Lecture 14: Machine Learning

Core 109S IDWT?, Spring 2017

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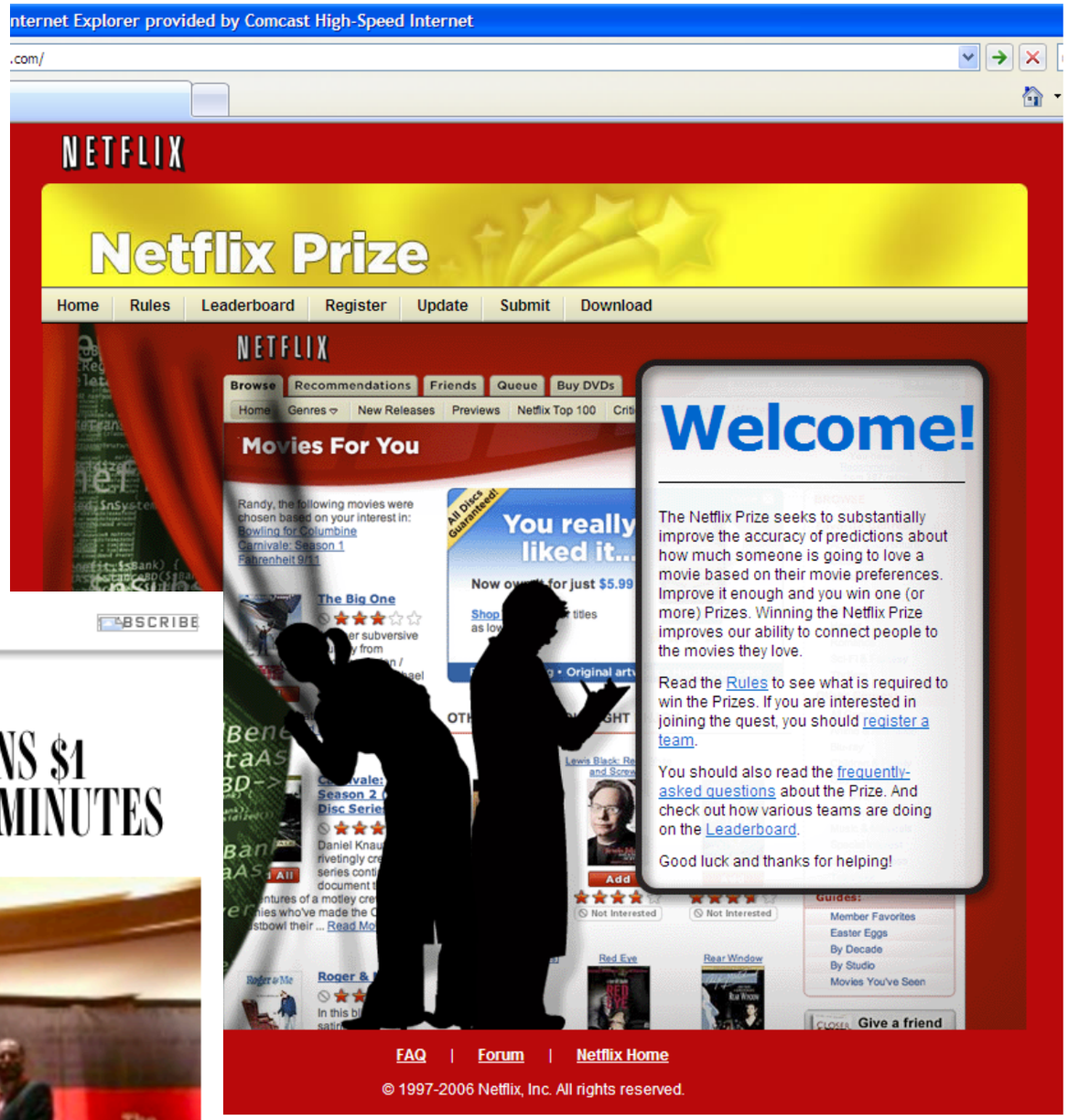
Motivating example #1

- Predict how a viewer will rate a movie

- 10% improvement
➡ $1 million prize!



Movie rating — a solution

Describe movie in terms of different "factors"

"Factors" learned automatically from data.

(Not as easily interpreted as example suggests.)

Credit: Yaser Abu Mostafa https://work.caltech.edu/

Example #2: Spam Filter

- Input: email
- Predict: "spam" or "ham"
- Data: old emails, each labeled “spam” or “ham”

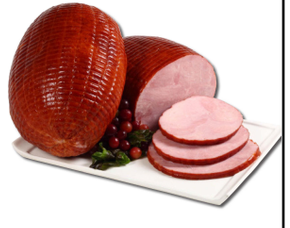
Dear Sir.

