

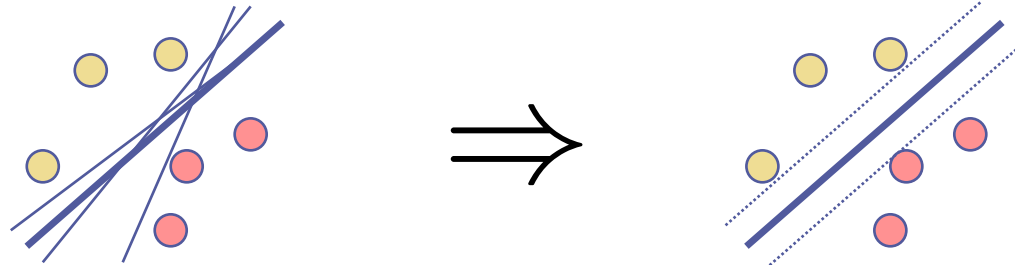
Machine Learning

Topic 6

- Review: Support Vector Machines
- Primal & Dual Solution
- Non-separable SVMs
- Kernels
- SVM Demo

Review: SVM

- Support vector machines are (in the simplest case) linear classifiers that do structural risk minimization (SRM)
- Directly maximize margin to reduce guaranteed risk $J(\theta)$
- Assume first the 2-class data is linearly separable:
have $\{(x_1, y_1), \dots, (x_N, y_N)\}$ where $x_i \in \mathbb{R}^D$ and $y_i \in \{-1, 1\}$
 $f(x; \theta) = \text{sign}(w^T x + b)$
- Decision boundary or hyperplane given by $w^T x + b = 0$
- Note: can scale w & b while keeping same boundary
- Many solutions exist which have empirical error $R_{\text{emp}}(\theta) = 0$
- Want widest or thickest one (max margin), also it's unique!



Support Vector Machines

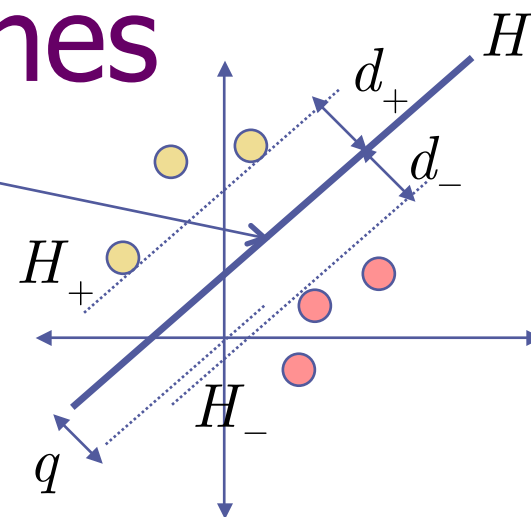
• Define:

$$w^T x + b = 0$$

H_+ = positive margin hyperplane

H_- = negative margin hyperplane

q = distance from decision plane to origin



$$q = \min_x \left\| \vec{x} - \vec{0} \right\| \quad \text{subject to} \quad w^T x + b = 0$$

$$\min_x \frac{1}{2} \left\| \vec{x} - \vec{0} \right\|^2 - \lambda (w^T x + b)$$

1) grad $\frac{\partial}{\partial x} \left(\frac{1}{2} x^T x - \lambda (w^T x + b) \right) = 0$ **2) plug into constraint**

$$x - \lambda w = 0$$

$$x = \lambda w$$

$$w^T x + b = 0$$

$$w^T (\lambda w) + b = 0$$

$$\lambda = -\frac{b}{w^T w}$$

3) Sol'n $\hat{x} = -\left(\frac{b}{w^T w}\right) w$

4) distance $q = \left\| \hat{x} - \vec{0} \right\| = \left\| -\frac{b}{w^T w} w \right\| = \frac{|b|}{w^T w} \sqrt{w^T w} = \frac{|b|}{\|w\|}$

