Course Outline

• Fundamentals (2 weeks)
  - Bayes Decision Theory
  - Probability Density Estimation

• Discriminative Approaches (5 weeks)
  - Linear Discriminant Functions
  - Statistical Learning Theory & SVMs
  - Ensemble Methods & Boosting
  - Randomized Trees, Forests & Ferns

• Generative Models (4 weeks)
  - Bayesian Networks
  - Markov Random Fields

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Recap: AdaBoost - “Adaptive Boosting”

• Main idea
  - Instead of resampling, reweight misclassified training examples.
    - Increase the chance of being selected in a sampled training set.
    - Or increase the misclassification cost when training on the full set.

• Components
  - \( h_m(x) \): “weak” or base classifier
    - Condition: <50% training error over any distribution
  - \( H(x) \): “strong” or final classifier

• AdaBoost:
  - Construct a strong classifier as a thresholded linear combination of the weighted weak classifiers:
    \[
    H(x) = \text{sign} \left( \sum_{m=1}^{M} \alpha_m h_m(x) \right)
    \]
Recap: AdaBoost - Intuition

Consider a 2D feature space with positive and negative examples.

Each weak classifier splits the training examples with at least 50% accuracy.

Examples misclassified by a previous weak learner are given more emphasis at future rounds.

Slide credit: Kristen Grauman

Figure adapted from Freund & Schapire
Recap: AdaBoost - Intuition

Weak Classifier 1

Weights Increased

Weak Classifier 2

Figure adapted from Freund & Schapire
Recap: AdaBoost - Intuition

Final classifier is combination of the weak classifiers

Slide credit: Kristen Grauman
Recap: AdaBoost - Algorithm

1. Initialization: Set \( w_n^{(1)} = \frac{1}{N} \) for \( n = 1, \ldots, N \).

2. For \( m = 1, \ldots, M \) iterations
   a) Train a new weak classifier \( h_m(x) \) using the current weighing coefficients \( \mathbf{W}^{(m)} \) by minimizing the weighted error function
      \[
      J_m = \sum_{n=1}^{N} w_n^{(m)} I(h_m(x) \neq t_n)
      \]
   b) Estimate the weighted error of this classifier on \( X \):
      \[
      \epsilon_m = \frac{\sum_{n=1}^{N} w_n^{(m)} I(h_m(x) \neq t_n)}{\sum_{n=1}^{N} w_n^{(m)}}
      \]
   c) Calculate a weighting coefficient for \( h_m(x) \):
      \[
      \alpha_m = \ln \left\{ \frac{1 - \epsilon_m}{\epsilon_m} \right\}
      \]
   d) Update the weighting coefficients:
      \[
      w_n^{(m+1)} = w_n^{(m)} \exp \left\{ \alpha_m I(h_m(x_n) \neq t_n) \right\}
      \]
Recap: Comparing Error Functions

- Ideal misclassification error function
- “Hinge error” used in SVMs
- Exponential error function
  - Continuous approximation to ideal misclassification function.
  - Sequential minimization leads to simple AdaBoost scheme.
  - Disadvantage: exponential penalty for large negative values!
  ⇒ Less robust to outliers or misclassified data points!

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Image source: Bishop, 2006
Recap: Comparing Error Functions

- Ideal misclassification error function
- “Hinge error” used in SVMs
- Exponential error function
- “Cross-entropy error” 
  \[ E = - \sum \{ t_n \ln y_n + (1 - t_n) \ln (1 - y_n) \} \]
  - Similar to exponential error for \( z > 0 \).
  - Only grows linearly with large negative values of \( z \).

⇒ Make AdaBoost more robust by switching ⇒ “GentleBoost”

Image source: Bishop, 2006
Topics of This Lecture

• **Decision Trees**
  - CART
  - Impurity measures
  - Stopping criterion
  - Pruning
  - Extensions
  - Issues
  - Historical development: ID3, C4.5

• **Random Forests**
  - Basic idea
  - Bootstrap sampling
  - Randomized attribute selection
  - Applications
Decision Trees

• Very old technique
  - Origin in the 60s, might seem outdated.

• But...
  - Can be used for problems with nominal data
    - E.g. attributes color ∈ \{red, green, blue\} or weather ∈ \{sunny, rainy\}.
    - Discrete values, no notion of similarity or even ordering.
  - Interpretable results
    - Learned trees can be written as sets of if-then rules.
  - Methods developed for handling missing feature values.
  - Successfully applied to broad range of tasks
    - E.g. Medical diagnosis
    - E.g. Credit risk assessment of loan applicants
  - Some interesting novel developments building on top of them...
Decision Trees

• Example:
  - “Classify Saturday mornings according to whether they’re suitable for playing tennis.”

