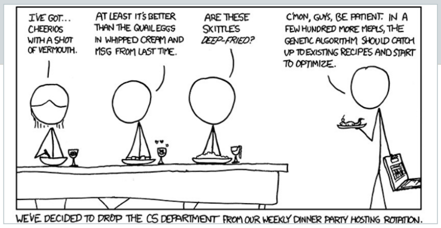
ML II



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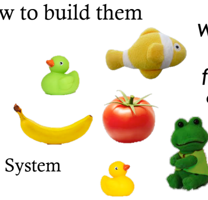
1

Last Time…

- Decision trees and how to build them
- Information Gain
- Entropy
- Next up:
  - Elements of a Learning System
  - What can go wrong?
  - How do we know how it went?



What might we learn from these examples?

2

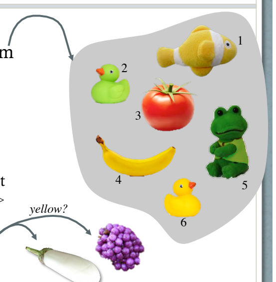
ML Intro: Review

What we have:

- **Data:** examples of our problem
  - Processed to produce **features**
    - Average R, G, B values of pixels
    - Fuzzy or not fuzzy
  - Turned into a **feature vector**
    - X_1: <200, 200, 40, yes> ...
    - X_3: <220, 10, 22, no> ...
  - Sometimes labeled, sometimes not
    - X1: <200, 200, 40, yes, yellow=yes>

What we want:

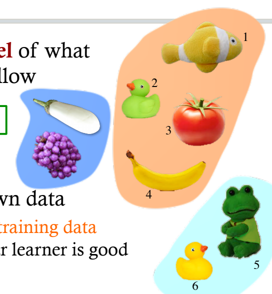
- A prediction over new data



3

Learning Produces Models

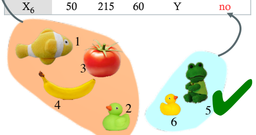
- Trying to build a **model** of what it means to be, e.g., yellow
  1. Train over data
  2. Test on different data
  3. Deploy: the real test
- Every step needs its own data
  - Split what we have into training data and test data to see if our learner is good

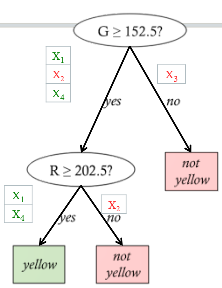


4

One Possible Decision Tree

sample	*attributes*				*label*
	R	*G*	*B*	*Fuzzy?*	*Yellow?*
X_1	205	200	40	Y	yes
X_2	90	250	90	N	no
~~X_3~~	~~220~~	~~10~~	~~22~~	~~N~~	~~no~~
X_4	205	210	10	N	yes
X_5	235	210	30	N	yes
X_6	50	215	60	Y	no

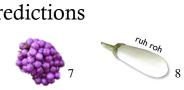




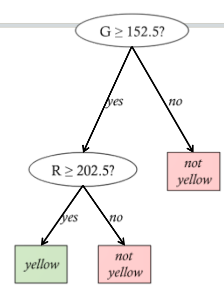
6

One Possible Decision Tree

- Predictions



	R	*G*	*B*	*Fuzzy?*	*Prediction: Is it yellow?*
X_7	215	45	190	N	



7

Overfitting

- Sometimes, model fits training data well but doesn't do well on test data
- Can be it "overfit" to the training data
  - Model is too **specific** to training data
  - Doesn't **generalize** to new information well

Examples (training data)	Attributes			Outcome
	Bipedal	Flies	Feathers	
Sparrow	Y	Y	Y	B
Monkey	Y	N	N	M
Ostrich	Y	N	Y	B
Bat	Y	Y	N	M
Elephant	N	N	N	M

- Learned model: $(Y \wedge Y \wedge Y \rightarrow B \vee Y \wedge N \wedge N \rightarrow M \vee \ldots)$

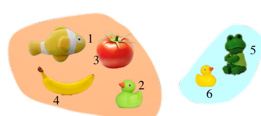
Overfitting 2

- Irrelevant attributes → overfitting
- If hypothesis space has many dimensions (many attributes), may find **meaningless regularity**
  - Ex: Name starts with [A-M] → Mammal

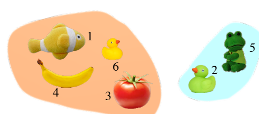
Examples (training data)	Attributes		Class
	Bi-pedal	Feath-ers	
Sparrow	Y	Y	B
Monkey	Y	N	M
Ostrich	Y	Y	B
Bat	Y	N	M
Elephant	N	N	M

