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- Plain-vanilla computation of SVM params from $\mathbf{a}$:
- $\mathbf{w}$ from opt: $\mathbf{w} = \sum_{i=1}^{N} a_i\, t_i\, \boldsymbol{\phi}(\mathbf{x}_i)$
- SV ($a_i \neq 0$): $t_i\, y(\mathbf{x}_i) = 1$, $y(\mathbf{x}_i) = \mathbf{w}^T \boldsymbol{\phi}(\mathbf{x}_i) + b$. Find b
- Prediction for a new point $\mathbf{x}$: $y(\mathbf{x}) = \mathbf{w}^T \boldsymbol{\phi}(\mathbf{x}) + b$ = $\sum_{i=1}^{N} a_i\, t_i\, \boldsymbol{\phi}^T(\mathbf{x}_i)\boldsymbol{\phi}(\mathbf{x}) + b$ = $\sum_{i=1}^{N} a_i\, t_i\, k(\mathbf{x}_i, \mathbf{x}) + b$
- $a_i = 0$: region; $[t_i\, y(\mathbf{x}_i) - 1] = 0$: support vectors
- Pred: $y(\mathbf{x}) = \sum_{j \in \mathscr{S}} a_j\, t_j\, k(\mathbf{x}_j, \mathbf{x}) + b$. sum: Only SVs
- Only SVs to classify, only kernel, not $\mathbf{x}$ space
- SVs: $[t_i\, y(\mathbf{x}_i) - 1] = 0 \implies t_i\, y(\mathbf{x}_i) = 1$. Optimal b:
- $t_i \sum_{j \in \mathscr{S}} a_j\, t_j\, k(\mathbf{x}_i, \mathbf{x}_j) + b = 1$, solve for SV i, better:
- Mult by t_i: $\sum_{j \in \mathscr{S}} a_j\, t_j\, k(\mathbf{x}_i, \mathbf{x}_j) + b = t_i$. Num stable:
- $b = [t_i - \sum_{j \in \mathscr{S}} a_j\, t_j\, k(\mathbf{x}_i, \mathbf{x}_j)]$. Sum $\forall i \in \mathscr{S}$
- $N_{\mathscr{S}} b = \sum_{i \in \mathscr{S}} [t_i - \sum_{j \in \mathscr{S}} a_j\, t_j\, k(\mathbf{x}_i, \mathbf{x}_j)]$. Obtain b

SVM: The Primal-Dual Question

- If KKT hold, solve the dual instead of the primal
- Primal: $\min \frac{1}{2}||\mathbf{w}||^2$ subject to $t_i\ [\mathbf{w}^T \boldsymbol{\phi}(\mathbf{x}_i) + b] \geq 1$
- $\min\ L(\mathbf{w}, b, \mathbf{a}) \triangleq \frac{1}{2}||\mathbf{w}||^2 - \sum_{i=1}^{N} a_i\ (t_i\ [\mathbf{w}^T \boldsymbol{\phi}(\mathbf{x}_i) + b] - 1)$
- Dual: $\max\ \widetilde{L}(\mathbf{a}) = \sum_{i=1}^{N} a_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} a_i\, a_j\, t_i\, t_j\, k(\mathbf{x}_i, \mathbf{x}_j)$
- Primal & Dual expressions: identical at extremum
- $L(\mathbf{w}, b, \mathbf{a}) = \widetilde{L}(\mathbf{a})$ at the extremum
- Primal Optimisation: $\min\ L(\mathbf{w}, b, \mathbf{a})$
- Dual optimisation: $\max\ \widetilde{L}(\mathbf{a})$
- Optimisation theory: these are equivalent at KKT
- $\min$ wrt $\mathbf{w}, b$; $\max$ wrt $\mathbf{a}$

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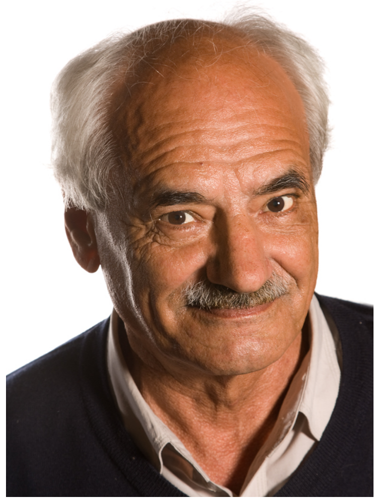
The SVM Story

V. Vapnik
[1936-]



A. Y. Chervonenkis
[1938-2014]

http://engineering.columbia.edu/files/engineering/vapnik.jpg

http://www.clrc.rhul.ac.uk/people/photos/AClarge.JPG

1963: SVM (Vapnik, Chervonenkis)

1992: Kernel trick (Boser, Gayoun, Vapnik)

1995: Soft Margin (Cortes, Vapnik)

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Important: Why this formulation?

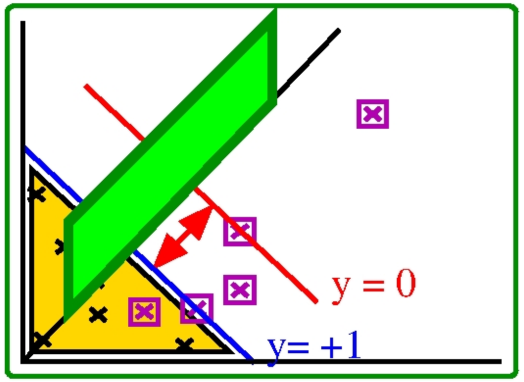
- This is one of the many possible formulations
- Mathematically elegant, numerically stable
- One of the simplest SVM formulations
- Historically, the first! [Vapnik, Chervonenkis'63]