First, I must solicit your confidence in this transaction, this is by virture of its nature as being utterly confidencial and top secret. …

- **Features**: The attributes used to make the ham / spam decision
  - Words: FREE!
  - Text Patterns: $dd, CAPS, spelling errors, …
  - Non-text: SenderInContacts
  - …

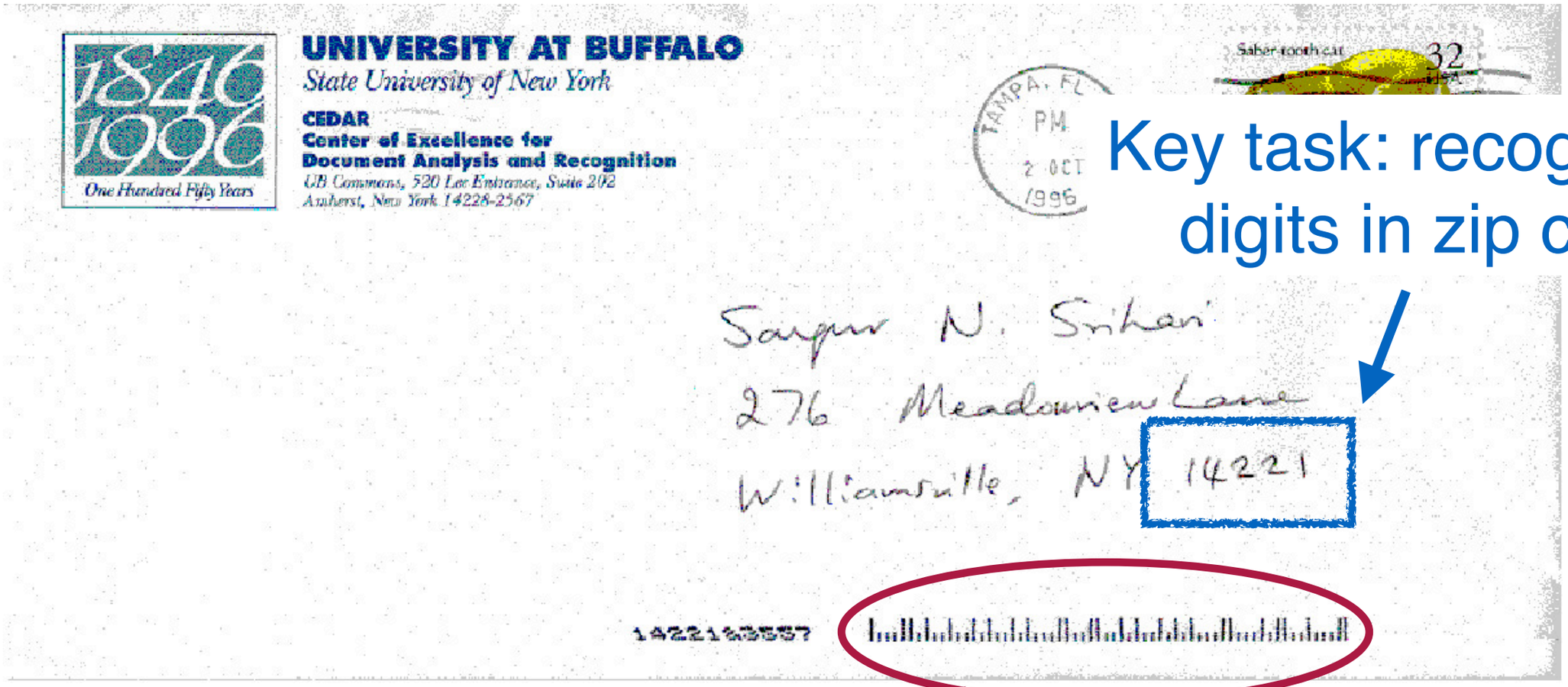
TO BE REMOVED FROM FUTURE MAILINGS, SIMPLY REPLY TO THIS MESSAGE AND PUT "REMOVE" IN THE SUBJECT.

99 MILLION EMAIL ADDRESSES FOR ONLY $99



Ok, I know this is blatantly OT but I'm beginning to go insane. Had an old Dell Dimension XPS sitting in the corner and decided to put it to use, I know it was working pre being stuck in the corner, but when I plugged it in, hit the power nothing happened.

Example #3: Digit Recognition



Key task: recognizing digits in zip code

Postnet Bar Code representing Delivery Point

Credit: Sargur Srihari http://www.cedar.buffalo.edu/~srihari/talks/Telcordia.pdf

Example #3: Digit Recognition

- Input: images / pixel grids
- Predict: which digit 0-9
- Data: images of hand-written digits, each labeled

0

1

- **Features**: The attributes used to make the digit decision
  - Pixels: (6,8)=ON
  - Shape Patterns: NumComponents, AspectRatio, NumLoops, Vertical/ Horizontal Symmetry
  - …

2

1

??

