Support Vector Machine (SVM)

CSE 4334 / 5334 Data Mining
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(Slides courtesy of Mark Craven and David Page Jr. at UW - Madison)

Goals for this lecture

you should understand the following concepts

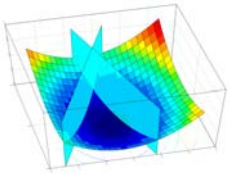
- the margin
- slack variables
- the linear support vector machine
- hinge loss
- non-linear SVMs
- the kernel trick
- the primal and dual formulations of SVM learning
- support vectors
- the kernel matrix
- valid kernels
- polynomial kernel
- Gaussian kernel
- string kernels
- support vector regression

Four key SVM ideas

- **Maximize the margin**
  don't choose just *any* separating hyperplane

- **Penalize misclassified examples**
  use soft constraints and slack variables

- **Use optimization methods to find model**
  linear programming
  quadratic programming



- **Use kernels to represent nonlinear functions and handle complex instances (sequences, trees, graphs, etc.)**

Some key vector concepts

the *dot product* between two vectors $\boldsymbol{w}$ and $\boldsymbol{x}$ is defined as:

$$\boldsymbol{w} \cdot \boldsymbol{x} = \boldsymbol{w}^{\mathsf{T}} \boldsymbol{x} = \sum_i w_i x_i$$

for example

$$\begin{bmatrix} 1 \\ 3 \\ -5 \end{bmatrix} \cdot \begin{bmatrix} 4 \\ -2 \\ -1 \end{bmatrix} = (1)(4) + (3)(-2) + (-5)(-1) = 3$$

the 2-norm (Euclidean length) of a vector $\boldsymbol{x}$ is defined as:

$$\|\boldsymbol{x}\|_2 = \sqrt{\sum_i |x_i|^2}$$

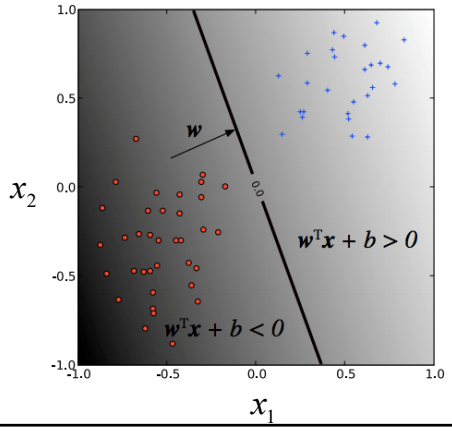
Linear separator learning revisited

suppose we encode our classes as $\{-1, +1\}$ and consider a linear classifier

$$h(\boldsymbol{x}) = \begin{cases} 1 \text{ if } \left(\sum_{i=1}^{n} w_i x_i\right) + b > 0 \\ -1 \text{ otherwise} \end{cases}$$

an instance $\langle \boldsymbol{x}, y \rangle$ will be classified correctly if

$$y(\boldsymbol{w}^{\mathsf{T}}\boldsymbol{x} + b) > 0$$



Large margin classification

- Given a training set that is linearly separable, there are infinitely many hyperplanes that could separate the positive/negative instances.
  - Which one should we choose?
- In SVM learning, we find the hyperplane that maximizes the margin.

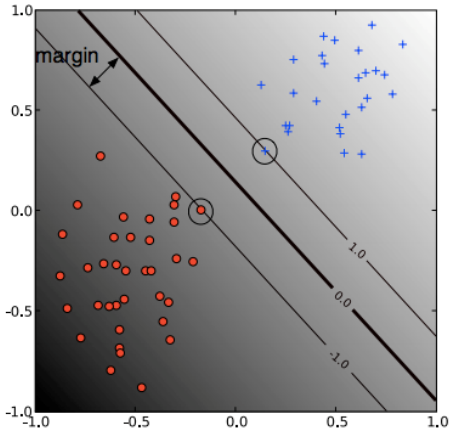
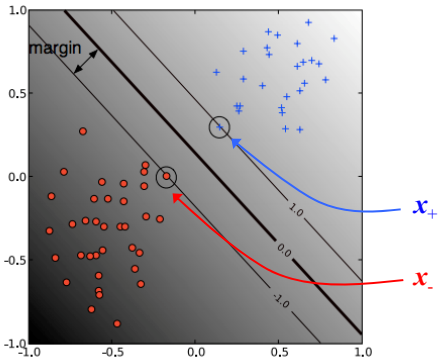


