Outline

• Basics
  – The importance of a good representation
  – Different types of learning problems
  – Different types of learning algorithms

• Supervised learning
  – Decision trees
  – Naïve Bayes
  – Perceptrons, Multi-layer Neural Networks
  – Boosting

• Unsupervised Learning
  – K-means
  – Latent space representations

• Applications: learning to detect faces in images
Deep Learning in Physics: Searching for Exotic Particles

Thanks to Pierre Baldi
Thanks to Pierre Baldi
Searching for exotic particles in high-energy physics with deep learning

P. Baldi¹, P. Sadowski¹ & D. Whiteson²

Collisions at high-energy particle colliders are a traditionally fruitful source of exotic particle discoveries. Finding these rare particles requires solving difficult signal-versus-background classification problems, hence machine-learning approaches are often used. Standard approaches have relied on ‘shallow’ machine-learning models that have a limited capacity to learn complex nonlinear functions of the inputs, and rely on a painstaking search through manually constructed nonlinear features. Progress on this problem has slowed, as a variety of techniques have shown equivalent performance. Recent advances in the field of deep learning make it possible to learn more complex functions and better discriminate between signal and background classes. Here, using benchmark data sets, we show that deep-learning methods need no manually constructed inputs and yet improve the classification metric by as much as 8% over the best current approaches. This demonstrates that deep-learning approaches can improve the power of collider searches for exotic particles.
Higgs Boson Detection

Deep network improves AUC by 8%

BDT = Boosted Decision Trees in TMVA package

Nature Communications, July 2014

<table>
<thead>
<tr>
<th>Technique</th>
<th>Low-level</th>
<th>High-level</th>
<th>Complete</th>
</tr>
</thead>
<tbody>
<tr>
<td>BDT</td>
<td>0.73</td>
<td>0.78</td>
<td>0.81</td>
</tr>
<tr>
<td>NN</td>
<td>0.733 (0.007)</td>
<td>0.777 (0.001)</td>
<td>0.816 (0.004)</td>
</tr>
<tr>
<td>DN</td>
<td>0.880 (0.001)</td>
<td>0.800 (&lt; 0.001)</td>
<td>0.885 (0.002)</td>
</tr>
</tbody>
</table>

Thanks to Pierre Baldi
Application to Extra-Tropical Cyclones

Gaffney et al, *Climate Dynamics*, 2007

Thanks to Padhraic Smyth
Iceland Cluster

Greenland Cluster

Horizontal Cluster

Original Data

Thanks to Padhraic Smyth
Cluster Shapes for Pacific Typhoon Tracks

Thanks to Padhraic Smyth
An ICS Undergraduate Success Story

“The key student involved in this work started out as an ICS undergrad. Scott Gaffney took ICS 171 and 175, got interested in AI, started to work in my group, decided to stay in ICS for his PhD, did a terrific job in writing a thesis on curve-clustering and working with collaborators in climate science to apply it to important scientific problems, and is now one of the leaders of Yahoo! Labs reporting directly to the CEO there, http://labs.yahoo.com/author/gaffney/. Scott grew up locally in Orange County and is someone I like to point as a great success story for ICS.”

--- From Padhraic Smyth
p53 and Human Cancers

- p53 is a central tumor suppressor protein
  “The guardian of the genome”

- Cancer Mutants:
  About 50% of all human cancers have p53 mutations.

- Rescue Mutants:
  Several second-site mutations restore functionality to some p53 cancer mutants in vivo.

