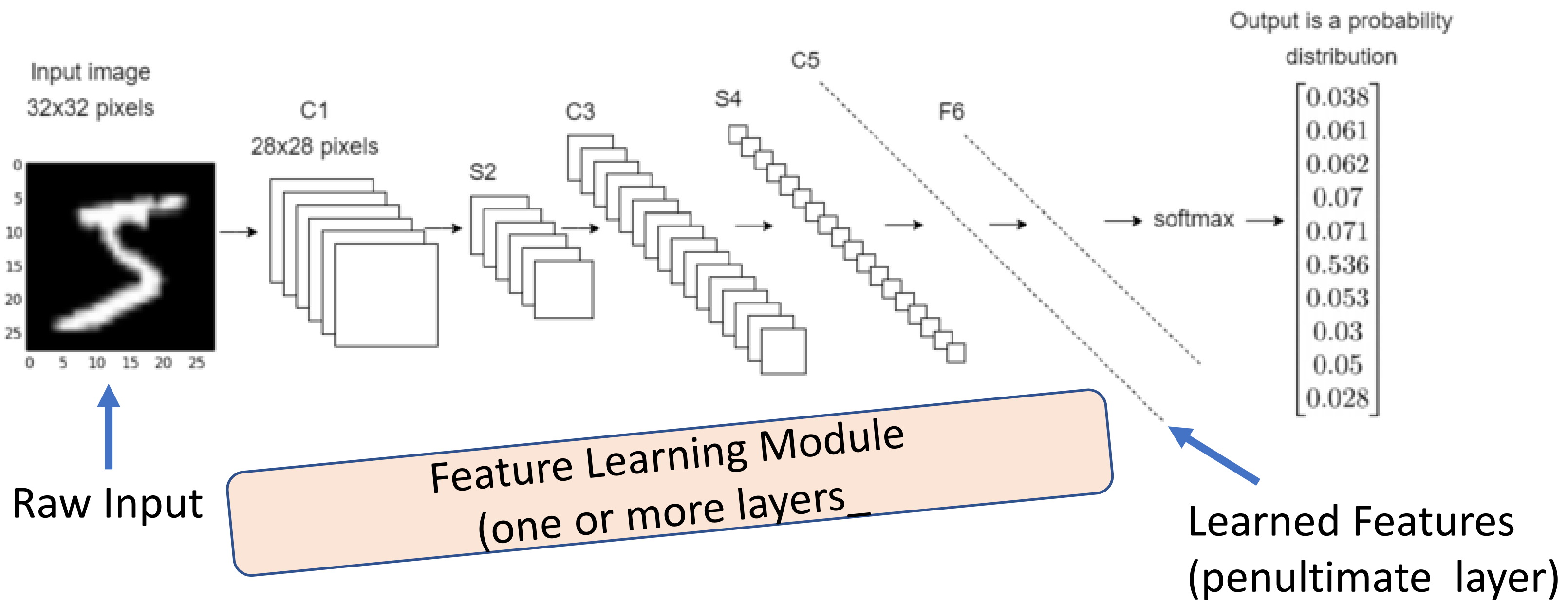