5) Define without loss of generality since can scale b & w

$$H \rightarrow w^T x + b = 0$$

$$H_+ \rightarrow w^T x + b = +1$$

$$H_- \rightarrow w^T x + b = -1$$

Support Vector Machines

- The constraints on the SVM for $R_{\text{emp}}(\theta)=0$ are thus:

$$w^T x_i + b \geq +1 \quad \forall y_i = +1$$

$$w^T x_i + b \leq -1 \quad \forall y_i = -1$$

- Or more simply: $y_i (w^T x_i + b) - 1 \geq 0$
- The margin of the SVM is:

$$m = d_+ + d_-$$

- Distance to origin: $H \rightarrow q = \frac{|b|}{\|w\|}$ $H_+ \rightarrow q_+ = \frac{|b-1|}{\|w\|}$ $H_- \rightarrow q_- = \frac{|-1-b|}{\|w\|}$

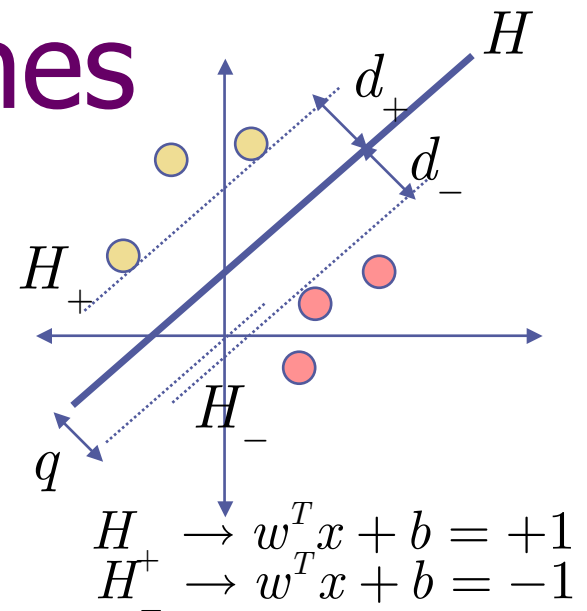
- Therefore: $d_+ = d_- = \frac{1}{\|w\|}$ and margin $m = \frac{2}{\|w\|}$

- Want to max margin, or equivalently minimize: $\|w\|$ or $\|w\|^2$

- SVM Problem: $\min \frac{1}{2} \|w\|^2$ subject to $y_i (w^T x_i + b) - 1 \geq 0$

- This is a quadratic program!

- Can plug this into a matlab function called "qp()", done!



SVM in Dual Form

- We can also solve the problem via convex duality
- Primal SVM problem L_P : $\min \frac{1}{2} \|w\|^2$ subject to $y_i (w^T x_i + b) - 1 \geq 0$
- This is a quadratic program, quadratic cost function with multiple linear inequalities (these carve out a convex hull)

- Subtract from cost each inequality times an α Lagrange multiplier, take derivatives of w & b :

$$L_P = \min_{w,b} \max_{\alpha \geq 0} \frac{1}{2} \|w\|^2 - \sum_i \alpha_i (y_i (w^T x_i + b) - 1)$$

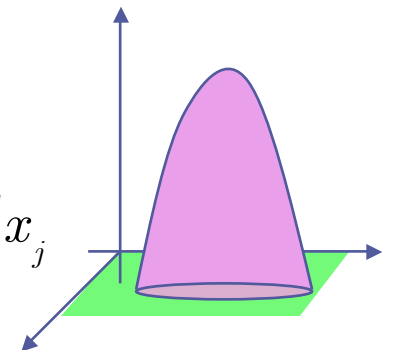
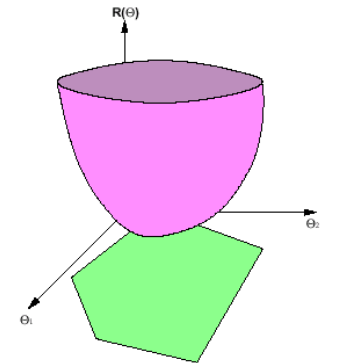
$$\frac{\partial}{\partial w} L_P = w - \sum_i \alpha_i y_i x_i = 0 \rightarrow w = \sum_i \alpha_i y_i x_i$$

$$\frac{\partial}{\partial b} L_P = - \sum_i \alpha_i y_i = 0$$

- Plug back in, dual: $L_D = \sum_i \alpha_i - \frac{1}{2} \sum_i \sum_j \alpha_i \alpha_j y_i y_j x_i^T x_j$