Figure from Ben-Hur & Weston, *Methods in Molecular Biology* 2010

The margin

- suppose we learn a hyperplane h given a training set D
- let $\boldsymbol{x}_+$ denote the closest instance to the hyperplane among positive instances, and similarly for $\boldsymbol{x}_-$ and negative instances
- since $\boldsymbol{w}^T\boldsymbol{x} + b = 0$ and $c(\boldsymbol{w}^T\boldsymbol{x} + b) = 0$ define the same hyperplane, we have the freedom to choose the normalization of $\boldsymbol{w}$
- choose normalization such that $\boldsymbol{w}^T\boldsymbol{x}_+ + b = 1$ and $\boldsymbol{w}^T\boldsymbol{x}_- + b = -1$ for positive and negative support vectors respectively
- then the margin is given by

$$\begin{aligned}\text{margin}_D(h) &= \frac{1}{2}\frac{\boldsymbol{w}}{\|\boldsymbol{w}\|_2}\cdot(\boldsymbol{x}_+ - \boldsymbol{x}_-) \\ &= \frac{\boldsymbol{w}^{\mathrm{T}}(\boldsymbol{x}_+ - \boldsymbol{x}_-)}{\|\boldsymbol{w}\|_2} \\ &= \frac{1}{\|\boldsymbol{w}\|_2}\end{aligned}$$



The hard-margin SVM

- given a training set $D = \{\langle \boldsymbol{x}^{(1)}, y^{(1)}\rangle, \ldots, \langle \boldsymbol{x}^{(m)}, y^{(m)}\rangle\}$
- we can frame the goal of maximizing the margin as a constrained optimization problem

$$\underset{\boldsymbol{w},b}{\text{minimize}} \quad \frac{1}{2}\|\boldsymbol{w}\|_2^2$$

adjust these parameters

to minimize this

$$\text{subject to constraints: } y^{(i)}(\boldsymbol{w}^{\mathrm{T}}\boldsymbol{x}^{(i)} + b) \geq 1$$

$$\text{for } i = 1, \ldots, m$$

correctly classify $\boldsymbol{x}^{(i)}$ with room to spare

- and use standard algorithms to find an optimal solution to this problem

The soft-margin SVM [Cortes & Vapnik, *Machine Learning* 1995]

- if the training instances are not linearly separable, the previous formulation will fail
- we can adjust our approach by using *slack variables* (denoted by ξ) to tolerate errors

$$\underset{\boldsymbol{w}, b, \xi^{(1)}, \ldots, \xi^{(m)}}{\text{minimize}} \quad \frac{1}{2}\|\boldsymbol{w}\|_2^2 + C\sum_{i=1}^{m}\xi^{(i)}$$

subject to constraints: $y^{(i)}(\boldsymbol{w}^{\mathsf{T}}\boldsymbol{x}^{(i)} + b) \geq 1 - \xi^{(i)}$