Overfitting 3

- Incomplete training data → overfitting



- Bad training/test split → overfitting



Overfitting

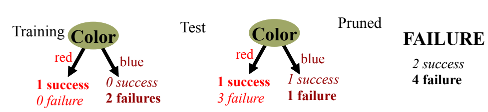
- Fix by by removing irrelevant features
  - E.g., remove 'first letter' from feature vector
- Fix by getting more training data
- Fix by pruning low nodes in the decision tree
  - E.g., if improvement from best attribute at a node is below a threshold, stop and make this node a leaf rather than generating child nodes
- Lots of other choices…

Noisy Data

- Many kinds of "noise" can occur in the examples:
  - Two examples have same attribute/value pairs, but different classifications
  - Some values of attributes are incorrect
    - Errors in the data acquisition process, the preprocessing phase, //
  - Classification is wrong (e.g., + instead of -) because of some error
  - Some attributes are irrelevant to the decision-making process, e.g., color of a die is irrelevant to its outcome
  - Some attributes are missing (are pangolins bipedal?)

Pruning Decision Trees

- Replace a whole subtree by a leaf node
- If: a **decision rule** establishes that he expected error rate in the subtree is greater than in the single leaf. E.g.,
  - Training: one training red success and two training blue failures
  - Test: three red failures and one blue success
  - Consider replacing this subtree by a single Failure node. (leaf)
- After replacement we will have only two errors instead of five:



Summary: Decision Tree Learning

- One of the most widely used learning methods in practice
- Can out-perform human experts in many problems
- Strengths include
  - Fast
  - Simple to implement
  - Can convert result to a set of easily interpretable rules
  - Empirically valid in many commercial products
  - Handles noisy data
- Weaknesses:
  - Univariate splits/partitioning using only one attribute at a time (limits types of possible trees)
  - Large decision trees may be hard to understand
  - Requires fixed-length feature vectors
  - Non-incremental (i.e., batch method)

Next Up

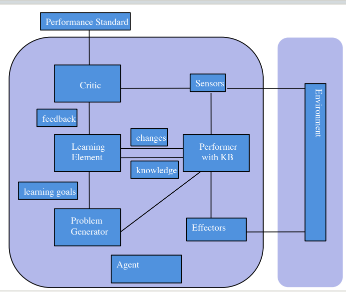
- Evaluating a Learned Model
- Elements of a Learning System

A Learning System

Four components of a machine learning system:

1. **Representation:** how do we describe the problem space?
2. **Actor:** the part of the system that actually does things
3. **Critic:** Provides the experience we learn from
4. **Learner:** the actual learning algorithm

General Model of Learning Agents



Representing The Problem

- Representing the problem to be solved is the first decision to be made (and most important)
- Requires understanding the domain – the field in which the problem is set
- There are two aspects of representing a problem:
  1. Behavior that we want to learn
  2. Inputs we will learn from

Representation: Examples to think about

- How do we describe a problem?
  - Guessing an animal?
  - Playing checkers?
  - Labeling spam email?
  - OCRing a check?
  - Noticing new help desk topics?
- What data do you need to represent for each of these? What model might you learn?

Representation: Examples

- Guessing an animal: a tree of questions and answers
- Playing checkers: board, piece positions, rules; weights for legal moves.
- Labeling spam email: the frequencies of words used in this email and in our entire mailbox; Naive Bayes.
- OCRing: matrix of light/dark pixels; % light pixels; # straight lines, etc.; neural net.
- Noticing new help desk topics: Clustering algorithms

Actor

- Want a system to **do** something.
  - Make a prediction
  - Sort into categories
  - Look for similarities
- Once a model has been learned, we keep using this piece

How Does the Actor Act?

- Guessing an animal: walk the tree, ask the questions
- Playing checkers: look through rules and weights to identify a move
- Identifying spam: examine the set of features, calculate the probability of spam
- OCRing a check: input the features for a digit, output probability for each of 0 through 9
- Help desk topics: output a representation of clusters

Critic

- Provides the experience we learn from
- Typically a set of examples + action that should be taken
- But, can be **any kind** of feedback that indicates how close we are to where we want to be
- Feedback may be after one action, or a sequence

Critic: Think About

- How do we judge correct actions?
  - Guessing an animal:
  - OCRing digits:
  - Identifying spam:
  - Playing checkers:
  - Grouping documents:

Critic: Possible Answers

- How do we judge correct actions?
  - Guessing an animal: Human feedback.
  - OCRing digits: Human-categorized training set.
  - Identifying spam: Match to a set of human-categorized test documents.
  - Playing checkers: Who won?
  - Grouping documents: Which are most similar in language or content?
- Can be generally categorized as supervised, unsupervised, reinforcement.

