The Perceptron and Kernels

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Adapted from slides by Nakul Verma

Announcement

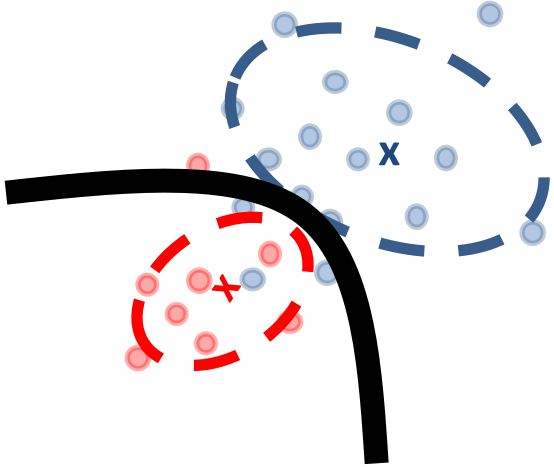
- HW1 is out http://jamesmc.com/COMS4771.html
- Due Oct 6th

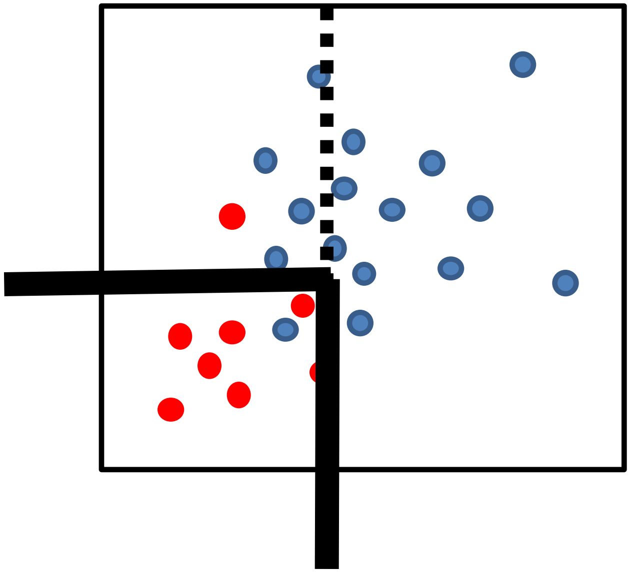
Topic from previous weeks

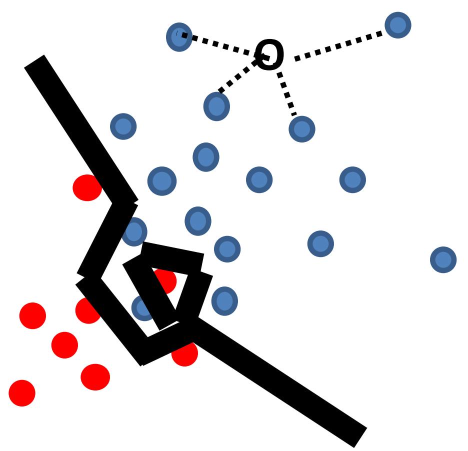
- Discriminative Classifiers
  - Nearest neighbors
  - Decision trees

- Generative Classifier
  - Naïve Bayes
  - Gaussian discriminant analysis

A Closer Look Classification

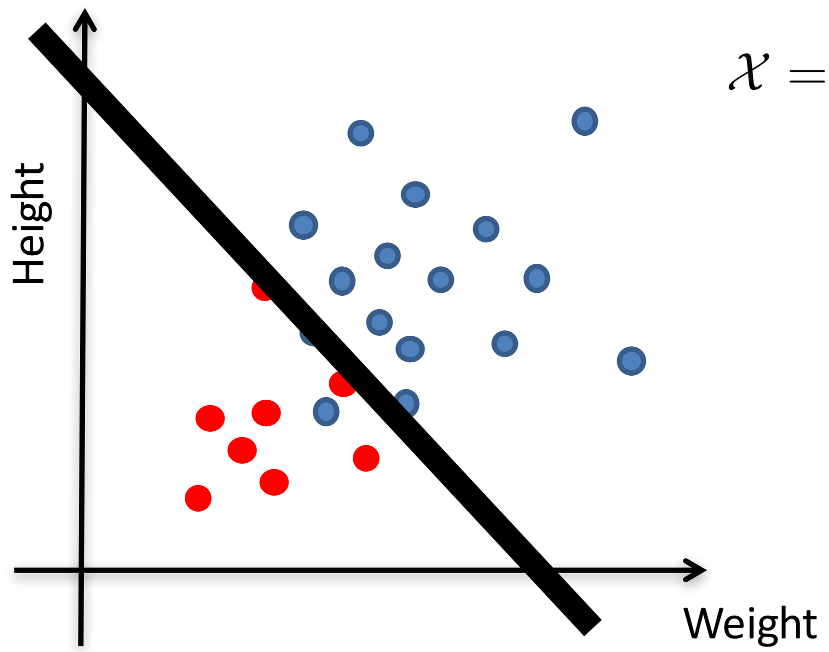




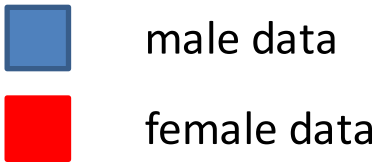


Knowing the boundary is enough for classification

Linear Decision Boundary



$$\mathcal{X} = \mathbf{R}^2 = \text{Weight} \times \text{Height}$$



Assume binary classification y= {-1,+1}

(What happens in multi-class case?)

