Department of COMPUTER SCIENCE

WARWICK
THE UNIVERSITY OF WARWICK

Machine Learning
CS342

Lecture 1: Introduction to ML

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Office hours (CS 307): Mon 10-11am
Fri 10-11am

Module Organisation

- TAs/Tutors:
  - Helen McKay: H.McKay@warwick.ac.uk
  - Shan Lin: Shan.Lin@warwick.ac.uk

- Module website:
  - https://www2.warwick.ac.uk/fac/sci/dcs/teaching/modules/cs342/
  - Check Syllabus and **Online Material**

- Assessment:
  - 60% Final exam (Lecture material & PPs)
  - 40% Coursework:
    - 15% First assignment
    - 25% Second assignment

- Help? Questions? Contact me directly or the TAs

Module Organisation

- Lectures:
  - Monday, 11:00-12:00, MS.05
  - Tuesday, 14:00-15:00, CS1.04
  - Friday, 11:00-12:00, CS1.04

- Labs:
  - Thursday, 11:00-12:00, CS0.06
  - Friday, 1400-1500, CS0.01

  Necessary to understand material and practise
  Lab components in final exam and assignment
  TA + Instructor
  Python (Weka/Matlab/R)

- Background:
  - Linear Algebra, Probability Theory, Programming
  - Work and help each other - do not copy codes or assignments, we run Plagiarism detection software.
  - Come at office hours, ask me or your TAs!

Learning Outcomes & Goals of CS342

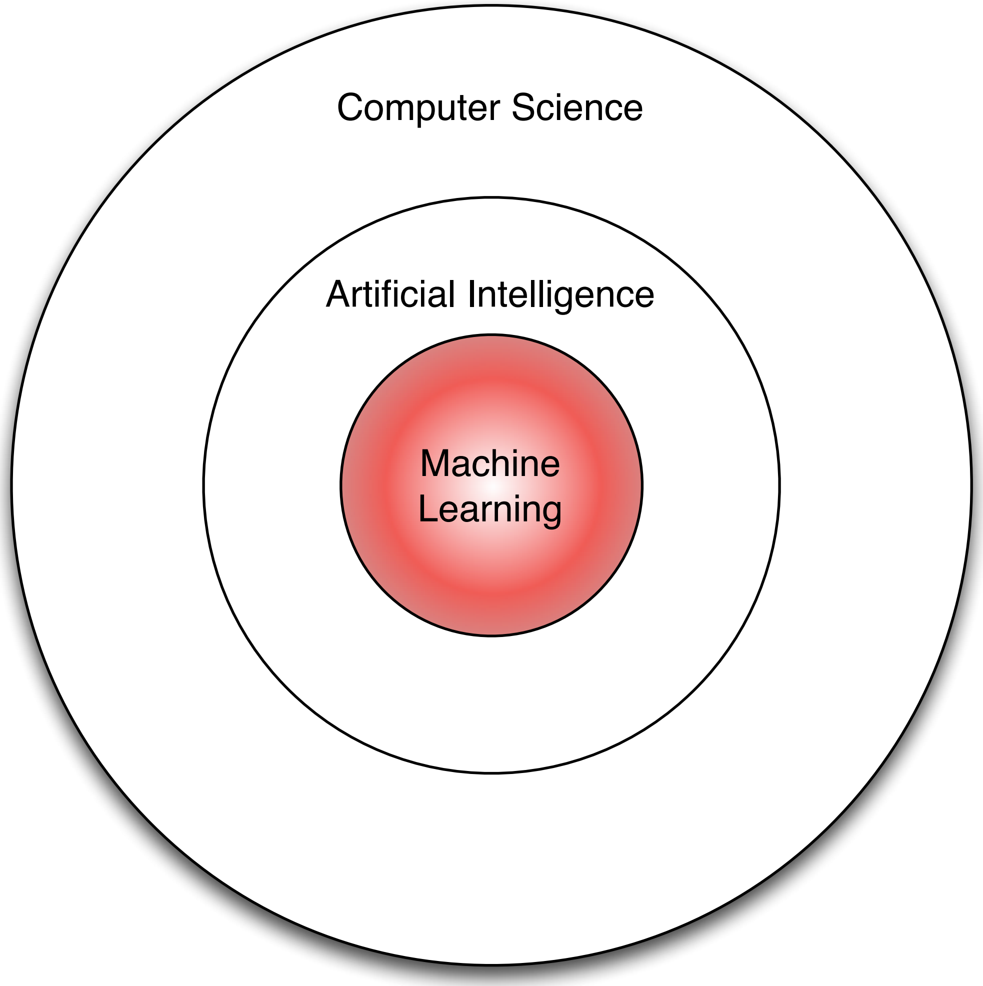
- What is Machine Learning?
    - Main areas, subfields, applications
- Learning models from data - basic principles
- Understand a wide variety of learning algorithms
- Understand how to fit and evaluate learning algorithms
- Apply various learning algorithms to real problems
- Have fun while teaching your computer how to learn from data!

Syllabus

- ***A First Course in Machine Learning***, S. Rogers & M. Girolami [Allowed to give you 1st Chapter] http://www.dcs.gla.ac.uk/~srogers/firstcourseml/
- ***Machine Learning***, T. Mitchell
- ***Pattern Recognition and Machine Learning***, C. Bishop
- *Pattern Classification*, Duda, Hart and Stork, Wiley-interscience
- *Machine Learning: A Probabilistic Perspective*, K. P. Murphy
- *Bayesian Reasoning and Machine Learning*, D. Barber

What fields make up Machine Learning?

- Computer Science?
- Statistics?
- Mathematics?
- Physics?
- Computational Neuroscience?
- Computational Psychology?