$$\xi^{(i)} \geq 0$$

for $i = 1, \ldots, m$

- C determines the relative importance of maximizing margin vs. minimizing slack

The effect of C in a soft-margin SVM

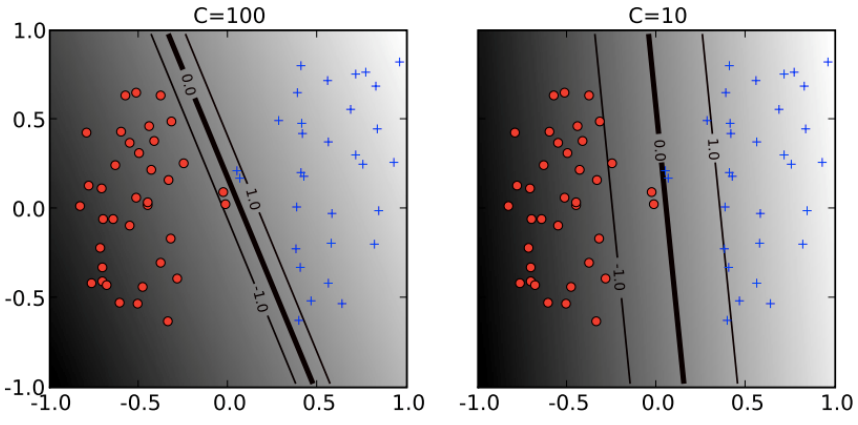
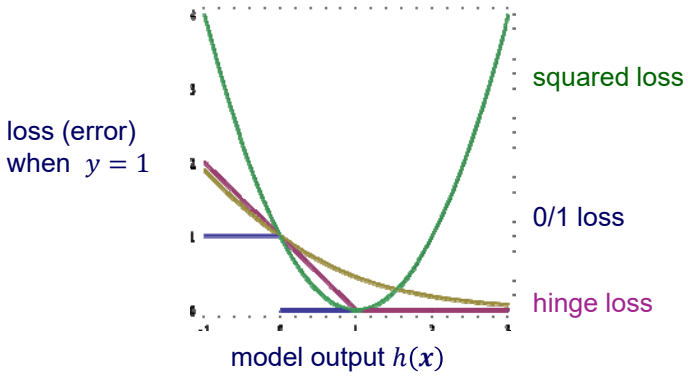


Figure from Ben-Hur & Weston, *Methods in Molecular Biology* 2010

Hinge loss

- when we covered neural nets, we talked about minimizing squared loss and cross-entropy loss
- soft-margin SVMs minimize *hinge loss*



Non-linear classifiers

- What if a linear separator is not an appropriate decision boundary for a given task?
- For any data set, there exists a mapping ϕ to a higher-dimensional space such that the data is linearly separable

$$\phi(\boldsymbol{x}) = \left(\phi_1(\boldsymbol{x}),\ \phi_2(\boldsymbol{x}),\ \square\ ,\ \phi_k(\boldsymbol{x})\right)$$

- Example: mapping to quadratic space

$$\boldsymbol{x} = \left\langle x_1,\ x_2 \right\rangle$$ suppose $\boldsymbol{x}$ is represented by 2 features

$$\phi(\boldsymbol{x}) = \left(x_1^2,\ \sqrt{2}x_1x_2,\ x_2^2,\ \sqrt{2}x_1,\ \sqrt{2}x_2,\ 1\right)$$

- now try to find a linear separator in this space

Non-linear classifiers

- for the linear case, our discriminant function was given by

$$h(\boldsymbol{x}) = \begin{cases} 1 \text{ if } \boldsymbol{w}\cdot\boldsymbol{x} + b > 0 \\ -1 \text{ otherwise} \end{cases}$$

- for the nonlinear case, it can be expressed as

$$h(\boldsymbol{x}) = \begin{cases} 1 \text{ if } \hat{\boldsymbol{w}}\cdot\boldsymbol{\phi}(\boldsymbol{x}) + b > 0 \\ -1 \text{ otherwise} \end{cases}$$

where $\hat{\boldsymbol{w}}$ is a higher dimensional vector

SVM with polynomial kernels

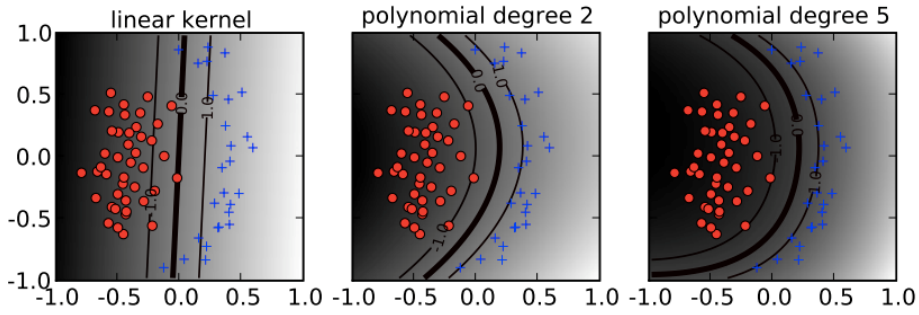


Figure from Ben-Hur & Weston,
Methods in Molecular Biology 2010

The kernel trick

- explicitly computing this nonlinear mapping does not scale well
- a dot product between two higher-dimensional mappings can sometimes be implemented by a *kernel function*
- example: quadratic kernel

