

Wrap-Up and Review

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cs540 section 2

Announcements

- HW5 Graded
 - Solution and grades will be up on the web
- Projects not yet graded
- Team Reviews due today
- Final Dec 19th, 10:05am CS&S 1325

What Have We Learned (first half)

- Search
 - Different Global and Local Search Techniques
 - DFS, BFS, Greedy Search, A* Search
 - Hill Climbing, Simulated Annealing, Genetic Algorithms
 - Searching With an Opponent
 - Game Playing – Mini-Max with alpha beta pruning
 - Game Theory
- Logic
 - Propositional Logic
 - First Order Logic

What we have learned (second half)

- Learning
 - Induction of models
 - Inference with models
 - Lots of models
 - K-NN, Decision Trees, Neural Nets, Naïve Bayes, Bayesian Networks, Ensembles, Support Vector Machines, Inductive Logic Programming, etc.
 - Each model is trying to capture a function: $f(x)$ that is a mapping from feature space to a classification for every possible input
 - Model Bias
- Evaluation of Models: How well have you learned the function
 - Accuracy, precision, recall, confusion matrix, etc.

Review

- For each model know:
 - How to create the model (Induction)
 - How to label unseen examples (Inference)
 - Learning Bias
- Types of Learning
 - Unsupervised
 - Reinforcement learning
 - Supervised
- Converting to Fixed Length Feature Vectors

Review

- K-NN
 - Euclidean Distance
 - Weighted Features
 - Choosing K
- Decision Trees
 - Information, Information Gain
 - Pruning
- Ensembles
 - Boosting
 - Occam's Razor

Review

- Types of Data
 - Noisy data
 - Missing Values
 - Continuous Features
 - Skewed Data
 - Irrelevant Features
- Feature Subset Selection
 - Forward chaining
 - Backward chaining

Review

- Methodology
 - Accuracy
 - Learning curves
 - Precision, Recall
 - N-Fold cross validation
 - Confusion Matrix
 - Train/Tune/Test set splits
 - Laplacian Priors

Review

- Perceptrons
 - Step Function, Sigmoid Function
 - Perceptron Training Rule, Delta rule
 - Threshold
 - Gradient Descent
 - Perceptrons and Logic
- Artificial Neural Networks (ANNs)
 - BackPropagation Algorithm
 - Non-boolean features
 - More than two classes
 - Overfitting Problems
- K-Means Clustering

Review

- Basic Probability
 - Joint probability, Full joint probability
 - Conditional probability
 - Marginalization
 - Bayes Rule
 - Chain Rule
 - Independence, Conditional Independence
- Naïve Bayes

Review

- Bayesian Networks
 - Exact Methods of Inference
 - Inference by Enumeration
 - Variable Elimination
 - Approximate Methods of Inference
 - Direct Sampling
 - Rejection Sampling
 - Likelihood Weighting
 - Markov Chain Monte Carlo
 - Induction
 - Parameter Learning
 - Maximum Likelihood (ML)
 - Maximum A-Posteriori (MAP)
 - Topology Learning

Review

- Inductive Logic Programming
 - More than fixed length feature vectors
 - Covering Algorithms in general
 - Top Down Approaches
 - FOIL
 - PROGOL
 - Seeds and Bottom Clauses
 - Bottom Up Approaches
 - GOLEM
- Support Vector Machines
 - Support Vector
 - Maximizing the margin
 - Kernels (mapping to higher dimensions)

Information and Gain Example

F1	F2	F3	Class
0	1	0	A
1	2	0	A
1	0	1	B
0	1	1	B
2	1	1	A
1	0	2	C
2	2	0	A
2	2	1	C

Information is:
$$\sum_{i=1}^n -P(v_i) \log_2(P(v_i))$$

Calculate Information of the above dataset.
Calculate Information Gain for each F1.

Back-Propagation Example

- Calculate Errors:

- Output Units:

$$\delta_k \leftarrow o_k(1-o_k)(t_k-o_k)$$

- Hidden Units:

$$\delta_i \leftarrow o_i(1-o_i) \sum_k (w_{ki} \delta_k)$$

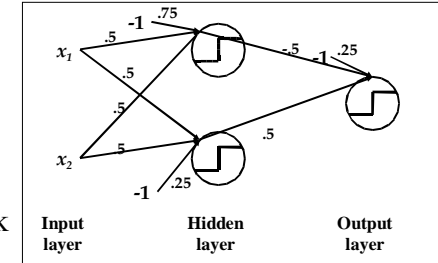
- Update each network weight:

$$w_{ji} \leftarrow w_{ji} + \Delta w_{ji}$$

where $\Delta w_{ji} = \alpha \delta_j x_{ji}$

- Sigmoid Function:

$$\frac{1}{1 + e^{-(\vec{w} \cdot \vec{x})}}$$



- Update weights using back-prop and the example: 1,0,1 and the learning rate 0.2

Probability Example

- Full Joint Probability is

	A		~A	
	B	~B	B	~B
C	0.15	0.2	0.1	0.025
~C	0.3	0.15	0.05	0.025

$P(A,B,C)=?$

$P(A|B,C)=?$

$P(A)=?$

$P(A,B)=?$

$P(A|B)=?$

is A independent of B?

Bayes Rule:

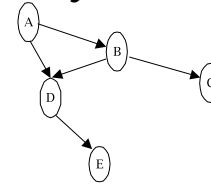
$$P(A|B) = P(B|A)P(A)/P(B)$$

Chain Rule:

$$P(A,B,C,\dots,Z) =$$

$$P(A|B,C,\dots,Z)P(B|C,\dots,Z)\dots P(Z)$$

Bayesian Network Example



$$P(D|A,E) =$$

$$\sum_B \sum_C P(A)P(B|A)P(C|B)P(D|A,B)P(E|D) =$$

$$P(A)P(E|D) \sum_B P(B|A)P(D|A,B) \sum_C P(C|B) =$$

Continued on board...