- Also have constraints: $\sum_i \alpha_i y_i = 0$ & $\alpha_i \geq 0$

- Above L_D must be maximized! convex duality... also qp()

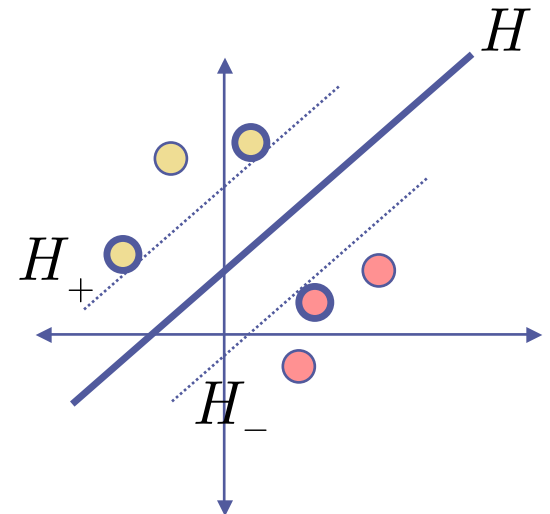


SVM Dual Solution Properties

- We have dual convex program:

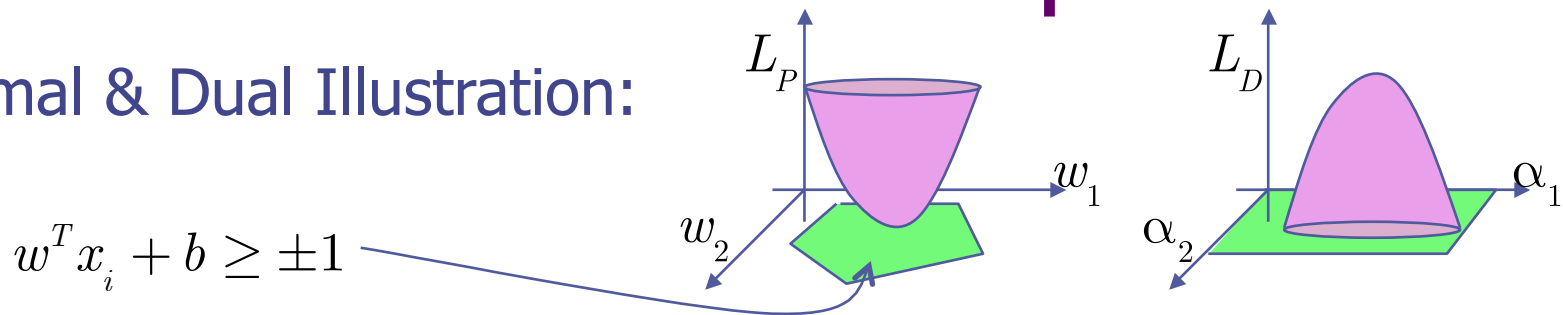
$$\sum_i \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j x_i^T x_j \quad \text{subject to} \quad \sum_i \alpha_i y_i = 0 \quad \& \quad \alpha_i \geq 0$$

- Solve for N alphas (one per data point) instead of D w's
- Still convex (qp) so unique solution, gives alphas
- Alphas can be used to get w: $w = \sum_i \alpha_i y_i x_i$
- **Support Vectors:** have non-zero alphas
shown with thicker circles, all live on the margin: $w^T x_i + b = \pm 1$
- Solution is sparse, most alphas=0
these are *non-support vectors*
SVM ignores them if they move (without crossing margin) or if they are deleted, SVM doesn't change (stays robust)



