Machine Learning
ITCS 6156/8156

Introduction

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How to Automate Solutions to Computational Problems?

- Spam email:
  - Binary classification of emails into Spam vs. Ham.

- **Expert Systems** approach (also called rule-based):
  1. A group of experts write rules determining whether an email is spam or not.
  2. A programmer implement the rules into computer code.

- Example rules:
  - ”MONEY” appears in the text?
    - What if email sent by grandmother?

How to Automate Solutions to Computational Problems?

- **Expert Systems** approach (also called **rule-based**):
  - **Cognitively demanding**:
    - Difficult for humans to reason with many useful but imprecise features that are indicative (signals) of spam or not spam:
      - Words, phrases, images, meta-data, time series, …
      - Need to *combine a large number of signals*, figure out their *relative importance* in determining spam vs. ham label.
  - **Brittle**: Always going to miss some useful features or patterns.
    - "*All grammars leak.*" (Edward Sapir).
    - Spam filtering is adversarial, new features need to be added over time.

Why Machine Learning?

- **Machine Learning (ML)** approach:
  - Because ML is hot? No!
    - Rule-based (knowledge-based) may work very well.

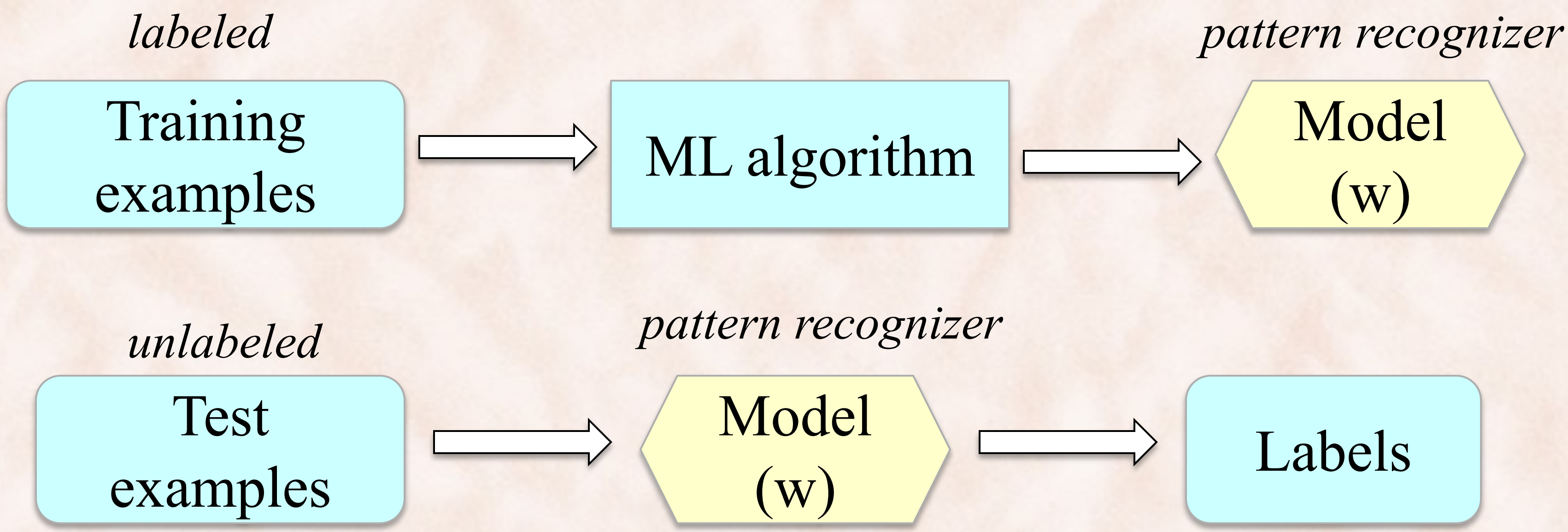
Input		=>	Output
30.2	2.1	=>	63.3
65.4	3.5	=>	229.1
46.2	0.5	=>	22.9
…	…	=>	…
25.3	4.0	=>	?

Why Machine Learning?

- **Machine Learning (ML)** approach:
  1. Acquire a large enough dataset of *labeled examples*:
     - Email is the *instance*, the *label* is spam (+1) vs. not spam (-1).
  2. Represent emails as *feature vectors*:
     - Each feature has a *weight*, the sign of the weighted sum of features should match the label.
       A. Traditional ML: engineer the features.
       B. Deep ML: **learn the features**.
  3. **Learn the weights** s.t. the model (weighted combination of features) does well on labeled examples.

What is Machine Learning?

- **Machine Learning** = constructing computer programs that *learn* from *experience* to perform well on a given task.
  - Supervised Learning i.e. discover patterns from labeled examples that enable predictions on (previously unseen) unlabeled examples.

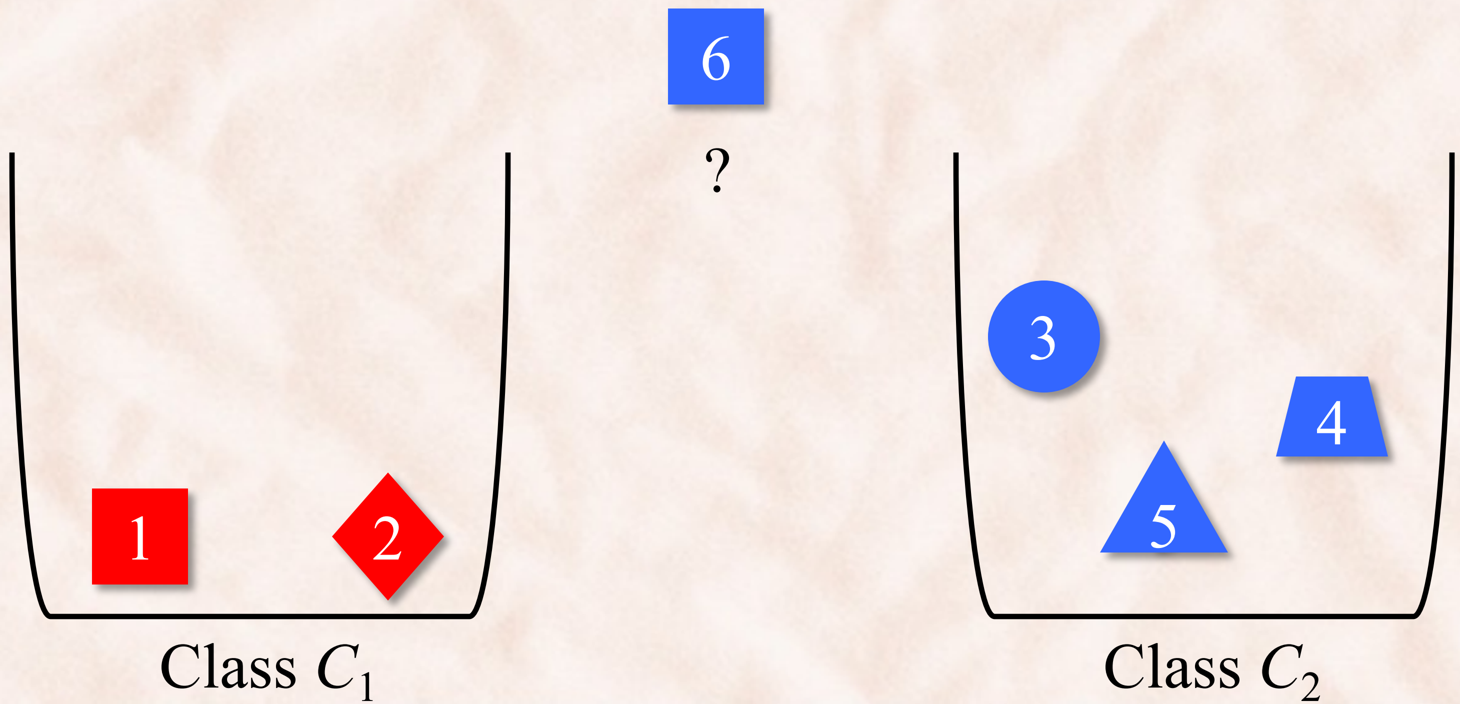


Example

M_1: x is Red => $x \in C_1$

M_2: x is a Square or x is a Diamond => $x \in C_1$

M_3: x is Red and x is a Quadrilateral => $x \in C_1$



Occam's Razor

William of Occam (1288 – 1348)

English Franciscan friar, theologian and philosopher.

"*Entia non sunt multiplicanda praeter necessitatem*"

- Entities must not be multiplied beyond necessity.

i.e. Do not make things needlessly complicated.

i.e. Prefer the simplest hypothesis that fits the data.

ML Objective

- Find a model **M**

  that is *simple* + that *fits the training data*.

$$\hat{\mathbf{M}} = \underset{\mathbf{M}}{\operatorname{argmin}}\ \ Complexity(\mathbf{M}) + Error(\mathbf{M}, Data)$$

- **Inductive hypothesis**: Models that perform well on training examples are expected to do well on test (unseen) examples.

- **Occam's Razor**: Simpler models are expected to do better than complex models on test examples (assuming similar training performance).