Learning Linear Decision Boundaries

g = decision boundary

d=1 case: $g(x) = w_1 x + w_0$

general: $g(\vec{x}) = \vec{w} \cdot \vec{x} + w_0$

f = linear classifier

$$f(\vec{x}) := \begin{cases} +1 & \text{if } g(\vec{x}) \geq 0 \\ -1 & \text{if } g(\vec{x}) < 0 \end{cases}$$

$$= \operatorname{sign}(\vec{w} \cdot \vec{x} + w_0)$$

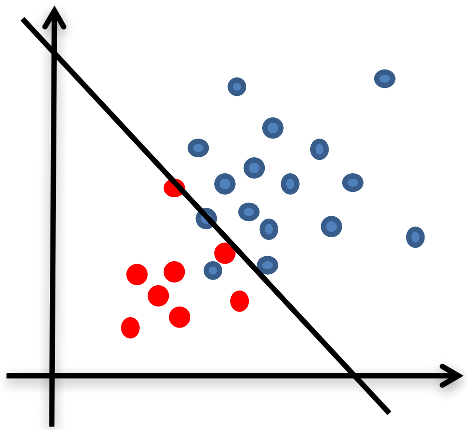
# of parameters to learn in $\mathbf{R}^d$*?*

Dealing with w_0

$$g(\vec{x}) = \vec{w} \cdot \vec{x} + w_0$$

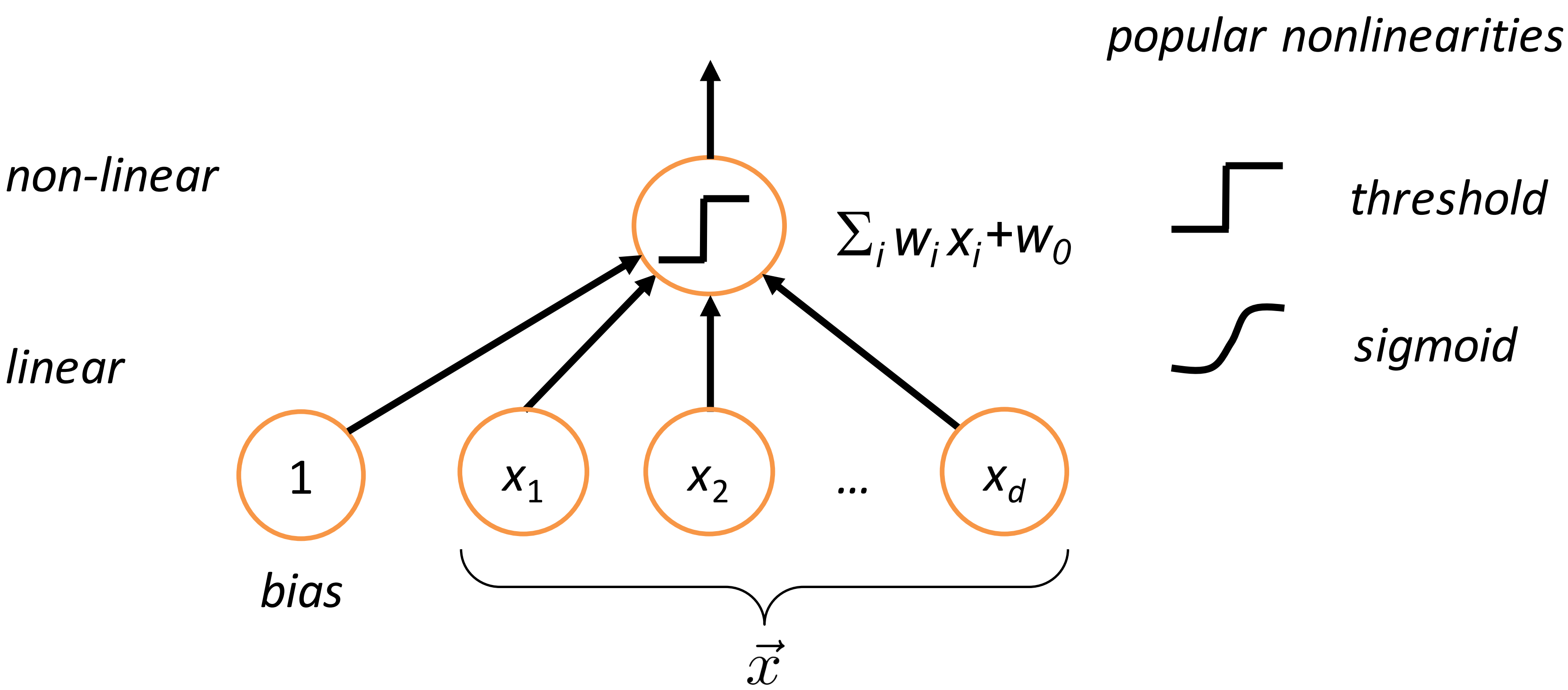
$$= \begin{bmatrix} \vec{w} \\ w_0 \end{bmatrix} \cdot \begin{bmatrix} \vec{x} \\ 1 \end{bmatrix}$$ *bias*