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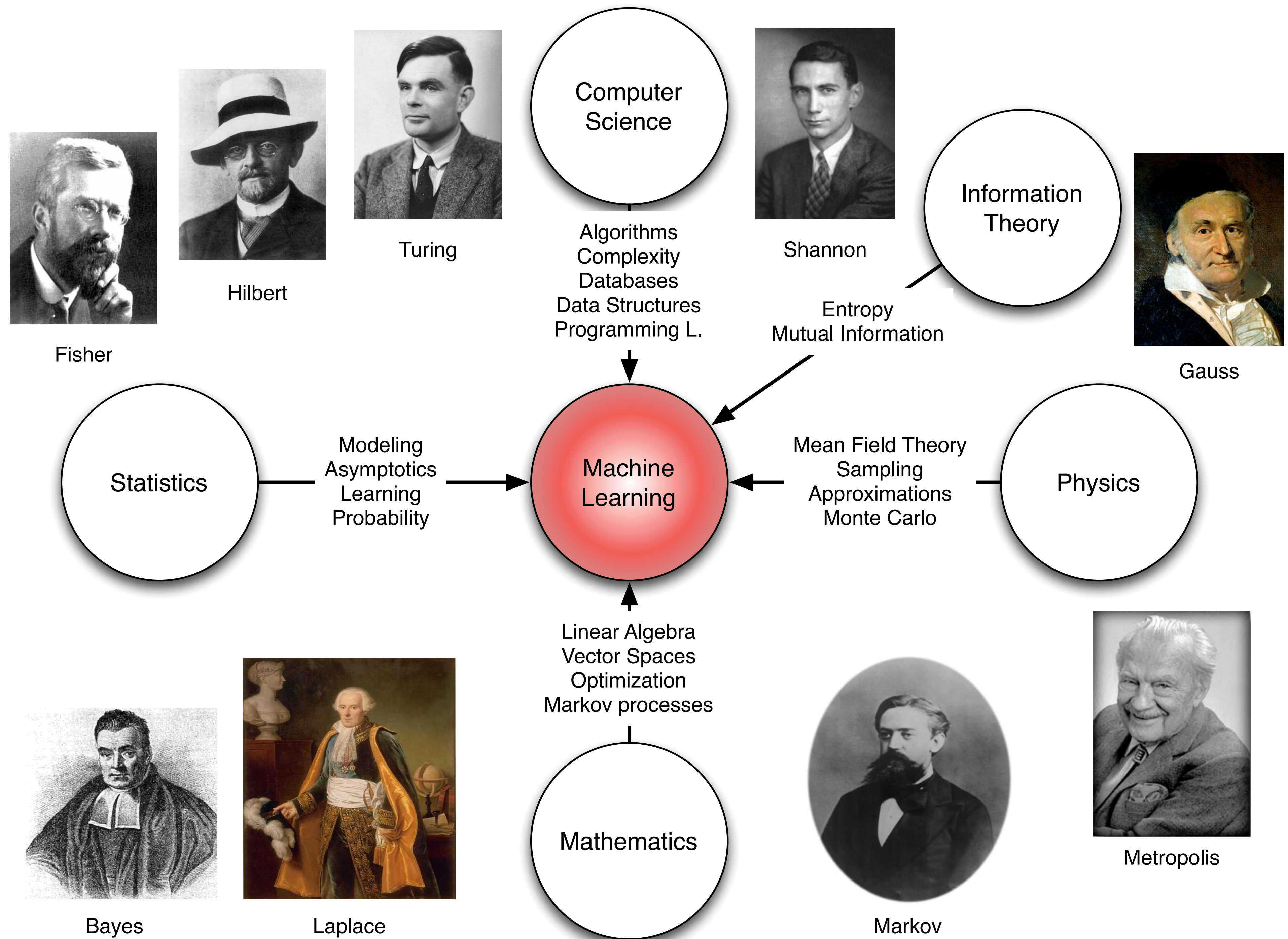
What fields make up Machine Learning?



Some AI/ML History

(ENIAC/Enigma) 1940 - 1950

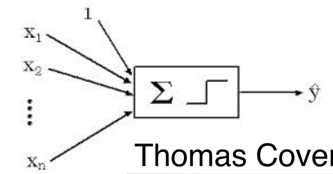
(First learning system) 1952

Arthur Samuels

Connectionism

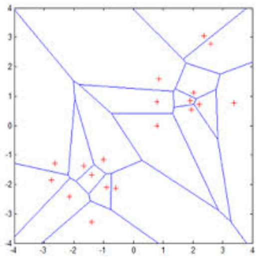
(Perceptron) 1957

Frank Rosenblatt



(Machine Translation) 1966

(k-NN) 1967



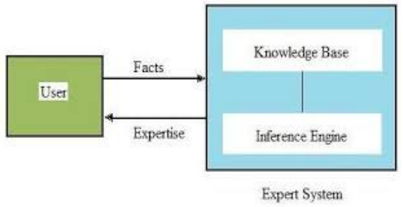
Thomas Cover

Symbolic

(Lighthill report) 1973

Expert Systems

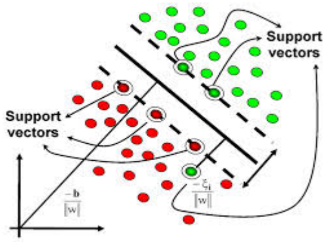
Edward Feigenbaum



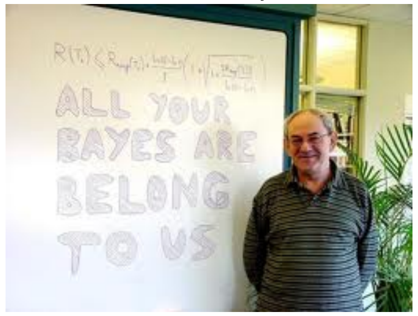
(LISP machines) 1987

Statistical ML

SVM 1993



Vladimir Vapnik

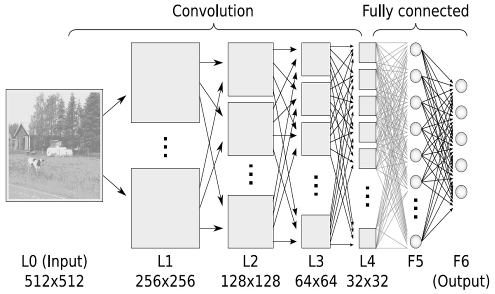


Probabilistic ML

OR/OPT ML

Connectionism #2 (Deep L.)

