# CS 6375 (Extra Lecture)
# Lagrange Multipliers,
# Duality of SVMs, and Kernel SVMs

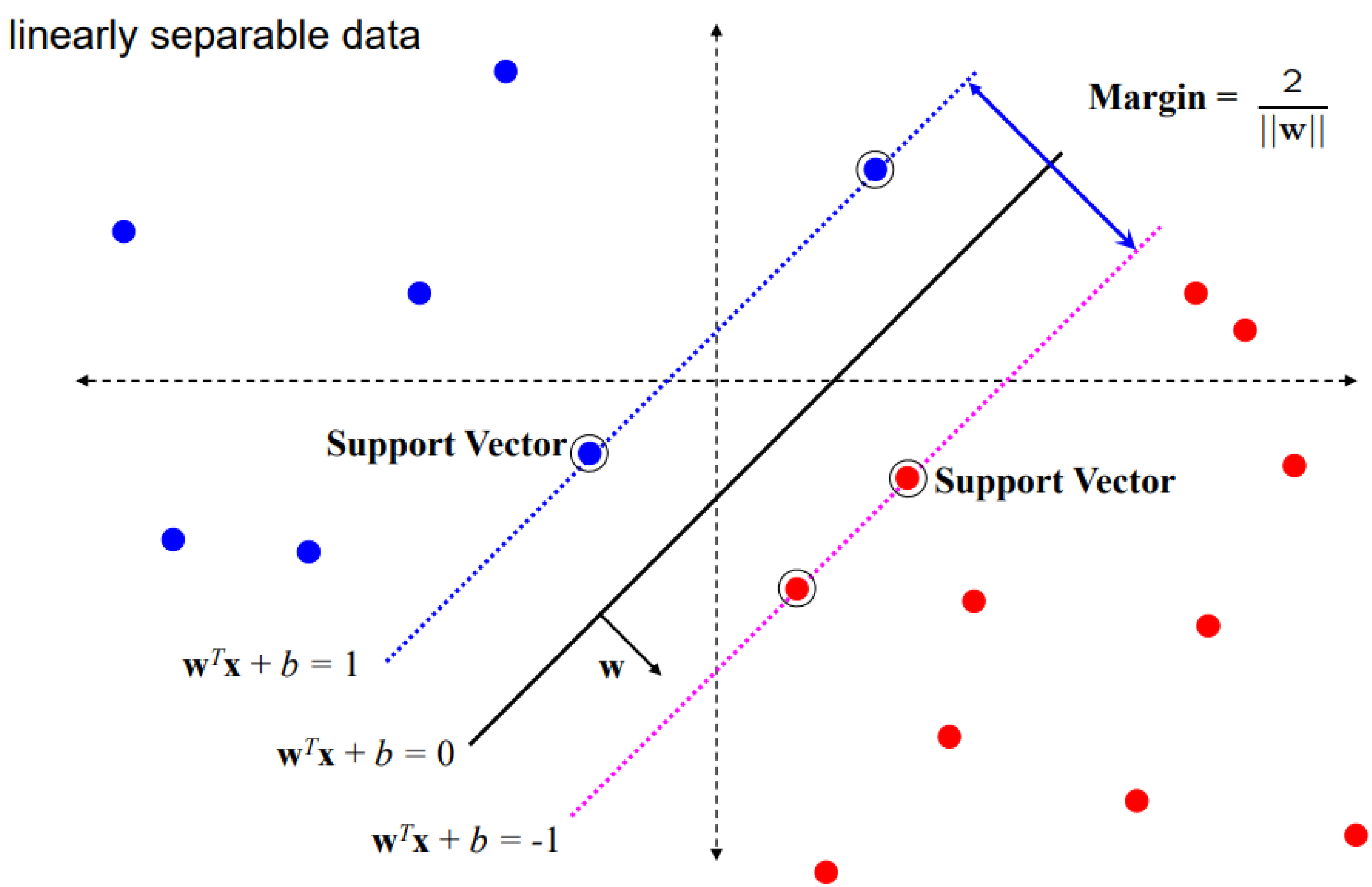
Rishabh Iyer
University of Texas at Dallas

Most Slides are from Nick Rouzzi! Thanks Nick!!