Computational Active Learning

Pick the Best (= Most Informative) Unknown Examples to Label

Known

Example 1
Example 2
Example 3
...
Example N

Training Set

Train the Classifier

Classifier

Unknown

Example N +1
Example N +2
Example N +3
...
Example M

Choose Example(s) to Label

Add New Example(s) To Training Set
Visualization of Selected Regions

- **Positive Region:**
  Predicted Active
  96-105 (Green)

- **Negative Region:**
  Predicted Inactive
  223-232 (Red)

- **Expert Region:**
  Predicted Active
  114-123 (Blue)

<table>
<thead>
<tr>
<th></th>
<th>MIP Positive (96-105)</th>
<th>MIP Negative (223-232)</th>
<th>Expert (114-123)</th>
</tr>
</thead>
<tbody>
<tr>
<td># Strong Rescue</td>
<td>8</td>
<td>0 (p &lt; 0.008)</td>
<td>6 (not significant)</td>
</tr>
<tr>
<td># Weak Rescue</td>
<td>3</td>
<td>2 (not significant)</td>
<td>7 (not significant)</td>
</tr>
<tr>
<td>Total # Rescue</td>
<td>11</td>
<td>2 (p &lt; 0.022)</td>
<td>13 (not significant)</td>
</tr>
</tbody>
</table>

No significant differences between the MIP Positive and Expert regions.

Both were statistically significantly better than the MIP Negative region.

The Positive region rescued for the first time the cancer mutant P152L.

No previous single-a.a. rescue mutants in any region.
Complete architectures for intelligence?

• Search?
  – Solve the problem of what to do.

• Learning?
  – Learn what to do.

• Logic and inference?
  – Reason about what to do.
  – Encoded knowledge/”expert” systems?
    • Know what to do.

• Modern view: It’s complex & multi-faceted.
Automated Learning

Why is it useful for our agent to be able to learn?
- Learning is a key hallmark of intelligence
- The ability to take in real data and feedback and improve performance over time
- Check out USC Autonomous Flying Vehicle Project!

Types of learning
- Supervised learning: learn mapping from attributes to “target”
  - Classification: target variable is discrete (e.g., spam email)
  - Regression: target variable is real-valued (e.g., stock market)

- Unsupervised learning: no target variable; “understand” data structure
  - Clustering: grouping data into K groups
  - Latent space embeddings: learn “simpler” representation of the data

- Other types of learning
  - Reinforcement learning: e.g., game-playing agent
  - Learning to rank, e.g., document ranking in Web search
  - And many others....
Importance of representation

Properties of a good representation:

• Reveals important features
• Hides irrelevant detail
• Exposes useful constraints
• Makes frequent operations easy-to-do
• Supports local inferences from local features
  • Called the “soda straw” principle or “locality” principle
  • Inference from features “through a soda straw”
• Rapidly or efficiently computable
  • It’s nice to be fast
Reveals important features / Hides irrelevant detail

- “You can’t learn what you can’t represent.” --- G. Sussman

- **In search:** A man is traveling to market with a fox, a goose, and a bag of oats. He comes to a river. The only way across the river is a boat that can hold the man and exactly one of the fox, goose or bag of oats. The fox will eat the goose if left alone with it, and the goose will eat the oats if left alone with it.

- A good representation makes this problem easy:
Simple illustrative learning problem

Problem:

decide whether to wait for a table at a restaurant, based on the following attributes:

1. Alternate: is there an alternative restaurant nearby?
2. Bar: is there a comfortable bar area to wait in?
3. Fri/Sat: is today Friday or Saturday?
4. Hungry: are we hungry?
5. Patrons: number of people in the restaurant (None, Some, Full)
6. Price: price range ($, $$, $$$)
7. Raining: is it raining outside?
8. Reservation: have we made a reservation?
9. Type: kind of restaurant (French, Italian, Thai, Burger)
10. WaitEstimate: estimated waiting time (0-10, 10-30, 30-60, >60)
# Training Data for Supervised Learning