SVM Dual Solution Properties

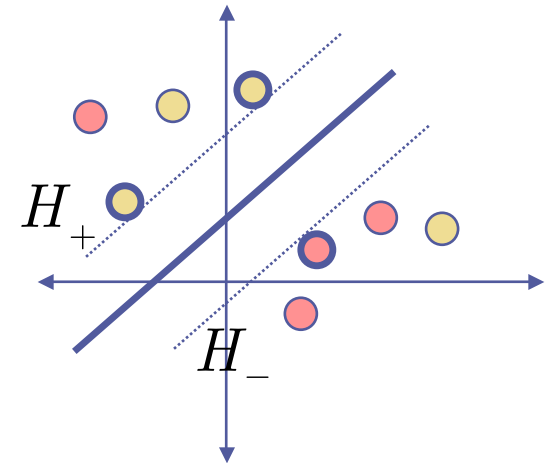
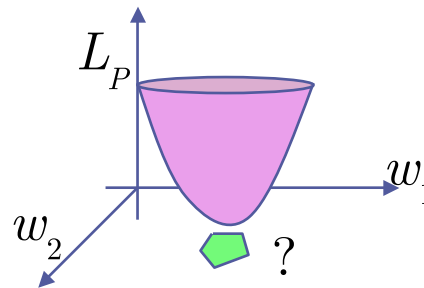
- Primal & Dual Illustration:



- Recall we could get w from alphas: $w = \sum_i \alpha_i y_i x_i$
- Or could use as is: $f(x) = \text{sign}(x^T w + b) = \text{sign}\left(\sum_i \alpha_i y_i x^T x_i + b\right)$
- **Karush-Kuhn-Tucker Conditions (KKT):** solve value of b on margin (for nonzero alphas) have: $w^T x_i + b = y_i$
using known w , compute b for each support vector
 $\tilde{b}_i = y_i - w^T x_i \quad \forall i : \alpha_i > 0 \quad \text{then...} \quad b = \text{average}(\tilde{b}_i)$
- Sparsity (few nonzero alphas) is useful for several reasons
- Means SVM only uses some of training data to learn
- Should help improve its ability to generalize to test data
- Computationally faster when using final learned classifier

Non-Separable SVMs

- What happens when non-separable?
- There is no solution and convex hull shrinks to nothing



- Not all constraints can be resolved, their alphas go to ∞
- Instead of perfectly classifying each point: $y_i(w^T x_i + b) \geq 1$ we "Relax" the problem with (positive) **slack variables** ξ_i 's allow data to (sometimes) fall on wrong side, for example:

$$w^T x_i + b \geq -0.03 \quad \text{if } y_i = +1$$

- New constraints: $w^T x_i + b \geq +1 - \xi_i \quad \text{if } y_i = +1 \quad \text{where } \xi_i \geq 0$
 $w^T x_i + b \leq -1 + \xi_i \quad \text{if } y_i = -1 \quad \text{where } \xi_i \geq 0$

- But too much ξ_i 's means too much slack, so penalize them

$$L_P : \min \frac{1}{2} \|w\|^2 + C \sum_i \xi_i \quad \text{subject to } y_i(w^T x_i + b) - 1 + \xi_i \geq 0$$

Non-Separable SVMs

- This new problem is still convex, still qp()!
- User chooses scalar C (or cross-validates) which controls how much slack ξ_i to use (how non-separable) and how robust to outliers or bad points on the wrong side

Large margin \rightarrow **Low slack** \rightarrow **On right side** \rightarrow **For ξ_i positivity** \rightarrow

$$L_P : \min \frac{1}{2} \|w\|^2 + C \sum_i \xi_i - \sum_i \alpha_i \left(y_i (w^T x_i + b) - 1 + \xi_i \right) - \sum_i \beta_i \xi_i$$

$\frac{\partial}{\partial b} L_P$ and $\frac{\partial}{\partial w} L_P$ as before...