# The Strategy So Far...

- Choose hypothesis space
- Construct loss function (ideally convex)
- Minimize loss to “learn” correct parameters

# Recap: SVM


linearly separable data
Margin = $\frac{2}{||\mathbf{w}||}$
Support Vector
Support Vector
$\mathbf{w}$
$\mathbf{w}^T\mathbf{x} + b = 1$
$\mathbf{w}^T\mathbf{x} + b = 0$
$\mathbf{w}^T\mathbf{x} + b = -1$

# SVM Optimization Problem

- Recall: The SVM optimization problem:

$$\min_{w,b} ||w||^2$$

such that

$$y^{(i)}\left(w^T x^{(i)} + b\right) \geq 1, \text{for all } i$$

- This is a standard quadratic programming problem
  - Falls into the class of convex optimization problems
  - Can be solved with many specialized optimization tools (e.g., quadprog() in MATLAB)

# Constrained Optimization

A mathematical detour, we'll come back to SVMs soon!

$$\min_{x \in \mathbb{R}^n} f_0(x)$$

subject to:

$$\begin{aligned} f_i(x) &\leq 0, \qquad i = 1, \dots, m \\ h_i(x) &= 0, \qquad i = 1, \dots, p \end{aligned}$$

# Constrained Optimization

$$\min_{x \in \mathbb{R}^n} f_0(x)$$

$f_0$ is not necessarily convex

subject to:

$$f_i(x) \leq 0, \qquad i = 1, \dots, m$$
$$h_i(x) = 0, \qquad i = 1, \dots, p$$

# General Optimization

$$\min_{x \in \mathbb{R}^n} f_0(x)$$

subject to:

Constraints do not need to be linear

$$\begin{aligned} f_i(x) &\le 0, \quad & i &= 1, \ldots, m \\ h_i(x) &= 0, \quad & i &= 1, \ldots, p \end{aligned}$$

# Example

$$\min_{x \in \mathbb{R}^3} x_1 \log x_1 + x_2 \log x_2$$

subject to:

$$x_1 + x_2 = 1$$
$$x_1 \geq 0$$
$$x_2 \geq 0$$

# Example

$$\min_{x\in\mathbb{R}^3} x_1 \log x_1 + x_2 \log x_2$$

subject to:

$$1 - x_1 - x_2 = 0$$
$$-x_1 \leq 0$$
$$-x_2 \leq 0$$

# Lagrangian

$$L(x, \lambda, \nu) = f_0(x) + \sum_{i=1}^{m} \lambda_i f_i(x) + \sum_{i=1}^{p} \nu_i h_i(x)$$

- Incorporate constraints into a new objective function
- $\lambda \geq 0$ and $\nu$ are vectors of ***Lagrange multipliers***
- The Lagrange multipliers can be thought of as enforcing soft constraints

# Example

$$\min_{x \in \mathbb{R}^3} x_1 \log x_1 + x_2 \log x_2$$

subject to:

$$1 - x_1 - x_2 = 0$$
$$-x_1 \leq 0$$
$$-x_2 \leq 0$$

$$L(x_1, x_2, \nu_1, \lambda_1, \lambda_2)$$
$$= x_1 \log x_1 + x_2 \log x_2 + \nu_1 \cdot (1 - x_1 - x_2) - \lambda_1 x_1 - \lambda_2 x_2$$

# Duality

- Construct a dual function by minimizing the Lagrangian over the primal variables

$$g(\lambda, \nu) = \inf_x L(x, \lambda, \nu)$$

- $g(\lambda, \nu) = -\infty$ whenever the Lagrangian is not bounded from below for a fixed $\lambda$ and $\nu$

