

A photograph showing several saguaro cacti silhouetted against a vibrant orange and red sunset sky. The sun is low on the horizon, casting a warm glow.

ISTA 421 + INFO 521

Introduction to Machine Learning

Lecture 2: Linear Models

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22 August 2018

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Today

- Introduction
- A simple learning problem
- Linear Model (what is the *model*)
- Loss Function (what is a *good* model)
- Least Squares (finding the '*best*' model)
- Prediction
- Moving to higher dimensions

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What is Machine Learning?

- The goal of machine learning is to build computer systems that can adapt and learn from their experience. ([Dietterich, 1999](#))
- Machine learning usually refers to changes in systems that perform tasks associated with artificial intelligence. Such tasks involve recognition, diagnosis, planning, robot control, prediction, etc. ([Nilsson, 1996](#))
- Some reasons for adaptation:
 - Some tasks can be hard to define except via examples
 - Adaptation can improve a human-built system, or track changes over time
- Goals can be **autonomous** machine performance, or enabling humans to learn from and understand data (data mining and modeling)

Ack: this and some following content adapted from Chris Williams 2006



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Some of the Roots of Machine Learning

- **Philosophy:** epistemology, philosophy of science, logical inference: [the Problem of Induction](#)
- **Mathematics:** structure, operations, optimization
- **Physics:** statistical mechanics
- **Statistics:** statistical inference, frequentist & Bayesian
- **Psychological** models (of learning and development)
- **Brain** models, e.g. neural networks
- **Artificial Intelligence:** e.g., discovering rules using decision trees, inductive logic programming, autonomy
- **Engineering:** Statistical pattern recognition, operations research, adaptive control theory



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Typical Supervised Machine Learning Workflow

① **Define the problem.** What is the task we want to teach a computer to do?

② **Collect data.** Gather data for training and testing sets. The larger and more diverse the data the better.

③ **Design features.** What kind of features best describes the data?

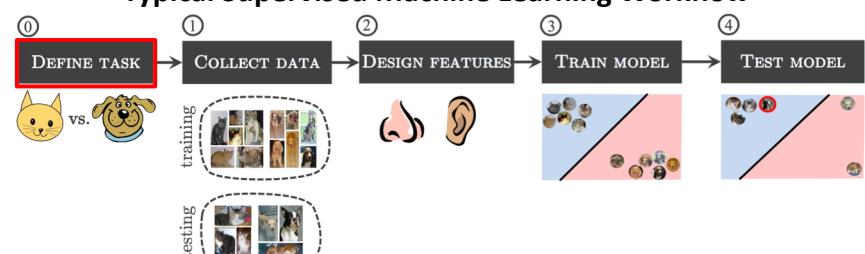
④ **Train the model.** Tune the parameters of an appropriate model on the training data using numerical optimization.

⑤ **Test the model.** Evaluate the performance of the trained model on the testing data. If the results of this evaluation are poor, re-think the particular features used and gather more data if possible.

MACHINE LEARNING REFINED
From Watt, Borhani & Katsaggelos (2016) *Machine Learning Refined*
<http://mlrefined.wix.com/home-page>

