CSCI 181 / E-181 Spring 2014

2nd midterm review

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1 Support Vector Machines

1.1 Background

Characteristics of SVMs:

- *stock* – SVMs are "off the shelf" and ready to use. No special modification is necessary.

- *linearly separable* – assumes that linear separation is possible. Used natively as a binary classifier.

- *convex optimization.* SVM originated as a backlash against neural nets due to nets' non-convexity. In Neural Nets, results were often non-reproducible as different researchers found different results due to different initializations.

- *global optimum* – SVMs will find the global optimum.

SVMs are based on three "big ideas":

- *margin* Maximizes distance between the closest points

- *duality* Take a hard problem and transform it into an easier problem to solve.

- *kernel trick* Map input vectors to higher dimensional, more expressive features.

1.2 Setup

Data: $\{x_n, t_n\}_{n=1}^{N}, t_n \in \{-1, +1\}$

J Basis functions: $\phi_j(x) \to \Re$, therefore

Vector function: $\Phi X \to \Re^J$ produces a column vector.

Objective function: $f(\mathbf{x}, \mathbf{w}, b) = \mathbf{w}^\mathsf{T}\phi(\mathbf{x}) + b$ where b is the bias.

The sign of $f(\cdot)$ will determine classification $(-1, +1)$

So the actual classifier will be:

$$y(\mathbf{x}, \mathbf{w}, b) \quad = \quad \begin{cases} +1, & \text{if } \mathbf{w}^\mathsf{T}\phi(\mathbf{x}) + b > 0 \\ -1, & \text{otherwise} \end{cases}$$

Decision boundary is the hyperplane where $\mathbf{w}^\mathsf{T}\phi(\mathbf{x}) + b = 0$. We want to find the decision boundary that creates the most separation between the two different classes by maximizing the distance between the two closest points. The points closest to the separating hyperplane are known as the *support vectors*.

The distance from the decision boundary to the closest point is determined by:

$$\frac{|\mathbf{w}^\mathsf{T}\mathbf{x} + b|}{||\mathbf{w}||} \tag{1}$$

1.3 Duality

1.4 other stuff

Mercer function, infinite dimensions (justification for duality)

1.5 Sources

1. Lecture 14, March 24, 2014

2. Lecture 15

3. Bishop 6.0-6.2

4. Bishop 7.0-7.1

5. Course notes - maxmargin

6. Section 7 review

7. Section 8 review

8. Machine Learning in Action, Chapter 6

2 Markov Decision Processes

Lecture 16

Course notes - MDP

Section 9

2.1 Partially Observable MDP

Course notes - POMDP

Section 10

2.2 Hidden Markov Models

Bishop 13.0-13.2

2.3 Mixture Models

Bishop 9.0-9.2

3 Reinforcement Learning

Course notes - RL

Section 9

3.1 Value and Policy Iteration

Lecture 17

Course notes - policyiter

4 Expectation Maximization

Bishop 9.3

Section 11