Class Overview and General Introduction to Machine Learning

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CS5350/6350: Machine Learning

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Modified by Longin Jan Latecki

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  - Designing algorithms that can learn *patterns* from data (and exploit them)
  - Approach: human supplies training examples, the machine learns

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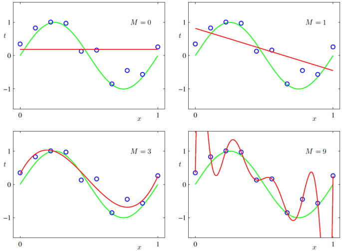
- **Desirable Property:** Generalization
  - The model shouldn't overfit on the training data
  - It should *generalize* well on unseen (future) **test data**

Generalization (Pictorially)

Pictures below: The X axis is the input. The Y axis is the response.



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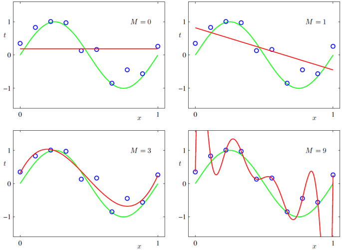

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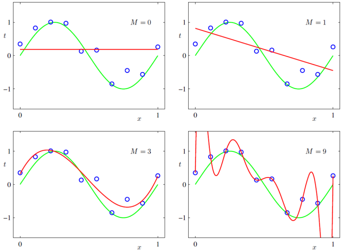

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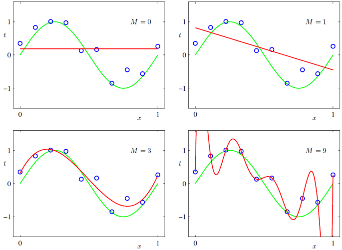

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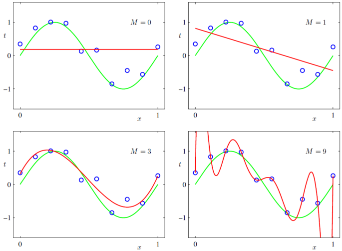

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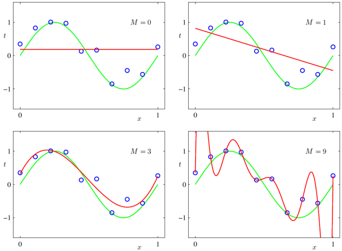

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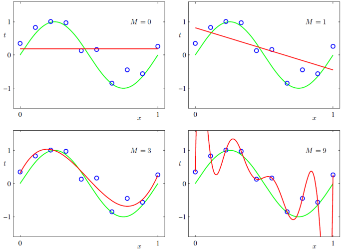

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  - Caution: Too simple a model can underfit (e.g., $M = 0$ above)
  - **General guideline:** Choose a model not-too-simple, yet not-too-complex

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Broadly applicable in many domains (e.g., finance, robotics, bioinformatics, vision, natural language, etc.). Some applications:

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12 IT skills that employers can't say no to (Machine Learning is #1)

http://www.computerworld.com/s/article/9026623/12_IT_skills_that_employers_can_t_say_no_to_

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  - **Example:** Automatic vehicle navigation, (computer) learning to play Chess

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- Assumption: The training and the test examples are drawn from the same data distribution
- Things to keep in mind:
  - No single learning algorithm is universally good ("no free lunch")
  - Different learning algorithms work with different assumptions
  - Generalization is particularly important for supervised learning

Supervised Learning: Problem Settings

- $f : \mathbf{x} \rightarrow \mathbf{y}$
- **Classification:** when $\mathbf{y}$ is a discrete variable
  - Discrete variable: takes a value from a **discrete set** $\mathbf{y} \in \{1, \ldots, K\}$
  - **Example:** Category of a webpage (sports, politics, business, science, etc.)
- **Regression:** when $\mathbf{y}$ is a real-valued variable
  - **Example:** Price of a stock


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Europe's Debt Crisis Weakens Quarterly Growth

By JACK EWING
Published: August 16, 2011

FRANKFURT — Europe's sovereign debt crisis threatened to spill over into the broader economy after official figures released Tuesday showed that growth in the euro zone fell to its lowest rate in two years. Germany — the Continent's powerhouse — slowed almost to a standstill.

Enlarge This Image

Most of Europe's main stock indexes lost ground after the data suggested that the debt and economic problems in countries like Greece and Italy were infecting the rest of the 17-country euro zone. The crisis has led a number of governments to sharply cut spending while weathering market turmoil that has damaged business and consumer confidence.