Essence of machine learning

- A pattern exists
- We cannot pin it down mathematically
- We have data on it

Credit: Yaser Abu Mostafa https://work.caltech.edu/

Running example

- Task: credit approval
- Input: applicant information
- Output: approve credit?
- Data: applications of past customers

attribute	value
age	23 years
gender	male
salary	$45,000
years in residence	1
years in job	1
current debt	$15,000

Credit: Yaser Abu Mostafa https://work.caltech.edu/

Components of learning

Input: $X = X_1, X_2, \ldots, X_d$ (customer application)

Feature engineering

- Process of taking raw data (e.g., email) and converting into a set of features
- "Feature" synonymous with attributes, predictor variables, input variables, …
- ***Big*** impact on learning!

Features can be…

- **binary**: hasALLCAPS (Y or N)
- **numerical**: Number of times Viagra occurs
- **categorical**: Top-level domain of sender (.com, .edu, …)

Components of learning

Input:	$X = X_1, X_2, \ldots, X_d$	(customer application)
Output:	Y	(approve/deny credit?)

Components of learning

Input:	$X = X_1, X_2, \ldots, X_d$	(customer application)
Output:	Y	(approve/deny credit?)
Target function f:	$Y = f(X)$	(ideal credit approval function)

The function f is ***unknown***. Our goal is to learn it, or learn a close approximation of it

Components of learning

Input:	$X = X_1, X_2, \ldots, X_d$	(customer application)
Output:	Y	(approve/deny credit?)
Target function f:	$Y = f(X)$	(ideal credit approval function)
Data:	$(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$	(historical records)

Components of learning

Input:	$X = X_1, X_2, \ldots, X_d$	(customer application)
Output:	Y	(approve/deny credit?)
Target function f:	$Y = f(X)$	(ideal credit approval function)
Data:	$(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$	(historical records)
	$\downarrow \quad \downarrow \quad \downarrow$	
	$\downarrow \quad \downarrow \quad \downarrow$	
Hypothesis	$g(X)$	(function learned from data)

(ideal credit approval function)

Unknown Target Function

$f(X) \rightarrow Y$

(historical records of customers)

Training Examples

$(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$

Learning Algorithm

Final Hypothesis

$g \approx f$

(credit approval function, learned from data)

Hypothesis Set

$\mathcal{H}$

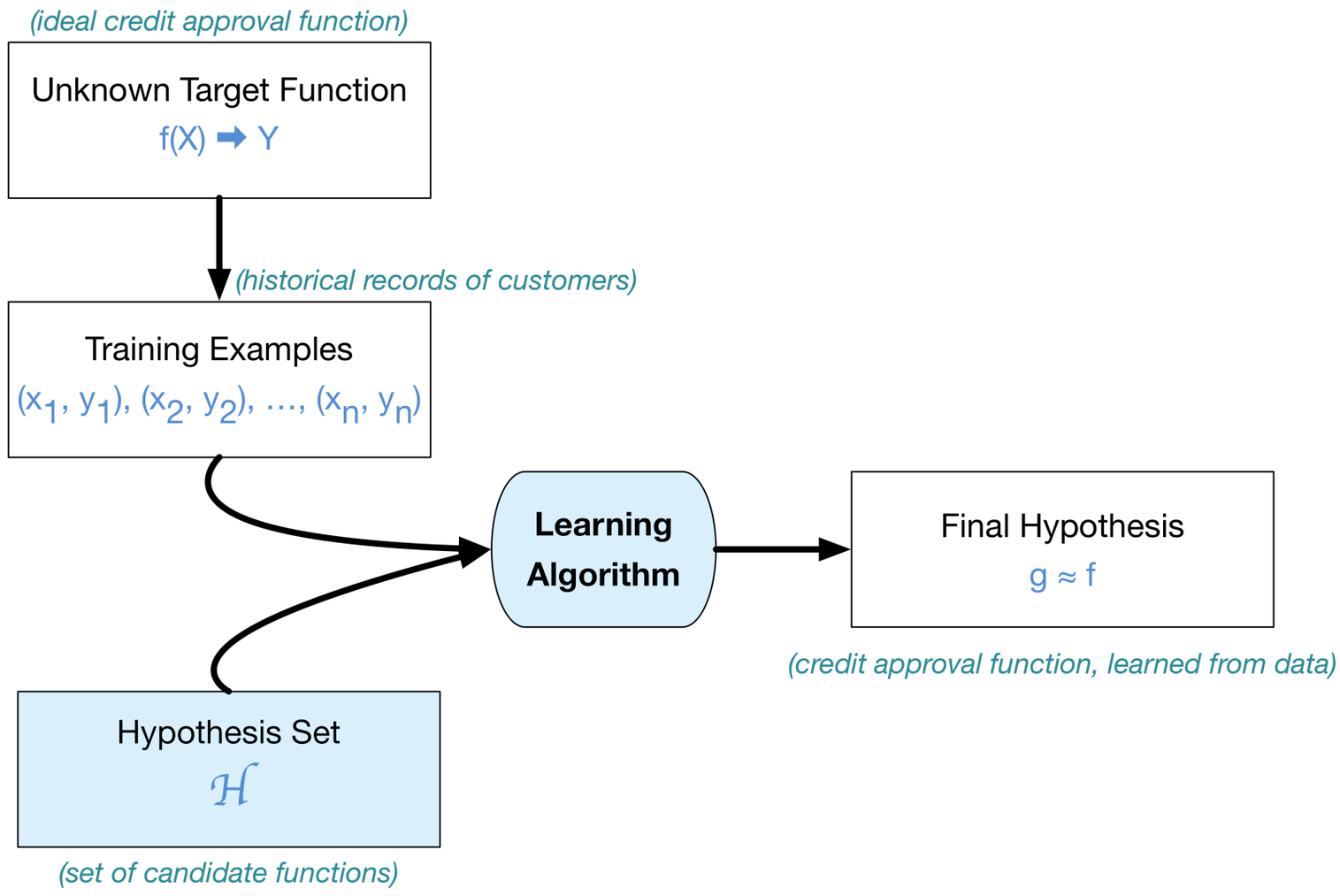
(set of candidate functions)