<table>
<thead>
<tr>
<th>Example</th>
<th>Attr</th>
<th>则</th>
<th>餐厅</th>
<th>Hun</th>
<th>其他</th>
<th>Pat</th>
<th>Price</th>
<th>Rain</th>
<th>Res</th>
<th>Type</th>
<th>Est</th>
<th>Wait</th>
</tr>
</thead>
<tbody>
<tr>
<td>$X_1$</td>
<td>T</td>
<td>F</td>
<td>F</td>
<td>T</td>
<td>Some</td>
<td>$$$</td>
<td>F</td>
<td>T</td>
<td>F</td>
<td>French</td>
<td>0–10</td>
<td>T</td>
</tr>
<tr>
<td>$X_2$</td>
<td>T</td>
<td>F</td>
<td>F</td>
<td>T</td>
<td>Full</td>
<td>$</td>
<td>F</td>
<td>F</td>
<td>F</td>
<td>Thai</td>
<td>30–60</td>
<td>F</td>
</tr>
<tr>
<td>$X_3$</td>
<td>F</td>
<td>T</td>
<td>F</td>
<td>F</td>
<td>Some</td>
<td>$</td>
<td>F</td>
<td>F</td>
<td>F</td>
<td>Burger</td>
<td>0–10</td>
<td>T</td>
</tr>
<tr>
<td>$X_4$</td>
<td>T</td>
<td>F</td>
<td>T</td>
<td>T</td>
<td>Full</td>
<td>$</td>
<td>F</td>
<td>F</td>
<td>F</td>
<td>Thai</td>
<td>10–30</td>
<td>T</td>
</tr>
<tr>
<td>$X_5$</td>
<td>T</td>
<td>F</td>
<td>T</td>
<td>F</td>
<td>Full</td>
<td>$$$</td>
<td>F</td>
<td>T</td>
<td>F</td>
<td>French</td>
<td>&gt;60</td>
<td>F</td>
</tr>
<tr>
<td>$X_6$</td>
<td>F</td>
<td>T</td>
<td>F</td>
<td>T</td>
<td>Some</td>
<td>$$</td>
<td>T</td>
<td>T</td>
<td>T</td>
<td>Italian</td>
<td>0–10</td>
<td>T</td>
</tr>
<tr>
<td>$X_7$</td>
<td>F</td>
<td>T</td>
<td>F</td>
<td>F</td>
<td>None</td>
<td>$</td>
<td>T</td>
<td>F</td>
<td>F</td>
<td>Burger</td>
<td>0–10</td>
<td>F</td>
</tr>
<tr>
<td>$X_8$</td>
<td>F</td>
<td>F</td>
<td>F</td>
<td>T</td>
<td>Some</td>
<td>$$</td>
<td>T</td>
<td>T</td>
<td>T</td>
<td>Thai</td>
<td>0–10</td>
<td>T</td>
</tr>
<tr>
<td>$X_9$</td>
<td>F</td>
<td>T</td>
<td>T</td>
<td>F</td>
<td>Full</td>
<td>$</td>
<td>T</td>
<td>F</td>
<td>F</td>
<td>Burger</td>
<td>&gt;60</td>
<td>F</td>
</tr>
<tr>
<td>$X_{10}$</td>
<td>T</td>
<td>T</td>
<td>T</td>
<td>T</td>
<td>Full</td>
<td>$$$</td>
<td>F</td>
<td>T</td>
<td>T</td>
<td>Italian</td>
<td>10–30</td>
<td>F</td>
</tr>
<tr>
<td>$X_{11}$</td>
<td>F</td>
<td>F</td>
<td>F</td>
<td>F</td>
<td>None</td>
<td>$</td>
<td>F</td>
<td>F</td>
<td>F</td>
<td>Thai</td>
<td>0–10</td>
<td>F</td>
</tr>
<tr>
<td>$X_{12}$</td>
<td>T</td>
<td>T</td>
<td>T</td>
<td>T</td>
<td>Full</td>
<td>$</td>
<td>F</td>
<td>F</td>
<td>T</td>
<td>Burger</td>
<td>30–60</td>
<td>T</td>
</tr>
</tbody>
</table>
Terminology

• Attributes
  – Also known as features, variables, independent variables, covariates

• Target Variable
  – Also known as goal predicate, dependent variable, ...