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**Decision Trees**

- **Elements**
  - Each node specifies a test for some attribute.
  - Each branch corresponds to a possible value of the attribute.

Decision Trees

• Assumption
  - Links must be mutually distinct and exhaustive
  - I.e. one and only one link will be followed at each step.

• Interpretability
  - Information in a tree can then be rendered as logical expressions.
  - In our example:
    \[
    (\text{Outlook} = \text{Sunny} \land \text{Humidity} = \text{Normal}) \\
    \lor (\text{Outlook} = \text{Overcast}) \\
    \lor (\text{Outlook} = \text{Rain} \land \text{Wind} = \text{Weak})
    \]

Training Decision Trees

• Finding the optimal decision tree is NP-hard...

• Common procedure: Greedy top-down growing
  - Start at the root node.
  - Progressively split the training data into smaller and smaller subsets.
  - In each step, pick the *best attribute* to split the data.
  - If the resulting subsets are pure (only one label) or if no further attribute can be found that splits them, terminate the tree.
  - Else, recursively apply the procedure to the subsets.

• CART framework
  - Classification And Regression Trees (Breiman et al. 1993)
  - Formalization of the different design choices.
CART Framework

- Six general questions
  1. Binary or multi-valued problem?  
     - I.e. how many splits should there be at each node?
  2. Which property should be tested at a node?  
     - I.e. how to select the query attribute?
  3. When should a node be declared a leaf?  
     - I.e. when to stop growing the tree?
  4. How can a grown tree be simplified or pruned?  
     - Goal: reduce overfitting.
  5. How to deal with impure nodes?  
     - I.e. when the data itself is ambiguous.
  6. How should missing attributes be handled?
CART - 1. Number of Splits

- Each multi-valued tree can be converted into an equivalent binary tree:

⇒ Only consider binary trees here...

CART - 2. Picking a Good Splitting Feature

• Goal
  - Want a tree that is as simple/small as possible (Occam’s razor).
  - But: Finding a minimal tree is an NP-hard optimization problem.

• Greedy top-down search
  - Efficient, but not guaranteed to find the smallest tree.
  - Seek a property \( T \) at each node \( N \) that makes the data in the child nodes as pure as possible.
  - For formal reasons more convenient to define impurity \( i(N) \).
  - Several possible definitions explored.
CART - Impurity Measures

Problem: discontinuous derivative!

- Misclassification impurity

\[ i(N) = 1 - \max_j p(C_j | N) \]

“Fraction of the training patterns in category \( C_j \) that end up in node \( N \).”

CART - Impurity Measures

- Entropy impurity

\[ i(N) = - \sum_j p(C_j | N) \log_2 p(C_j | N) \]

“Reduction in entropy = gain in information.”

**Gini impurity (variance impurity)**

\[
i(N) = \sum_{i \neq j} p(C_i | N) p(C_j | N)
\]

\[
= \frac{1}{2} \left[ 1 - \sum_j p^2(C_j | N) \right]
\]

“Expected error rate at node \( N \) if the category label is selected randomly.”

CART - Impurity Measures

- Which impurity measure should we choose?
  - Some problems with misclassification impurity.
    - Discontinuous derivative.
      ⇒ Problems when searching over continuous parameter space.
    - Sometimes misclassification impurity does not decrease when Gini impurity would.
  - Both entropy impurity and Gini impurity perform well.
    - No big difference in terms of classifier performance.
    - In practice, stopping criterion and pruning method are often more important.
CART - 2. Picking a Good Splitting Feature

• Application
  ➢ Select the query that decreases impurity the most

\[
\Delta i(N) = i(N) - P_L i(N_L) - (1 - P_L) i(N_R)
\]

• Multiway generalization (gain ratio impurity):
  ➢ Maximize

\[
\Delta i(s) = \frac{1}{Z} \left( i(N) - \sum_{k=1}^{K} P_k i(N_k) \right)
\]

  ➢ where the normalization factor ensures that large \( K \) are not inherently favored:

\[
Z = - \sum_{k=1}^{K} P_k \log_2 P_k
\]
CART - Picking a Good Splitting Feature

- For efficiency, splits are often based on a single feature
  - “Monothetic decision trees”

- Evaluating candidate splits
  - Nominal attributes: exhaustive search over all possibilities.
  - Real-valued attributes: only need to consider changes in label.
    - Order all data points based on attribute \( x_i \).
    - Only need to test candidate splits where \( \text{label}(x_i) \neq \text{label}(x_{i+1}) \).
CART - 3. When to Stop Splitting

- **Problem: Overfitting**
  - Learning a tree that classifies the training data perfectly may not lead to the tree with the best generalization to unseen data.
  - **Reasons**
    - Noise or errors in the training data.
    - Poor decisions towards the leaves of the tree that are based on very little data.