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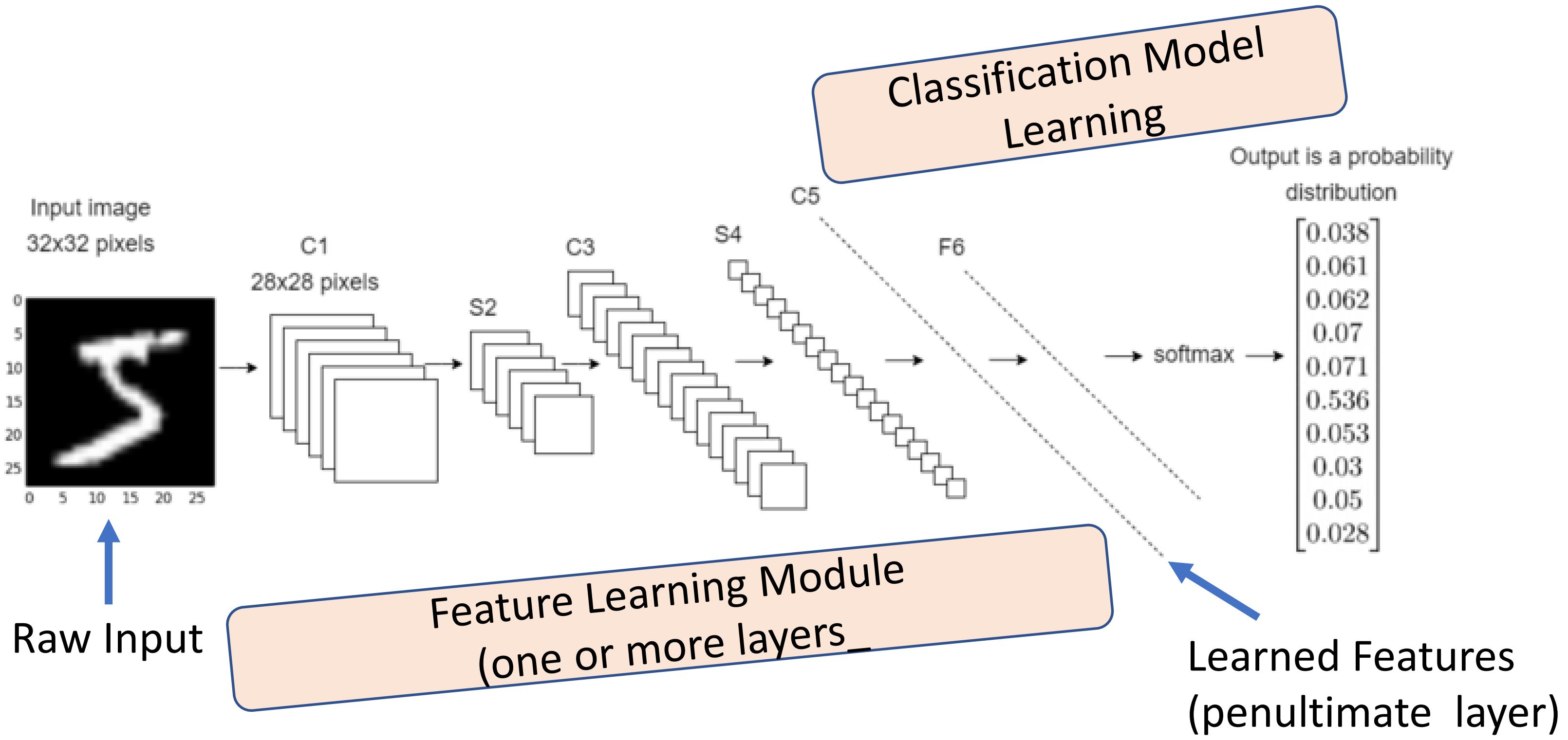