Credit: Yaser Abu Mostafa https://work.caltech.edu/

Solution components

The solution has two components

- Hypothesis set
- Learning algorithm



5 min. break

Example: perceptron

- Given input $x = (x_1, \ldots, x_d)$ *(the d attributes of customer app.)*

- Assign a **weight** w_i for each attribute value x_i. and choose some **threshold** value

$$\text{Approve credit if} \quad \sum_{i=1}^{d} w_i x_i \geq \text{threshold}$$

$$\text{Deny credit if} \quad \sum_{i=1}^{d} w_i x_i < \text{threshold}$$

Credit: Yaser Abu Mostafa https://work.caltech.edu/

Writing as function *h(x)*

$$h(x) = \text{sign}\left(\left(\sum_{i=1}^{d} w_i x_i\right) - \text{threshold}\right)$$

$$= \text{sign}\left(\left(\sum_{i=1}^{d} w_i x_i\right) + w_0\right)$$

$$= \text{sign}\left(\left(\sum_{i=1}^{d} w_i x_i\right) + w_0 x_0\right)$$

$$= \text{sign}\left(\sum_{i=0}^{d} w_i x_i\right)$$

sign(x) = 1 if x ≥ 0
-1 if x < 0

(rename "threshold" as w_0)

(introduce artificial attribute x_0=1)

Geometry of perceptron

(shown on board)

Exercise

Instructions: ~1 minute to think/ answer on your own; then discuss with neighbors; then I will call on one of you

Perceptron: $h(x) = \text{sign}\left(\sum_{i=0}^{d} w_i x_i\right)$

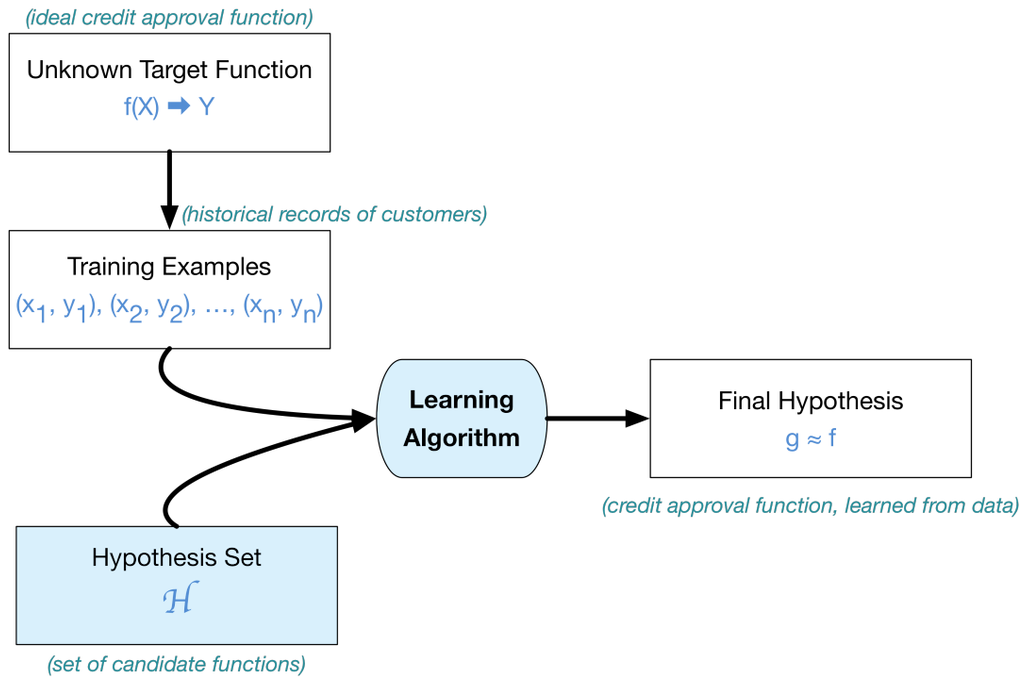
Suppose x = (x_1, x_2) where x_1 is current debt (in thousands of dollars) and x_2 is current salary (in thousands of dollars).