$$
\begin{aligned}
k(\boldsymbol{x},\boldsymbol{z}) &= (\boldsymbol{x}\cdot\boldsymbol{z}+1)^2 \\
&= (x_1 z_1 + x_2 z_2 + 1)^2 \\
&= x_1^2 z_1^2 + 2x_1 x_2 z_1 z_2 + x_2^2 z_2^2 + 2x_1 z_1 + 2x_2 z_2 + 1 \\
&= \left(x_1^2,\ \sqrt{2}x_1 x_2,\ x_2^2,\ \sqrt{2}x_1,\ \sqrt{2}x_2,\ 1\right)\square \\
&\quad \left(z_1^2,\ \sqrt{2}z_1 z_2,\ z_2^2,\ \sqrt{2}z_1,\ \sqrt{2}z_2,\ 1\right) \\
&= \phi(\boldsymbol{x})\cdot\phi(\boldsymbol{z})
\end{aligned}
$$

The kernel trick

- thus we can use a kernel to compute the dot product without explicitly mapping the instances to a higher-dimensional space

$$k(\boldsymbol{x},\boldsymbol{z}) = (\boldsymbol{x}\cdot\boldsymbol{z}+1)^2 = \phi(\boldsymbol{x})\cdot\phi(\boldsymbol{z})$$

But why is the kernel trick helpful?

The kernel trick

- given a training set $D = \{ \langle \boldsymbol{x}^{(1)}, y^{(1)} \rangle , \ldots, \langle \boldsymbol{x}^{(m)}, y^{(m)} \rangle \}$
- suppose the weight vector can be represented as a linear combination of the training instances

$$\boldsymbol{w} = \sum_{i=1}^{m} \alpha_i \boldsymbol{x}^{(i)}$$

- then we can represent a linear SVM as

$$\sum_{i=1}^{m} \alpha_i \boldsymbol{x}^{(i)} \cdot \boldsymbol{x} + b$$

- and a nonlinear SVM as

$$\sum_{i=1}^{m} \alpha_i \phi\left(\boldsymbol{x}^{(i)}\right) \cdot \phi\left(\boldsymbol{x}\right) + b$$

$$= \sum_{i=1}^{m} \alpha_i k\left(\boldsymbol{x}^{(i)}, \boldsymbol{x}\right) + b$$

The *primal* and *dual* form of the hard-margin SVM

primal

$$\underset{\boldsymbol{w}, b}{\text{minimize}} \quad \frac{1}{2} \| \boldsymbol{w} \|_2^2$$

subject to constraints: $y^{(i)}(\boldsymbol{w}^{\mathsf{T}} \boldsymbol{x}^{(i)} + b) \geq 1$

for $i = 1, \ldots, m$

dual

$$\underset{\alpha_1, \ldots, \alpha_m}{\text{maximize}} \quad \sum_{i=1}^{m} \alpha_i - \frac{1}{2} \sum_{j=1}^{m} \sum_{k=1}^{m} \alpha_j \alpha_k y^{(j)} y^{(k)} \left(\boldsymbol{x}^{(j)} \cdot \boldsymbol{x}^{(k)} \right)$$

subject to constraints: $\alpha_i \geq 0$ for $i = 1, \ldots, m$

$$\sum_{i=1}^{m} \alpha_i y^{(i)} = 0$$

The *dual* form with a kernel (hard margin version)

primal

$$\underset{\boldsymbol{w},b}{\text{minimize}} \quad \frac{1}{2}\|\boldsymbol{w}\|_2^2$$

subject to constraints : $y^{(i)}(\boldsymbol{w}^{\mathsf{T}}\boldsymbol{\phi}(\boldsymbol{x}^{(i)}) + b) \geq 1$