• Classification
  – Also known as discrimination, supervised classification, ...

• Error function
  – Objective function, loss function, ...
Inductive learning

• Let $x$ represent the input vector of attributes

• Let $f(x)$ represent the value of the target variable for $x$
  - The implicit mapping from $x$ to $f(x)$ is unknown to us
  - We just have training data pairs, $D = \{x, f(x)\}$ available

• We want to learn a mapping from $x$ to $f$, i.e.,
  $h(x; \theta)$ is “close” to $f(x)$ for all training data points $x$

  $\theta$ are the parameters of our predictor $h(\cdot)$

• Examples:
  - $h(x; \theta) = \text{sign}(w_1x_1 + w_2x_2 + w_3)$
  - $h_k(x) = (x_1 \text{ OR } x_2) \text{ AND } (x_3 \text{ OR NOT}(x_4))$
Empirical Error Functions

• Empirical error function:
  \[ E(h) = \sum_x \text{distance}[h(x; \theta), f] \]
  
e.g., distance = squared error if h and f are real-valued (regression)
  distance = delta-function if h and f are categorical (classification)
  
Sum is over all training pairs in the training data D

In learning, we get to choose

1. what class of functions \( h(\cdot) \) that we want to learn
   - potentially a huge space! ("hypothesis space")

2. what error function/distance to use
   - should be chosen to reflect real "loss" in problem
   - but often chosen for mathematical/algorithmic convenience
Inductive Learning as Optimization or Search

- Empirical error function:
  \[ E(h) = \sum_x \text{distance}[h(x; \theta), f] \]

- Empirical learning = finding \( h(x) \), or \( h(x; \theta) \) that minimizes \( E(h) \)
  - In simple problems there may be a closed form solution
    - E.g., “normal equations” when \( h \) is a linear function of \( x \), \( E = \) squared error
  - If \( E(h) \) is differentiable as a function of \( q \), then we have a continuous optimization problem and can use gradient descent, etc
    - E.g., multi-layer neural networks
  - If \( E(h) \) is non-differentiable (e.g., classification), then we typically have a systematic search problem through the space of functions \( h \)
    - E.g., decision tree classifiers

- Once we decide on what the functional form of \( h \) is, and what the error function \( E \) is, then machine learning typically reduces to a large search or optimization problem

- Additional aspect: we really want to learn an \( h(\cdot) \) that will generalize well to new data, not just memorize training data – will return to this later
Our training data example (again)

<table>
<thead>
<tr>
<th>Example</th>
<th>Attributes</th>
<th>Target</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Alt</td>
<td>Bar</td>
</tr>
<tr>
<td>$X_1$</td>
<td>T</td>
<td>F</td>
</tr>
<tr>
<td>$X_2$</td>
<td>T</td>
<td>F</td>
</tr>
<tr>
<td>$X_3$</td>
<td>F</td>
<td>T</td>
</tr>
<tr>
<td>$X_4$</td>
<td>T</td>
<td>F</td>
</tr>
<tr>
<td>$X_5$</td>
<td>T</td>
<td>F</td>
</tr>
<tr>
<td>$X_6$</td>
<td>F</td>
<td>T</td>
</tr>
<tr>
<td>$X_7$</td>
<td>F</td>
<td>T</td>
</tr>
<tr>
<td>$X_8$</td>
<td>F</td>
<td>F</td>
</tr>
<tr>
<td>$X_9$</td>
<td>F</td>
<td>T</td>
</tr>
<tr>
<td>$X_{10}$</td>
<td>T</td>
<td>T</td>
</tr>
<tr>
<td>$X_{11}$</td>
<td>F</td>
<td>F</td>
</tr>
<tr>
<td>$X_{12}$</td>
<td>T</td>
<td>T</td>
</tr>
</tbody>
</table>

- If all attributes were binary, \( h(\cdot) \) could be any arbitrary Boolean function

- Natural error function \( E(h) \) to use is classification error, i.e., how many incorrect predictions does a hypothesis \( h \) make

- Note an implicit assumption:
  - For any set of attribute values there is a unique target value
  - This in effect assumes a “no-noise” mapping from inputs to targets
    - This is often not true in practice (e.g., in medicine). Will return to this later
Learning Boolean Functions

• Given examples of the function, can we learn the function?