Learner

- The **learner** is the core of a machine learning system. It will:
  - Examine information provided by the critic
  - Modify the representation to improve performance
  - Repeat until performance is satisfactory, or until it stops improving
- The **learner** component is what people mean when they talk about a machine learning algorithm

What Does the Learner Do?

- Guessing an animal: ask user for a question, add it to the binary tree
- OCRing digits: modify importance of different input features
- Identifying spam: change words likely to be in spam
- Playing checkers: increase chance of using some rules, decrease the chance for others
- Grouping documents: find clusters of similar documents

Information Gain

- Concept: make decisions that increase the homogeneity of the data subsets (for outcomes)
- **Information gain** is based on:
  - **Decrease in entropy**
  - After a dataset is split on an attribute.
  - → High homogeneity – e.g., likelihood samples will have the same class (outcome)

Extensions of the Decision Tree Learning Algorithm

- **Using gain ratios**
- Real-valued data
- Noisy data and overfitting
- Generation of rules
- Setting parameters
- Cross-validation for experimental validation of performance
- C4.5 is an extension of ID3 that accounts for unavailable values, continuous attribute value ranges, pruning of decision trees, rule derivation, and so on

Using Gain Ratios

- Information gain favors attributes with a **large number of values**
  - If we have an attribute D that has a distinct value for each record, then *Info*(D,T) is 0, thus *Gain*(D,T) is maximal
- To compensate, use the following ratio instead of Gain:
  GainRatio(D,T) = Gain(D,T) / SplitInfo(D,T)
- SplitInfo(D,T) is the information due to the split of T on the basis of value of categorical attribute D
  $\text{SplitInfo}(D,T) = I(|T_1|/|T|, |T_2|/|T|, .., |T_m|/|T|)$

where $\{T_1, T_2, .. T_m\}$ is the partition of T induced by value of D

Real-Valued Data

- Select a set of thresholds defining intervals
  - Each interval becomes a discrete value of the attribute
- How?
  - Use simple heuristics…
    - Always divide into quartiles
  - Use domain knowledge…
    - Divide age into infant (0-2), toddler (3 - 5), school-aged (5-8)
  - Or treat this as another learning problem
    - Try a range of ways to discretize the continuous variable and see which yield "better results" w.r.t. some metric
    - E.g., try midpoint between every pair of values

Measuring Model Quality

- Training error
  - Train on all data; measure error on all data
  - Subject to overfitting (of course we'll make good predictions on the data on which we trained!)
- Regularization
  - Attempt to avoid overfitting
  - Explicitly minimize the complexity of the function while minimizing loss
  - Tradeoff is modeled with a *regularization parameter*

Measuring Model Quality

- How good is a model?
  - Predictive accuracy
  - False positives / false negatives for a given cutoff threshold
    - Loss function (accounts for cost of different types of errors)
  - Area under the curve
  - Minimizing loss can lead to problems with overfitting

Cross-Validation

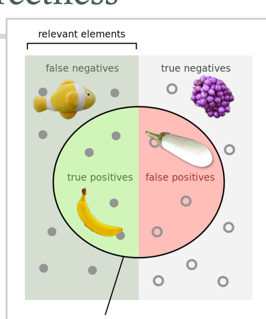
- Holdout cross-validation:
  - Divide data into training set and test set
  - Train on training set; measure error on test set
  - Better than training error, since we are measuring *generalization to new data*
  - To get a good estimate, we need a reasonably large test set
  - But this gives less data to train on, reducing our model quality!

Cross-Validation, cont.

- k-fold cross-validation:
  - Divide data into *k* folds
  - Train on *k-1* folds, use the *k*th fold to measure error
  - Repeat *k* times; use average error to measure generalization accuracy
  - Statistically valid and gives good accuracy estimates
- Leave-one-out cross-validation (LOOCV)
  - *k*-fold cross validation where *k*=*N* (test data = 1 instance!)
  - Quite accurate, but also quite expensive, since it requires building *N* models

Correctness

- True positive
- True negative
- False positive
- False negative



Precision/Recall