$\vec{w}'$ $\vec{x}'$



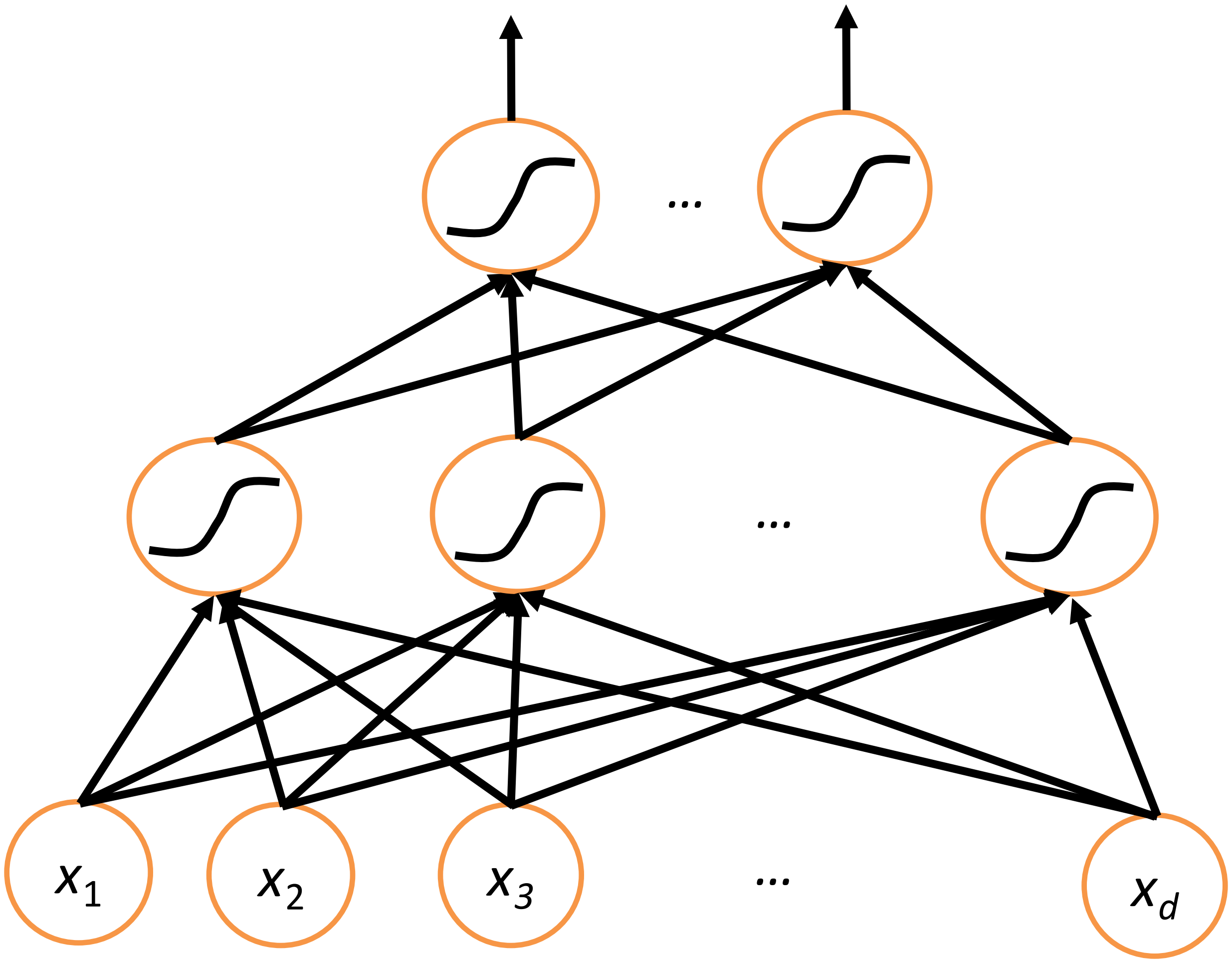
$$g(\vec{x}') = \vec{w}' \cdot \vec{x}'$$ *homogeneous*

The Linear Classifier



A basic computational unit in a neuron

Can Be Combined to Make a Network



Amazing fact:

Can approximate any smooth function!