The weights are w_0=-15 and w_1=-2, and w_2=1.

Suppose Bob makes $40K/year and has $15K in debt. Would he be approved for credit?

Perceptron = hypothesis set

- Solution components:
  - Hypothesis set
  - Learning algorithm



- **Perception hypothesis set**: what is it?

> $\mathcal{H}$ = all possible settings of weights $w_0, w_1, \ldots w_d$. (infinite set)

Exercise

Instructions: ~1 minute to think/ answer on your own; then discuss with neighbors; then I will call on one of you

Suppose you used a perceptron to classify email as spam or ham. We will interpret +1 to mean that the email is spam and -1 to mean ham.

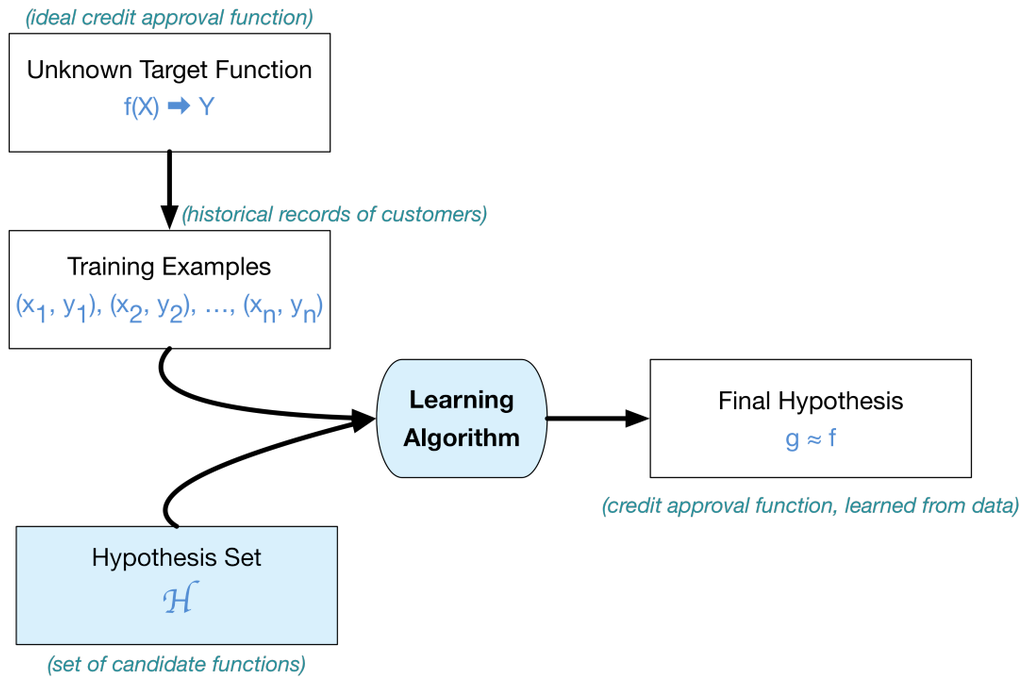
Attributes are word occurrences. For example, x_{Viagra} is 1 if the word "Viagra" appears in the email and 0 if not. We have a feature for every word in language (!).

- Q: Can you think up some words that should receive a positive weight? Negative weight?

- Q: How would an empty email (no words) be classified by the perceptron?

Perceptron learning

- Solution components:
  - Hypothesis set
  - Learning algorithm



- **Learning algorithm** = procedure for choosing the "best" hypothesis *g* from among the set $\mathcal{H}$

- **Perceptron learning algorithm** = procedure for picking values for weights $w_0, w_1, \ldots, w_d$.

