SMAI-M20-L26:Nonlinear methods: SVM, Kernels and MLP

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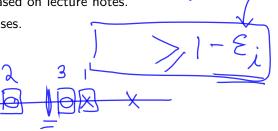
Class Review

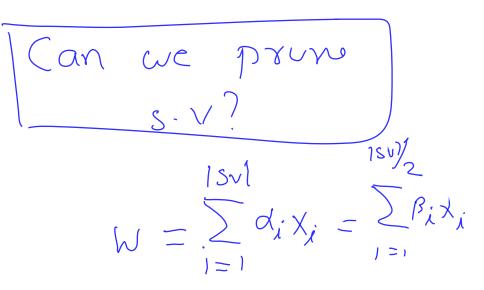




- Hard Margin SVM
- Soft Margin SVM
- Kernel SVM
- Specific Questions based on lecture notes.

Properties and limiting cases.





Recap:

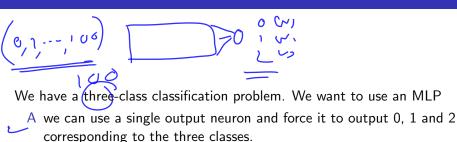
- Supervised Learning: Formulation, Conceptual Issues, Concerns etc.
- Classifiers: (i) Nearest Neighbour, (ii) Notion of a Linear Classifier (iii) Perceptrons (iv) Bayesian Optimal Classifier (v) Logistic Regression (vi) Multiclass classification architectures (v) SVMs (hard margin, soft margin, kernel) (vi) MLP
- Dimensionality Reduction and Applications: (i) Feature Selection and Extraction (ii) PCA (iii) LDA (iv) Eigen face
- Matrix Factorization and Applications: (i) SVD, (ii) Eigen
 Decomposition (iii) Matrix Completion (iv) LSI (v) Recommendations
- Other Topics:
 - Linear Regression
 - Probabilistic View, Bayesian View, MLE
 - Gradient Descent: Stochastic and Batch GD
 - Loss Functions and Optimization
 - Eigen Vector based optimization
 - Neuron model, Single Layer Perceptrons
 - Kernel Functions and Kernel Matrix

This Lecture:

- MLP Architecture
 - Role of Activations
 - 2 Regression, Classification and choice of output neurons.
 - 3 Expressive power of neural networks.
- Chain rule for computing gradients
 - How gradients can be computed
 - What should we keep in mind while defining the layers.
- Backpropagation through chain rule.
 - Appreciate how BP works
 - Why "back" in the BP ?
- Mernel Ridge Regression
 - Another example of Kernelization
 - Familiarity of K and Φ

Questions? Comments?

Discussions Point - I



B we can have three output neurons with classes coded as [1,0,0], [0,1,0] and [0,0,1].

Which one will you prefer? Why?

a what should be the control

a / g 1



Discussions Point -II

Kernel Ridge Regression:

We used the result

$$(BA + \lambda I)^{-1}B = B(AB + \lambda I)^{-1}$$

verify this.

What are the steps in the training time for K-Ridge regression? What. are the steps during testing?

Inpd:

(xi) Ni izi--- N, Kernel Xi, Qi, [X]

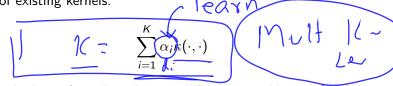
(p)

Qi i=1- N

M-- Zai R(Xi, X)

Discussion Point - III

(Advanced; Out of Syllabus!!) We know that a new kernel can be defined in terms of existing kernels:



Then why don't we formulate the overall learning problem in SVM, including that of learning these α_i

- Discuss why it is a good idea?
- 4 How do we use it for "fusing" different features?
- **3** Why do we limit to \sum ?

See some of the works relevant¹ and ². Read later.

¹http://manikvarma.org/pubs/varma07c.pdf

²https://cvit.iiit.ac.in/images/ConferencePapers/2009/Rakesh09More.pdf

Discussion Point - IV

(Advanced; Out of Syllabus!!)

We know that linear SVMs are superefficient (compared to K-SVMs). Can we find a ϕ () corresponding to a Kernel and solve the problem as

$$\mathbf{w}^T \phi(x)$$

Indeed, this may become difficult for many kernels (eg. RBFs). **why?**Can we find a finite dimensional approximation of ϕ ()? How does it help in speeding up SVM with no major reduction in accuracy? \uparrow read 3 and 4 later.

- Discuss why it is a good idea?
- Suggest an application where speed matters (eg. in the reference is that ofobject detection).

 $^{{\}color{blue}{}^{3}} https://cvit.iiit.ac.in/images/Conference Papers/2010/Sreekanth 10 Generalized.pdf$

⁴https://www.robots.ox.ac.uk/ vgg/publications/2011/Vedaldi11/vedaldi11.pdf

What Next:? (next three)

- SVMs and Kernels (winding up?)
- NN Architectures and NN Learning ()
- Programming for Deep Learning.
- Next Lecture (Mon or Wed): Problem Solving related to SVM and Kernels. (no new video content!).