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Problem Types:

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  - **Example:** Image annotation (each image can have multiple labels)

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- **Structured Prediction:** When **y** is a vector with a structure
  - Elements of **y** are not independent but related to each-other
  - **Example:** Predicting parts-of-speech (POS) tags for a sentence

Input	The	man	ate	the	really	tasty	sandwich
Output	DET	NOUN	VERB	DET	ADV	ADJ	NOUN

Supervised Learning: Regression

Problem Types:

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  - **Example:** Predicting the future price of a stock

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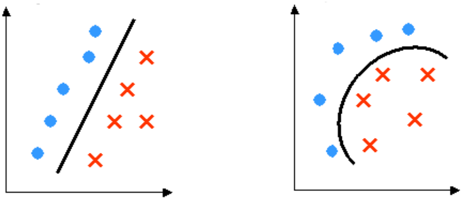
- **Multivariate Regression:** $\mathbf{y}$ is a real-valued vector
  - Each element of $\mathbf{y}$ tells the value of one response variable
  - **Example:** Torque values in multiple joints of a robotic arm
  - Akin to multi-label classification

Supervised Learning: Pictorially

Classification is about finding separation boundaries (linear/non-linear):



Supervised Learning: Pictorially

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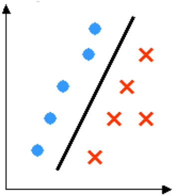
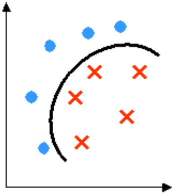
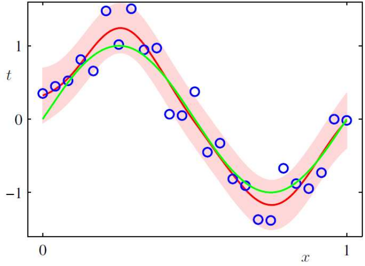




Regression is more like fitting a curve/surface to the data:



Unsupervised Learning

- Unsupervised Learning: learning without a teacher
  - Given: a set of unlabeled inputs $\{\mathbf{x}_1, \ldots, \mathbf{x}_N\}$
  - Goal: learn some intrinsic structure in the data
- Some Examples: Data Clustering, Dimensionality Reduction

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  - Used for data visualization by reducing data to smaller dimensions

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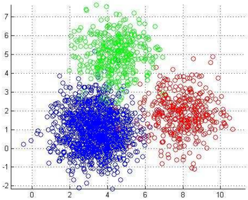

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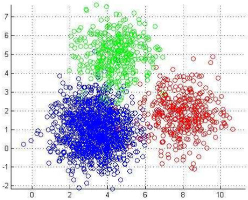

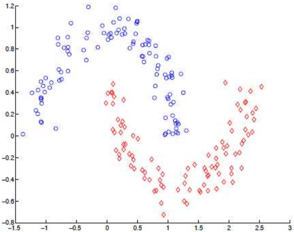

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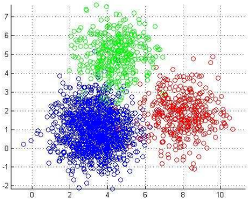

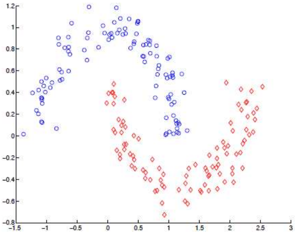

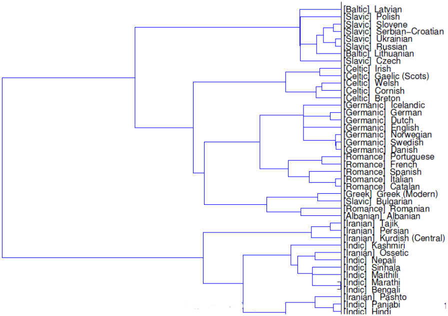

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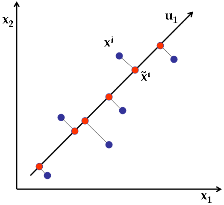
- 2-D data lying close to 1-D space



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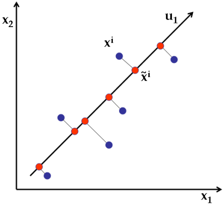
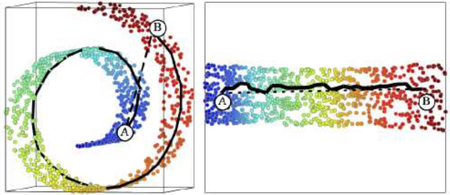


- 3-D data living on a manifold, instrinsically 2-D



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- **Example problems:** Chess, Robot control, autonomous driving

In RL, the key trade-off is exploration versus exploitation

Other Paradigms: Semi-supervised Learning

- Supervised Learning requires labeled data (the more, the better!)
- Problem 1: Labeling is expensive (usually done by humans)
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  - Speech-analysis: transcribing an hour of speech can take several hundred hours!