for $i = 1, \ldots, m$

dual

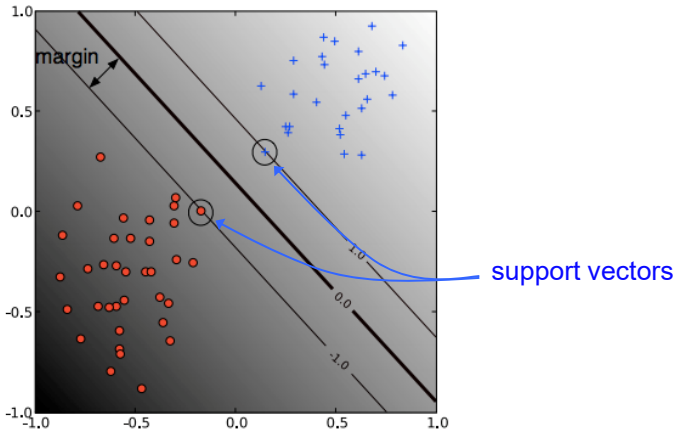
$$\underset{\alpha_1, \ldots, \alpha_m}{\text{maximize}} \quad \sum_{i=1}^{m}\alpha_i - \frac{1}{2}\sum_{j=1}^{m}\sum_{k=1}^{m}\alpha_j\alpha_k y^{(j)}y^{(k)}k(\boldsymbol{x}^{(j)}, \boldsymbol{x}^{(k)})$$

subject to constraints : $\alpha_i \geq 0$ for $i = 1, \ldots, m$

$$\sum_{i=1}^{m}\alpha_i y^{(i)} = 0$$

Support vectors

- the solution to the dual formulation is a sparse linear combination of the training instances
- those instances having $\alpha_i > 0$ are called *support vectors* – they lie on the margin boundary
- the solution wouldn't change if all the instances with $\alpha_i = 0$ were deleted



The kernel matrix

- the kernel matrix (a.k.a. Gram matrix) represents pairwise similarities for instances in the training set

$$\begin{bmatrix} k(\boldsymbol{x}^{(1)},\boldsymbol{x}^{(1)}) & k(\boldsymbol{x}^{(1)},\boldsymbol{x}^{(2)}) & \cdots & k(\boldsymbol{x}^{(1)},\boldsymbol{x}^{(m)}) \\ k(\boldsymbol{x}^{(2)},\boldsymbol{x}^{(1)}) & \ddots & & \\ \vdots & & & \\ k(\boldsymbol{x}^{(m)},\boldsymbol{x}^{(1)}) & & & k(\boldsymbol{x}^{(m)},\boldsymbol{x}^{(m)}) \end{bmatrix}$$

- it represents the information about the training set that is provided as input to the optimization process

Some common kernels

- polynomial of degree d

$$k(\boldsymbol{x},\boldsymbol{z}) = (\boldsymbol{x}\cdot\boldsymbol{z})^d$$

- polynomial of degree up to d

$$k(\boldsymbol{x},\boldsymbol{z}) = (\boldsymbol{x}\cdot\boldsymbol{z}+1)^d$$

- radial basis function (RBF) (a.k.a. Gaussian)

$$k(\boldsymbol{x},\boldsymbol{z}) = \exp\left(-\gamma\left|\left|\boldsymbol{x}-\boldsymbol{z}\right|\right|^2\right)$$

The RBF kernel

- the feature mapping ϕ for the RBF kernel is infinite dimensional!
- recall that $k(\boldsymbol{x}, \boldsymbol{z}) = \phi(\boldsymbol{x}) \bullet \phi(\boldsymbol{z})$

$$k(\boldsymbol{x},\boldsymbol{z}) = \exp\left(-\frac{1}{2}\|\boldsymbol{x}-\boldsymbol{z}\|^2\right) \quad \text{for } \gamma = \frac{1}{2}$$