$$\frac{\partial}{\partial \xi_i} L_P = C - \alpha_i - \beta_i = 0$$

$$\alpha_i = C - \beta_i \text{ but... } \alpha_i \ \& \ \beta_i \geq 0$$

$$\therefore 0 \leq \alpha_i \leq C$$

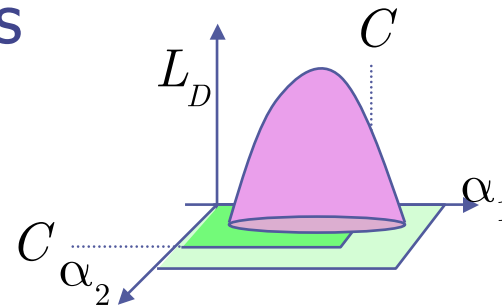
- Can now write dual problem (to maximize):

$$L_D : \max \sum_i \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j x_i^T x_j \text{ subject to } \sum_i \alpha_i y_i = 0 \text{ and } \alpha_i \in [0, C]$$

- Same dual as before but alphas can't grow beyond C

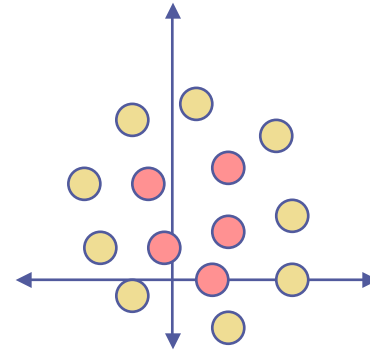
Non-Separable SVMs

- As we try to enforce a classification for a data point its Lagrange multiplier alpha keeps growing endlessly
- Clamping alpha to stop growing at C makes SVM “give up” on those non-separable points
- The dual program is now:
- Solve as before with extra constraints that alphas positive AND less than C... from alphas get $w = \sum_i \alpha_i y_i x_i$
- **Karush-Kuhn-Tucker Conditions (KKT):** solve value of b on margin for not=zero alphas AND not=C alphas for all others have support vectors, assume $\xi_i = 0$ and use formula $y_i (w^T x_i + \tilde{b}_i) - 1 + \xi_i = 0$ to get \tilde{b}_i and $b = \text{average}(\tilde{b}_i)$
- Mechanical analogy: support vector forces & torques



Nonlinear SVMs

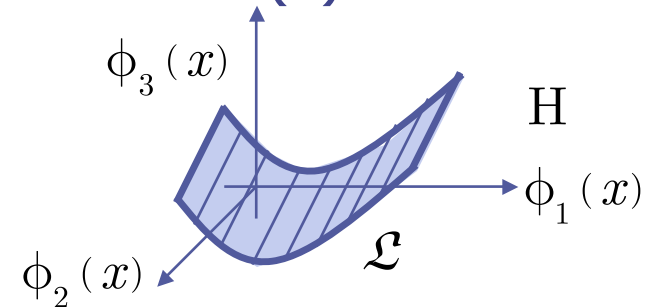
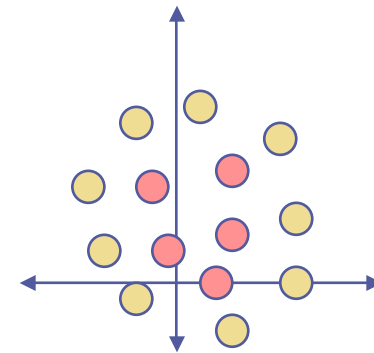
- What if the problem is not linear?



Nonlinear SVMs

- What if the problem is not linear?
- We can use our old trick...
- Map d-dimensional x data from L-space to high dimensional H (Hilbert) feature-space via basis functions $\Phi(x)$
- For example, quadratic classifier:

$$x_i \rightarrow \Phi(x_i) \quad \text{via} \quad \Phi(\vec{x}) = \begin{bmatrix} \vec{x} \\ \text{vec}(\vec{x}\vec{x}^T) \end{bmatrix}$$



- Call phi's **feature vectors** computed from original x inputs
- Replace all x's in the SVM equations with phi's
- Now solve the following learning problem:

$$L_D : \max \sum_i \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j \phi(x_i)^T \phi(x_j) \quad \text{s.t.} \quad \alpha_i \in [0, C], \sum_i \alpha_i y_i = 0$$

- Which gives a nonlinear classifier in original space:

$$f(x) = \text{sign} \left(\sum_i \alpha_i y_i \phi(x)^T \phi(x_i) + b \right)$$

Kernels (see <http://www.youtube.com/watch?v=3liCbRZPrZA>)