Example

M_1: x is Red => $x \in C_1$

M_2: x is a Square or x is a Diamond => $x \in C_1$

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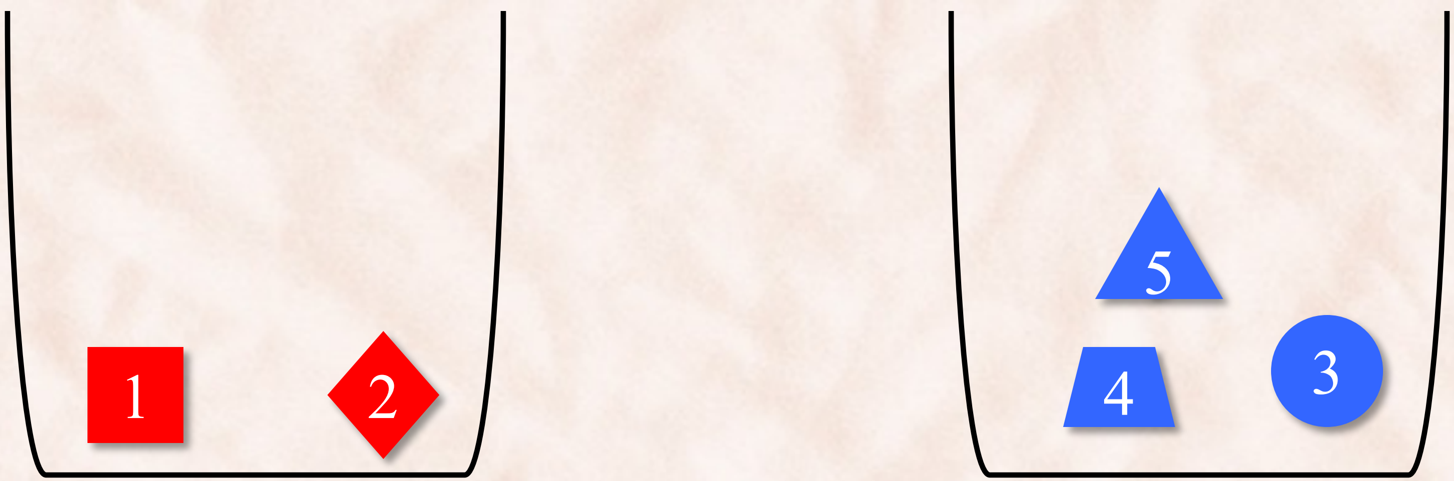


Class C_1 Class C_2

Feature Vectors

Features	$\varphi(x_1)$	$\varphi(x_2)$	$\varphi(x_3)$	$\varphi(x_4)$	$\varphi(x_5)$
(φ_1) Red?	1	1	0	0	0
(φ_2) Quad?	1	1	0	1	0
(φ_3) Square?	1	0	0	0	0
(φ_4) Diamond?	0	1	0	0	0
(y) Label	y_1=+1	y_2=+1	y_3=−1	y_4=−1	y_5=−1

Class C_1 Class C_2

Learning with Labeled Feature Vectors

Features	$\varphi(x_1)$	$\varphi(x_2)$	$\varphi(x_3)$	$\varphi(x_4)$	$\varphi(x_5)$
(φ_1) Red?	1	1	0	0	0
(φ_2) Quad?	1	1	0	1	0
(φ_3) Square?	1	0	0	0	0
(φ_4) Diamond?	0	1	0	0	0
(y) Label	$y_1=+1$	$y_2=+1$	$y_3=-1$	$y_4=-1$	$y_5=-1$

$\varphi(x_1) = [1, 1, 1, 0]^T$ $\varphi(x_2) = [1, 1, 0, 1]^T$ $\varphi(x_3) = [0, 0, 0, 0]^T$ ...
$y_1=+1$ $y_2=+1$ $y_3=-1$ ...

Learning = finding parameters $\mathbf{w} = [w_1, w_2, w_3, w_4]^T$ and τ such that:

- $\mathbf{w}^T\varphi(x_i) \geq \tau$, if $y_i = +1$
- $\mathbf{w}^T\varphi(x_i) < \tau$, if $y_i = -1$

where $\mathbf{w}^T\varphi(x) = w_1\varphi_1(x) + w_2\varphi_2(x) + w_3\varphi_3(x) + w_4\varphi_4(x)$

Model M_1: $\mathbf{x}_i$ is Red => $y_i = +1$

Red? Quad? Square? Diamond?

$\varphi(x_1) = [1, 1, 1, 0]^T$ label $y_1 = +1$ => $\mathbf{w}^T\varphi(x_1) = 1 \geq 1$

$\varphi(x_2) = [1, 1, 0, 1]^T$ label $y_2 = +1$ => $\mathbf{w}^T\varphi(x_2) = 1 \geq 1$

$\varphi(x_3) = [0, 0, 0, 0]^T$ label $y_3 = -1$ => $\mathbf{w}^T\varphi(x_3) = 0 < 1$

$\varphi(x_4) = [0, 1, 0, 0]^T$ label $y_3 = -1$ => $\mathbf{w}^T\varphi(x_4) = 0 < 1$

$\varphi(x_5) = [0, 0, 0, 0]^T$ label $y_3 = -1$ => $\mathbf{w}^T\varphi(x_5) = 0 < 1$

$\mathbf{w} = [1, 0, 0, 0]^T$

= > **M_1 error is 0%**

Learning = finding parameters $\mathbf{w} = [w_1, w_2, w_3, w_4]^T$ such that:

- $\mathbf{w}^T\varphi(x_i) \geq 1$, if $y_i = +1$
- $\mathbf{w}^T\varphi(x_i) < 1$, if $y_i = -1$

$\tau = 1$

where $\mathbf{w}^T\varphi(x) = w_1\varphi_1(x) + w_2\varphi_2(x) + w_3\varphi_3(x) + w_4\varphi_4(x)$

M_2: $\mathbf{x}_i$ is Square or Diamond => $y_i = +1$

Red? Quad? Square? Diamond?

$\varphi(x_1) = [1, 1, 1, 0]^T$ label $y_1 = +1$ => $\mathbf{w}^T\varphi(x_1) = 1 \geq 1$

$\varphi(x_2) = [1, 1, 0, 1]^T$ label $y_2 = +1$ => $\mathbf{w}^T\varphi(x_2) = 1 \geq 1$

$\varphi(x_3) = [0, 0, 0, 0]^T$ label $y_3 = -1$ => $\mathbf{w}^T\varphi(x_3) = 0 < 1$

$\varphi(x_4) = [0, 1, 0, 0]^T$ label $y_3 = -1$ => $\mathbf{w}^T\varphi(x_4) = 0 < 1$

$\varphi(x_5) = [0, 0, 0, 0]^T$ label $y_3 = -1$ => $\mathbf{w}^T\varphi(x_5) = 0 < 1$

$\boxed{\mathbf{w} = [0, 0, 1, 1]^T}$

$\boxed{= > \mathbf{M_2} \text{ error is 0\%}}$

Learning = finding parameters $\mathbf{w} = [w_1, w_2, w_3, w_4]^T$ such that (τ =1):

- $\mathbf{w}^T\varphi(x_i) \geq 1$, if $y_i = +1$
- $\mathbf{w}^T\varphi(x_i) < 1$, if $y_i = -1$

where $\mathbf{w}^T\varphi(x) = w_1\varphi_1(x) + w_2\varphi_2(x) + w_3\varphi_3(x) + w_4\varphi_4(x)$

M_1 or M_2?

- Model M_1: **$\mathbf{x}_i$ is Red => $y_i = +1$**
  - **$\mathbf{w}^{(1)} = [1, 0, 0, 0]^T$**
  - **Error = 0%**

- Model M_2: **$\mathbf{x}_i$ is Square or Diamond => $y_i = +1$**
  - **$\mathbf{w}^{(2)} = [0, 0, 1, 1]^T$**
  - **Error = 0%**

- Which one should we choose?
  - Which one is expected to perform better on unseen (new) examples?

ML Objective

- Find a model **w** that is *simple* and that *fits the training data*.

$$\hat{\mathbf{w}} = \arg\min_{\mathbf{w}} \ \text{Complexity}(\mathbf{w}) + \text{Error}(\mathbf{w}, \mathit{Data})$$

M_1 or M_2?

- Model M_1: **$\mathbf{x}_i$ is Red => $y_i = +1$**
  - **$\mathbf{w}^{(1)} = [1, 0, 0, 0]^T$**
  - **Error = 0%**
- Model M_2: **$\mathbf{x}_i$ is Square or Diamond => $y_i = +1$**
  - **$\mathbf{w}^{(2)} = [0, 0, 1, 1]^T$**
  - **Error = 0%**

$$\hat{\mathbf{w}} = \arg\min_{\mathbf{w}} \ \text{Complexity}(\mathbf{w}) + \text{Error}(\mathbf{w}, \mathit{Data})$$

Complexity($\mathbf{w}$) = ?

- $\|\mathbf{w}\|_0$ i.e. # non-zero values
- $\|\mathbf{w}\|_1$ i.e. sum of absolute values
- $\|\mathbf{w}\|_2^2$ i.e sum of squared values

ML Objectives

- Find a model **w** that is *simple* and that *fits the training data*.

$$\hat{\mathbf{w}} = \arg\min_{\mathbf{w}} \ \text{Complexity}(\mathbf{w}) + \text{Error}(\mathbf{w}, \mathit{Data})$$

Ridge Regression: $$\operatorname*{argmin}_{\mathbf{w}} \ \frac{\lambda}{2}\|\mathbf{w}\|^2 + \frac{1}{2}\sum_{n=1}^{N}\{y(x_n, \mathbf{w}) - t_n\}^2$$

Logistic Regression: $$\operatorname{argmin} \frac{\alpha}{2}\|\mathbf{w}\|^2 - \sum_{n=1}^{N} \ln p(t_n | x_n)$$

ML Objectives

Support Vector Machines:

Upper bound on the number of misclassified training examples

$$\operatorname*{argmin}_{\mathbf{w}} \; \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{n=1}^{N}\xi_n$$

subject to:

$$t_n(\mathbf{w}^T\varphi(\mathbf{x}_n)+b) \geq 1-\xi_n, \qquad \forall n \in \{1,\ldots,N\}$$
$$\xi_n \geq 0$$

Definition: *Bias* $w_0 = -$ *Threshold* τ

$w_1\varphi_1(x) + w_2\varphi_2(x) + w_3\varphi_3(x) + w_4\varphi_4(x) \geq \tau$

$w_1\varphi_1(x) + w_2\varphi_2(x) + w_3\varphi_3(x) + w_4\varphi_4(x) - \tau \geq 0$

Define the **intercept** or **bias** $w_0 = -\tau$.

$w_1\varphi_1(x) + w_2\varphi_2(x) + w_3\varphi_3(x) + w_4\varphi_4(x) + w_0 \geq 0$

$h(\mathbf{x}) = \mathbf{w}^T\varphi(\mathbf{x}) + w_0 \;\geq 0$
where:
  $\mathbf{w} = [w_1, w_2, w_3, w_4]$
  $\varphi(x) = [\varphi_1(x), \varphi_2(x), \varphi_3(x), \varphi_4(x)]$

$h(\mathbf{x}) = \mathbf{w}^T\varphi(\mathbf{x}) \;\geq 0$
where:
  $\mathbf{w} = [w_0, w_1, w_2, w_3, w_4]$
  $\varphi(x) = [1, \varphi_1(x), \varphi_2(x), \varphi_3(x), \varphi_4(x)]$

Geometric Interpretation

- Often we drop the φ and use bolded **x** itself to denote the feature vector $\mathbf{x} = [x_1, x_2, \ldots, x_K]$.
- Example **x** is a point in a K-dimensional feature space.
- Parameters **w** form a vector.
- What does it mean that $\mathbf{w}^T\mathbf{x} + w_0 > 0$?