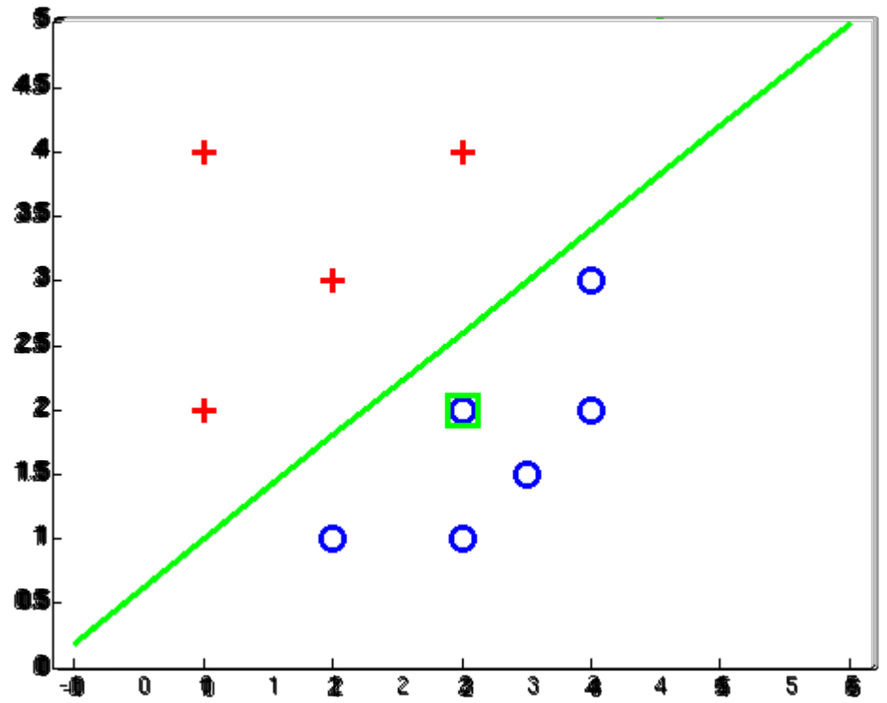
Algorithm 1 Algorithm for learning weights of a perceptron

procedure PERCEPTRONLEARNER(training data)
    Training data: collection of (x, y) pairs where $x = (x_1, \ldots, x_d)$ and $y = +1$ or $y = -1$.
    Initialize $w_0 = w_1 = \cdots = w_d = 0$
    repeat
        ▷ Pick a misclassified example:
        Find some (x, y) pair such that $h(x) = \text{sign}\left(\sum_{i=0}^{d} w_i x_i\right) \neq y$
        ▷ Update the weight vector:
        for $i = 1$ to d **do**
            Set $w_i \leftarrow w_i + y \times x_i$
        end for
    until There are no more misclassified points (or some other stopping criterion)
    Return weights $w_0, \ldots, w_d$.
end procedure

Intuition:

- Suppose Bob makes $15K in salary
- Perceptron incorrectly denies Bob credit
    - h(Bob) = -1 but y = 1
- Weight update will *increase* the weight on salary, and therefore *increase* h(Bob)