Application of an SVM

- Use a QP solver on the Dual problem to get $\mathbf{a}$
- Compute $\mathbf{w} = \sum_{i=1}^{N} a_i \, t_i \, \boldsymbol{\phi}(\mathbf{x}_i)$
- Find SVs $\mathscr{S}$: those indices for which $a_i > 0$
- Compute $b = \frac{1}{N_{\mathscr{S}}} \sum_{i \in \mathscr{S}} [t_i - \sum_{j \in \mathscr{S}} a_j \, t_j \, k(\mathbf{x}_i, \mathbf{x}_j)]$
- test point $\mathbf{x}$: $sgn(y(\mathbf{x}))$: $y(\mathbf{x}) = \mathbf{w}^T \boldsymbol{\phi}(\mathbf{x}) + b$

Soft-Margin SVMs: Overlapping

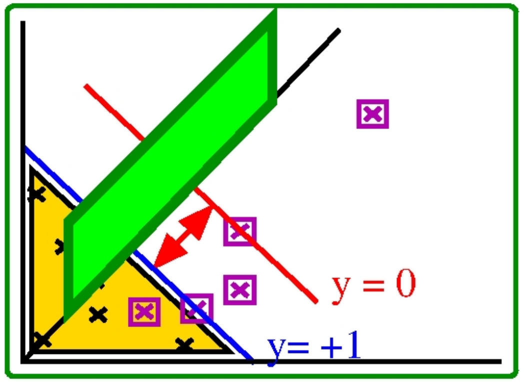
- Practical: when training data not linearly separable in the original $\mathbf{x}-$ or transformed $\boldsymbol{\phi}(\mathbf{x})-$ space
- The Oracle/QP solver earlier gave us direction $\mathbf{w}$ (& b). Adjusted the line to give symmetric margins
- This case: Oracle/QP solver tells us the optimal decision boundary, margins & outliers



- Points in magenta: new
- Consider wrt one class (+1)
- correct, in the margin zone, on the boundary, outlier
- Points in terms of lines
- || the decision boundary, & the 2 margin lines
- Points can be on the wrong side of decision boundary; penalty $\propto$ distance from boundary

The ξ Story...

- 'Correct' part: $\xi_i \triangleq 0$. Else, $\xi_i \triangleq |t_i - y(\mathbf{x}_i)|$
- Penalty: linear fn of distance from boundary
- Why this? Simple. Elegant. Historically, the first!
- [Bennet'92], [Cortes & Vapnik '95]



- Earlier: hard margin. Utopian: training data was linearly separable in original $\mathbf{x}-$ or kernel $\boldsymbol{\phi}(\mathbf{x})-$ space
- Now relax this: even training data not linearly separable
- A green vertical board atop the 'distance' line
- 'Green-board space': Vertical axis: ξ_i. Horizontal axis: distance from the 'near' margin line
- 'Green-board space': (0,0): 'near' margin, $t_i = +1$

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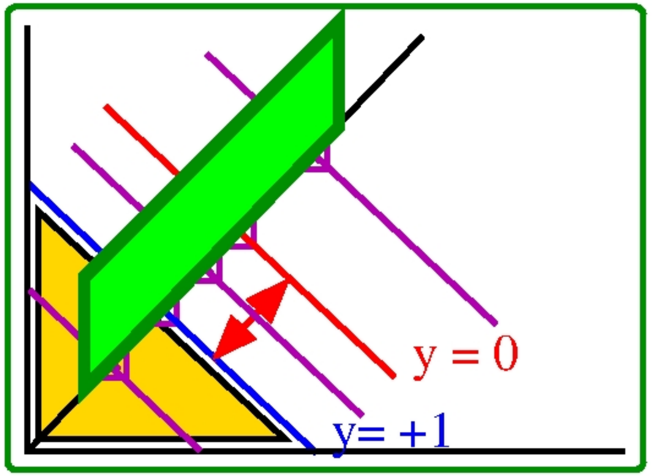

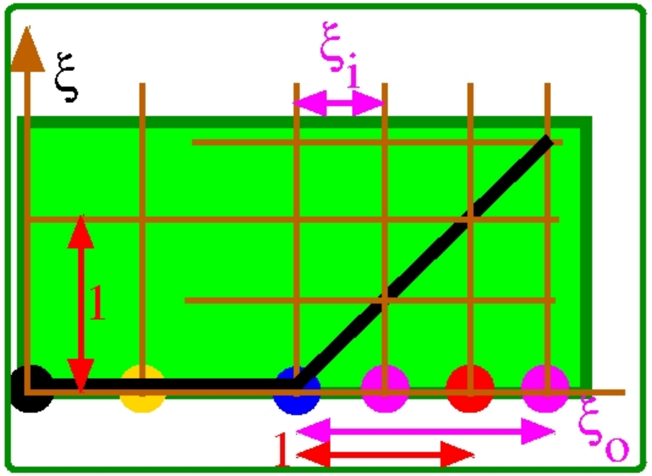

- ‘near’ margin: $\xi_i = |t_i - y(\mathbf{x}_i)|$=$|+1-(+1)|$=0:[0,0]
- boundary: $\xi_i = |t_i - y(\mathbf{x}_i)|$=$|+1-0|$=1:[1,1]
- An inliner excursion point in the ‘zone’: Consider a point at a distance ξ_i from the ‘near’ margin.
  - $\frac{\xi_i}{||\mathbf{w}||}$ farther from origin than the ‘near’ margin
  - eqn: $\mathbf{w}^T\boldsymbol{\phi}(\mathbf{x}_i) + (b - 1 + \xi_i) = 0$: $y_i = 1 - \xi_i$
  - $\xi_i = |t_i - y(\mathbf{x}_i)|$=$|+1-(1-\xi_i)|$=$\xi_i$:$[\xi_i, \xi_i]$