Linear Discriminant Functions: Two classes (K = 2)

- Use a linear function of the input vector:

$$h(\mathbf{x}) = \mathbf{w}^T\mathbf{x} + w_0$$

weight vector

bias = – threshold

- Decision:

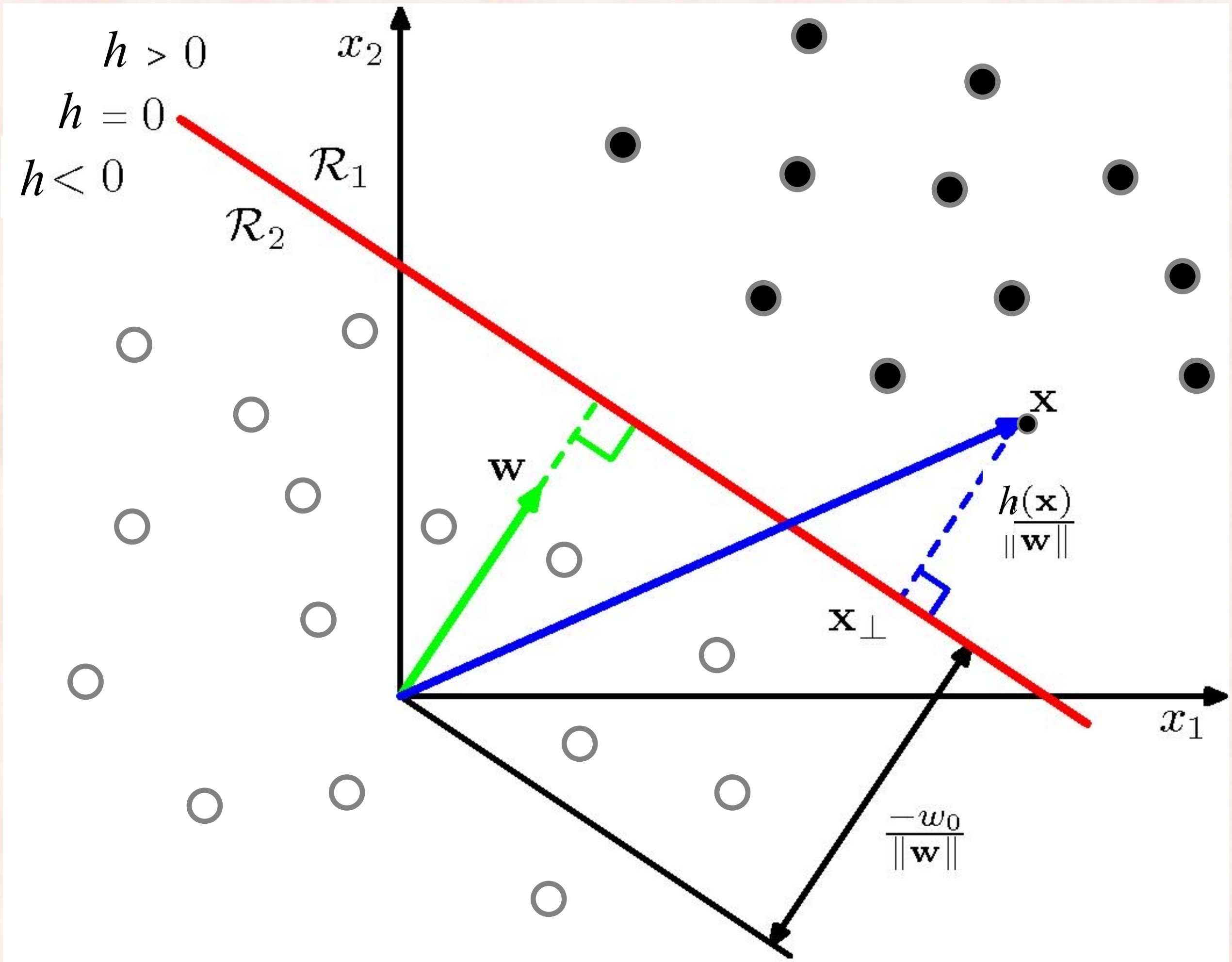
$\mathbf{x} \in C_1$ if $h(\mathbf{x}) \geq 0$, otherwise $\mathbf{x} \in C_2$.

$\Rightarrow$ **decision boundary** is hyperplane $h(\mathbf{x}) = 0$.

- Properties:
  - $\mathbf{w}$ is orthogonal to vectors lying within the decision surface.
  - w_0 controls the location of the decision hyperplane.

Geometric Interpretation

$$h(\mathbf{x}) = \mathbf{w}^T\mathbf{x} + w_0$$



Outline

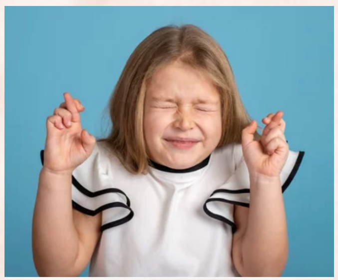
- We want to use a linear function of the feature vector:

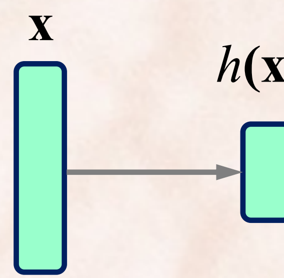
$$h(\mathbf{x}) = \mathbf{w}^T\mathbf{x} + w_0$$

- How to find **w** automatically? Use ML!
  - **Perceptron**.
  - **Logistic Regression**.
  - **SVMs**.
- What if the data is not linearly separable? Make it!
  - Engineer new features or use kernels (Perceptron, SVMs).
  - Learn new features (**Neural Networks**).

Machine Learning (most of ML pre-2006)

- Hope raw data **x** is linearly separable.

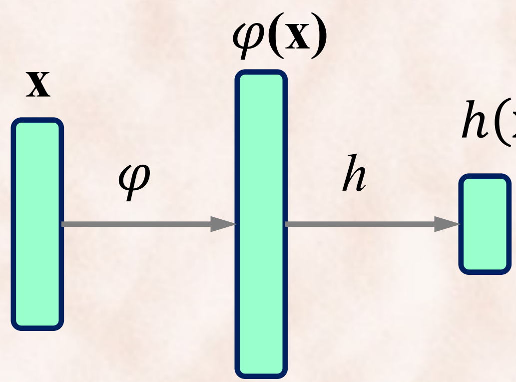




$$h(\mathbf{x}) = \mathbf{w}^T\mathbf{x} + w_0$$

Use a Perceptron or LR or SVMs to learn **w**.

- Engineer features $\varphi(\mathbf{x})$, aim to make data linearly separable.

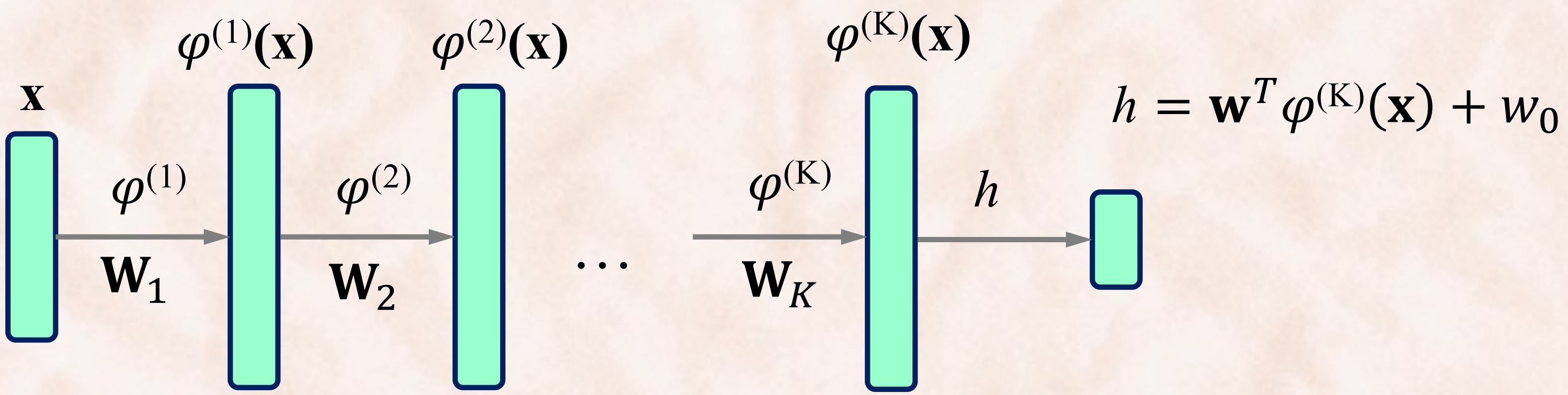


$$h(\mathbf{x}) = \mathbf{w}^T\varphi(\mathbf{x}) + w_0$$

Use a Perceptron or LR or SVMs to learn **w**.

Deep Learning

- A raw observation vector **x** is pre-processed and further transformed into a sequence of higher-level feature vectors $\varphi(\mathbf{x}) = [\varphi^{(1)}(\mathbf{x}), \varphi^{(2)}(\mathbf{x}), \ldots, \varphi^{(K)}(\mathbf{x})]^T$ that are **learned**.



Linear Models: $h(\mathbf{x}) = \mathbf{w}^T \mathbf{x}$

- Given N training examples $(\mathbf{x}_1,t_1)$, $(\mathbf{x}_2,t_2)$, … $(\mathbf{x}_N,t_N)$ where:
  - Labels $t_j \in \{-1, +1\}$.
  - Each example $\mathbf{x}_j$ is assumed to also contain a bias feature set to 1, corresponding to parameter w_0.

- Find parameter vector $\mathbf{w}$ such the the linear model $h(\mathbf{x}) = \mathbf{w}^T \mathbf{x}$ fits the training examples.

The Perceptron Algorithm: Two Classes

$$sgn(z) = \begin{cases} +1 & \text{if } z > 0, \\ 0 & \text{if } z = 0, \\ -1 & \text{if } z < 0 \end{cases}$$

1. **initialize** parameters $\mathbf{w} = 0$
2. **for** $n = 1 \ldots N$
3. $\quad h_n = sgn(\mathbf{w}^T \mathbf{x}_n)$
4. $\quad$ **if** $h_n \neq t_n$ **then**
5. $\quad\quad \mathbf{w} = \mathbf{w} + t_n \mathbf{x}_n$

Repeat:
a) until convergence.
b) for a number of epochs E.