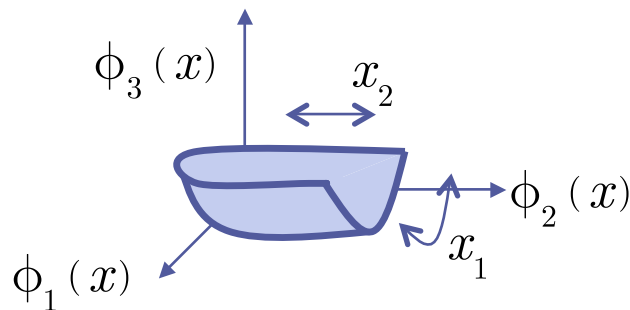
- One important aspect of SVMs: all math involves only the *inner products* between the phi features!

$$f(x) = \text{sign} \left(\sum_i \alpha_i y_i \phi(x)^T \phi(x_i) + b \right)$$

- Replace all inner products with a general kernel function
- **Mercer kernel:** accepts 2 inputs and outputs a scalar via:

$$k(x, \tilde{x}) = \langle \phi(x), \phi(\tilde{x}) \rangle = \begin{cases} \phi(x)^T \phi(\tilde{x}) & \text{for finite } \phi \\ \int_t \phi(x, t) \phi(\tilde{x}, t) dt & \text{otherwise} \end{cases}$$

- Example: quadratic polynomial



$$\phi(x) = \begin{bmatrix} x_1^2 & \sqrt{2}x_1x_2 & x_2^2 \end{bmatrix}^T$$

$$\begin{aligned} k(x, \tilde{x}) &= \phi(x)^T \phi(\tilde{x}) \\ &= x_1^2 \tilde{x}_1^2 + 2x_1 \tilde{x}_1 x_2 \tilde{x}_2 + x_2^2 \tilde{x}_2^2 \\ &= (x_1 \tilde{x}_1 + x_2 \tilde{x}_2)^2 \end{aligned}$$

Kernels

- Sometimes, many $\Phi(x)$ will produce the same $k(x, x')$
- Sometimes $k(x, x')$ computable but features huge or infinite!
- Example: polynomials

If explicit polynomial mapping, feature space $\Phi(x)$ is huge
 d-dimensional data, p-th order polynomial, $\dim(H) = \binom{d+p-1}{p}$
 images of size 16x16 with p=4 have $\dim(H)=183$ million

but can equivalently just use kernel: $k(x, y) = (x^T y)^p$

$$k(x, \tilde{x}) = (x^T \tilde{x})^p = \left(\sum_i x_i \tilde{x}_i \right)^p$$

Multinomial Theorem

$$\propto \sum_r \frac{p!}{r_1! r_2! r_3! \dots (p - r_1 - r_2 - \dots)!} x_1^{r_1} x_2^{r_2} \dots x_d^{r_d} \tilde{x}_1^{r_1} \tilde{x}_2^{r_2} \dots \tilde{x}_d^{r_d}$$

$$\propto \sum_r \left(\sqrt{w_r} x_1^{r_1} x_2^{r_2} \dots x_d^{r_d} \right) \left(\sqrt{w_r} \tilde{x}_1^{r_1} \tilde{x}_2^{r_2} \dots \tilde{x}_d^{r_d} \right)$$

w=weight on term

$$\propto \phi(x) \phi(\tilde{x})$$

Equivalent!

Kernels

- Replace each $x_i^T x_j \rightarrow k(x_i, x_j)$, for example:

P-th Order Polynomial Kernel:

$$k(x, \tilde{x}) = (x^T \tilde{x} + 1)^p$$

RBF Kernel (infinite!):

$$k(x, \tilde{x}) = \exp\left(-\frac{1}{2\sigma^2} \|x - \tilde{x}\|^2\right)$$

Sigmoid (hyperbolic tan) Kernel: $k(x, \tilde{x}) = \tanh(\kappa x^T \tilde{x} - \delta)$