Geoff Hinton



Human vs Machine Learning


How do humans learn…?

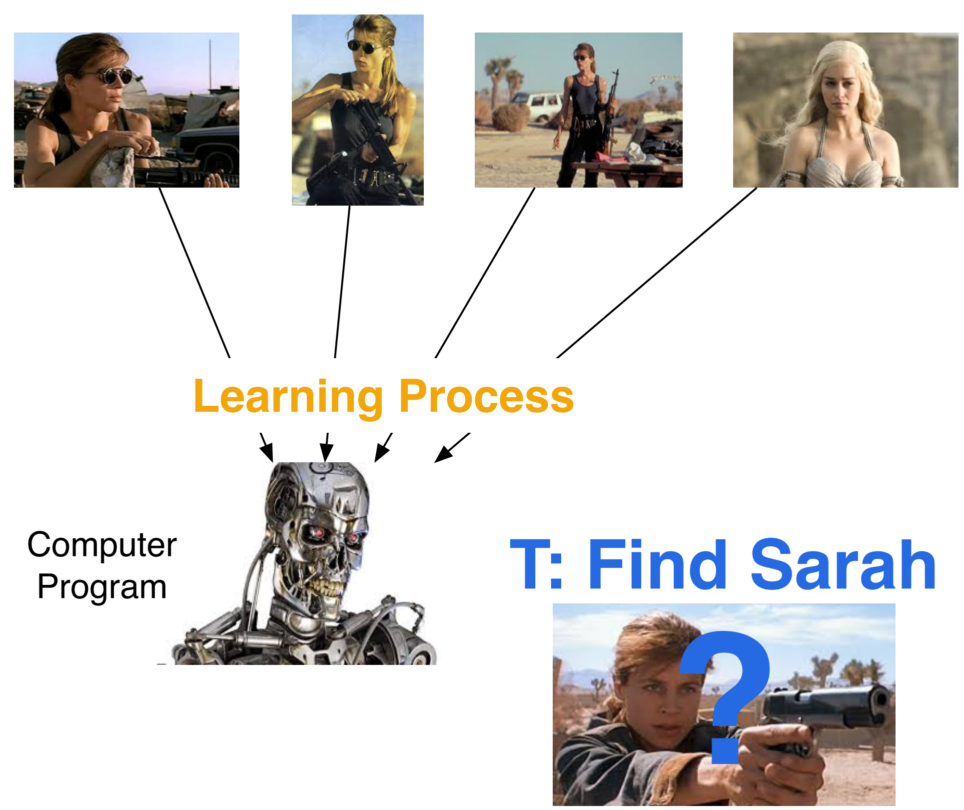
- **Supervisory** role?
- **Unsupervised** [grouping, similarity, patterns]
- Internal **reward** system [dopamine]
- Neural structure [Hebbian learning]
- Classical Conditioning (Pavlov’s dog)

What is the common basis/goal?

- Study of systems and algorithms that “**learn from data**”

- *A computer program is said to learn from experience **E** **(data)** 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, 1998]

E: Data on Sarah



P: % Correct recognitions

Lets try

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

You are given an algorithm that watches which phone-calls you mark as "noise complaints" or not and learns how to automatically mark calls. What is T?

A. *Watching you mark calls*

B. *Classifying phone-calls as noise complaints or not*

C. *Number of calls correctly classified as noise complaints or not*

D. *This is not a ML problem*

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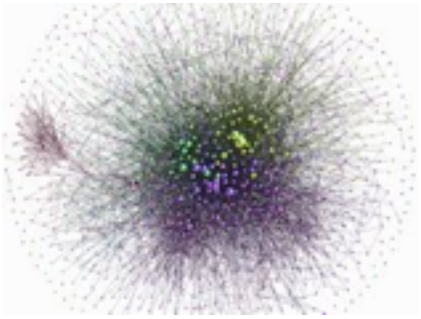
Examples of deployed ML systems

Recommendation Systems

Recognition Systems

Pattern Analysis



and many more.. pretty much whenever we want to **learn from data**

Main subfields of Machine Learning

Machine Learning

- **Supervised Learning**
  - Regression ← **We will start here**
  - Classification
  - Ranking
  - Structured Prediction

  $\mathcal{D} = \{\mathbf{X}, \mathbf{t}\}, \quad e.g. \quad \mathbf{X} \in \Re^{N \times D}, \mathbf{t} \in \Re^{N}$

- **Unsupervised Learning**
  - Clustering
  - Dimensionality Reduction
  - Manifold Learning

  $\mathcal{D} = \{\mathbf{X}\}, \quad \mathbf{X} \in \Re^{N \times D}$

- **Reinforcement Learning**
  - Markov Decision Process (e.g. Robotics)
  - Multi-Agent Systems
  - TD/Q-Learning (State-Action-Reward)

  $\mathcal{D} = \{\mathbf{S}, \mathbf{A}, \mathbf{R}, \pi^*, \mathbf{V}\}$

What are these symbols??

$$\mathcal{D} = \{\mathbf{X}, \mathbf{t}\}$$

Here is a dataset D

Student reg. no.	ML grade	P. Skills grade	final degree
1	92%	84%	78%
2	54%	100%	62%
3	58%	50%	52%
4	85%	96%	72%
5	67%	98%	68%
6	75%	86%	72%
7	52%	100%	61%
8	82%	90%	85%

Choose a task T. What is the data/experience E you will use to predict T? Why? What is the input **X** and what is the target **t**? their dimensions?