# Example

$$\min_{x \in \mathbb{R}^2} x_1 \log x_1 + x_2 \log x_2$$

subject to:

$$1 - x_1 - x_2 = 0$$
$$-x_1 \leq 0$$
$$-x_2 \leq 0$$

# Example

$$\min_{x \in \mathbb{R}^3} x_1 \log x_1 + x_2 \log x_2$$

subject to:

$$1 - x_1 - x_2 = 0$$
$$-x_1 \leq 0$$
$$-x_2 \leq 0$$

$$L(x_1, x_2, \nu_1, \lambda_1, \lambda_2)$$
$$= x_1 \log x_1 + x_2 \log x_2 + \nu_1 \cdot (1 - x_1 - x_2) - \lambda_1 x_1 - \lambda_2 x_2$$

# Example

$$\min_{x \in \mathbb{R}^3} x_1 \log x_1 + x_2 \log x_2$$

subject to:

$$1 - x_1 - x_2 = 0$$
$$-x_1 \leq 0$$
$$-x_2 \leq 0$$

# The Primal Problem

$$\min_{x \in \mathbb{R}^n} f_0(x)$$

subject to:

$$f_i(x) \leq 0, \qquad i = 1, \dots, m$$
$$h_i(x) = 0, \qquad i = 1, \dots, p$$

Equivalently,

$$\inf_x \sup_{\lambda \geq 0, \nu} L(x, \lambda, \nu)$$

Why are these equivalent?

# The Primal Problem

$$\min_{x \in \mathbb{R}^n} f_0(x)$$

subject to:

$$\begin{aligned} f_i(x) &\leq 0, \qquad & i &= 1, \dots, m \\ h_i(x) &= 0, \qquad & i &= 1, \dots, p \end{aligned}$$

Equivalently,

$$\inf_x \sup_{\lambda \geq 0, \nu} L(x, \lambda, \nu)$$

$$\sup_{\lambda \geq 0, \nu} \left[ f_0(x) + \sum_{i=1}^{m} \lambda_i f_i(x) + \sum_{i=1}^{p} \nu_i h_i(x) \right] = \infty$$

whenever $x$ violates the constraints

# The Dual Problem

$$\sup_{\lambda \geq 0, \nu} g(\lambda, \nu)$$

Equivalently,

$$\sup_{\lambda \geq 0, \nu} \inf_{x} L(x, \lambda, \nu)$$

- The dual problem is always concave, even if the primal problem is not convex
  - For each $x$, $L(x, \lambda, \nu)$ is a linear function in $\lambda$ and $\nu$
  - Minimum (or infimum) of linear functions is concave!

# Primal vs. Dual

$$\sup_{\lambda \geq 0, \nu} \inf_x L(x, \lambda, \nu) \leq \inf_x \sup_{\lambda \geq 0, \nu} L(x, \lambda, \nu)$$

- Why?
  - $g(\lambda, \nu) \leq L(x, \lambda, \nu)$ for all $x$
  - $L(x', \lambda, \nu) \leq f_0(x')$ for any feasible $x'$, $\lambda \geq 0$
    - $x$ is feasible if it satisfies all of the constraints
  - Let $x^*$ be the optimal solution to the primal problem and $\lambda \geq 0$

$$g(\lambda, \nu) \leq L(x^*, \lambda, \nu) \leq f_0(x^*)$$

# Example: Solving the Dual Problem

$$\min_{x \in \mathbb{R}^3} x_1 \log x_1 + x_2 \log x_2$$

subject to:

$$1 - x_1 - x_2 = 0$$
$$-x_1 \leq 0$$
$$-x_2 \leq 0$$

# More Examples

- Minimize $x^2 + y^2$ subject to $x + y \geq 1$

- Given a point $z \in \mathbb{R}^n$ and a hyperplane $w^T x + b = 0$, find the projection of the point $z$ onto the hyperplane

# Duality

- Under certain conditions, the two optimization problems are equivalent

$$\sup_{\lambda \geq 0, \nu} \inf_x L(x, \lambda, \nu) = \inf_x \sup_{\lambda \geq 0, \nu} L(x, \lambda, \nu)$$