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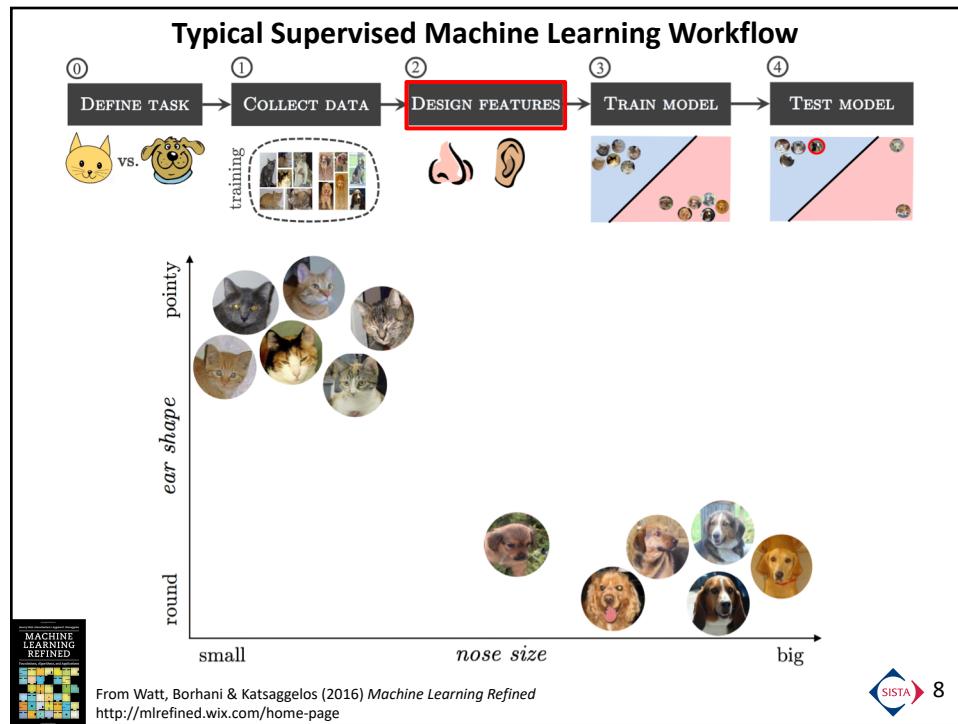
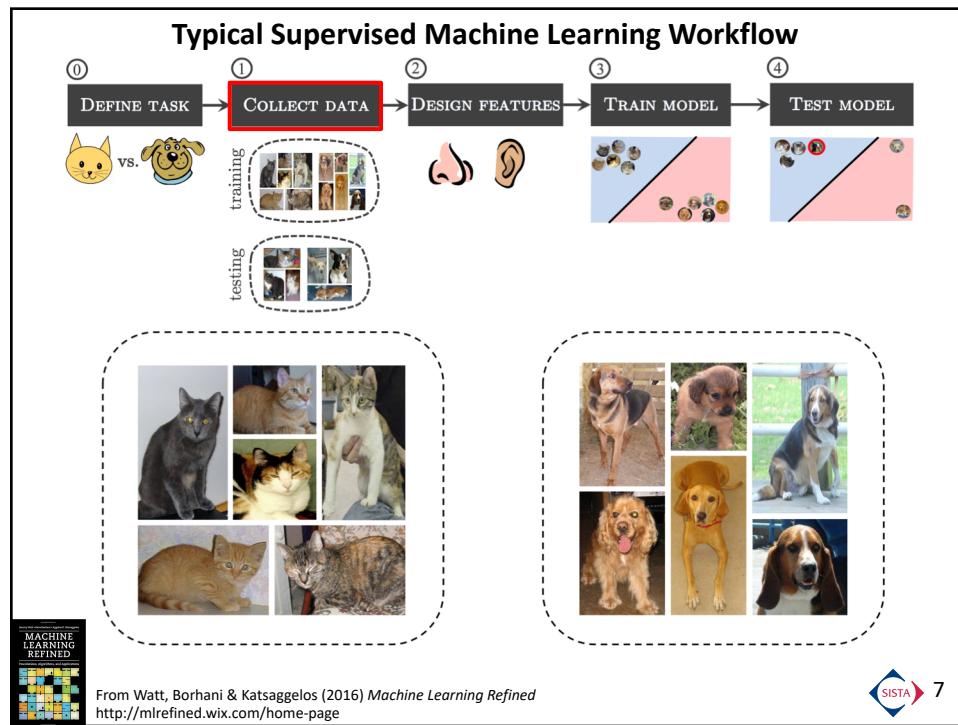
Typical Supervised Machine Learning Workflow