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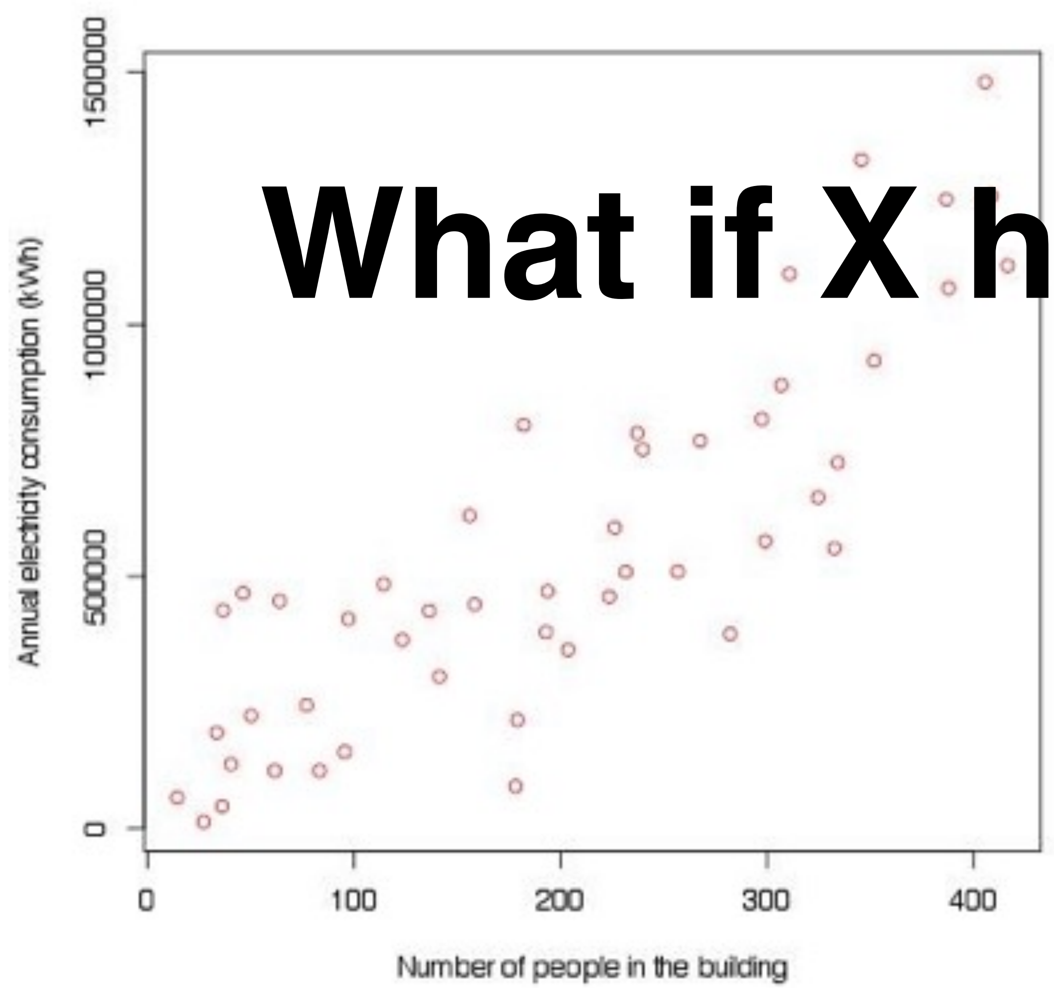
Supervised learning intro: when t is continuous

From Rogers & Girolami book

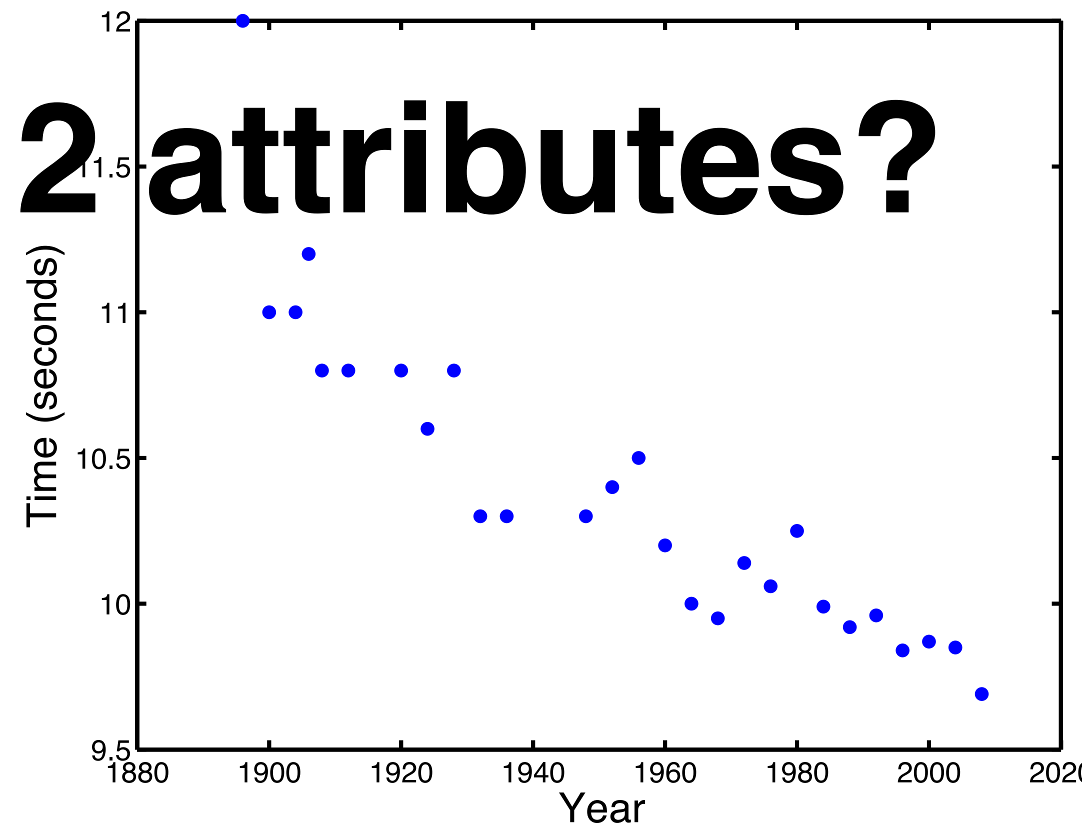
What if X has 2 attributes?

t



X

t



X

Predict electricity consumption given number of people

Predict winning men's 100m time given the year

Data and terminology (hell!)