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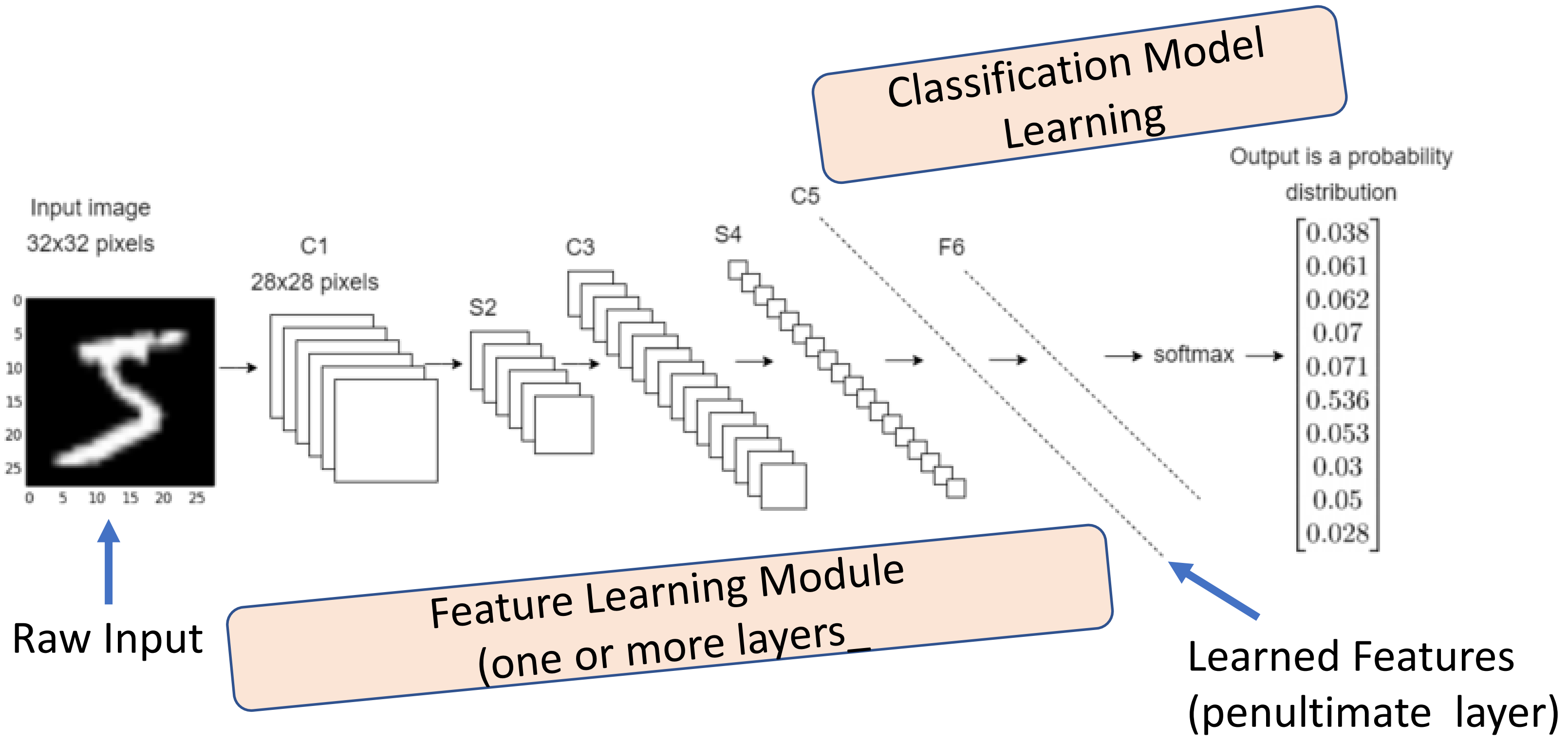

Pic an adaptation of the original from: https://deepai.org/

Some Notation/Nomenclature/Convention

input-output pairs $\{(\mathbf{x_n}, y_n)\}_{n=1}^{N}$

- inputs $\{\mathbf{x_n}\}_{n=1}^{N}$
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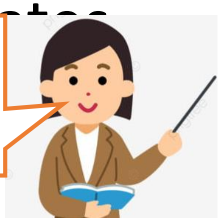

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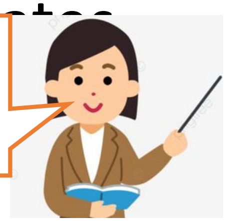

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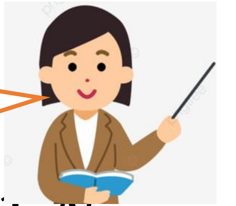

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- Often, the features can be of mixed types (some real, some categorical, some ordinal, etc.)

Some Basic Operations of Inputs

$\in R^D$ to of size D

- inputs $\{\mathbf{x}_n\}_{n=1}^N$, their average or mean can be computed as
  $= \frac{1}{N}\sum_{n=1}^N \mathbf{x}_n$
- and $\mathbf{x}_m$
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- and $\mathbf{x}_m$