Theorem [Rosenblatt, 1962]:

If the training dataset is linearly separable, the perceptron learning algorithm is guaranteed to find a solution in a finite number of steps.

- see Theorem 1 (Block, Novikoff) in [Freund & Schapire, 1999].

The Perceptron Algorithm: Two Classes

1. **initialize** parameters $\mathbf{w} = 0$
2. **for** $n = 1 \ldots \mathrm{N}$
3. $h_n = \mathbf{w}^{\mathrm{T}} \mathbf{x}_n$
4. **if** $h_{\mathrm{n}} t_n \leq 0$ **then**
5. $\mathbf{w} = \mathbf{w} + t_n \mathbf{x}_n$

$$sgn(z) = \begin{cases} +1 & \text{if } z > 0, \\ 0 & \text{if } z = 0, \\ -1 & \text{if } z < 0 \end{cases}$$

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The Perceptron Algorithm: Two Classes

1. **initialize** parameters $\mathbf{w} = 0$
2. **for** $n = 1 \ldots \text{N}$
3. $h_n = \mathbf{w}^{\text{T}}\mathbf{x}_n$
4. **if** $h_{\text{n}} \geq 0$ and $t_n = -1$
5. $\mathbf{w} = \mathbf{w} - \mathbf{x}_n$
6. **if** $h_{\text{n}} \leq 0$ and $t_n = +1$
7. $\mathbf{w} = \mathbf{w} + \mathbf{x}_n$

$$sgn(z) = \begin{cases} +1 & \text{if } z > 0, \\ 0 & \text{if } z = 0, \\ -1 & \text{if } z < 0 \end{cases}$$

Repeat:
a) until convergence.
b) for a number of epochs E.

What is the impact of the perceptron update on the score $\mathbf{w}^{\text{T}}\mathbf{x}_n$ of the misclassified example $\mathbf{x}_n$?

The Perceptron Algorithm: Two Classes

initialize parameters $\mathbf{w} = 0$

for epoch $e = 1 \ldots \mathrm{E}$

mistakes = 0

for example $n = 1 \ldots \mathrm{N}$

$h_n = sgn(\mathbf{w}^{\mathrm{T}}\mathbf{x}_n)$

if $h_{\mathrm{n}} \neq t_n$ **then**

$\mathbf{w} = \mathbf{w} + t_n\mathbf{x}_n$

mistakes = mistakes + 1

if mistakes = 0

break

Converged!

1 epoch = one pass over all training examples.

The Perceptron Algorithm: Two Classes

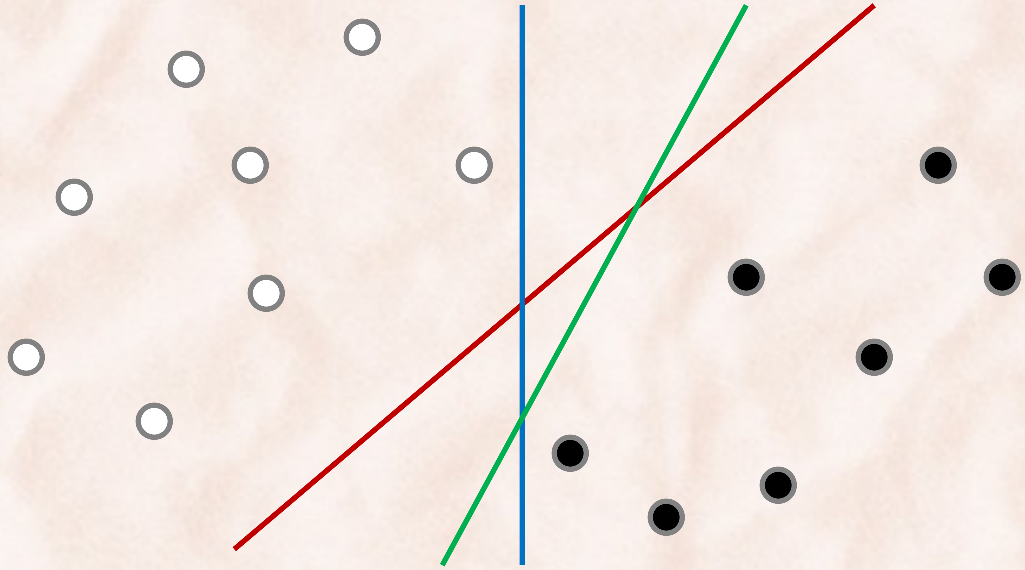
1. **initialize** parameters $\mathbf{w} = 0$
2. **for** $n = 1 \ldots N$
3. $\quad h_n = sgn(\mathbf{w}^{\mathrm{T}}\mathbf{x}_n)$
4. $\quad$ **if** $h_n \neq t_n$ **then**
5. $\quad\quad \mathbf{w} = \mathbf{w} + t_n\mathbf{x}_{\mathrm{n}}$

Repeat:
a) until convergence.
b) for a number of epochs E.

Loop invariant: **w** is a weighted sum of training vectors:

$$\mathbf{w} = \sum_n \alpha_n t_n \mathbf{x}_n \quad \Rightarrow \quad \mathbf{w}^T\mathbf{x} = \sum_n \alpha_n t_n \mathbf{x}_n^T \mathbf{x}$$

Classifiers & Margin

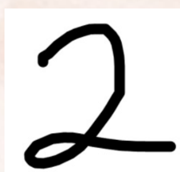


- Which classifier has the smallest generalization error?
  - The one that maximizes the margin [Computational Learning Theory]
    - **margin** = the distance between the decision boundary and the closest sample.

ML Concepts & Notation

- A (labeled) example ($\mathbf{x}$, t) consists of:
  - Instance / observation / raw feature vector $\mathbf{x}$.
  - Label t.

- Examples:
  1. Digit recognition:



instance $\mathbf{x}$ = ?

label t = ?

  2. Language modeling:
     - "machine .... is a hot topic in AI"

eat … *learning* … *on*

instance $\mathbf{x}$ = ?

label t = ?

ML Concepts & Notation

- A training dataset is a set of (training) examples $(\mathbf{x}_1,t_1)$, $(\mathbf{x}_2,t_2)$, … $(\mathbf{x}_N,t_N)$:
  - The data matrix X contains all instance vectors $\mathbf{x}_1$, $\mathbf{x}_2$, …, $\mathbf{x}_N$ row-wise.
  - The label vector $\mathbf{t} = [t_1, t_2, \ldots, t_N]^\mathrm{T}$.

- A test dataset is a set of (test) examples $(\mathbf{x}_{N+1},t_{N+1})$, …, $(\mathbf{x}_{N+\mathrm{M}},t_{N+\mathrm{M}})$:
  - **Must be unseen, i.e. new, i.e. different from the training examples**!

ML Concepts & Notation

- There is a function f that maps an instance $\mathbf{x}$ to its label $t = f(\mathbf{x})$.
  - f is unknown / not given.
  - But we observe samples from f : $(\mathbf{x}_1, t_1 = f(\mathbf{x}_1))$, $(\mathbf{x}_2, t_2)$, … $(\mathbf{x}_N, t_N)$.

- Learning means finding a model h that maps an instance $\mathbf{x}$ to a label $h(\mathbf{x}) \approx f(\mathbf{x})$, i.e. close to the true label of $\mathbf{x}$.
  - Machine learning = finding a model h that approximates well the unknown function f.
  - Machine learning = function approximation.

ML Concepts & Notation

- Machine learning is inductive:
  - Inductive hypothesis: if a model performs well on training examples, it is expected to also perform well on unseen (test) examples.
    - Assume within-distribution test examples.

- The model h is often specified through a set of parameters $\mathbf{w}$:
  - $\mathbf{x}$ is mapped by the model to $h(\mathbf{x}, \mathbf{w})$.

- The objective function $J(\mathbf{w})$ captures how poorly the model does on the training dataset:
  - Want to find $\hat{\mathbf{w}} = \underset{\mathbf{w}}{\operatorname{argmin}} J(\mathbf{w})$
    - Machine learning = optimization.

Fitting vs. Generalization

- Fitting performance = how well the model performs on training examples.

- Generalization performance = how well the model performs on unseen (test) examples.

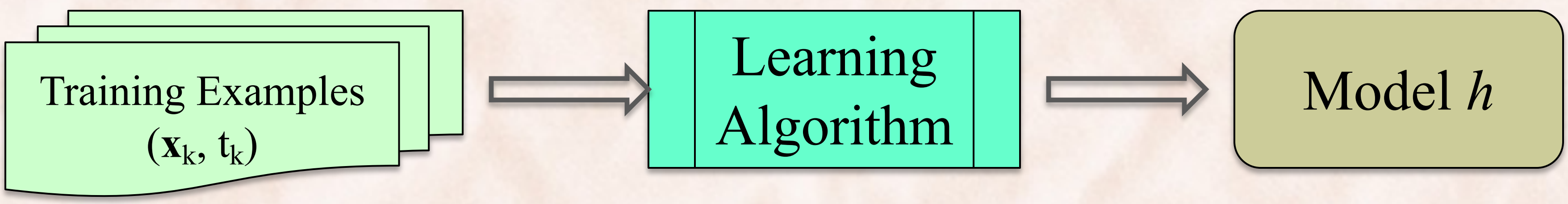
- We are interested in **Generalization**:
  - Prefer finding patterns to memorizing examples!
    - Overfitting:
    - Underfitting:
    - Regularization:

Regularization = Any Method that Alleviates Overfitting

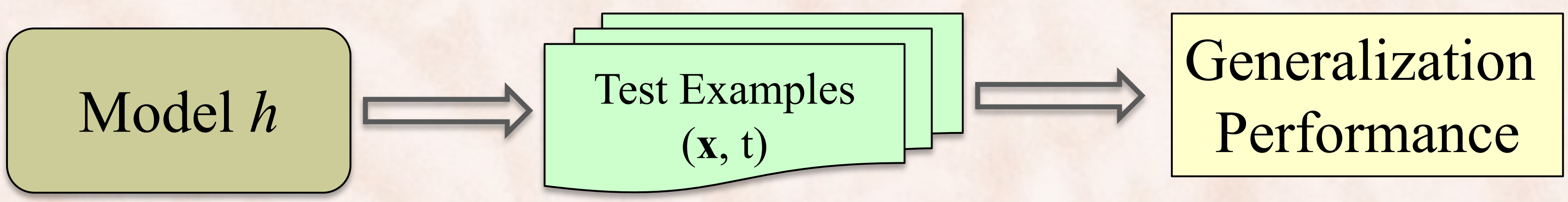
- **Parameter norm penalties** (term in the objective).
- Limit parameter norm (constraint).
- **Dataset augmentation**.
- **Dropout**.
- **Ensembles**.
- Semi-supervised learning.
- **Early stopping**.
- Noise robustness.
- Sparse representations.
- Adversarial training.