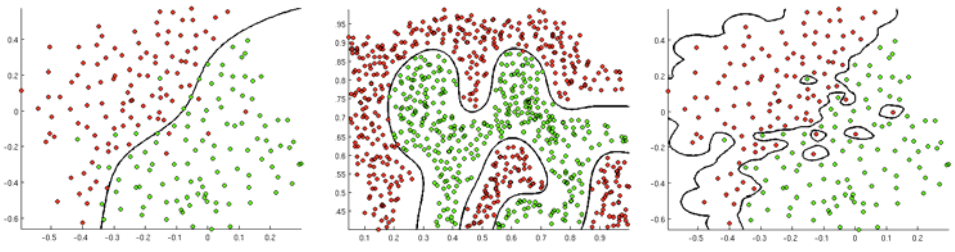
$$= \exp\left(-\frac{1}{2}\|\boldsymbol{x}\|^2\right)\exp\left(-\frac{1}{2}\|\boldsymbol{z}\|^2\right)\exp(\boldsymbol{x}\cdot\boldsymbol{z})$$

$$= \exp\left(-\frac{1}{2}\|\boldsymbol{x}\|^2\right)\exp\left(-\frac{1}{2}\|\boldsymbol{z}\|^2\right)\left(\sum_{n=0}^{\infty}\frac{(\boldsymbol{x}\cdot\boldsymbol{z})^n}{n!}\right)$$

from the Taylor series expansion of $\exp(\boldsymbol{x} \bullet \boldsymbol{z})$

The RBF kernel illustrated

$\gamma = 10$ $\gamma = 100$ $\gamma = 1000$



Figures from openclassroom.stanford.edu (Andrew Ng)

What makes a valid kernel?

- $k(\boldsymbol{x}, \boldsymbol{z})$ is a valid kernel if there is some ϕ such that

$$k(\boldsymbol{x}, \boldsymbol{z}) = \phi(\boldsymbol{x}) \cdot \phi(\boldsymbol{z})$$

- this holds for a symmetric function $k(\boldsymbol{x}, \boldsymbol{z})$ if and only if the kernel matrix $\boldsymbol{K}$ is positive semidefinite for any training set (Mercer's theorem)

definition of positive semidefinite (p.s.d): $\forall \boldsymbol{v} : \boldsymbol{v}^{\mathsf{T}} \boldsymbol{K} \boldsymbol{v} \geq \boldsymbol{0}$

Kernel algebra

- given a valid kernel, we can make new valid kernels using a variety of operators

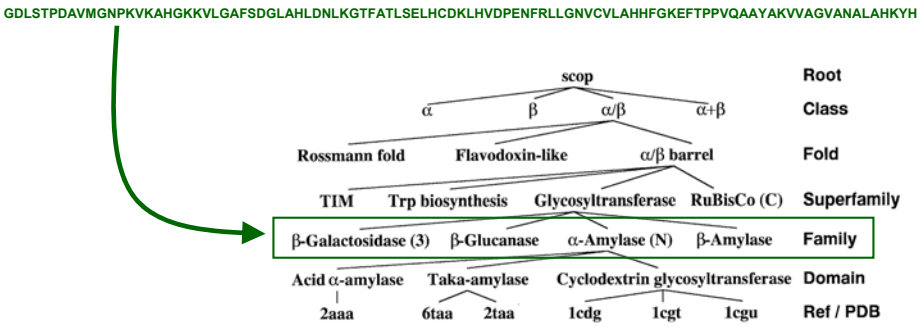
kernel composition	mapping composition
$k(\boldsymbol{x}, \boldsymbol{v}) = k_a(\boldsymbol{x}, \boldsymbol{v}) + k_b(\boldsymbol{x}, \boldsymbol{v})$	$\phi(\boldsymbol{x}) = \left(\phi_a(\boldsymbol{x}),\ \phi_b(\boldsymbol{x})\right)$
$k(\boldsymbol{x}, \boldsymbol{v}) = \gamma\ k_a(\boldsymbol{x}, \boldsymbol{v}),\ \gamma > 0$	$\phi(\boldsymbol{x}) = \sqrt{\gamma}\ \phi_a(\boldsymbol{x})$
$k(\boldsymbol{x}, \boldsymbol{v}) = k_a(\boldsymbol{x}, \boldsymbol{v}) k_b(\boldsymbol{x}, \boldsymbol{v})$	$\phi_l(\boldsymbol{x}) = \phi_{ai}(\boldsymbol{x}) \phi_{bj}(\boldsymbol{x})$
$k(\boldsymbol{x}, \boldsymbol{v}) = \boldsymbol{x}^{\mathsf{T}} A \boldsymbol{v},\ \ A$ is p.s.d.	$\phi(\boldsymbol{x}) = L^{\mathsf{T}} \boldsymbol{x},\ \text{where } A = LL^{\mathsf{T}}$
$k(\boldsymbol{x}, \boldsymbol{v}) = f(\boldsymbol{x}) f(\boldsymbol{v}) k_a(\boldsymbol{x}, \boldsymbol{v})$	$\phi(\boldsymbol{x}) = f(\boldsymbol{x}) \phi_a(\boldsymbol{x})$