• How many Boolean functions can be defined on \( d \) attributes?
  - Boolean function = Truth table + column for target function (binary)
  - Truth table has \( 2^d \) rows
  - So there are \( 2^{2^d} \) different Boolean functions we can define
    (!)
  - This is the size of our hypothesis space

    - E.g., \( d = 6 \), there are \( 18.4 \times 10^{18} \) possible Boolean functions

• Observations:
  - Huge hypothesis spaces \( \rightarrow \) directly searching over all functions is impossible
  - Given a small data (n pairs) our learning problem may be underconstrained
    - Ockham’s razor: if multiple candidate functions all explain the data equally well, pick the simplest explanation (least complex function)
    - Constrain our search to classes of Boolean functions, e.g.,
      - decision trees
      - Weighted linear sums of inputs (e.g., perceptrons)
Decision Tree Learning

• Constrain \( h(\cdot) \) to be a decision tree
Decision Tree Representations

• Decision trees are fully expressive
  – can represent any Boolean function
  – Every path in the tree could represent 1 row in the truth table
  – Yields an exponentially large tree
• Truth table is of size $2^d$, where $d$ is the number of attributes
**Decision Tree Representations**

- Trees can be very inefficient for certain types of functions
  - Parity function: 1 only if an even number of 1’s in the input vector
    - Trees are very inefficient at representing such functions
  - Majority function: 1 if more than \( \frac{1}{2} \) the inputs are 1’s
    - Also inefficient
  - Simple DNF formulae can be easily represented
    - E.g., \( f = (A \text{ AND } B) \text{ OR } (\neg A \text{ AND } D) \)
    - DNF = disjunction of conjunctions

- Decision trees are in effect DNF representations
  - often used in practice since they often result in compact approximate representations for complex functions
  - E.g., consider a truth table where most of the variables are irrelevant to the function
Decision Tree Learning

- Find the smallest decision tree consistent with the n examples
  - Unfortunately this is provably intractable to do optimally

- Greedy heuristic search used in practice:
  - Select root node that is “best” in some sense
  - Partition data into 2 subsets, depending on root attribute value
  - Recursively grow subtrees
  - Different termination criteria
    - For noiseless data, if all examples at a node have the same label then declare it a leaf and backup
    - For noisy data it might not be possible to find a “pure” leaf using the given attributes
      - we’ll return to this later – but a simple approach is to have a depth-bound on the tree (or go to max depth) and use majority vote

- We have talked about binary variables up until now, but we can trivially extend to multi-valued variables
**Pseudocode for Decision tree learning**

```plaintext
function DTL(examples, attributes, default) returns a decision tree
    if examples is empty then return default
    else if all examples have the same classification then return the classification
    else if attributes is empty then return MODE(examples)
    else
        best ← CHOOSE-ATTRIBUTE(attributes, examples)
        tree ← a new decision tree with root test best
        for each value \( v_i \) of best do
            examples_i ← \{elements of examples with best = \( v_i \}\)
            subtree ← DTL(examples_i, attributes - best, MODE(examples))
            add a branch to \( \text{tree} \) with label \( v_i \) and subtree \( \text{subtree} \)
        return \( \text{tree} \)
```

Choosing an attribute

- Idea: a good attribute splits the examples into subsets that are (ideally) "all positive" or "all negative"

- **Patrons?** is a better choice
  - How can we quantify this?
  - One approach would be to use the classification error $E$ directly (greedily)
    - Empirically it is found that this works poorly
  - Much better is to use information gain (next slides)
Entropy and Information