INPUTS

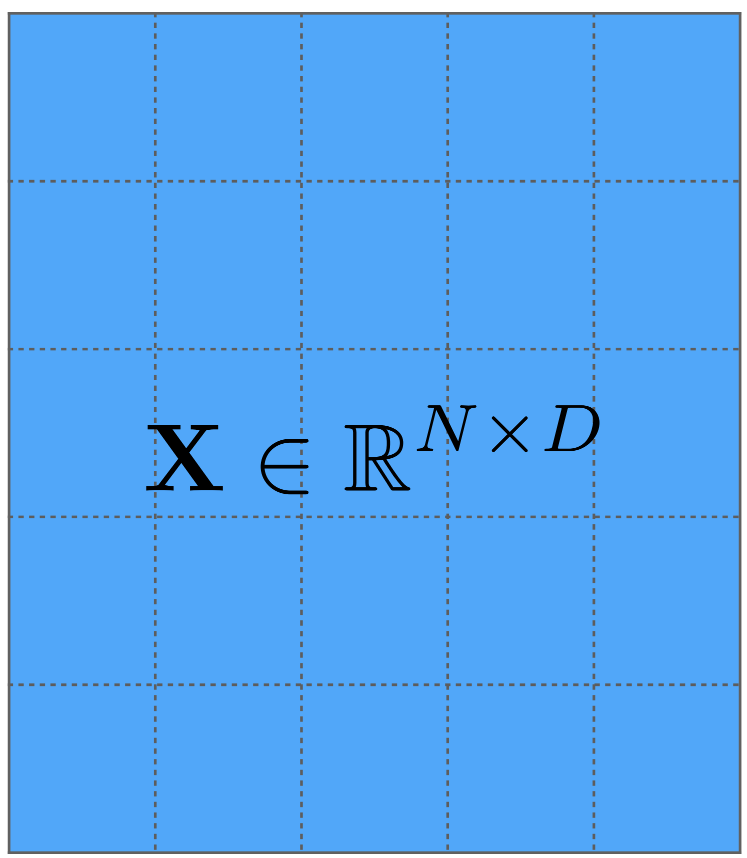
Attributes, Dimensions, Independent variables,

Predictor variables, Covariates, Features

D

Observations
Samples
Objects
Instances

N



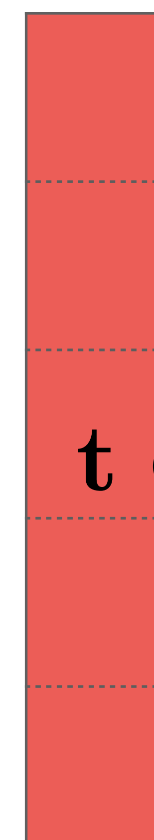
$$\mathbf{X} \in \mathbb{R}^{N \times D}$$