  - This is called strong duality

- If the inequality is strict, then we say that there is a duality gap

  - Size of gap measured by the difference between the two sides of the inequality

# Slater's Condition

For any optimization problem of the form

$$\min_{x \in \mathbb{R}^n} f_0(x)$$

subject to:

$$f_i(x) \leq 0, \qquad i = 1, \dots, m$$
$$Ax = b$$

where $f_0, \dots, f_m$ are convex functions, strong duality holds if there exists an $x$ such that

$$f_i(x) < 0, \qquad i = 1, \dots, m$$
$$Ax = b$$

# Dual SVM

$$\min_{w} \frac{1}{2}||w||^2$$

such that

$$y_i\left(w^T x^{(i)} + b\right) \geq 1, \text{for all } i$$

- Note that Slater's condition holds as long as the data is linearly separable

# Dual SVM

$$L(w, b, \lambda) = \frac{1}{2} w^T w + \sum_i \lambda_i (1 - y_i (w^T x^{(i)} + b))$$

Convex in $w$, so take derivatives to form the dual

$$\frac{\partial L}{\partial w_k} = w_k + \sum_i -\lambda_i y_i x_k^{(i)} = 0$$

$$\frac{\partial L}{\partial b} = \sum_i -\lambda_i y_i = 0$$

# Dual SVM

$$L(w, b, \lambda) = \frac{1}{2} w^T w + \sum_i \lambda_i (1 - y_i (w^T x^{(i)} + b))$$

Convex in $w$, so take derivatives to form the dual

$$w = \sum_i \lambda_i y_i x^{(i)}$$

$$\sum_i \lambda_i y_i = 0$$

# Dual SVM

$$\max_{\lambda \geq 0} -\frac{1}{2} \sum_i \sum_j \lambda_i \lambda_j y_i y_j {x^{(i)}}^T x^{(j)} + \sum_i \lambda_i$$

such that

$$\sum_i \lambda_i y_i = 0$$

- By strong duality, solving this problem is equivalent to solving the primal problem
  - Given the optimal $\lambda$, we can easily construct $w$ ($b$ can be found by complementary slackness…)

# Complementary Slackness

- Suppose that there is zero duality gap
- Let $x^*$ be an optimum of the primal and $(\lambda^*, \nu^*)$ be an optimum of the dual

$$
\begin{aligned}
f_0(x^*) &= g(\lambda^*, \nu^*) \\
&= \inf_x \left[ f_0(x) + \sum_{i=1}^{m} \lambda_i^* f_i(x) + \sum_{i=1}^{p} \nu_i^* h_i(x) \right] \\
&\leq f_0(x^*) + \sum_{i=1}^{m} \lambda_i^* f_i(x^*) + \sum_{i=1}^{p} \nu_i^* h_i(x^*) \\
&= f_0(x^*) + \sum_{i=1}^{m} \lambda_i^* f_i(x^*) \\
&\leq f_0(x^*)
\end{aligned}
$$

# Complementary Slackness

- This means that

$$\sum_{i=1}^{m} \lambda_i^* f_i(x^*) = 0$$

- As $\lambda \geq 0$ and $f_i(x_i^*) \leq 0$, this can only happen if $\lambda_i^* f_i(x^*) = 0$ for all $i$
- Put another way,
  - If $f_i(x^*) < 0$ (i.e., the constraint is not tight), then $\lambda_i^* = 0$
  - If $\lambda_i^* > 0$, then $f_i(x^*) = 0$
  - ONLY applies when there is no duality gap

# Dual SVM (Obtaining b)

$$\max_{\lambda \geq 0} -\frac{1}{2}\sum_i \sum_j \lambda_i \lambda_j y_i y_j x^{(i)^T} x^{(j)} + \sum_i \lambda_i$$

such that

$$\sum_i \lambda_i y_i = 0$$

- By complementary slackness, $\lambda_i^* > 0$ means that $x^{(i)}$ is a support vector (can then solve for $b$ using $w$)
- In particular,

$$b = y_i - w . x_i$$

for any $i$ where $\lambda_i > 0$

# Dual SVM

$$\max_{\lambda \geq 0} -\frac{1}{2}\sum_i \sum_j \lambda_i \lambda_j y_i y_j x^{(i)^T} x^{(j)} + \sum_i \lambda_i$$

such that

$$\sum_i \lambda_i y_i = 0$$

- Takes $O(n^2)$ time just to evaluate the objective function
  - Active area of research to try to speed this up

