# Computational Learning Theory There is no Free Lunch

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# What is Machine Learning?

• Machine learning is the subfield of computer science that gives "computers the ability to learn without being explicitly programmed".

- term coined by Arthur Samuel in 1959 while at IBM

• The study of algorithms that can learn from data.

# Another View of Machine Learning

- Learning from historical data to make decisions about unseen data.
- Traditional Programming



Machine Learning



# When is Machine Learning a Good Idea?

### Situations where ...

- humans can not describe how they do a task
  - character recognition
- the desired function changes frequently
  - recommend stock transactions
- each user needs a customized function *f* 
  - email spam / ham
  - email importance (perhaps delete without presenting?)
  - recommendations on Amazon

Can you write a program that recognizes these digits?

# 4 7 \ / 7 / 92322 733333 **U 4 4 4 4 4** 555655 C 6 6 6 6 6 **U U U U 1** 8 8 8 8 8 8 99**9**99 0

# What Machine Learning Does

Class A



Class B



• Want to be able to generalize the classification to unseen data.

http://ciml.info/

(Credit: Hal Daumé III)

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#### s no Free Lunch

#### We Need Bias

## **Classify These**



(Credit: Hal Daumé III)

## Let's See ...



We Need Bias

• Bird vs non-bird • Flies

- Flies vs not-flies
- We need **bias** in order to be able to generalize to unseen data.

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# No Free-Lunch Theorems

### Theorem 1

Let  $\mathcal{F}$  be the set of all possible Boolean functions on n variables. Let  $Acc_G(\mathcal{L})$  be the (generalization) accuracy of  $\mathcal{L}$  on non-training examples. Then, for any consistent learner  $\mathcal{L}$ , it holds

$$rac{1}{|\mathcal{F}|}\cdot\sum_{\mathcal{F}}Acc_G(\mathcal{L})=1/2$$
 .

### Proof Sketch.

Let *S* be the set of training examples. Let  $f \in \mathcal{F}$  such that  $Acc_G(f) = \frac{1}{2} + \delta$ . Then,  $\exists f' \in \mathcal{F}$  such that  $Acc_G(f') = \frac{1}{2} - \delta$ . To see why, note that we can have an  $f' \in \mathcal{F}$  that satisfies:

$$\begin{cases} (\forall x \in S)(f'(x) = f(x)) \\ (\forall x \notin S)(f'(x) = \neg f(x)) & \Box \end{cases}$$

## No Free-Lunch Theorems

### Theorem 2

Let  $\mathcal{F}$  be the set of all possible Boolean functions on n variables. Let  $Acc_G(\mathcal{L})$  be the (generalization) accuracy of  $\mathcal{L}$  on non-training examples. Then, for any consistent learner  $\mathcal{L}$ , it holds

$$\frac{1}{|\mathcal{F}|} \cdot \sum_{\mathcal{F}} Acc_G(\mathcal{L}) = 1/2.$$

Corollary 3

For any two learners  $\mathcal{L}_1, \mathcal{L}_2$ , if there exists a learning problem P such that  $Acc_G(\mathcal{L}_1) > Acc_G(\mathcal{L}_2)$ , then there exists another learning problem P' such that  $Acc_G(\mathcal{L}_1) < Acc_G(\mathcal{L}_2)$ .

• You can read more in [1].

## **References** I

[1] David H. Wolpert. The Lack of A Priori Distinctions Between Learning Algorithms. *Neural Computation*, 8(7):1341–1390, 1996.