OUTPUTS

Target, Response, Label
Dependent variable

1

N



$$\mathbf{t} \in \mathbb{R}^{N}$$

Convention of notation

x is a scalar = small letter and regular font

$\mathbf{x}$ is a vector = small letter and **bold** font

$\mathbf{X}$ is a matrix = large letter and **bold** font

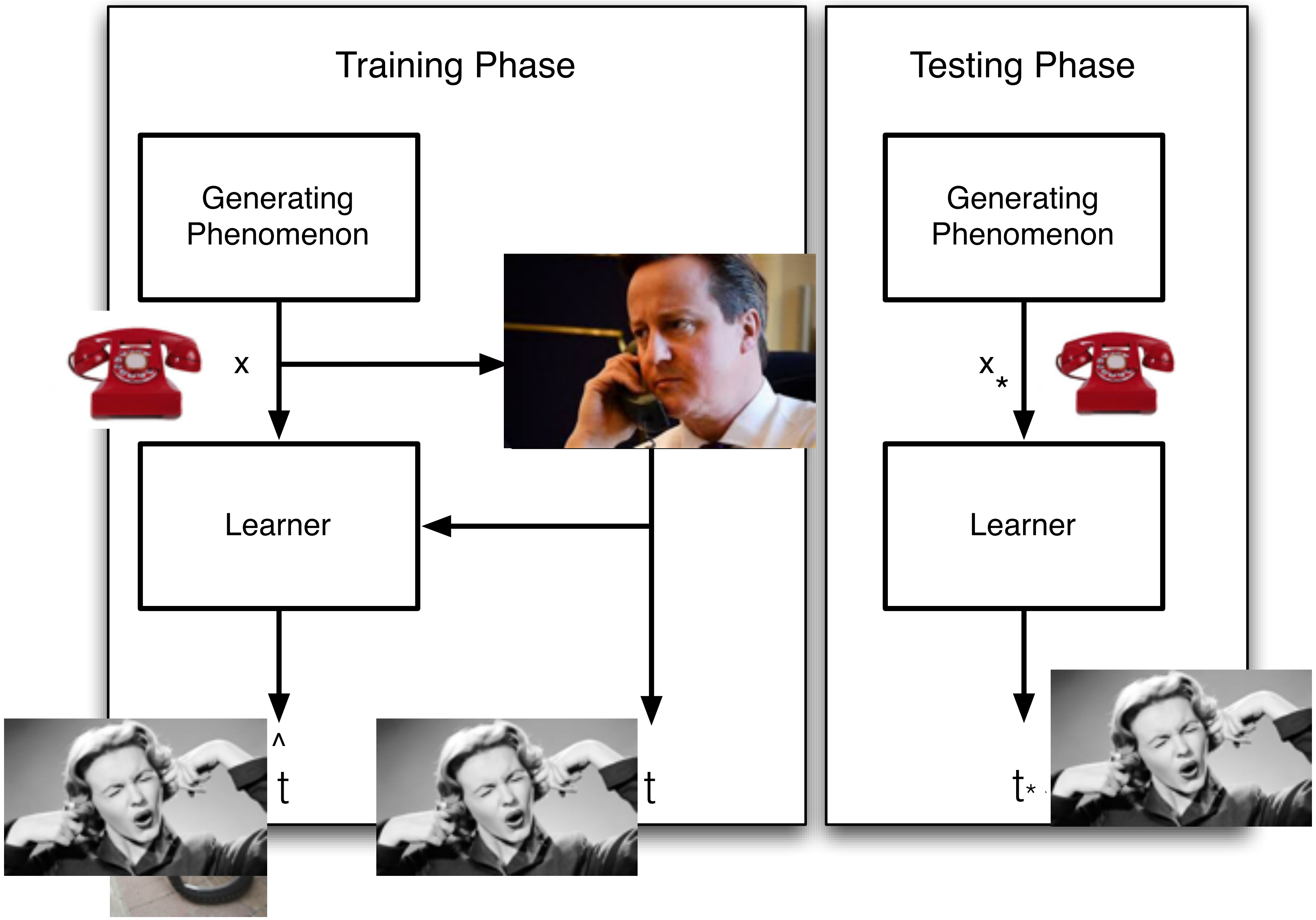
$\mathbf{x}_n$ is a row vector of **X** = small letter, index, and **bold** font

$f(\mathbf{x}_n; \mathbf{w})$ implies function f is acting on $\mathbf{x}_n$ with parameters **w**

bold symbols indicate **multiple dimensions**

Supervised learning

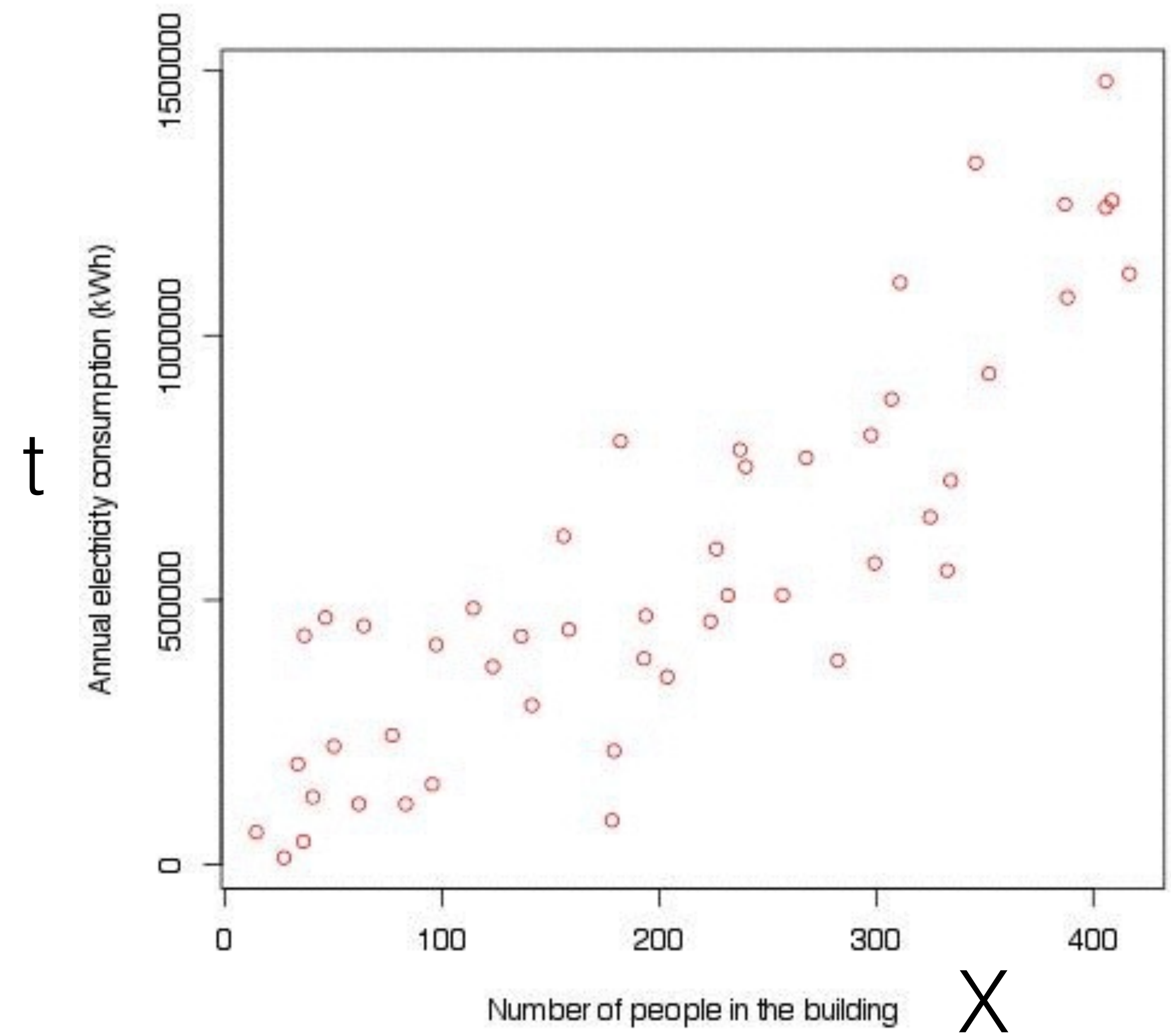
Learning Prediction



$$D_{\text{training}} = \{\mathbf{X}, \mathbf{t}\} = \{\mathbf{x}_n, t_n\}_{n=1}^{N} \qquad D_{\text{testing}} = \{\mathbf{X}_*\}$$