# The Kernel Trick

- For some feature vectors, we can compute the inner products quickly, even if the feature vectors are very large

- This is best illustrated by example

  - Let $\phi(x_1, x_2) = \begin{bmatrix} x_1 x_2 \\ x_2 x_1 \\ x_1^2 \\ x_2^2 \end{bmatrix}$

  - $\phi(x_1, x_2)^T \phi(z_1, z_2) = x_1^2 z_1^2 + 2 x_1 x_2 z_1 z_2 + x_2^2 z_2^2$

$$= (x_1 z_1 + x_2 z_2)^2$$

$$= (x^T z)^2$$

# The Kernel Trick

- For some feature vectors, we can compute the inner products quickly, even if the feature vectors are very large

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  - $\phi(x_1, x_2)^T \phi(z_1, z_2) = x_1^2 z_1^2 + 2x_1 x_2 z_1 z_2 + x_2^2 z_2^2$

$$= (x_1 z_1 + x_2 z_2)^2$$

$$= (x^T z)^2$$

Reduces to a dot product in the original space

# The Kernel Trick

- The same idea can be applied for the feature vector $\phi$ of all polynomials of degree (exactly) $d$
  - $\phi(x)^T \phi(z) = (x^T z)^d$
- More generally, a kernel is a function $k(x, z) = \phi(x)^T \phi(z)$ for some feature map $\phi$
- Rewrite the dual objective

$$\max_{\lambda \geq 0, \sum_i \lambda_i y_i = 0} -\frac{1}{2} \sum_i \sum_j \lambda_i \lambda_j y_i y_j k(x^{(i)}, x^{(j)}) + \sum_i \lambda_i$$

# Examples of Kernels

- Polynomial kernel of degree exactly $d$
  - $k(x, z) = (x^T z)^d$
- General polynomial kernel of degree $d$ for some $c$
  - $k(x, z) = (x^T z + c)^d$
- Gaussian kernel for some $\sigma$ (RBF Kernel)
  - $k(x, z) = \exp\left(\frac{-\|x-z\|^2}{2\sigma^2}\right)$
  - The corresponding $\phi$ is infinite dimensional!
- Sigmoid Kernel
  - $k(x, z) = \tanh(\gamma . x^T z + r)$

# Gaussian Kernels

- Consider the Gaussian kernel

$$\exp\left(\frac{-\|x-z\|^2}{2\sigma^2}\right) = \exp\left(\frac{-(x-z)^T(x-z)}{2\sigma^2}\right)$$

$$= \exp\left(\frac{-\|x\|^2 + 2x^Tz - \|z\|^2}{2\sigma^2}\right)$$

$$= \exp\left(-\frac{\|x\|^2}{2\sigma^2}\right)\exp\left(-\frac{\|z\|^2}{2\sigma^2}\right)\exp\left(\frac{x^Tz}{\sigma^2}\right)$$

- Use the Taylor expansion for $\exp()$

$$\exp\left(\frac{x^Tz}{\sigma^2}\right) = \sum_{n=0}^{\infty}\frac{(x^Tz)^n}{\sigma^{2n}n!}$$

# Gaussian Kernels

- Consider the Gaussian kernel

$$\exp\left(\frac{-\|x-z\|^2}{2\sigma^2}\right) = \exp\left(\frac{-(x-z)^T(x-z)}{2\sigma^2}\right)$$