Supervised Learning

Training



Testing



Features

- Learning = finding parameters $\mathbf{w} = [w_1, w_2, w_3, w_4]$ and τ such that:

  $\mathbf{w}^T\varphi(x_i) \geq \tau$, if $y_i = +1$

  $\mathbf{w}^T\varphi(x_i) < \tau$, if $y_i = -1$

  where $\mathbf{w}^T\varphi(x) = w_1\times\varphi_1(x) + w_2\times\varphi_2(x) + w_3\times\varphi_3(x) + w_4\times\varphi_4(x)$

Red? Quad? Square? Diamond?

Where do these features come from?

Object Recognition: Cats






Pixels as Features?

$\varphi(x) = [25, 63, 125, 32, 84, 257, ..., 13,$
$27, 39, 8, 213, 107, 54, 73, ..., 91,$
$67, 59, 72, 33, 112, 54, 35, ..., 9,$
[illegible] $..., 28,$
$93, 44, 69, 85, 68, 54, 87, ..., 11,$
$117, 59, 117, 210, 177, 54, 72, ...]^T$

Poor recognition accuracy!

- Learning = finding parameters $\mathbf{w} = [w_1, w_2, w_3, ... w_k]^T$ such that:

  $\mathbf{w}^T\varphi(x_i) \geq \tau$, if $y_i = +1$ (cat)

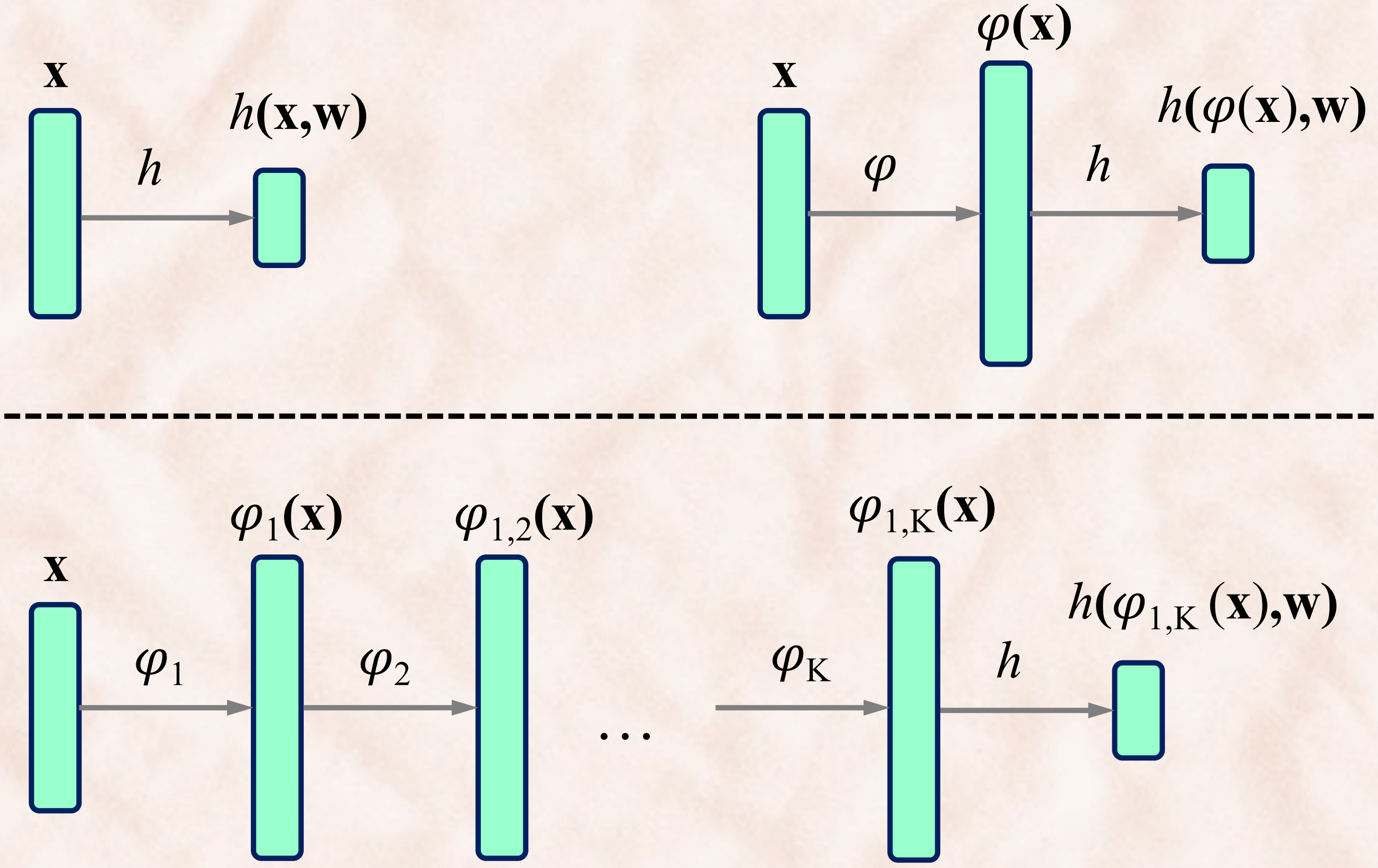
  $\mathbf{w}^T\varphi(x_i) < \tau$, if $y_i = -1$ (other)

  where $\mathbf{w}^T\varphi(x) = w_1 \times \varphi_1(x) + w_2 \times \varphi_2(x) + w_3 \times \varphi_3(x) + ... w_k \times \varphi_k(x)$

ML Concepts & Notation

- Often, a raw observation $\mathbf{x}$ is pre-processed and further transformed into a feature vector $\varphi(\mathbf{x}) = [\varphi_1(\mathbf{x}), \varphi_1(\mathbf{x}), \ldots, \varphi_K(\mathbf{x})]^T$.
  - Where do the features φ_k come from?
    - Feature engineering, e.g. in polynomial curve fitting:
      - manual, can be time consuming (e.g. SIFT).
    - (Unsupervised) feature learning, e.g. in modern computer vision
      - automatic, used in deep learning models.

Machine Learning vs. Deep Learning



What is Machine Learning?

- **Machine Learning** = constructing computer programs that *automatically improve with experience*:
  - Supervised Learning i.e. learning from labeled examples:
    - Classification
    - Regression
  - Unsupervised Learning i.e. learning from unlabeled examples:
    - Clustering.
    - Dimensionality reduction (visualization).
    - Density estimation.
  - Reinforcement Learning i.e. learning with delayed feedback.

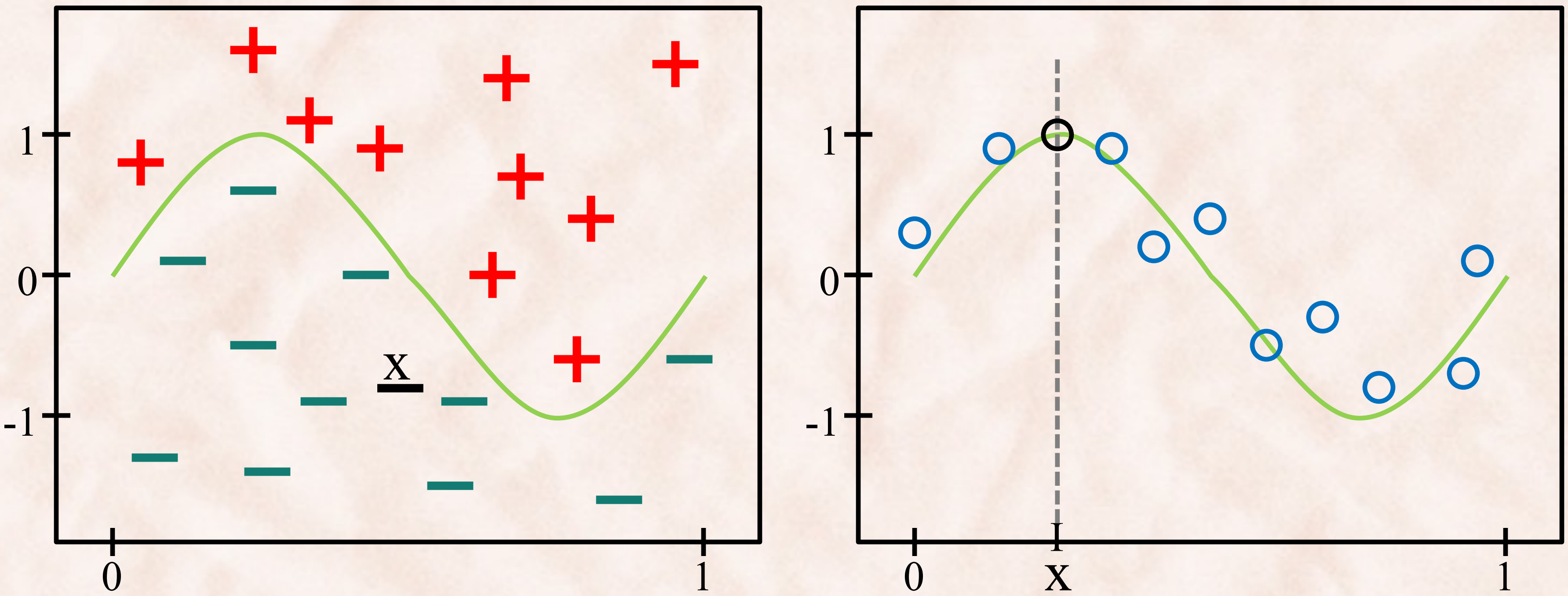
Supervised Learning

- Task = learn a function f : X $\rightarrow$ T that maps input instances $\mathbf{x} \in$ X to output targets $t \in$ T:
  - **Classification**:
    - The output $t \in$ T is one of a finite set of discrete categories.
  - **Regression**:
    - The output $t \in$ T is continuous, or has a continuous component.