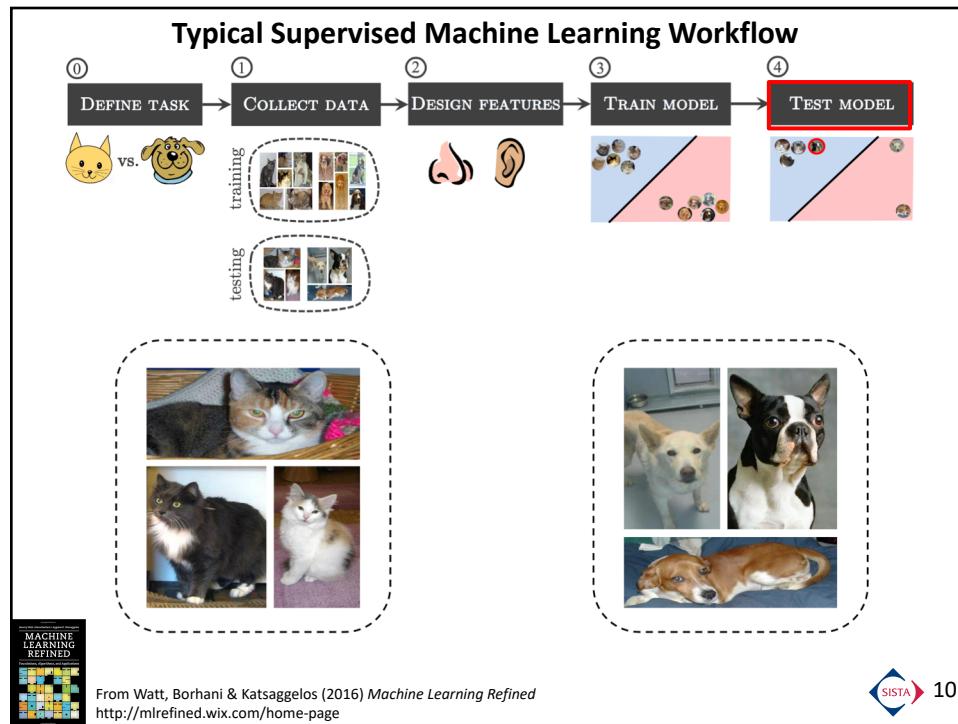
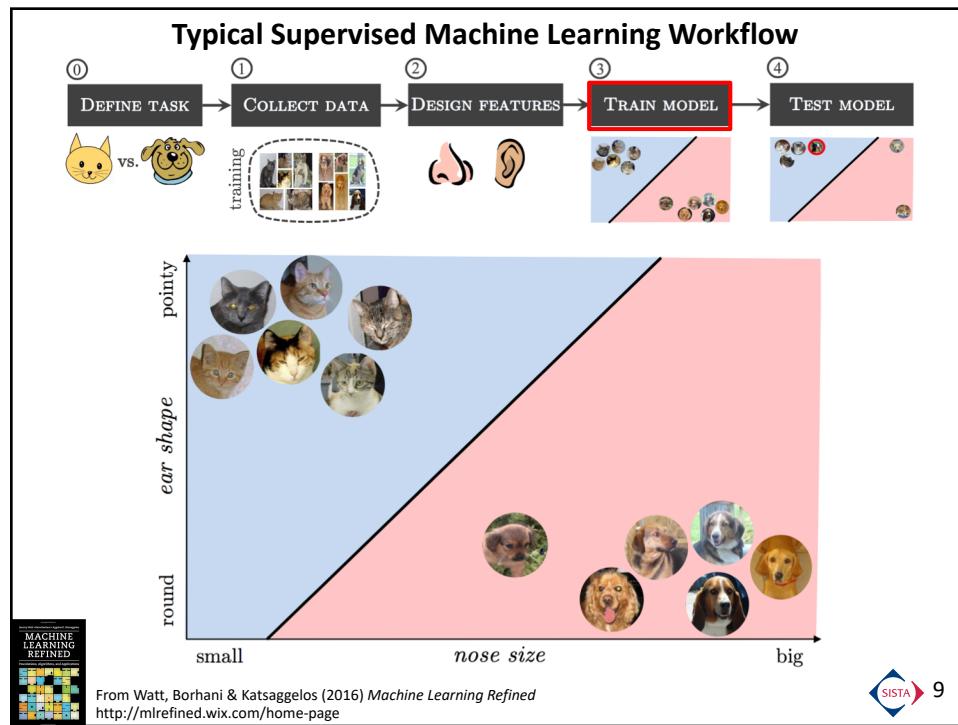


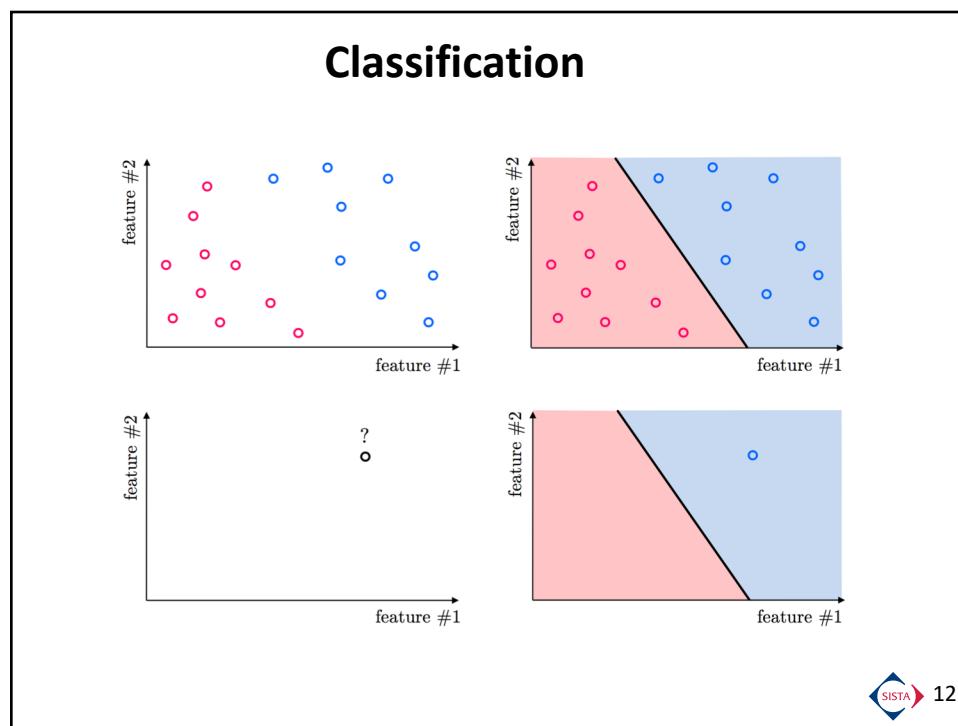
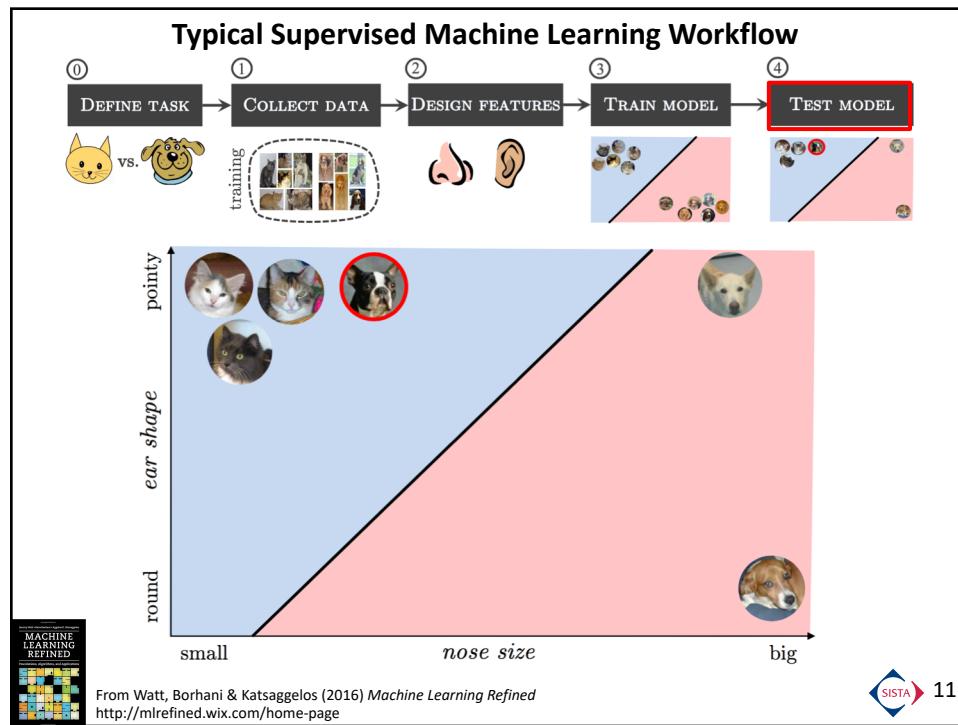
① **DEFINE TASK** → ① **COLLECT DATA** → ② **DESIGN FEATURES** → ③ **TRAIN MODEL** → ④ **TEST MODEL**

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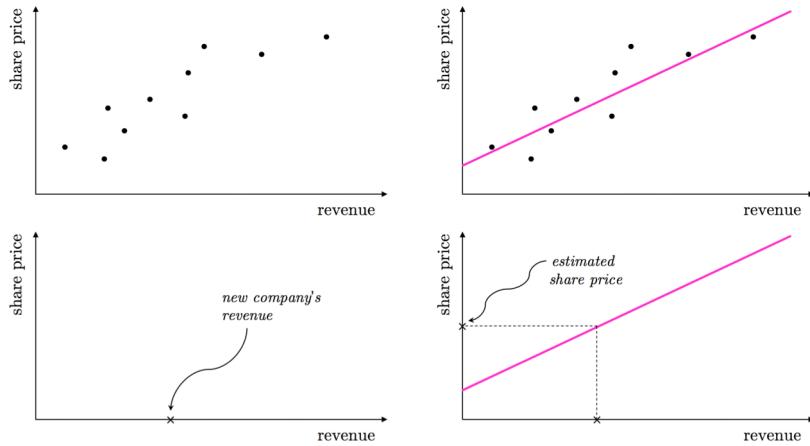
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Regression



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Three General Classes of ML

- **Supervised learning** – model $p(y|x)$
 - Given model and data with correct output (label)
 - Regression, Classification, etc.
- **Unsupervised Learning** – model $p(x)$
 - Only given input data (no output)
 - Clustering, Latent Models, Projection methods, etc.
- **Reinforcement Learning** – model $p(s_{t+1}|s_t, a)$
 - Given input data choose output (action), get grade for output
 - Learning to choose better actions
 - Markov decision processes, POMDPs, planning

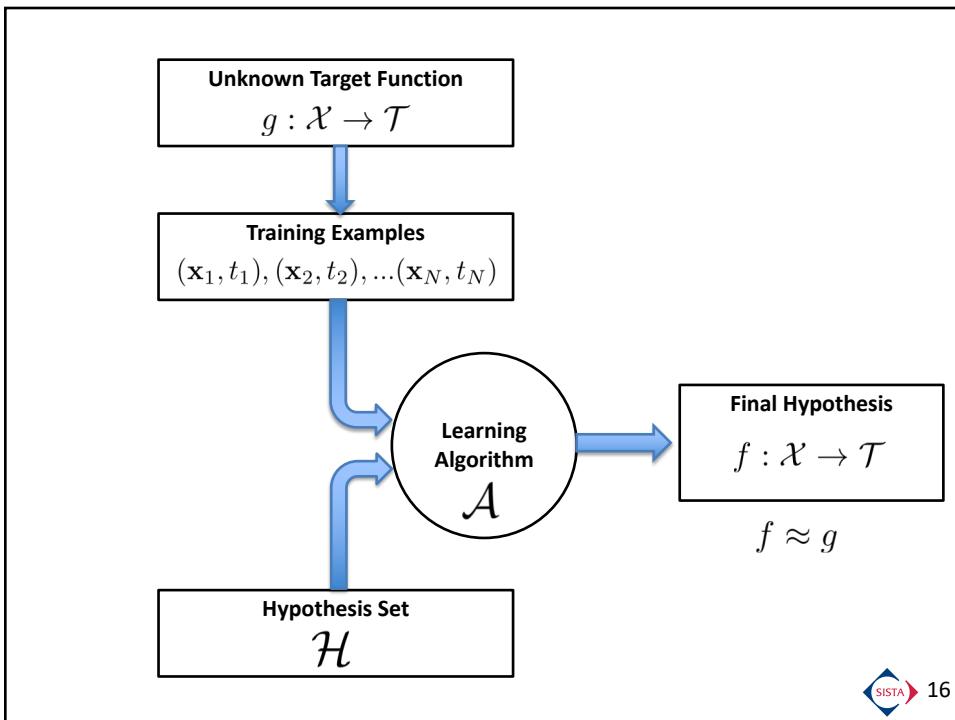
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Supervised Learning: Some Terminology