• “Entropy” is a measure of randomness
  – How hard is it to communicate a result to you?
  – Depends on the probability of the outcomes

• Communicating fair coin tosses
  – Output: H H T H T T H H H T ...
  – Sequence takes n bits – each outcome totally unpredictable

• Communicating my daily lottery results
  – Output: 0 0 0 0 0 0 ...
  – Most likely to take one bit – I lost every day.
  – Small chance I’ll have to send more bits (won & when)

• Takes less work to communicate because it’s less random
  – Use a few bits for the most likely outcome, more for less likely ones

Lost: 0
Won 1: 1(...)0
Won 2: 1(...)1(...)0
Entropy and Information

- Entropy $H(x) \equiv \mathbb{E}[ \log 1/p(x) ] = \sum p(x) \log 1/p(x)$
  - Log base two, units of entropy are “bits”
  - Two outcomes: $H = - p \log(p) - (1-p) \log(1-p)$

- Examples:

\[
H(x) = .25 \log 4 + .25 \log 4 + .25 \log 4 + .25 \log 4 = \log 4 = 2 \text{ bits}
\]

\[
H(x) = .75 \log 4/3 + .25 \log 4 \approx .8133 \text{ bits}
\]

\[
H(x) = 1 \log 1 = 0 \text{ bits}
\]

Max entropy for 4 outcomes

Min entropy
Entropy with only 2 outcomes

Consider 2 class problem: \( p = \) probability of class 1, \( 1 - p = \) probability of class 2

In binary case, \( H(p) = -p \log p - (1-p) \log (1-p) \)
Information Gain

- \( H(p) = \) entropy of class distribution at a particular node

- \( H(p \mid A) = \) conditional entropy = average entropy of conditional class distribution, after we have partitioned the data according to the values in \( A \)

- Gain(A) = \( H(p) - H(p \mid A) \)

- Simple rule in decision tree learning
  - At each internal node, split on the node with the largest information gain (or equivalently, with smallest \( H(p \mid A) \))

- Note that by definition, conditional entropy can’t be greater than the entropy
Root Node Example

For the training set, 6 positives, 6 negatives, \( H(6/12, 6/12) = 1 \) bit

\[
H(\frac{6}{12}, \frac{6}{12}) = -\frac{6}{12} \log_2(\frac{6}{12}) - \frac{6}{12} \log_2(\frac{6}{12}) = 1 \text{ bit}
\]

Consider the attributes \textit{Patrons} and \textit{Type}:

\[
IG(\text{Patrons}) = 1 - \left[ \frac{2}{12} H(0, 1) + \frac{4}{12} H(1, 0) + \frac{6}{12} H(\frac{2}{6}, \frac{4}{6}) \right] = 0.541 \text{ bits}
\]

\[
IG(\text{Type}) = 1 - \left[ \frac{2}{12} H(\frac{1}{2}, \frac{1}{2}) + \frac{2}{12} H(\frac{1}{2}, \frac{1}{2}) + \frac{4}{12} H(\frac{2}{4}, \frac{2}{4}) + \frac{4}{12} H(\frac{2}{4}, \frac{2}{4}) \right] = 0 \text{ bits}
\]

\textit{Patrons} has the highest IG of all attributes and so is chosen by the learning algorithm as the root

Information gain is then repeatedly applied at internal nodes until all leaves contain only examples from one class or the other.
Choosing an attribute
Decision Tree Learned

- Decision tree learned from the 12 examples:
True Tree (left) versus Learned Tree (right)
Assessing Performance

Training data performance is typically optimistic
e.g., error rate on training data

Reasons?
- classifier may not have enough data to fully learn the concept (but on training data we don’t know this)
- for noisy data, the classifier may overfit the training data

In practice we want to assess performance “out of sample”
how well will the classifier do on new unseen data? This is the true test of what we have learned (just like a classroom)