The power of kernel functions

- kernels can be designed and used to represent complex data types such as
  - strings
  - trees
  - graphs
  - etc.
- let's consider a specific example

The protein classification task

Given: amino-acid sequence of a protein
Do: predict the *family* to which it belongs



The *k*-spectrum feature map

- we can represent sequences by counts of all of their k-mers

x = AKQDYYYYEI

$k = 3$

$\phi(x) =$ (0 , 0 , … , 1 , … , 1 , … , 2)
AAA AAC … AKQ … DYY … YYY

- the dimension of $\phi(x) = |A|^k$ where $|A|$ is the size of the alphabet
  - using 6-mers for protein sequences, $|20|^6 = 64$ million
  - almost all of the elements in $\phi(x)$ are 0 since a sequence of length l has at most l-k+1 k-mers

The *k*-spectrum kernel

- consider the k-spectrum kernel applied to x and z with $k = 3$

x = AKQDYYYYEI

z = AKQIAKQYEI

$\phi(x) =$ (0 , … , 1 , … , 1 , … , 0)
AAA … AKQ … YEI … YYY

$\phi(z) =$ (0 , … , 2 , … , 1 , … , 0)
AAA … AKQ … YEI … YYY

$\phi(x) \bullet \phi(z) = 2 + 1 = 3$

(*k,m*)-mismatch feature map

- closely related protein sequences may have few exact matches, but many near matches
- the (k, m)-mismatch feature map uses the k-spectrum representation, but allows up to m mismatches

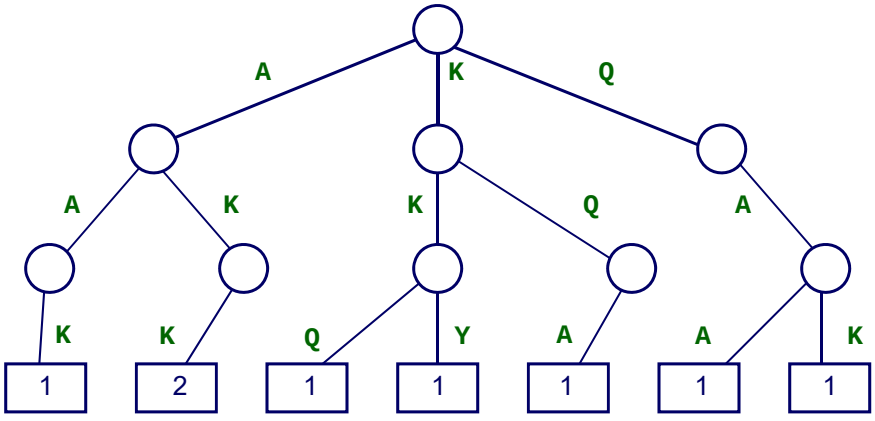
x = **AKQ**

$k = 3, m = 1$

$\phi(x) =$ **(0, … , 1 , … , 1 , … , 1 , … , 0)**
AAA AAQ … AKQ … DKQ … YYY

Using a trie to represent 3-mers

- example: representing all 3-mers of the sequence **QAAKKQAKKY**



Computing the kernels with tries [Leslie et al., *NIPS* 2002]

k-spectrum kernel

- for each sequence
  - build a trie representing its k-mers
- compute kernel $\phi(x) \cdot \phi(z)$ by traversing trie for x using k-mers from z
  - update kernel function when reaching a leaf