- and the mean $\boldsymbol{\mu}$ of all inputs

Some Basic Operations of Inputs

- $\mathbf{x}\,n\,\mathbf{xx}\,\mathbf{x}\,n\,nn\,\mathbf{x}\,n\,\}\{\,\mathbf{x}\,n\,\}\,n$=1, $N\,nn$=1, $\{\,\mathbf{x}\,n\,\}\,n$=1, $N\,NN\,\{\,\mathbf{x}\,n\,\}\,n$=1, N their average or mean can be computed as
- $R\,D\,RR\,R\,D\,DD\,R\,D$ to of size *D*
- *Assume* each input feature vector $x\,n \in\ n\,n\,n\ \in R^D$ to of size *D*
- Given N inputs $\{\,\mathbf{x}\,n\,\}\,n = 1, N$ their average or mean can be computed as
- inputs $\{\mathbf{x}_n\}_{n=1,}^{N}$ their average or mean can be computed as

$$= \frac{1}{N}\sum_{n=1}^{N}\mathbf{x}_n$$

- and $\mathbf{x}_m$
- and the mean μ of all inputs

Some Basic Operations of Inputs

- $1\ N\ 1\ 1\ N\ NN\ 1\ N\ \ n{=}1\ N\ \ \mathbf{x}\ n\ \ nn{=}1\ n{=}1\ N\ \ \mathbf{x}\ n\ \ NN\ n{=}1\ N\ \ \mathbf{x}\ n\ \ \ \mathbf{x}\ n\ \mathbf{xx}\ \mathbf{x}\ n\ nn\ \mathbf{x}\ n\ \ n{=}1\ N$ $\mathbf{x}\ n$
- $\mathbf{x}\ n\ \mathbf{xx}\ \mathbf{x}\ n\ nn\ \mathbf{x}\ n\ \}\ \{\ \mathbf{x}\ n\ \}\ n{=}1,\ N\ nn{=}1,\ \{\ \mathbf{x}\ n\ \}\ n{=}1,\ N\ NN\ \{\ \mathbf{x}\ n\ \}\ n{=}1,\ N$ their average or mean can be computed as
- $R\ D\ RR\ R\ D\ DD\ R\ D$ to of size *D*
- *Assume* each input feature vector $x\ n \in\ \ n\ n\ n\ \ \in R^D$ to of size *D*

$$\mu = \frac{1}{N}\sum_{n=1}^{N}\mathbf{x}_n$$

- inputs $\{\mathbf{x}_n\}_{n=1,}^{N}$ their average or mean can be computed as

$$= \frac{1}{N}\sum_{n=1}^{N}\mathbf{x}_n$$

- and $\mathbf{x}_m$

Some Basic Operations of Inputs

- $1 N 1 1 N NN 1 N \;\; n{=}1 N \;\; \mathbf{x} n \;\; nn{=}1 n{=}1 N \;\; \mathbf{x} n \;\; NN n{=}1 N \;\; \mathbf{x} n \;\; \mathbf{x} n \mathbf{xx} \mathbf{x} n nn \mathbf{x} n \;\; n{=}1 N$ $\mathbf{x} n$
- $\mathbf{x} n \mathbf{xx} \mathbf{x} n nn \mathbf{x} n \} \{ \mathbf{x} n \} n{=}1, N nn{=}1, \{ \mathbf{x} n \} n{=}1, N NN \{ \mathbf{x} n \} n{=}1$ mean can be computed as

What does such a
“mean” represent?

- $R D RR R D DD R D$ to of size *D*
- *Assume* each input feature vector $x n \in \;\; n n n \;\; \in R^D$ to of size *D*

$$\mu = \frac{1}{N} \sum_{n=1}^{N} \mathbf{x}_n$$

- inputs $\{\mathbf{x}_n\}_{n=1,}^{N}$ their average or mean can be computed as

$$= \frac{1}{N} \sum_{n=1}^{N} \mathbf{x}_n$$

- and $\mathbf{x}_m$

Some Basic Operations of Inputs

- 1 N 1 1 N NN 1 N n=1 N $\mathbf{x}$ n nn=1 n=1 N $\mathbf{x}$ n NN n=1 N $\mathbf{x}$ n $\mathbf{x}$ n $\mathbf{xx}$ $\mathbf{x}$ n nn $\mathbf{x}$ n n=1 N $\mathbf{x}$ n
- $\mathbf{x}$ n $\mathbf{xx}$ $\mathbf{x}$ n nn $\mathbf{x}$ n } { $\mathbf{x}$ n } n=1, N nn=1, { $\mathbf{x}$ n } n=1, N NN { $\mathbf{x}$ n } n=1 mean can be computed as
- R D RR R D DD R D to of size *D*
- *Assume* each input feature vector x n ∈ n n n ∈ R^D to of si

$$\mu = \frac{1}{N}\sum_{n=1}^{N}\mathbf{x}_n$$

- inputs $\{\mathbf{x}_n\}_{n=1,}^{N}$ their average or mean can be computed as

$$= \frac{1}{N}\sum_{n=1}^{N}\mathbf{x}_n$$

- and $\mathbf{x}_m$

What does such a "mean" represent?