- **Typical behavior**

Slide adapted from Raymond Mooney
CART - Overfitting Prevention (Pruning)

- Two basic approaches for decision trees
  - **Prepruning**: Stop growing tree as some point during top-down construction when there is no longer sufficient data to make reliable decisions.
  - **Postpruning**: Grow the full tree, then remove subtrees that do not have sufficient evidence.

- Label leaf resulting from pruning with the majority class of the remaining data, or a class probability distribution.

\[ C_N = \arg \max_k p(C_k | N) \]
CART - Stopping Criterion

- Determining which subtrees to prune:
  - **Cross-validation**: Reserve some training data as a hold-out set (validation set, tuning set) to evaluate utility of subtrees.
  - **Statistical test**: Determine if any observed regularity can be dismisses as likely due to random chance.
    - Determine the probability that the outcome of a candidate split could have been generated by a random split.
    - Chi-squared statistic (one degree of freedom)
      \[
      \chi^2 = \sum_{i=1}^{2} \frac{(n_{i,\text{left}} - \hat{n}_{i,\text{left}})^2}{\hat{n}_{i,\text{left}}}
      \]
    - Compare to critical value at certain confidence level (table lookup).
  - **Minimum description length (MDL)**: Determine if the additional complexity of the hypothesis is less complex than just explicitly remembering any exceptions resulting from pruning.
CART - 4. (Post-)Pruning

• Stopped splitting often suffers from “horizon effect”
  - Decision for optimal split at node $N$ is independent of decisions at descendent nodes.
  - Might stop splitting too early.
  - Stopped splitting biases learning algorithm towards trees in which the greatest impurity reduction is near the root node.

• Often better strategy
  - Grow tree fully (until leaf nodes have minimum impurity).
  - Then prune away subtrees whose elimination results only in a small increase in impurity.

• Benefits
  - Avoids the horizon effect.
  - Better use of training data (no hold-out set for cross-validation).
Decision Trees - Feature Choice

- Best results if proper features are used
Decision Trees - Feature Choice

- Best results if proper features are used
  - Preprocessing to find important axes often pays off.
Decision Trees - Non-Uniform Cost

- **Incorporating category priors**
  - Often desired to incorporate different priors for the categories.
  - Solution: weight samples to correct for the prior frequencies.

- **Incorporating non-uniform loss**
  - Create loss matrix $\lambda_{ij}$
  - Loss can easily be incorporated into Gini impurity

$$i(N) = \sum_{i,j} \lambda_{ij} p(C_i)p(C_j)$$
Historical Development

• ID3 (Quinlan 1986)
  - One of the first widely used decision tree algorithms.
  - Intended to be used with nominal (unordered) variables
    - Real variables are first binned into discrete intervals.
  - General branching factor
    - Use gain ratio impurity based on entropy (information gain) criterion.

• Algorithm
  - Select attribute $a$ that best classifies examples, assign it to root.
  - For each possible value $v_i$ of $a$,
    - Add new tree branch corresponding to test $a = v_i$.
    - If example_list($v_i$) is empty, add leaf node with most common label in example_list($a$).
    - Else, recursively call ID3 for the subtree with attributes $A \setminus a$. 
Historical Development

- **C4.5 (Quinlan 1993)**
  - Improved version with extended capabilities.
  - Ability to deal with real-valued variables.
  - Multiway splits are used with nominal data
    - Using gain ratio impurity based on entropy (information gain) criterion.
  - Heuristics for pruning based on statistical significance of splits.
  - Rule post-pruning

- **Main difference to CART**
  - Strategy for handling missing attributes.
  - When missing feature is queried, C4.5 follows all $B$ possible answers.
  - Decision is made based on all $B$ possible outcomes, weighted by decision probabilities at node $N$. 

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Decision Trees - Computational Complexity

- **Given**
  - Data points \( \{x_1, \ldots, x_N\} \)
  - Dimensionality \( D \)

- **Complexity**
  - **Storage:** \( \mathcal{O}(N) \)
  - **Test runtime:** \( \mathcal{O}(\log N) \)
  - **Training runtime:** \( \mathcal{O}(DN^2 \log N) \)
    - Most expensive part.
    - Critical step: selecting the optimal splitting point.
    - Need to check \( D \) dimensions, for each need to sort \( N \) data points.
      \[ \mathcal{O}(DN \log N) \]
Summary: Decision Trees

- Properties
  - Simple learning procedure, fast evaluation.
  - Can be applied to metric, nominal, or mixed data.
  - Often yield interpretable results.
Summary: Decision Trees