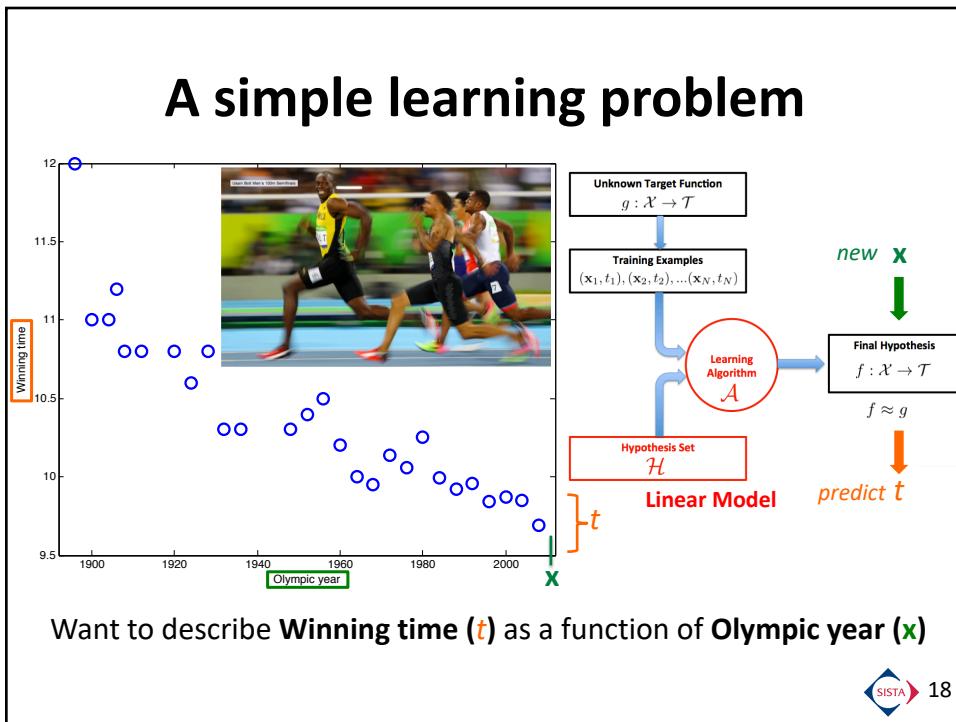
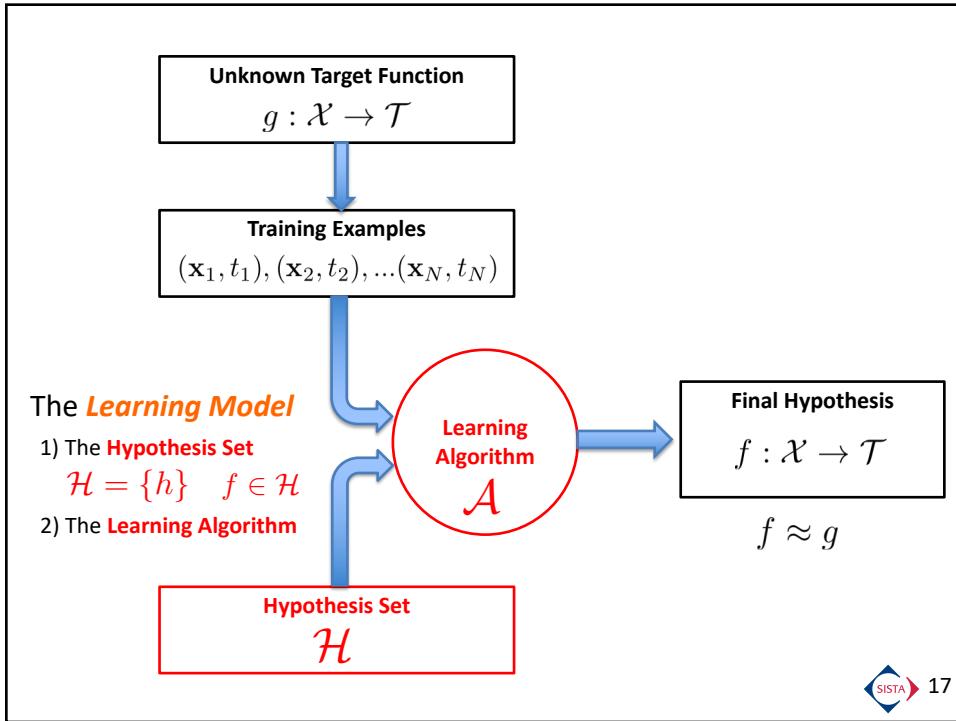
- Input: \mathbf{x} (customer application)
 - Output: t (good/bad customer?)
 - Target function: $g : \mathcal{X} \rightarrow \mathcal{T}$ (*ideal* credit approval fn)
 - Data: $(\mathbf{x}_1, t_1), (\mathbf{x}_2, t_2), \dots (\mathbf{x}_N, t_N)$ (historical records)
- \downarrow
learning
- Hypothesis: $f : \mathcal{X} \rightarrow \mathcal{T}$ (formula to be used)