If inputs are all cat images, mean vector would represents what an "average" cat looks like

Some Basic Operations of Inputs

- and $\mathbf{x}\, m\, \mathbf{xx}\, \mathbf{x}\, m\, mm\, \mathbf{x}\, m$
- $1\, N\, 1\, 1\, N\, NN\, 1\, N\;\; n{=}1\, N\;\; \mathbf{x}\, n\;\; nn{=}1\, n{=}1\, N\;\; \mathbf{x}\, n\;\; NN\, n{=}1\, N\;\; \mathbf{x}\, n\;\; \mathbf{x}\, n$ $n{=}1\, N$ $\mathbf{x}\, n$
- $\mathbf{x}\, n\, \mathbf{xx}\, \mathbf{x}\, n\, nn\, \mathbf{x}\, n\, \}\, \{\, \mathbf{x}\, n\, \}\, n{=}1, N\, nn{=}1, \{\, \mathbf{x}\, n\, \}\, n{=}1, N\, NN\, \{\, \mathbf{x}\, n\, \}\, n{=}1, N$ their avera mean can be computed as
- $R\, D\, RR\, R\, D\, DD\, R\, D$ to of size *D*
- *Assume* each input feature vector $x\, n \in\;\; n\, n\, n\;\; \in R^D$ to of size *D*

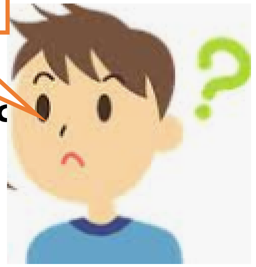
$$\mu = \frac{1}{N}\sum_{n=1}^{N}\mathbf{x}_n$$

- Can compute the Euclidean distance between any pair of inputs $x\, n\;\; n\, n\, n$ and $\mathbf{x}_m$

$$= \frac{1}{N}\sum_{n=1}^{N}\mathbf{x}_n$$

- and $\mathbf{x}_m$

What does such a "mean" represent?



If inputs are all cat images, mean vector would represents what an "average" cat looks like

Some Basic Operations of Inputs

- and $\mathbf{x}\, m\, \mathbf{xx}\, \mathbf{x}\, m\, mm\, \mathbf{x}\, m$
- $1\, N\, 1\, 1\, N\, NN\, 1\, N\;\; n{=}1\, N\;\; \mathbf{x}\, n\;\; nn{=}1\, n{=}1\, N\;\; \mathbf{x}\, n\;\; NN\, n{=}1\, N\;\; \mathbf{x}\, n\;\; \mathbf{x}\, n$ $n{=}1\, N$ $\mathbf{x}\, n$
- $\mathbf{x}\, n\, \mathbf{xx}\, \mathbf{x}\, n\, nn\, \mathbf{x}\, n\, \}\, \{\, \mathbf{x}\, n\, \}\, n{=}1, N\, nn{=}1, \{\, \mathbf{x}\, n\, \}\, n{=}1, N\, NN\, \{\, \mathbf{x}\, n\, \}\, n{=}1, N$ their avera mean can be computed as
- $R\, D\, RR\, R\, D\, DD\, R\, D$ to of size D
- *Assume* each input feature vector $x\, n \in\;\; n\, n\, n\;\; \in R^D$ to of size D
- Can cc$d(\boldsymbol{x}_n, \boldsymbol{x}_m) = ||\boldsymbol{x}_n - \boldsymbol{x}_m|| = \sqrt{(\boldsymbol{x}_n - \boldsymbol{x}_m)^\top (\boldsymbol{x}_n - \boldsymbol{x}_m)} = \sqrt{\sum_{d=1}^{D} (x_{nd} - x_{md})^2}$ n and $\mathbf{x}_m$