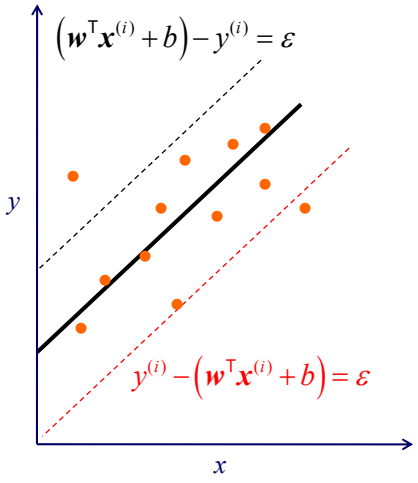
(k, m)-mismatch kernel

- for each sequence
  - build a trie representing its k-mers and also k-mers with at most m mismatches
- compute kernel $\phi(x) \cdot \phi(z)$ by traversing trie for x using k-mers from z
  - update kernel function when reaching a leaf

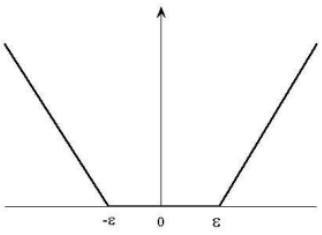
scales linearly with sequence length: $O\left(k^{m+1}|A|^m\left(|x|+|z|\right)\right)$

Support vector regression

- the SVM idea can also be applied in regression tasks
- an ε-insensitive error function specifies that a training instance is well explained if the model's prediction is within ε of $y^{(i)}$



ε-insensitive error function



Support vector regression

$$\underset{\boldsymbol{w}, b, \xi^{(1)}, \ldots, \xi^{(m)}, \hat{\xi}^{(1)}, \ldots, \hat{\xi}^{(m)}}{\text{minimize}} \quad \frac{1}{2}\| \boldsymbol{w} \|_2^2 + C\sum_{i=1}^{m}\left(\xi^{(i)} + \hat{\xi}^{(i)}\right)$$

subject to constraints: $\left(\boldsymbol{w}^{\mathsf{T}}\boldsymbol{x}^{(i)} + b\right) - y^{(i)} \le \varepsilon + \xi^{(i)}$

$$y^{(i)} - \left(\boldsymbol{w}^{\mathsf{T}}\boldsymbol{x}^{(i)} + b\right) \le \varepsilon + \hat{\xi}^{(i)}$$

$$\xi^{(i)}, \hat{\xi}^{(i)} \ge 0$$

for $i = 1, \ldots, m$

slack variables allow predictions for some training instances to be off by more than ε

Learning theory justification for maximizing the margin

$$error_{\mathcal{D}}(h) \le error_{\mathcal{D}}(h) + \sqrt{\frac{VC\left(\log\frac{2m}{VC} + 1\right) + \log\frac{4}{\delta}}{m}}$$

error on true distribution

training set error

VC-dimension of hypothesis class

Vapnik showed there is a connection between the margin and VC dimension

$$VC \le \frac{4R^2}{\text{margin}_D(h)^2}$$

← constant dependent on training data

thus to minimize the VC dimension (and to improve the error bound) ➔ maximize the margin

Comments…

- we can find solutions that are globally optimal (maximize the margin)
  - because the learning task is framed as a convex optimization problem
  - no local minima, in contrast to multi-layer neural nets
- there are two formulations of the optimization: *primal* and *dual*
  - dual represents classifier decision in terms of support vectors
  - dual enables the use of kernel functions
- we can use a wide range of optimization methods to learn SVM
  - standard quadratic programming solvers
  - SMO [Platt, 1999]
  - linear programming solvers for some formulations
  - etc.

Comments…

- kernels provide a powerful way to
  - allow nonlinear decision boundaries
  - represent/compare complex objects such as strings and trees
  - incorporate domain knowledge into the learning task
- using the kernel trick, we can implicitly use high-dimensional mappings without explicitly computing them
- one SVM can represent only a binary classification task; multi-class problems handled using multiple SVMs and some encoding
  - one class vs. rest
  - ECOC
  - etc.
- empirically, SVMs have shown state-of-the art accuracy for many tasks
- the kernel idea can be extended to other tasks (anomaly detection, etc.)