Adapted from Yaser S. Abu-Mostafa et al., *Learning from Data*

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Defining a Model

- Define function that maps inputs (Olympics year, x_i) to output or target values (Winning times, t_i)

$$t = f(x)$$

- The model itself likely has **parameters**, which we'll generically refer to as ' θ ' here. It is common to make them explicit within a function:

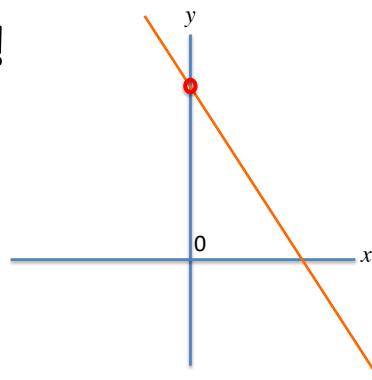
$$t = f(x ; \theta)$$

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Lines!

- Slope-intercept form**

$$y = mx + b^*$$



- General (standard) form**

$$ax + by + c = 0$$

slope $m = -\frac{a}{b}$

y-intercept $b^* = -\frac{c}{b}$

x-intercept $= -\frac{c}{a}$

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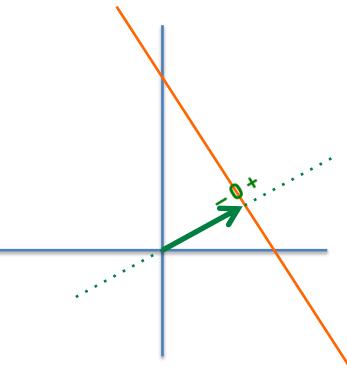
Lines!

- General (standard) form

$$\underline{ax} + \underline{by} + \underline{c} = 0$$

- Slope-intercept form

$$y = \underline{mx} + \underline{b^*}$$



slope $m = -\frac{a}{b}$

y-intercept $b^* = -\frac{c}{b}$

x-intercept $= -\frac{c}{a}$

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Linear Relationship

- $y = mx + b$ (or $t = w_1x + w_0$)
 - the classic line (in 2D space)
 - For a given line, m and b are the **parameters** and x is a **variable** in the relationship:
 $y = f(x; m, b)$
 - When considering alternate lines, we are adjusting m and b
- Generally, as long as the values that vary (assuming the others are constant) are not themselves involved in anything more than
 - (1) **addition** and
 - (2) **scalar multiplication**,
 ... then the relationship is **linear**.

Let's consider the relationship between y and x

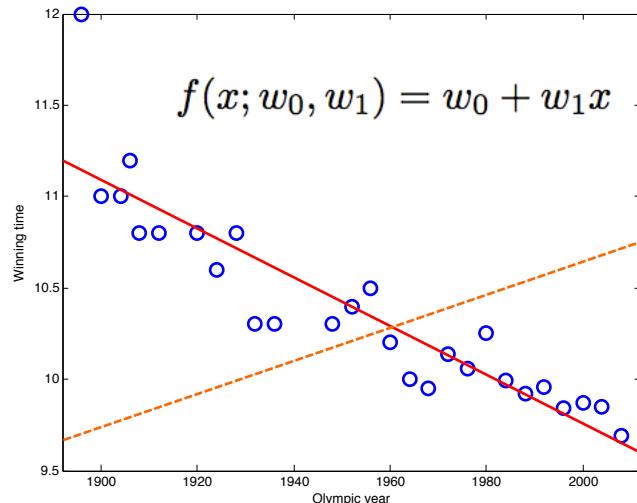
$$y = mx^2 + c \quad y = \sin(x) \quad \sqrt{y} = mx + c \quad \text{Not linear rel. btwn } x, y$$

$$y = mx + c^2 \quad y = x \sin(m) + c \quad \text{Is linear rel. btwn } x, y$$

What about the relationship between y and m (m is a parameter!)

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Data with line (particular w_0 & w_1)



(The red line happens to be a “best” fit)

(The dashed orange line does not describe the trend in the data very well; not a good fit)

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