- Using kernels we get generalized inner product SVM:

$$L_D : \max \sum_i \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j k(x_i, x_j) \quad s.t. \quad \alpha_i \in [0, C], \sum_i \alpha_i y_i = 0$$

$$f(x) = \text{sign}\left(\sum_i \alpha_i y_i k(x_i, x) + b\right)$$

- Still qp solver, just use Gram matrix K (positive definite)

$$K = \begin{bmatrix} k(x_1, x_1) & k(x_1, x_2) & k(x_1, x_3) \\ k(x_1, x_2) & k(x_2, x_2) & k(x_2, x_3) \\ k(x_1, x_3) & k(x_2, x_3) & k(x_3, x_3) \end{bmatrix} \quad K_{ij} = k(x_i, x_j)$$

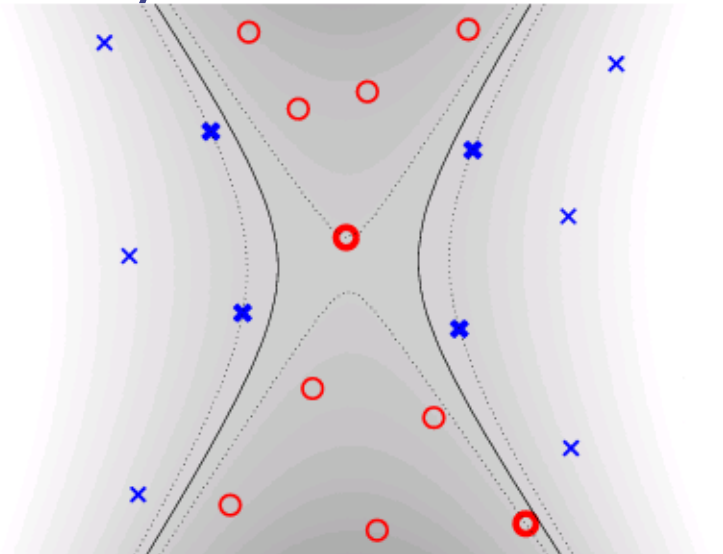
Kernelized SVMs

- Polynomial kernel:
- Radial basis function kernel:

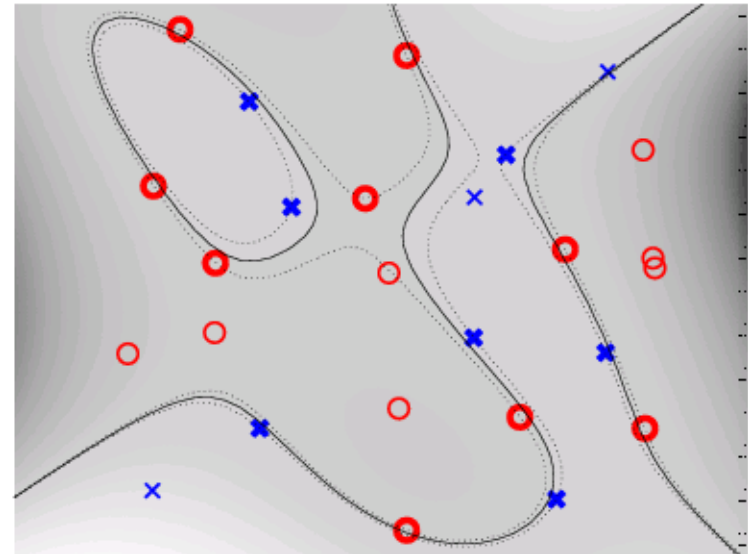
$$k(x_i, x_j) = (x_i^T x_j + 1)^p$$

$$k(x_i, x_j) = \exp\left(-\frac{1}{2\sigma^2} \|x_i - x_j\|^2\right)$$

Polynomial Kernel



RBF kernel



- Least-squares, logistic-regression, perceptron are also kernelizable

SVM Demo

- SVM Demo by Steve Gunn:
<http://www.isis.ecs.soton.ac.uk/resources/svminfo/>
- In svc.m replace
[alpha lambda how] = qp(...);
with
[alpha lambda how] = quadprog(H,c,[],[],A,b,vlb,vub,x0);

This replaces the old Matlab command qp (quadratic programming) with the new one for more recent versions