A supervised learning example: Regression

Regression:
t is continuous



Hypothesis: The relationship between X and t is **linear**

$$\hat{t} = f(x; w_0, w_1) = w_0 + w_1 x$$

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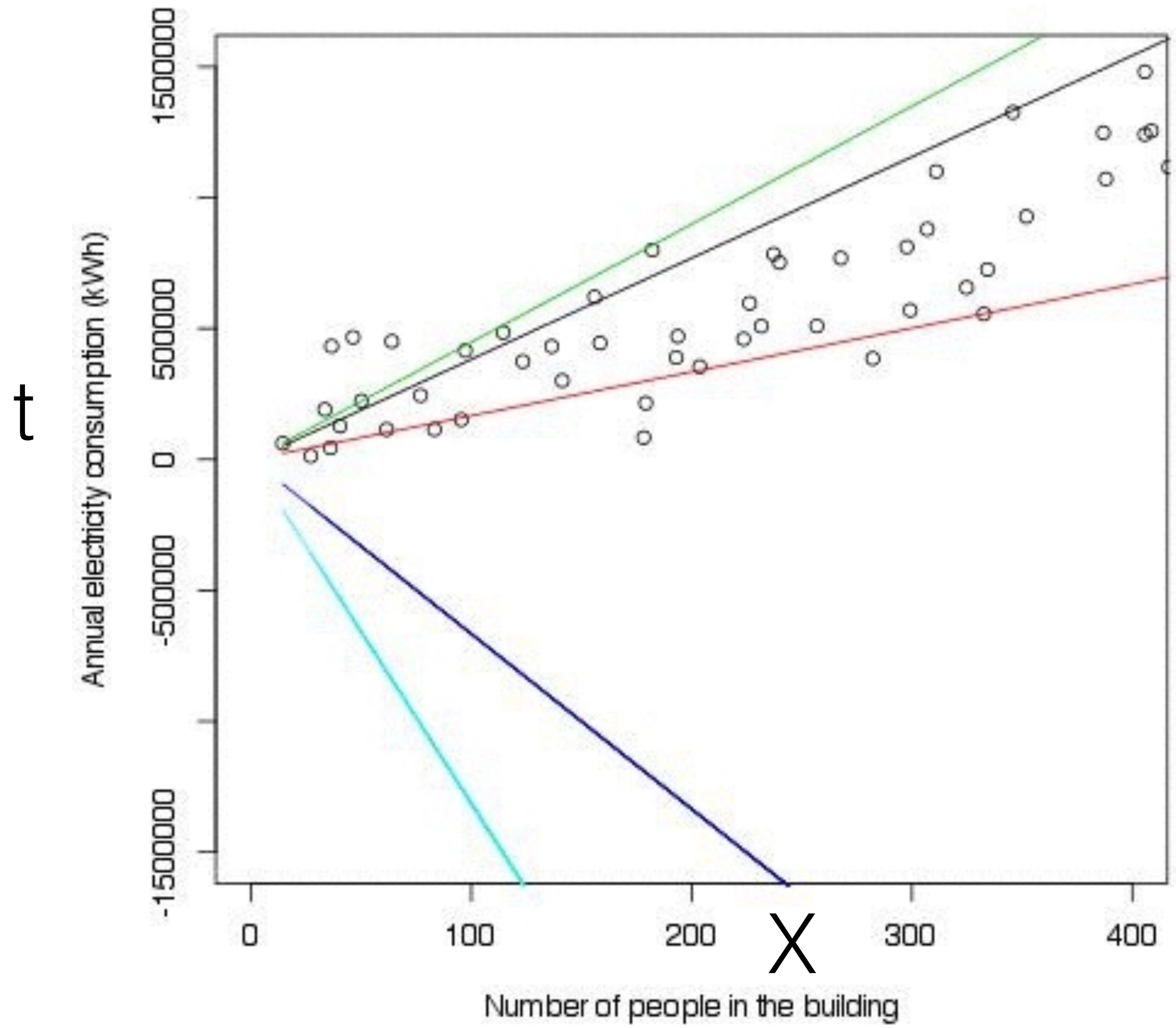
Which line is "better"?