- Supervision = set of training examples:

  $(\mathbf{x}_1,t_1)$, $(\mathbf{x}_2,t_2)$, ... $(\mathbf{x}_n,t_n)$

Classification vs. Regression



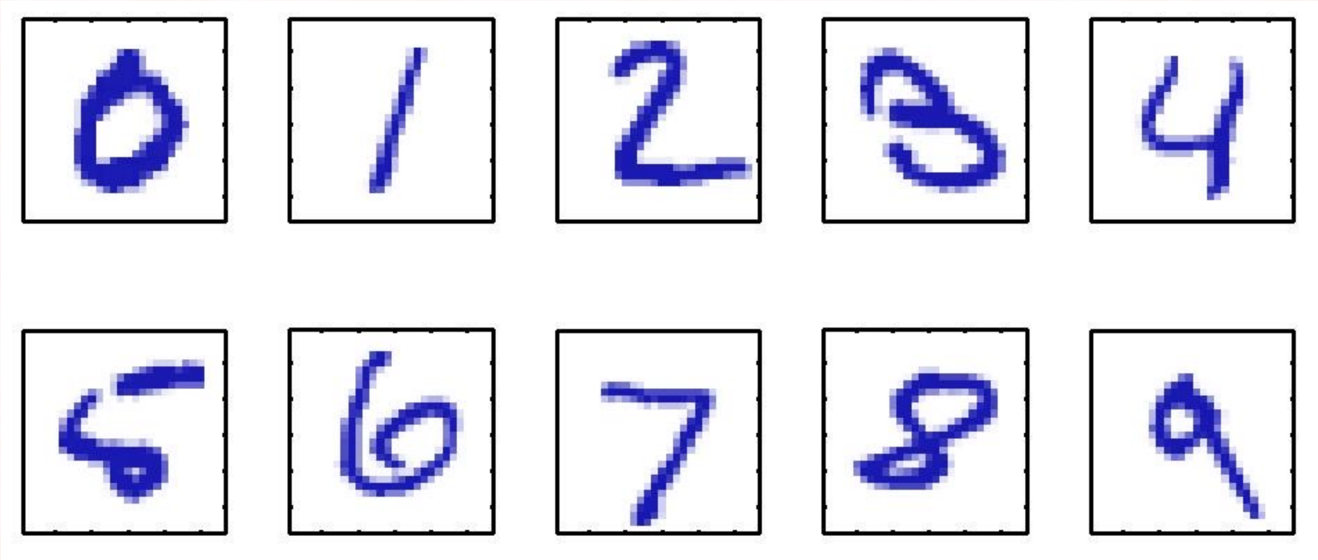
Classification: Junk Email Filtering

[Sahami, Dumais & Heckerman, AAAI'98]

From: Tammy Jordan	**From: UK National Lottery**
jordant@oak.cats.ohiou.edu	**edreyes@uknational.co.uk**
Subject: Spring 2015 Course	**Subject: Award Winning Notice**
-------------------------------------	**-------------------------------------**
CS690: Machine Learning Instructor: Razvan Bunescu Email: bunescu@ohio.edu Time and Location: Tue, Thu 9:00 AM , ARC 101 Website: http://ace.cs.ohio.edu/~razvan/courses/ml6830 Course description: Machine Learning is concerned with the design and analysis of algorithms that enable computers to automatically find patterns in the data. This introductory course will give an overview …	**UK NATIONAL LOTTERY. GOVERNMENT ACCREDITED LICENSED LOTTERY. REGISTERED UNDER THE UNITED KINGDOM DATA PROTECTION ACT;** **We happily announce to you the draws of (UK NATIONAL LOTTERY PROMOTION) International programs held in London , England Your email address attached to ticket number :3456 with serial number :7576/06 drew the lucky number 4-2-274, which subsequently won you the lottery in the first category …**

- Email filtering:
  - Provide emails labeled as *{Spam, Ham}*.
  - Train *Naïve Bayes* model to discriminate between the two.

Classification: Handwritten Zip Code Recognition [Le Cun et al., Neural Computation '89]



- Handwritten digit recognition:
  - Provide images of handwritten digits, labeled as {0, 1, …, 9}.
  - Train *Convolutional Neural Network* model to recognize digits.

Classification: Medical Diagnosis

[Krishnapuram et al., GENSIPS'02]

- Cancer diagnosis from gene expression signatures:
  - Create database of gene expression profiles (X) from tissues of known cancer status (Y):
    - Human accute leukemia dataset:
      - http://www.broadinstitute.org/cgi-bin/cancer/datasets.cgi
    - Colon cancer microarray data:
      - http://microarray.princeton.edu/oncology
  - Train *Logistic Regression* / *SVM* / *RVM* model to classify the gene expression of a tissue of unknown cancer status.

Classification: Other Examples

- Named Entity Recognition
- Named Entity Disambiguation
- Relation Extraction
- Word Sense Disambiguation
- Coreference Resolution
- Sentiment Analysis
- Chord Recognition
- Voice Separation
- Tone recognition
- Gesture Recognition
- Galaxy Morphology Recognition
- Dysarthria Prediction
- Tone Classification in Mandarin Chinese
- …

Regression: Examples

1. Stock market, oil price, GDP, income prediction:
   – Use the current stock market conditions ($x \in X$) to predict tomorrow's value of a particular stock ($t \in T$).

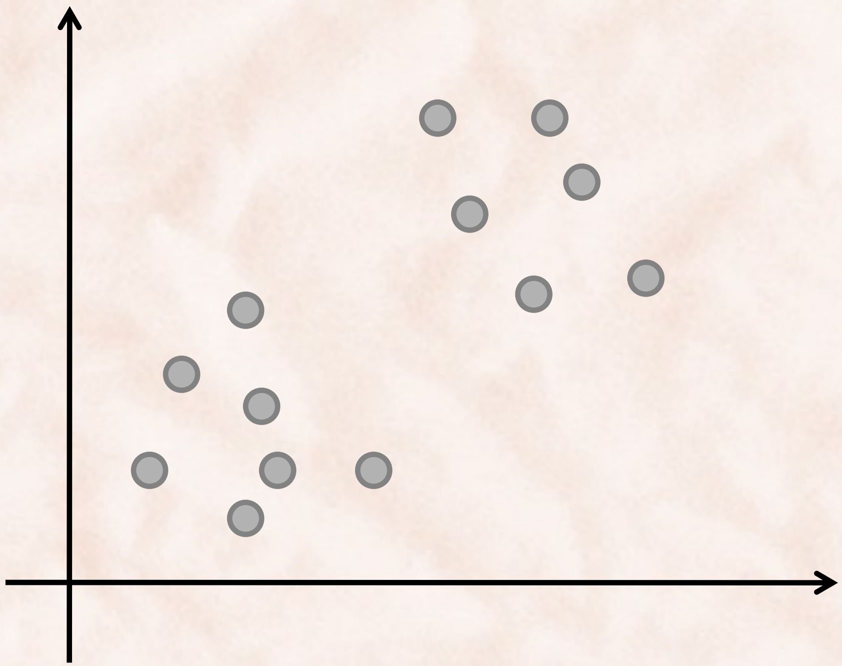
2. Blood glucose level prediction.

3. Chemical processes:
   – Predict the yield in a chemical process based on the concentrations of reactants, temperature and pressure.

- Algorithms:
  – *Linear Regression*, *Neural Networks*, *Support Vector Machines*, …

Unsupervised Learning: Clustering

- Partition unlabeled examples into disjoint clusters such that:
  - Examples in the same cluster are similar.
  - Examples in different clusters are different.



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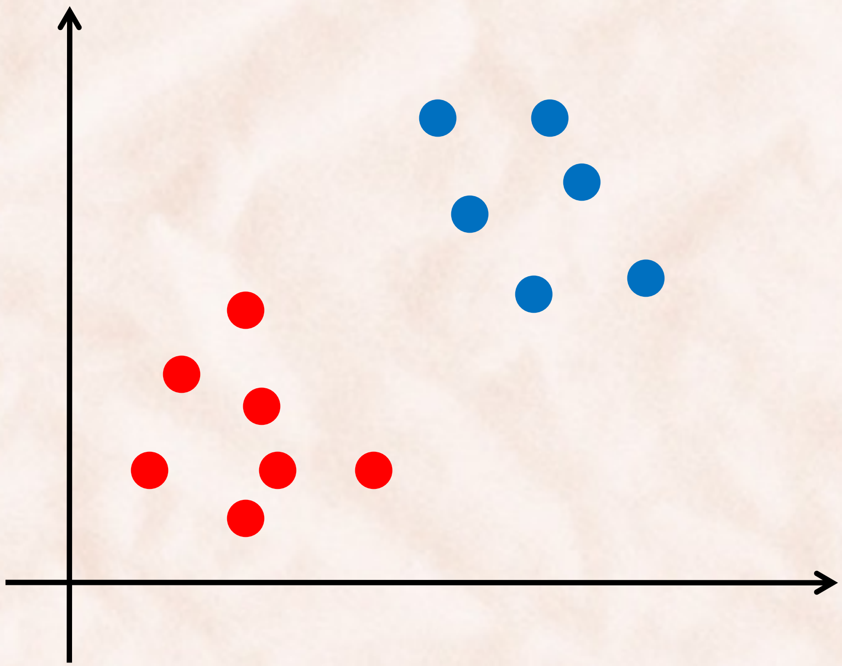
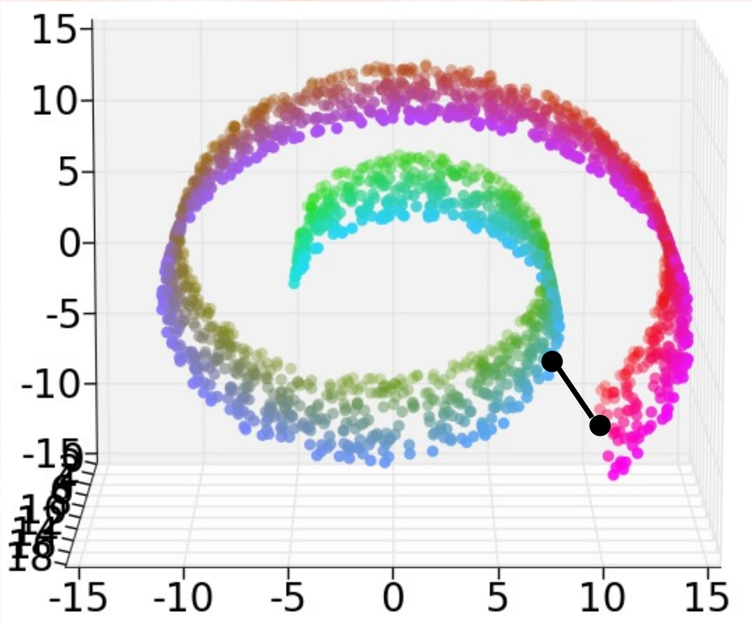
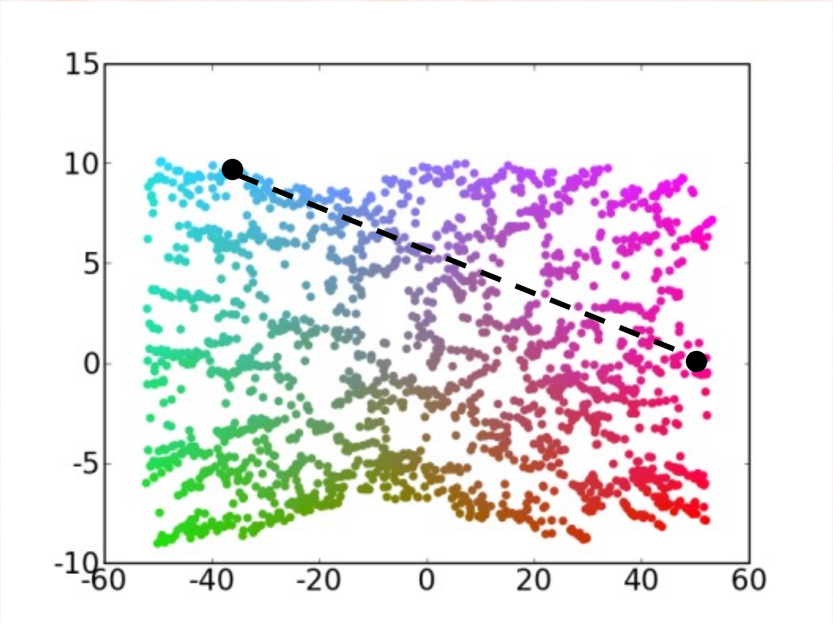