With large data sets we can partition our data into 2 subsets, train and test
- build a model on the training data
- assess performance on the test data
Example of Test Performance

Restaurant problem
- simulate 100 data sets of different sizes
- train on this data, and assess performance on an independent test set
- learning curve = plotting accuracy as a function of training set size
- typical “diminishing returns” effect (some nice theory to explain this)
Overfitting and Underfitting

A scatter plot showing a relationship between X and Y variables.
A Complex Model

$Y = \text{high-order polynomial in } X$
A Much Simpler Model

\[ Y = aX + b + \text{noise} \]
Example 2
Example 2
Example 2
Example 2
Example 2
How Overfitting affects Prediction

Predictive Error

Error on Training Data

Model Complexity
How Overfitting affects Prediction

- Predictive Error
- Error on Training Data
- Error on Test Data
- Model Complexity

Graph showing how predictive error decreases as model complexity increases, with a trade-off between error on training data and error on test data.
How Overfitting affects Prediction

- **Underfitting**
  - Predictive Error: High
  - Error on Training Data: High
  - Error on Test Data: High

- **Overfitting**
  - Predictive Error: Low
  - Error on Training Data: Low
  - Error on Test Data: High

**Ideal Range for Model Complexity**
Idea: train each model on the "training data" and then test each model’s accuracy on the validation data.
The k-fold Cross-Validation Method

• Why just choose one particular 90/10 “split” of the data?
  – In principle we could do this multiple times

• “k-fold Cross-Validation” (e.g., k=10)
  – randomly partition our full data set into k disjoint subsets (each roughly of size n/k, n = total number of training data points)
    • for i = 1:10 (here k = 10)
      – train on 90% of data,
      – Acc(i) = accuracy on other 10%
    • end
  • Cross-Validation-Accuracy = 1/k \( \sum_i \) Acc(i)
  – choose the method with the highest cross-validation accuracy
  – common values for k are 5 and 10
  – Can also do “leave-one-out” where k = n
Disjoint Validation Data Sets

Full Data Set

1st partition

Training Data

Validation Data (aka Test Data)
Disjoint Validation Data Sets

- **Full Data Set**
- **Training Data**
- **Validation Data (aka Test Data)**
  - 1st partition
  - 2nd partition

The diagram illustrates the process of partitioning the full data set into training and validation sets. The training data is used to train the model, while the validation data is used to validate the model's performance without overfitting to the training data.
Disjoint Validation Data Sets

Full Data Set

Validation Data (aka Test Data)

1\textsuperscript{st} partition

Training Data

2\textsuperscript{nd} partition

3\textsuperscript{rd} partition

4\textsuperscript{th} partition

5\textsuperscript{th} partition
More on Cross-Validation

• Notes
  – cross-validation generates an approximate estimate of how well the learned model will do on “unseen” data
  – by averaging over different partitions it is more robust than just a single train/validate partition of the data
  – “k-fold” cross-validation is a generalization
    • partition data into disjoint validation subsets of size n/k
    • train, validate, and average over the v partitions
    • e.g., k=10 is commonly used
  – k-fold cross-validation is approximately k times computationally more expensive than just fitting a model to all of the data
You will be expected to know

- Understand Attributes, Error function, Classification, Regression, Hypothesis (Predictor function)

- What is Supervised Learning?

- Decision Tree Algorithm

- Entropy

- Information Gain

- Tradeoff between train and test with model complexity

- Cross validation
Summary

• Inductive learning
  – Error function, class of hypothesis/models $\{h\}$
  – Want to minimize $E$ on our training data
  – Example: decision tree learning

• Generalization
  – Training data error is over-optimistic
  – We want to see performance on test data
  – Cross-validation is a useful practical approach

• Learning to recognize faces
  – Viola-Jones algorithm: state-of-the-art face detector, entirely learned from data, using boosting+decision-stumps