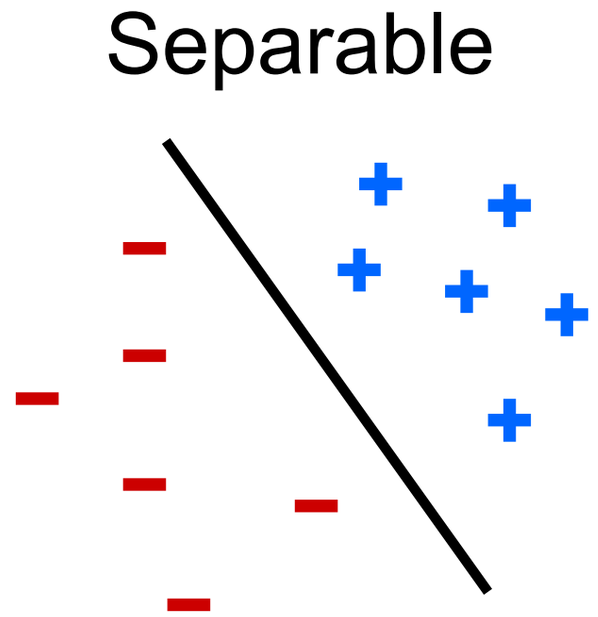
Example: Perceptron Learning

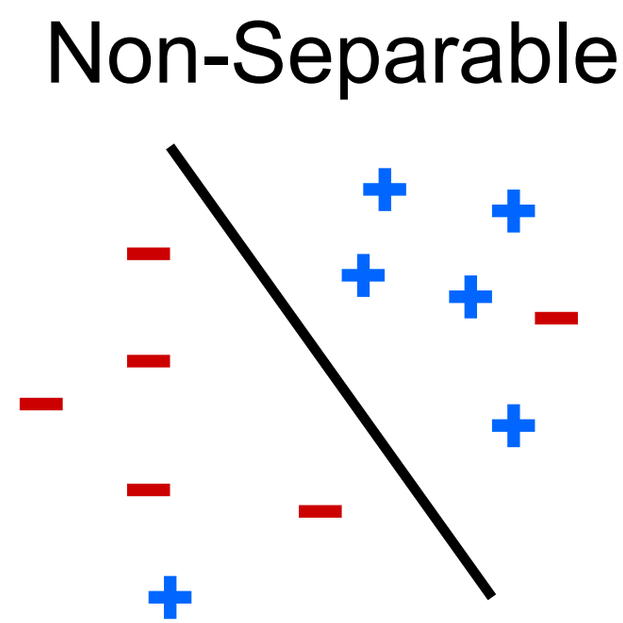


Properties of perceptrons

- **Separable data**: some parameters get the training data perfectly correct

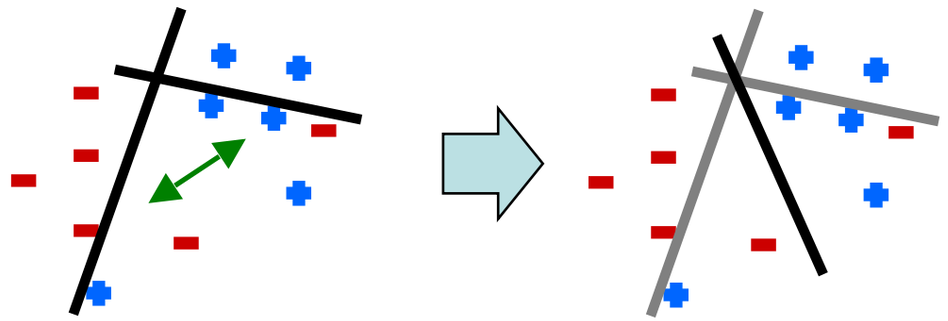
- **Perceptron convergence**: if training data is separable, perceptron will eventually converge (find weights that separate)



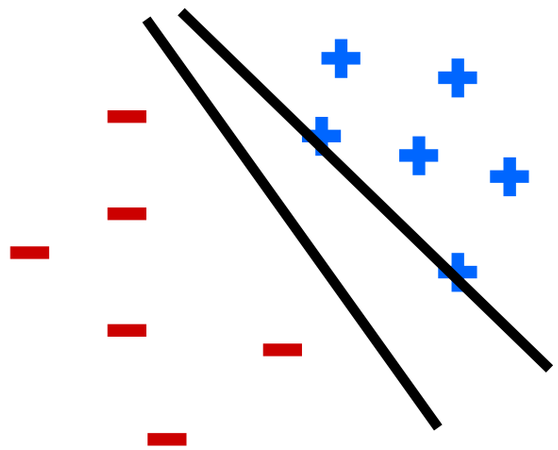


Problems with Perceptron

- **Inseparable data**: If the data isn't separable, learning might "thrash"
  - "Pocket algorithm": keep best weights you've seen so far and return this after so many attempts
  - Adding more features can also help



- Sometimes finds a "barely" separating solution.
  - Intuition suggests there are "better" separators.



Essence of machine learning

- A pattern exists
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Exercise

Instructions: ~1 minute to think/ answer on your own; then discuss with neighbors; then I will call on one of you

Which of the following problems are best suited for Machine Learning?

A. Classifying numbers into primes and non-primes.

B. Detecting potential fraud in credit card charges.

C. Determining the time it would take a falling object to hit the ground.

D. Determining the optimal cycle for traffic lights in a busy intersection.

E. More than one above

F. None of the above

Supervised vs. Unsupervised

- **Supervised**: We are given (x, y) pairs where y is related to x through unknown function $Y = f(X)$. Goal is to find hypothesis g such that $g \approx f$. Types:

  - **Regression**: when y is numerical

  - **Classification**: when y is binary/categorical

- **Unsupervised**: We only get x. Goal is to seek relationships between variables and/or between data points. Typically learn some g(x) that maps x to some simpler representation.