- k-Means, need to provide:
  - number of clusters ($k = 2$)
  - similarity measure (Euclidean)

Unsupervised Learning: Dimensionality Reduction

- Manifold Learning:
  - Data lies on a low-dimensional manifold embedded in a high-dimensional space.
  - Useful for *feature extraction* and *visualization*.





Unsupervised Feature Learning: Auto-encoders

[25, 63, 125, 32, 84, 257, ..., 13,
27, 39, 8, 213, 107, 54, 73, ..., 91
67, 59, 72, 33, 112, 54, 35, ..., 9
18, 37, 18, 142, 162, 54, 53, ..., 28
93, 44, 69, 85, 68, 54, 87, ..., 11,
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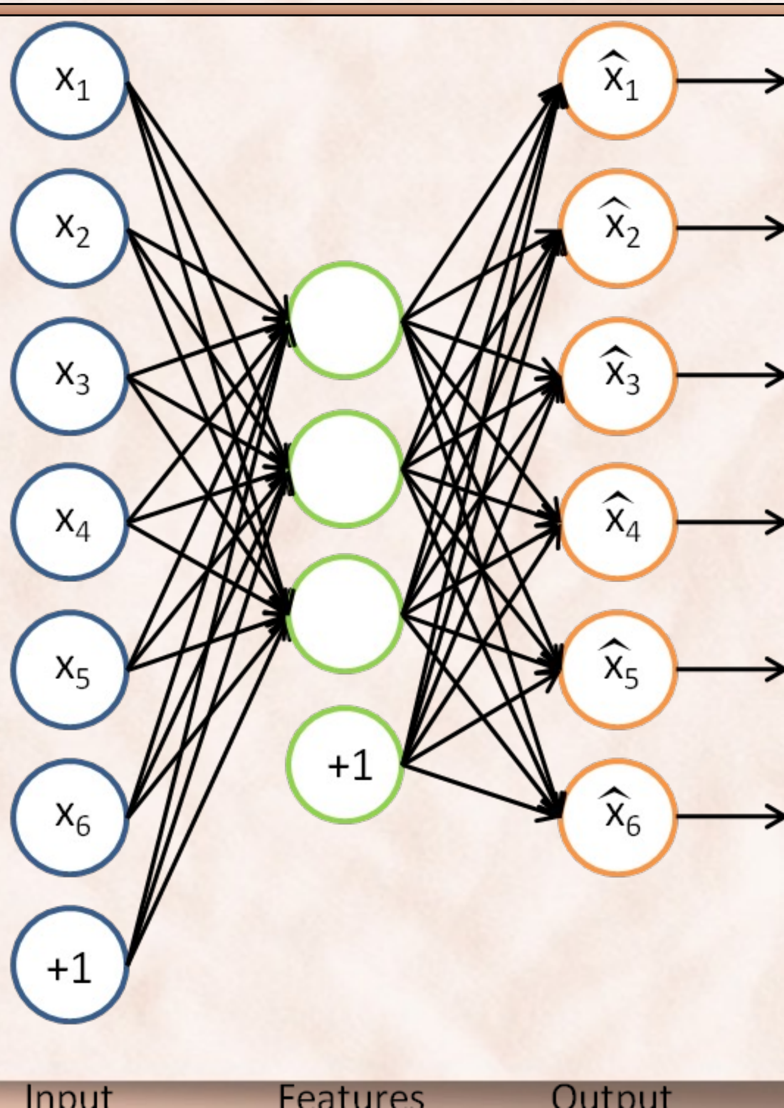

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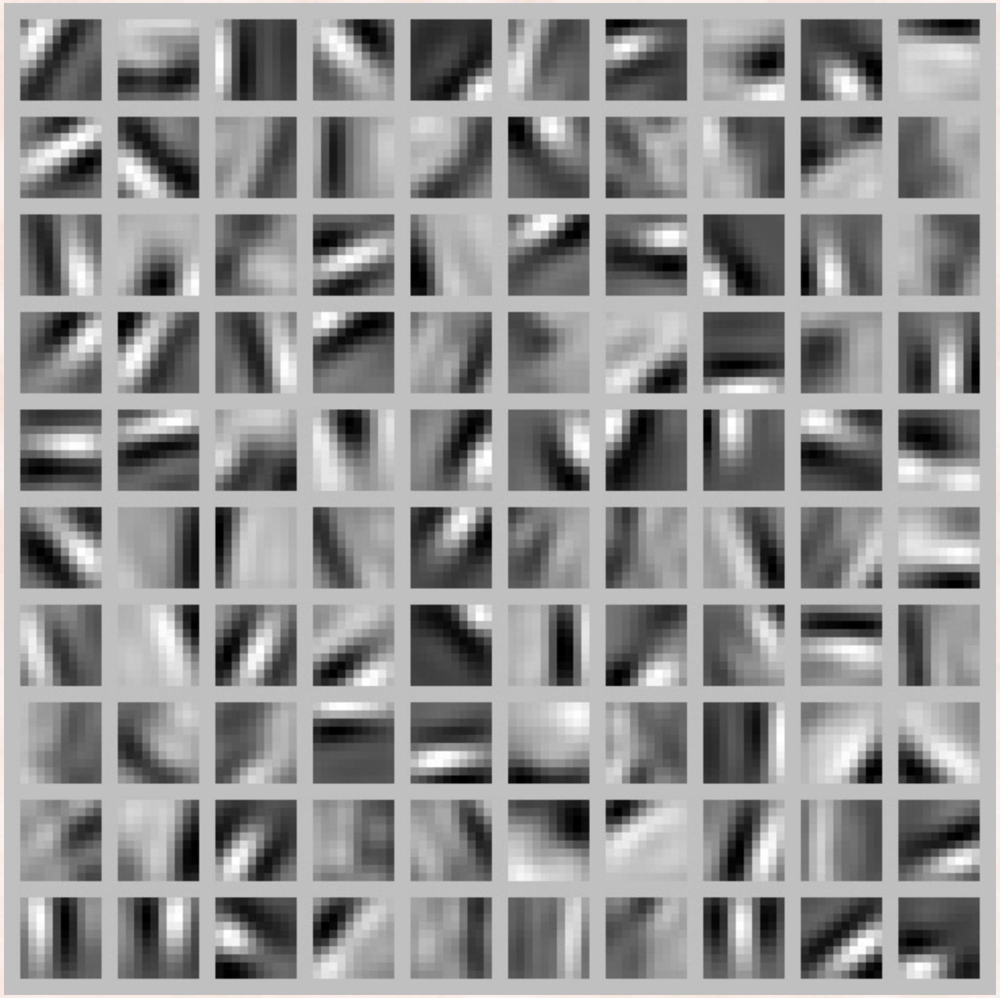
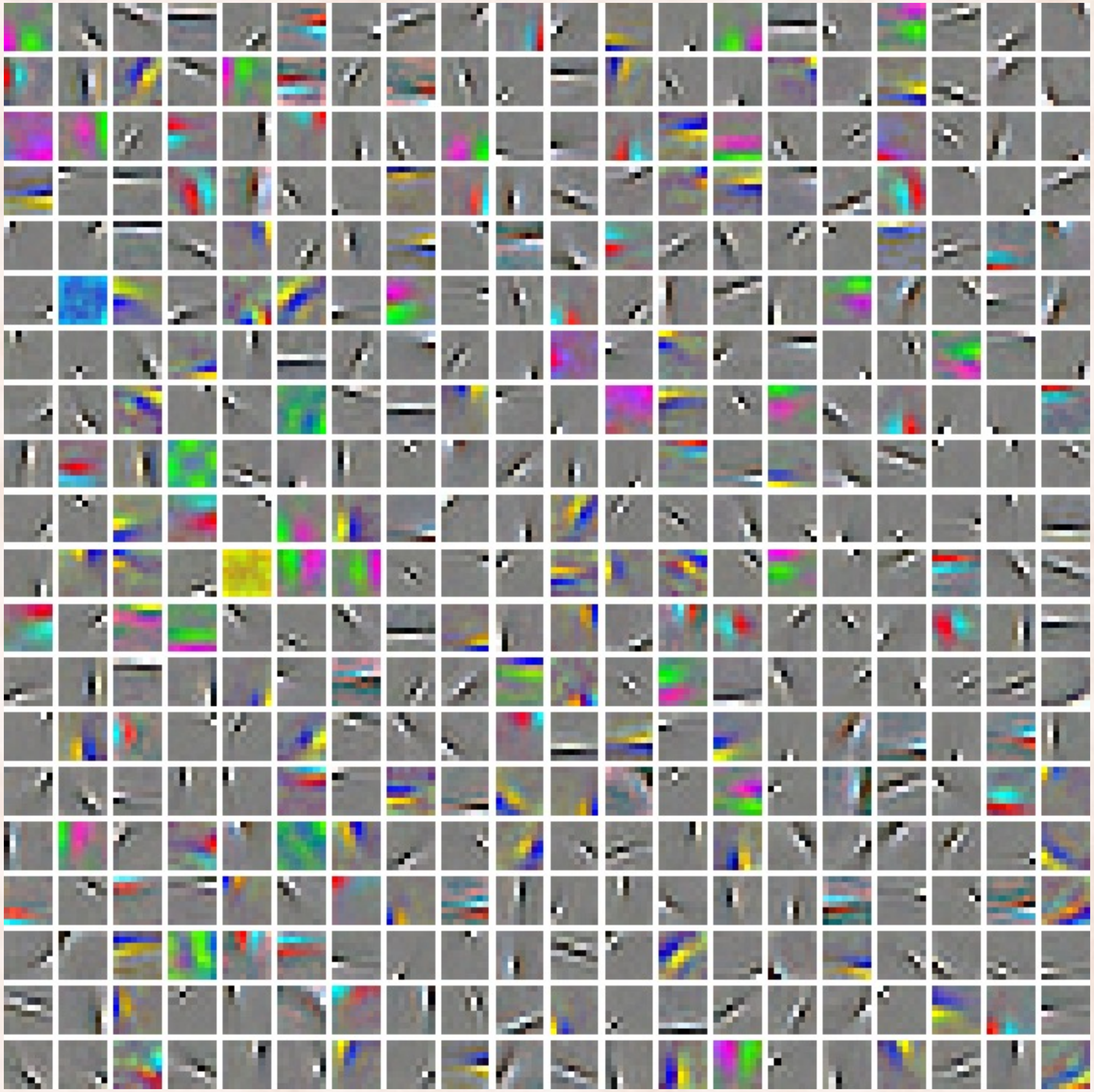
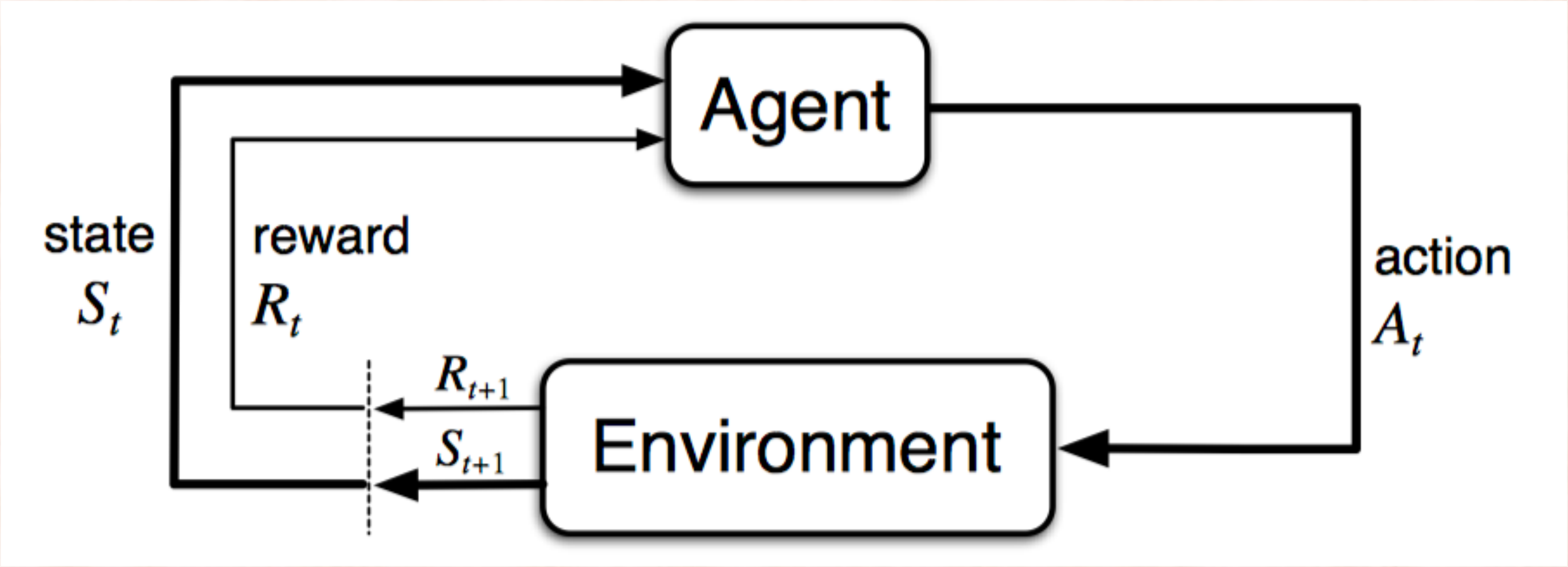
Learned Features (Representations)