$$= \frac{1}{N} \sum_{n=1}^{N} \mathbf{x}_n$$

- and $\mathbf{x}_m$

Some Basic Operations of Inputs

- and the mean $\boldsymbol{\mu}\boldsymbol{\mu}$ of all inputs
- and $\mathbf{x}\, m\, \mathbf{xx}\, \mathbf{x}\, m\, mm\, \mathbf{x}\, m$
- $1\, N\, 1\, 1\, N\, NN\, 1\, N\;\; n{=}1\, N\;\; \mathbf{x}\, n\;\; nn{=}1\, n{=}1\, N\;\; \mathbf{x}\, n\;\; NN\, n{=}1\, N\;\; \mathbf{x}\, n\;\;\; \mathbf{x}\, n$ xx x n n n
  $\mathbf{x}\, n$
- $\mathbf{x}\, n\, \mathbf{xx}\, \mathbf{x}\, n\, nn\, \mathbf{x}\, n\, \}\, \{\, \mathbf{x}\, n\, \}\, n{=}1,\, N\, nn{=}1,\, \{\, \mathbf{x}\, n\, \}\, n{=}1,\, N\, NN\, \{\, \mathbf{x}$ ra
  mean can be computed as
- $R\, D\, RR\, R\, D\, DD\, R\, D$ to of size D
- *Assur*

$$d(\mathbf{x}_n, \mathbf{x}_m) = ||\mathbf{x}_n - \mathbf{x}_m|| = \sqrt{(\mathbf{x}_n - \mathbf{x}_m)^\top (\mathbf{x}_n - \mathbf{x}_m)} = \sqrt{\sum_{d=1}^{D} (x_{nd} - x_{md})^2}$$

- Can compute the Euclidean distance between any pair of inputs $x\, n\;\; n\, n\, n$ and $\mathbf{x}_m$

$$= \frac{1}{N} \sum_{n=1}^{N} \mathbf{x}_n$$

- or Euclidean distance between an input $x\, n\;\; n\, n\, n$ and the mean $\boldsymbol{\mu}$ of all inputs

What does such a "mean" represent?

If inputs are all cat images, mean vector would represents what an "average" cat looks like

Some Basic Operations of Inputs

- and the mean $\boldsymbol{\mu\mu}$ of all inputs
- and $\mathbf{x}\,m\,\mathbf{xx}\,\mathbf{x}\,m\,mm\,\mathbf{x}\,m$
- $1\,N\,1\,1\,N\,NN\,1\,N\;\;n{=}1\,N\;\;\mathbf{x}\,n\;\;nn{=}1\,n{=}1\,N\;\;\mathbf{x}\,n\;\;NN\,n{=}1\,N\;\;\mathbf{x}\,n\;\;\;\mathbf{x}\,n\,\mathbf{xx}\,\mathbf{x}\,n\,n$ … n $\mathbf{x}\,n$
- $\mathbf{x}\,n\,\mathbf{xx}\,\mathbf{x}\,n\,nn\,\mathbf{x}\,n\,\}\,\{\,\mathbf{x}\,n\,\}\,n{=}1,N\,nn{=}1,\{\,\mathbf{x}\,n\,\}\,n{=}1,N\,NN\,\{\,\mathbf{x}$ … ra mean can be computed as
- $R\,D\,RR\,R\,D\,DD\,R\,D$ to of size D
- *Assur*

$$d(\mathbf{x}_n, \mathbf{x}_m) = ||\mathbf{x}_n - \mathbf{x}_m|| = \sqrt{(\mathbf{x}_n - \mathbf{x}_m)^\top(\mathbf{x}_n - \mathbf{x}_m)} = \sqrt{\sum_{d=1}^{D}(x_{nd} - x_{md})^2}$$

- Can compute the Euclidean distance between any pair of inputs $x\,n\;\;n\,n\,n$ and $\mathbf{x}_m$

$$= \frac{1}{N}\sum_{n=1}^{N}\mathbf{x}_n$$

- or Euclidean distance between an input $x\,n\;\;n\,n\,n$ and the mean $\boldsymbol{\mu}$ of all inputs

Next Class

- Introduction to Supervised Learning
- A simple Supervised Learning algorithm based on computing distances