  - **Clustering**: g(x) assigns each x into a group such that "similar" x's end up in the same group (e.g., cluster movies)

Credit: Yaser Abu Mostafa https://work.caltech.edu/

Clustering

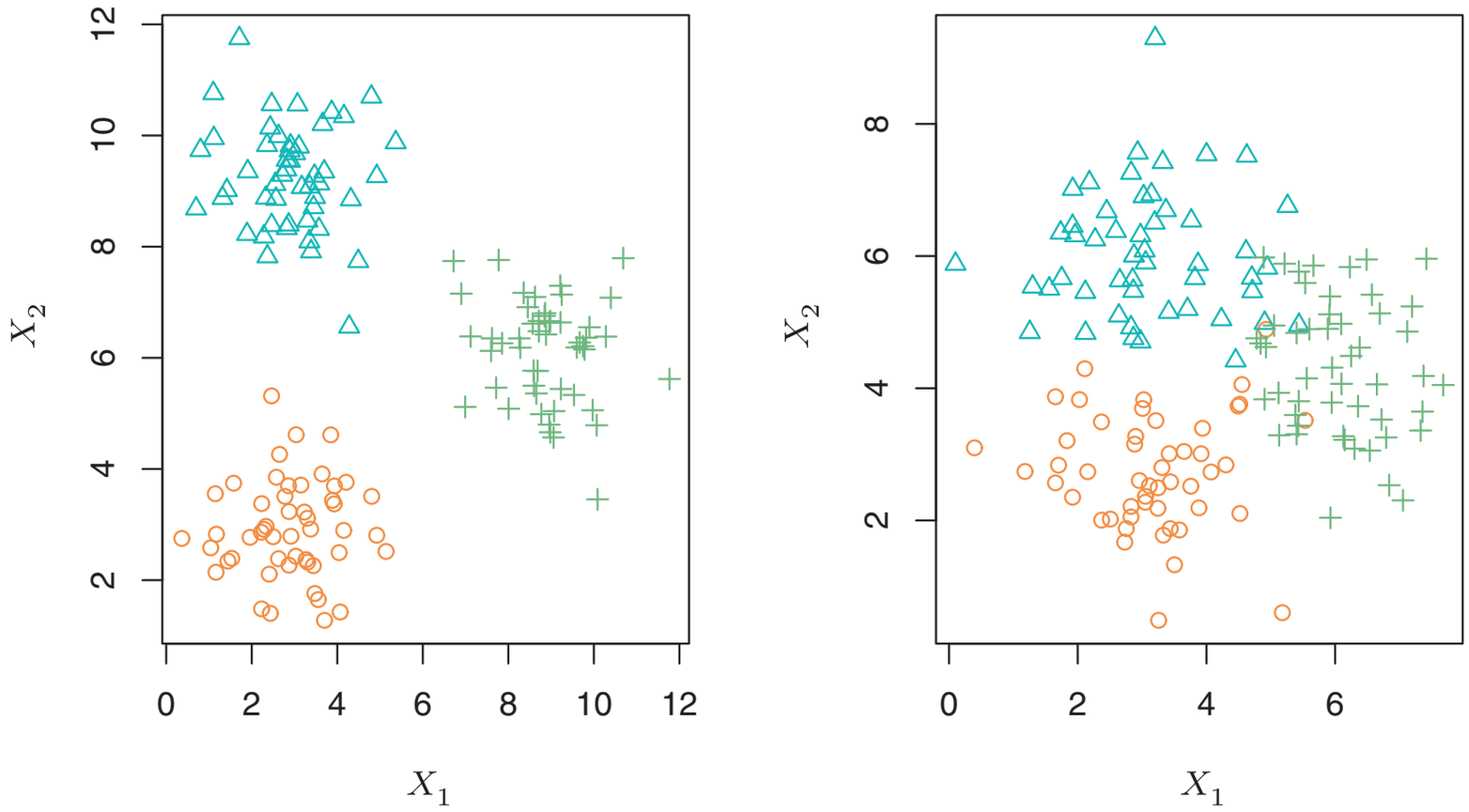

FIGURE 2.8. *A clustering data set involving three groups. Each group is shown using a different colored symbol.* Left: *The three groups are well-separated. In this setting, a clustering approach should successfully identify the three groups.* Right: *There is some overlap among the groups. Now the clustering task is more challenging.*

Credit: ISL http://www-bcf.usc.edu/~gareth/ISL/

Parametric vs. Non-parametric

- **Parametric**: means structure of h is fixed except for some parameters. Hypothesis set = { settings of parameters }

- Perceptron
- Linear regression
- Logistic regression
- Naive Bayes

- **Non-parametric**: form of *h* is not fixed in advanced but adapts with data (typically grows more complex with more data)

- Decision trees
- K-nearest neighbors

Generally speaking, parametric are more "interpretable" and non-parametric are more "flexible"

Goals of learning

- **Prediction**: use *g(X)* to predict *y* on future examples
  - Hypothesis set: anything goes, so long as we can accurate g
- **Inference**: uncover something about the structure of the true (but unknown) function *Y=f(X)*
  - Hypothesis set limited to *interpretable* functions

Generally speaking,
Machine learning focuses on prediction;
Statistics focuses on inference