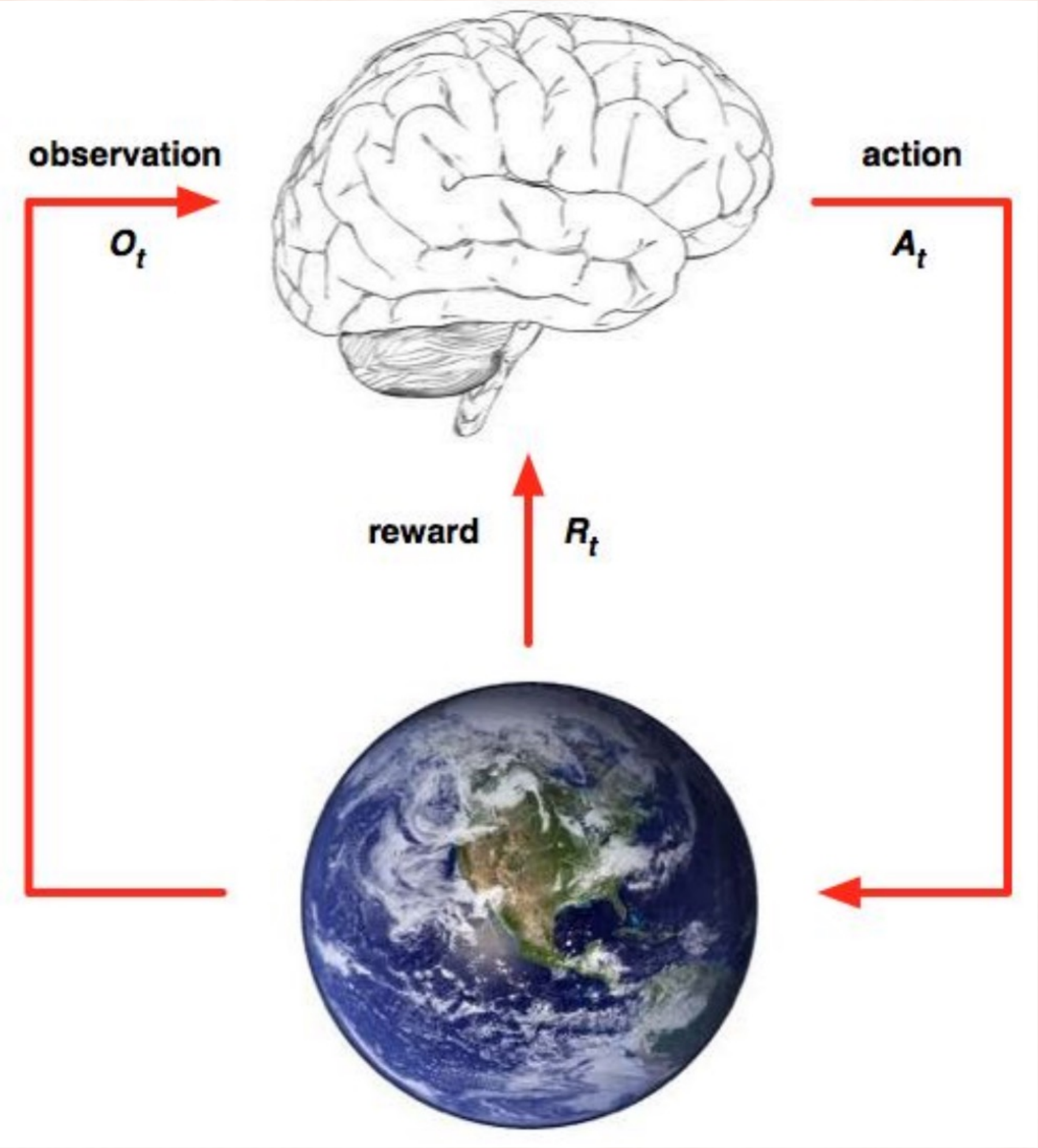


Learned Features (Representations)



Reinforcement Learning




observation
O_t
action
A_t
reward
R_t

Reinforcement Learning: TD-Gammon

[Tesauro, CACM'95]

- Learn to play Backgammon:
  - Immediate reward:
    - +100 if win
    - –100 if lose
    - 0 for all other states
  - *Temporal Difference Learning* with a *Multilayer Perceptron*.
  - Trained by playing 1.5 million games against itself.
  - Played competitively against top-ranked players in international tournaments.

Reinforcement Learning

- Interaction between agent and environment modeled as a sequence of *actions* & *states*:
  - Learn *policy* for mapping states to actions in order to maximize a *reward*.
  - Reward may be given only at the end state => *delayed reward*.
  - States may be only *partially observable*.
  - Trade-off between *exploration* and *exploitation*.

- Examples:
  - Backgammon [Tesauro, CACM'95], helicopter flight [Abbeel, NIPS'07].
  - 49 Atari games, using deep RL [Mnih et al., Nature'15].
  - AlphaGo [Silver et al., 2016], AlphaZero [Silver et al., 2017], …

Background readings

- **Python**:
  - Introductory Python lecture.
- **Probability theory**:
  - Basic probability theory (pp. 12-19) in Pattern Recognition and Machine Learning.
  - Chapter 3 in DL textbook on Probability and Information Theory.
- **Linear algebra**:
  - Chapter 2 in DL textbook on Linear Algebra.
  - Chapter 2 on Linear Algebra in Mathematics for Machine Learning.
- **Calculus**:
  - Basic properties for derivatives, exponentials, and logarithms.
  - Chapter 4.3 in DT textbook on Numerical Computation.