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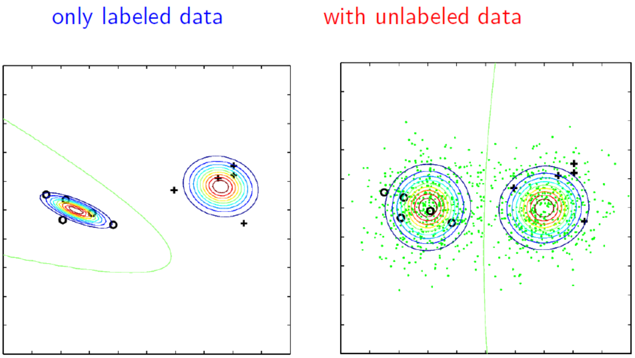
- How can we learn well even with small amounts of labeled data?
- One answer: **Semi-supervised Learning**
  - Using small amount of labeled + plenty of (freely available) unlabeled data

Other Paradigms: Semi-supervised Learning

- Often unlabeled data can give a good idea about class separation
- One intuition: Class boundary is expected to lie in a low-density region
    - Low density region: region that has very few examples



from [Semi-Supervised Learning, ICML 2007 Tutorial; Xiaojin Zhu]

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- Active Learning can lead to several benefits:
  - Less labeled data needed to learn
  - Better classifiers

Other Paradigms: Transfer Learning

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  - Plenty of labeled training data for 'A': Can learn 'A' well
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- Several variants/names of Transfer Learning
    - **Multitask Learning**
    - **Domain Adaptation**
    - **Co-variate Shift**

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- Bayesian Learning gives a way to quantify confidence/uncertainty
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  - So we also have mean and variance estimates of the parameters/predictions
- Another advantage: Incorporating prior knowledge about the problem, Bayesian methods can automatically control overfitting (and can learn well with small amounts of data)

Machine Learning vs Statistics

- Traditionally, Statistics mainly cares about fitting a model over the data
  - Main focus is on explaining the data
  - Issues such as generalization are typically ignored
  - Note: There may be some exceptions
- ML focuses more on the prediction aspect (generalization is important)
  - Although knowing about the data generating model can help prediction, such modeling can sometimes be expensive. ML therefore often goes easy on the modeling aspect and focuses directly on the prediction task
- Statistics traditionally does not focus much on computational issues
- Most ML algorithms nowadays consider the computational issues
- For some discussion, see:

  `http://brenocon.com/blog/2008/12/statistics-vs-machine-learning-fight/`

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Data has form: $\{(\mathbf{x}_1, \mathbf{y}_1), \ldots, (\mathbf{x}_N, \mathbf{y}_N)\}$ (labeled), or $\{\mathbf{x}_1, \ldots, \mathbf{x}_N\}$ (unlabeled)

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- For some problems, non-vectorial representations may be more appropriate

Some Notations

- $\mathbb{R}^D$ denotes the set of all $D \times 1$ real-valued column vectors
- $\mathbf{x} \in \mathbb{R}^D$ denotes a $D \times 1$ real-valued column vector
- $\mathbf{x}^T$ denotes the transpose of $\mathbf{x}$, a $1 \times D$ *row vector*
- $\mathbb{R}^{N \times D}$ denotes the set of all $N \times D$ real-valued matrices
- $\mathbf{X} \in \mathbb{R}^{N \times D}$ denotes an $N \times D$ real-valued matrix
- Supervised Learning: Often, we write $\{(\mathbf{x}_1, y_1), \ldots, (\mathbf{x}_N, y_N)\}$ as $(\mathbf{X}, \mathbf{Y})$
  - $\mathbf{X}$ is an $N \times D$ matrix
  - Each row of $\mathbf{X}$ denotes an example, each column denotes a feature
  - x_{ij} denotes the j-th feature of the i-th example
  - $\mathbf{Y}$ is an $N \times 1$ vector. Row i denotes the label of the i-th example

$$\mathbf{X} = \begin{pmatrix} \mathbf{x}_1^T \\ \vdots \\ \mathbf{x}_N^T \end{pmatrix} = \begin{pmatrix} x_{11} \cdots x_{1D} \\ \vdots \ddots \vdots \\ x_{N1} \cdots x_{ND} \end{pmatrix}$$

$$\mathbf{Y} = \begin{pmatrix} y_1 \\ \vdots \\ y_N \end{pmatrix}$$

Next class..

- Two supervised learning algorithms
  - K-Nearest Neighbors
  - Decision Trees
  - Both based more on intuition and less on maths :)