- Limitations
  - Often produce noisy (bushy) or weak (stunted) classifiers.
  - Do not generalize too well.
  - Training data fragmentation:
    - As tree progresses, splits are selected based on less and less data.
  - Overtraining and undertraining:
    - Deep trees: fit the training data well, will not generalize well to new test data.
    - Shallow trees: not sufficiently refined.
  - Stability
    - Trees can be very sensitive to details of the training points.
    - If a single data point is only slightly shifted, a radically different tree may come out!
      ⇒ Result of discrete and greedy learning procedure.
  - Expensive learning step
    - Mostly due to costly selection of optimal split.
Topics of This Lecture

• Decision Trees
  • CART
  • Impurity measures
  • Stopping criterion
  • Pruning
  • Extensions
  • Issues
  • Historical development: ID3, C4.5

• Random Forests
  • Basic idea
  • Bootstrap sampling
  • Randomized attribute selection
  • Applications
Random Forests (Breiman 2001)

- **Ensemble method**
  - Idea: Create ensemble of many (very simple) trees.

- **Empirically very good results**
  - Often as good as SVMs (and sometimes better)!
  - Often as good as Boosting (and sometimes better)!

- **Standard decision trees: main effort on finding good split**
  - Random Forests trees put very little effort in this.
  - CART algorithm with Gini coefficient, no pruning.
  - Each split is only made based on a random subset of the available attributes.
  - Trees are grown fully (important!).

- **Main secret**
  - Injecting the “right kind of randomness”.

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Random Forests - Algorithmic Goals

• Create many trees (50 - 1,000)

• Inject randomness into trees such that
  - Each tree has maximal strength
    - i.e. a fairly good model on its own
  - Each tree has minimum correlation with the other trees.
    - i.e. the errors tend to cancel out.

• Ensemble of trees votes for final result
  - Simple majority vote for category.

  ➢ Alternative (Friedman)
    - Optimally reweight the trees via regularized regression (lasso).
Random Forests - Injecting Randomness (1)

• Bootstrap sampling process
  - Select a training set by choosing \( N \) times with replacement from all \( N \) available training examples.
  - On average, each tree is grown on only \(~63\%\) of the original training data.
  - Remaining 37% “out-of-bag” (OOB) data used for validation.
    - Provides ongoing assessment of model performance.
    - Allows fitting to small data sets without explicitly holding back any data for testing.
Random Forests - Injecting Randomness (2)

- Random attribute selection
  - For each node, randomly choose subset of $T$ attributes on which the split is based (typically square root of number available).
  - Evaluate splits only on OOB data (out-of-bag estimate).
  ⇒ Very fast training procedure
    - Need to test few attributes.
    - Evaluate only on ~37% of the data.
  ⇒ Minimizes inter-tree dependence
    - Reduce correlation between different trees.

- Each tree is grown to maximal size and is left unpruned
  - Trees are deliberately overfit
  ⇒ Become some form of nearest-neighbor predictor.
Big Question

How can this *ever* possibly work???
A Graphical Interpretation

Different trees induce different partitions on the data.
A Graphical Interpretation

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A Graphical Interpretation

Different trees induce different partitions on the data.

By combining them, we obtain a finer subdivision of the feature space...

Slide credit: Vincent Lepetit

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A Graphical Interpretation

Different trees induce different partitions on the data.

By combining them, we obtain a finer subdivision of the feature space...

...which at the same time also better reflects the uncertainty due to the bootstrapped sampling.

Slide credit: Vincent Lepetit
Summary: Random Forests

• Properties
  - Very simple algorithm.
  - Resistant to overfitting - generalizes well to new data.
  - Very rapid training
    - Also often used for online learning.
  - Extensions available for clustering, distance learning, etc.

• Limitations
  - Memory consumption
    - Decision tree construction uses much more memory.
  - Well-suited for problems with little training data
    - Little performance gain when training data is really large.
You Can Try It At Home...

- Free implementations available
  - Original RF implementation by Breiman & Cutler
    - Code + documentation
    - in Fortran 77
  - But also newer version available in Fortran 90!
  - Fast Random Forest implementation for Java (Weka)

Applications

- **Computer Vision: fast keypoint detection**
  - Detect keypoints: small patches in the image used for matching
  - Classify into one of ~200 categories (visual words)

- **Extremely simple features**
  - E.g. pixel value in a color channel (CIELab)
  - E.g. sum of two points in the patch
  - E.g. difference of two points in the patch
  - E.g. absolute difference of two points

- **Create forest of randomized decision trees**
  - Each leaf node contains probability distribution over 200 classes
  - Can be updated and re-normalized incrementally
Application: Fast Keypoint Detection


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References and Further Reading

- More information on Decision Trees can be found in Chapters 8.2-8.4 of Duda & Hart.

  R.O. Duda, P.E. Hart, D.G. Stork
  Pattern Classification
  2nd Ed., Wiley-Interscience, 2000

- The original paper for Random Forests: