Sri Jayachamarajendra College of Engineering (SJCE), Mysore - 570 006

"Support Vector Machine Approach to Automated Cardiac SPECT diagnosis"

by

Dharmatheja Bhat (4JC08CS023) Varun B Patil (4JC08CS118)

Supreeth Nag V.P (4JC08CS107) Vinay M (4JC08CS124)

Under the guidance of

Dr. M.P Pushpalatha

Associate Professor,

Department of Computer Science & Engineering,

SJCE, Mysore

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

June 2012

SVM algorithm

- The SVM machine learning algorithm aims to find the best relationship between the features and its class so as to minimize the error in classification.
- The algorithm we employ is called SMO(Sequential Minimal Optimization) and it finds the best possible class to which a particular instance of SPECT data belongs to. The term “best class" here means the class which minimizes the classification error or likewise improves the classification accuracy.
- The two classes possible for any SPECT instance are: indicates possible cardiac disease, does not indicate cardiac disease(future enhancements to the project will include more fine grained classification or multiclass classification).

Choices in implementation

- The SVM algorithm we have implemented can either use a Linear Kernel or a Gaussian Kernel.
- A Linear Kernel can be imagined to be a straight-line seperation between the classes(or a planar seperation in the case of multidimensional data).
- The Gaussian Kernel on the other hand can be visualized as a non-linear seperation between classed which also means a non-planar or curved seperation between classes of multidimensional data.

$$K_{linear}(x^i, x^j) = x^i * x^j$$

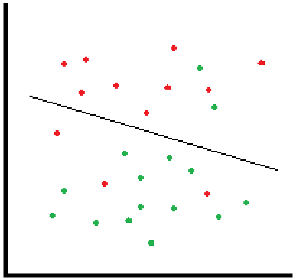
$$K_{gaussian}(x^i, x^j) = \exp(-\frac{||x^i - x^j||^2}{2\sigma^2})$$

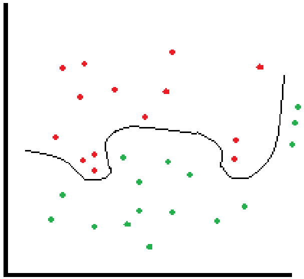
Linear Vs. Gaussian

Which one do you use ?

- With choice comes the problem of deciding which one to use for the particular problem at hand.
- A Linear Kernel is usually employed when the number of features is more than the number of samples and a Gaussian Kernel is employed when the number of samples is more than the number of features.
- And also, the kernel used depends on whether the data itself is linearly-seperable or not.

Linear Vs. Gaussian


Linear Kernel


Gaussian Kernel

Cost Function

The cost function in SVM is:

$$\sum_{i=1}^{m}(y^i * cost_1(z) + (1 - y^i) * cost_0(z)) + (\frac{\lambda}{2} * \sum_{i=1}^{m}(\Theta_i^2))$$

where $z = \Theta^T x$

- $cost_1()$ graph has 0 value for $z >= 1$ and a straight line for $z < 1$
- $cost_0()$ graph has 0 value for $z <= -1$ and a straight line for $z > -1$

So, to minimize cost function, we want z to be $>= 1$ when the class is 1 and we want z to be $<= -1$ when the class is 0.

Optimization

By convention, we optimize:

$$J = (C * A) + B$$

where

$$A = \Sigma(y^{i} * cost_1(z) + (1 - y^{i}) * cost_0(z))$$

$$B = \frac{1}{2}\Sigma(\Theta^2)$$

$$cost_1(z) \approx -\log(z)$$

$$cost_0(z) \approx -\log(1 - z)$$

Optimization

- We see that the definitions for $cost_0()$ and $cost_1()$ above are nothing but straight line approximations to the logarithmic curves. This is done in order to reduce execution time.
- By minimizing the above equation $J = C * A + B$, we learn the optimal parameters Θ
- Once we know Θ, we can predict the class as follows:

$$if(\Theta^T x) > 0, \text{predict class} = 1$$
$$if(\Theta^T x) < 0, \text{predict class} = 0$$

Role of C and σ

- We noted earlier that C and σ are two important parameters that need to be decided by examining the Cross Validation set.
- Informally, the C parameter is a positive value that controls the penalty for misclassified training examples. A large C parameter tells the SVM to try to classify all the examples correctly(large margin). However, large C means that it is more susceptible to outliers and does not give a natural fit for the data.

Role of C and σ

- SVM's are large margin classifiers meaning that the seperation between classes in maximum. In other words, the distance of the seperating boundary from the nearest data point is large. Such a large margin SVM classifier is obtained by setting C to a large value.
- A large value for C value means that the term A should be made close to 0 to make J less. In other words, if C is made large, then we only need to optimize $\frac{1}{2}\Sigma(\Theta^2)$
- The only problem is that large C means greater susceptibility to outliers. So we have no choice but to make C small.

Role of C and σ

- σ is a parameter of the Gaussian Kernel which determines how fast the “similarity measure" approaches 0 for data points that are further apart. If σ is large, the similarity changes slowly and can cause underfitting. If σ is small, the similarity changes fast and can cause overfitting.
- In practice, C and σ are selected from a set of highly possible values for both C and σ where the values vary approximately by a factor of 10, by testing all possible combinations of C and σ for the one that gives the least error in classification of the CV set. In our implementation, the values of C and σ take on the following set of values

$$C = [0.01, 0.03, 0.1, 0.3, 1, 3, 10, 30]$$

$$\sigma = [0.01, 0.03, 0.1, 0.3, 1, 3, 10, 30]$$

Non-linear decision boundaries

How SVM works for non-linear decision boundaries:

- Pick landmarks l_1, l_2,...(usually these are nothing but the data points themselves).
- Now the similarity(or kernel) function $= \exp(-\frac{||x-l_i||^2}{2\sigma^2})$
- The hypothesis here is $\Theta_1 * f_1 + \Theta_2 * f_2 + \Theta_3 * f_3 +$ .....
- f_1 is called the similarity of the data points to the landmark 1 (i.e, l_1) and so on.
- When the data point is very close to the landmark, we get the corrseponding feature almost equal to 1. When the data point is very far from the landmark, we get the corrseponding feature almost equal to 0. That is, as the data point moves farther from the landmark, the value of feature decreases.

Non-linear decision boundaries

- How fast the feature value decreases depends on the σ for gaussian kernels.
- If σ is large, the feature value decreases slowly as the data point moves away from the landmark. This is called high bias or lower variance(underfitting).
- If σ is small, the feature value decreases fast as the data point moves away from the landmark. This is called high variance or lower bias(overfitting).
- Using the kernals approach, the cost function is also changed. Instead of $z = \Theta^T x$, we use $z = \Theta^T f$