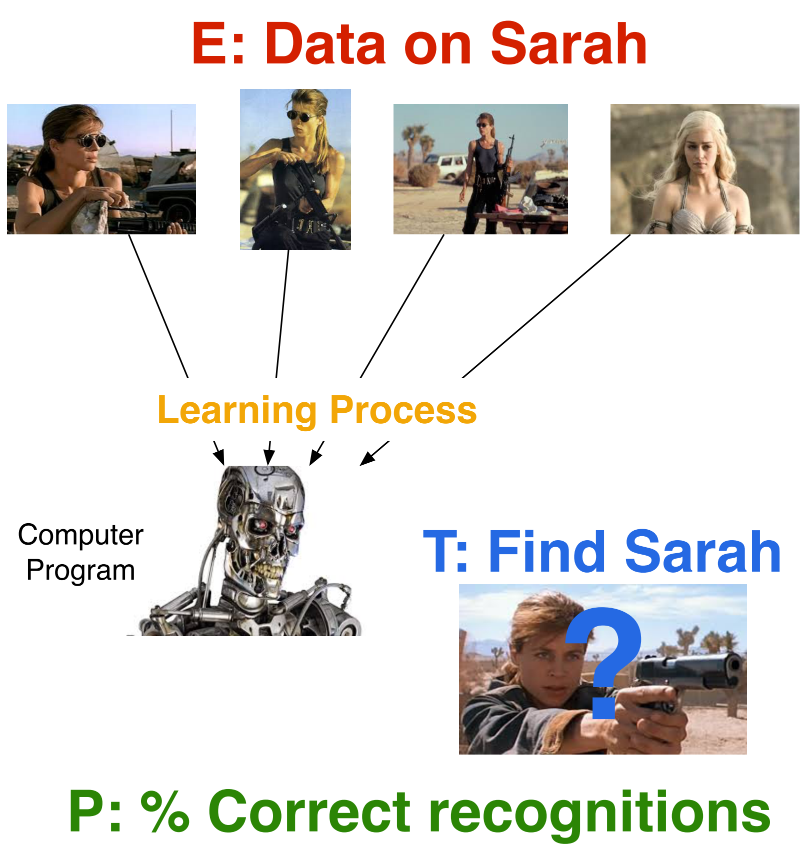
Hypothesis Space: All lines in this 2-D space

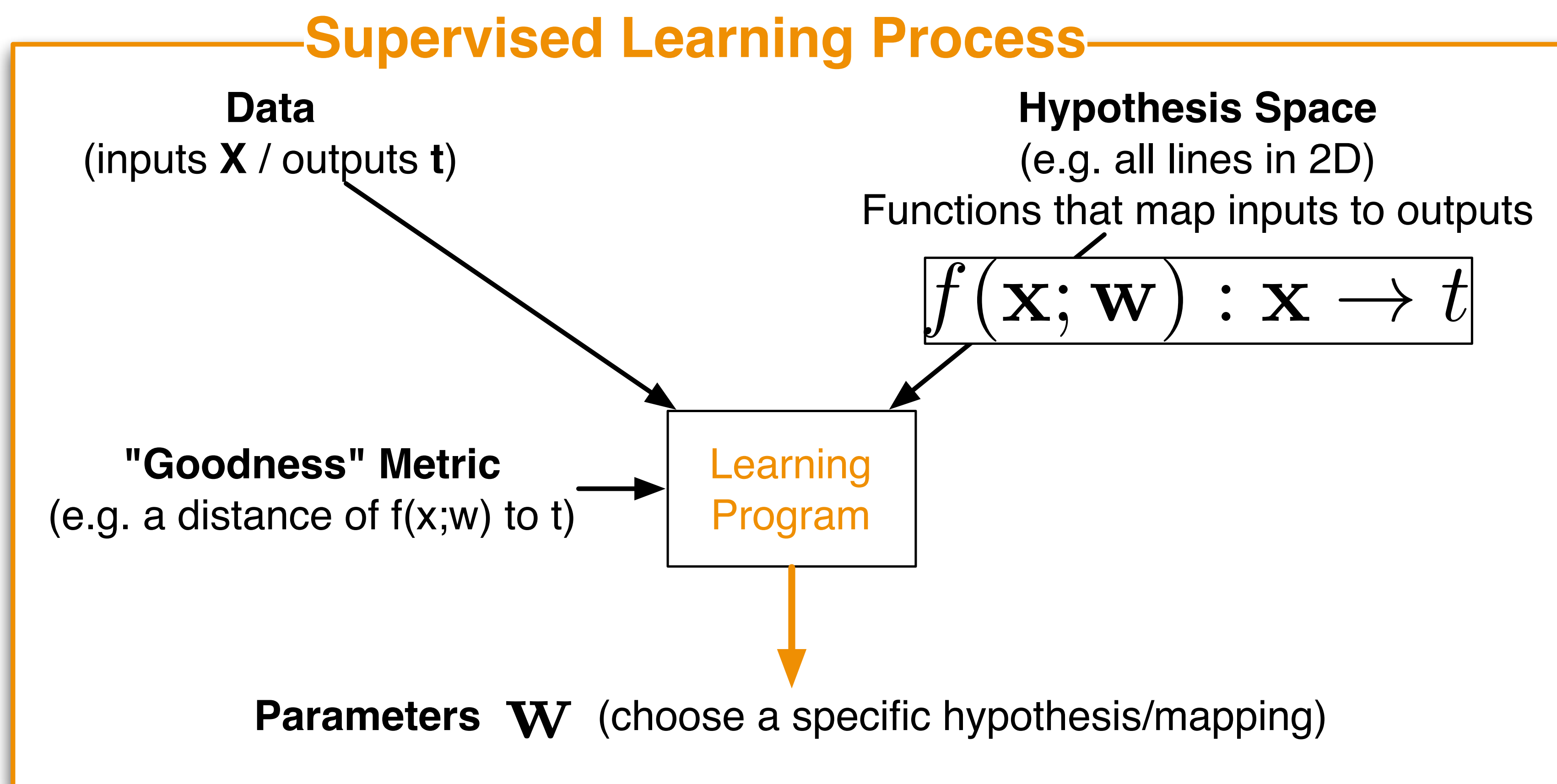


What can we "tune"?
What do we learn?

$$\hat{t} = f(x; w_0, w_1) = w_0 + w_1 x$$

Components of a (supervised) learning system





Learning as parameter (hypothesis) inference

What should X be for our program to have a chance of recognising Sarah?
this is a focus area of the Computer Vision field…

Some questions you should be already asking

- What is the appropriate task T we should be addressing?
- How do I choose the input data X and how do I encode it?
- What hypothesis space or function f(x;w) should I fit?
- How do I choose the model complexity / hypothesis space?
- What should be my performance metric?
- How much training data is needed?
- What do I do if training data is too small/big? (“big data”)
- What prior knowledge can I exploit?

Next lecture we dive in some of these questions within a linear regression setting (R&G Ch1)