$$= \exp\left(\frac{-\|x\|^2 + 2x^Tz - \|z\|^2}{2\sigma^2}\right)$$

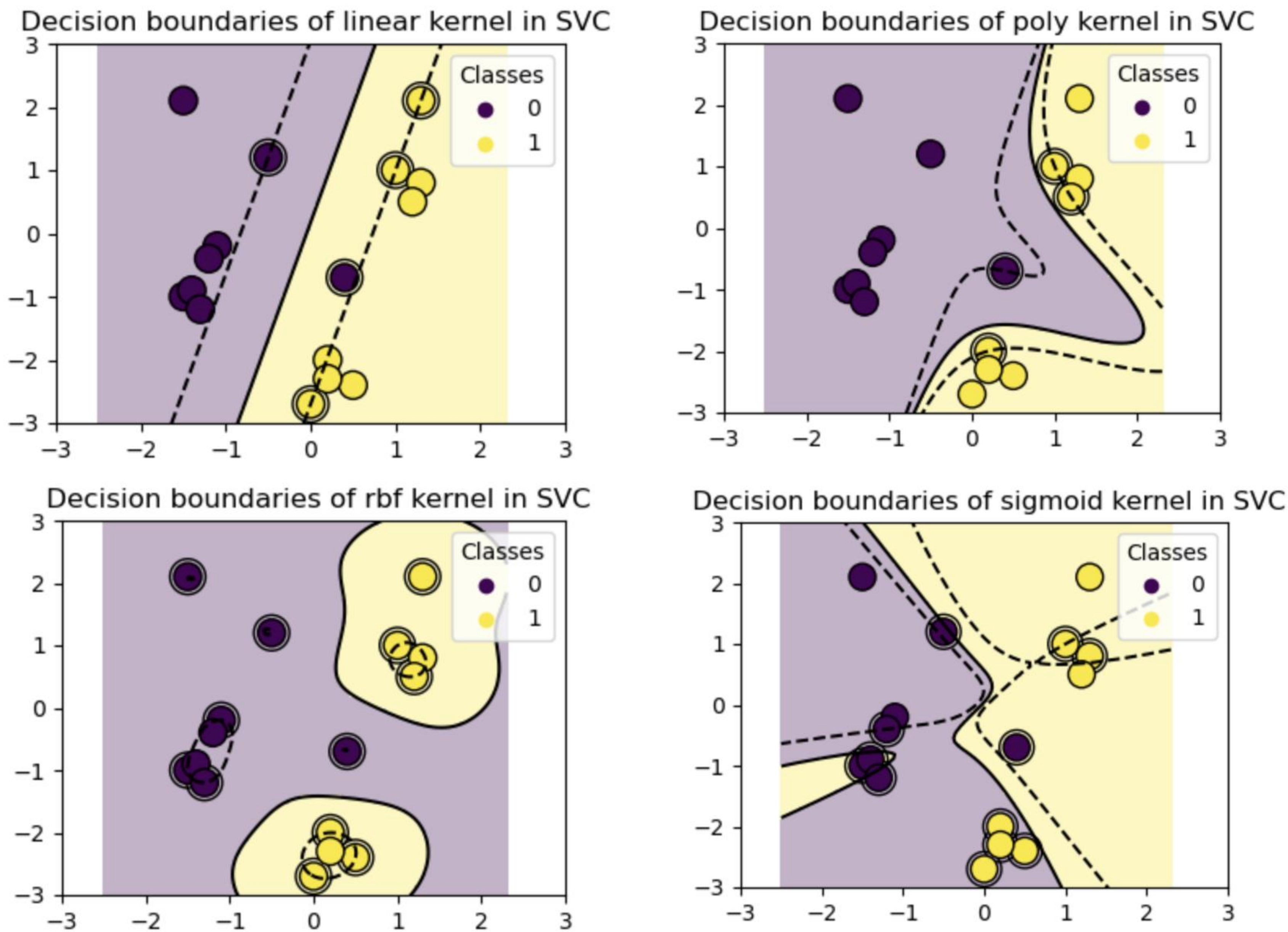
$$= \exp\left(-\frac{\|x\|^2}{2\sigma^2}\right)\exp\left(-\frac{\|z\|^2}{2\sigma^2}\right)\exp\left(\frac{x^Tz}{\sigma^2}\right)$$

- Use the Taylor expansion for exp()

$$\exp\left(\frac{x^Tz}{\sigma^2}\right) = \sum_{n=0}^{\infty}\frac{(x^Tz)^n}{\sigma^{2n}n!}$$

Polynomial kernels of every degree!

# Illustrating Different Kernels



# Kernels

- Bigger feature space increases the possibility of overfitting
  - Large margin solutions may still generalize reasonably well
- Alternative: add “penalties” to the objective to disincentivize complicated solutions