An artificial neural network

How to Learn the Weights?

Given labeled training data (bias included): $(\vec{x}_1, y_1), (\vec{x}_2, y_2), \ldots (\vec{x}_n, y_n)$

Want: $\vec{w}$, which **minimizes** the training error, i.e.

$$\arg\min_{\vec{w}} \frac{1}{n} \sum_{i=1}^{n} \mathbf{1}\left[\text{sign}(\vec{w} \cdot \vec{x}) \neq y_i\right]$$

$$= \arg\min_{\vec{w}} \sum_{\substack{x_i \\ \text{s.t.} y_i = 1}} \mathbf{1}[\vec{x}_i \cdot \vec{w} < 0] + \sum_{\substack{x_i \\ \text{s.t.} y_i = 0}} \mathbf{1}[\vec{x}_i \cdot \vec{w} \geq 0]$$

How do we ***minimize****?*

- Cannot use the standard technique (take derivate and examine the stationary points). Why?

Unfortunately: *NP-hard to solve*

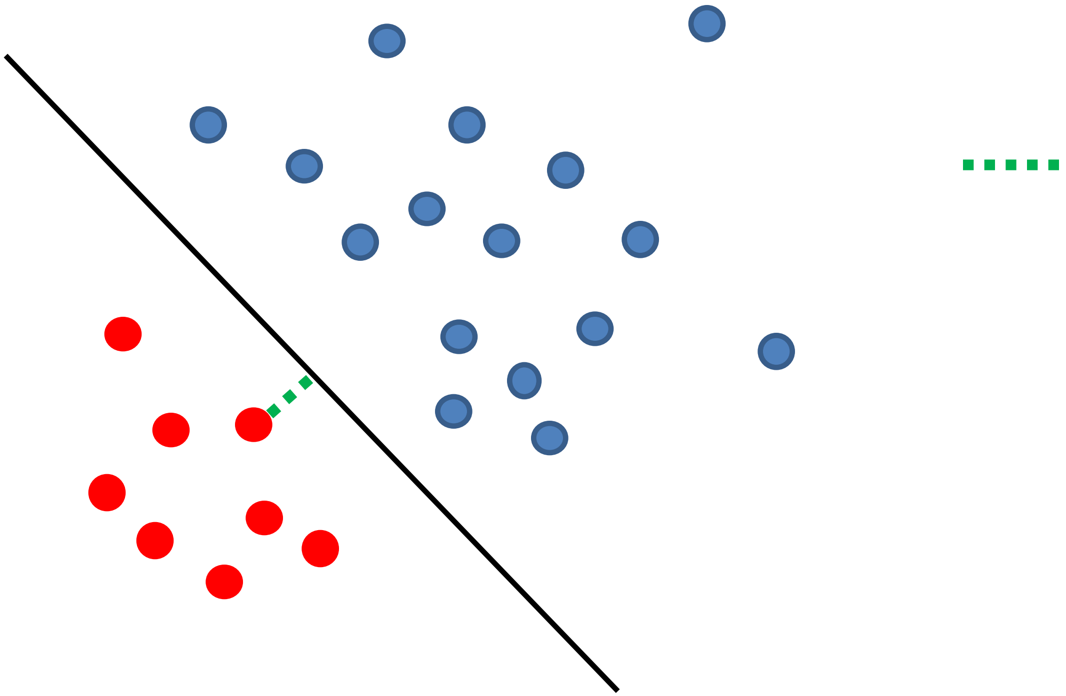
Finding Weights (Relaxed Assumptions)

Can we approximate the weights if we make reasonable assumptions?

What if the training data is linearly separable?

Linear Separablity

Say there is a **linear** decision boundary which can **perfectly separate** the training data



distance of the closest point to the boundary (margin γ)

Finding Weights

Given: labeled training data S = $(\vec{x}_1, y_1), (\vec{x}_2, y_2), \ldots (\vec{x}_n, y_n)$

Want to determine: is there a $\vec{w}$ which satisfies $y_i(\vec{w} \cdot \vec{x}_i) \geq 0$ (for all *i*)

i.e., is the training data linearly separable?

Since there are d+1 variables and |S| constraints, it is possible to solve efficiently it via a (constraint) optimization program.

*Can find it in a much **simpler** way!*

The Perceptron Algorithm

Given: labelled training data S = $(\vec{x}_1, y_1), (\vec{x}_2, y_2), \ldots (\vec{x}_n, y_n)$

Initialize $\vec{w}^{(0)}$ = 0

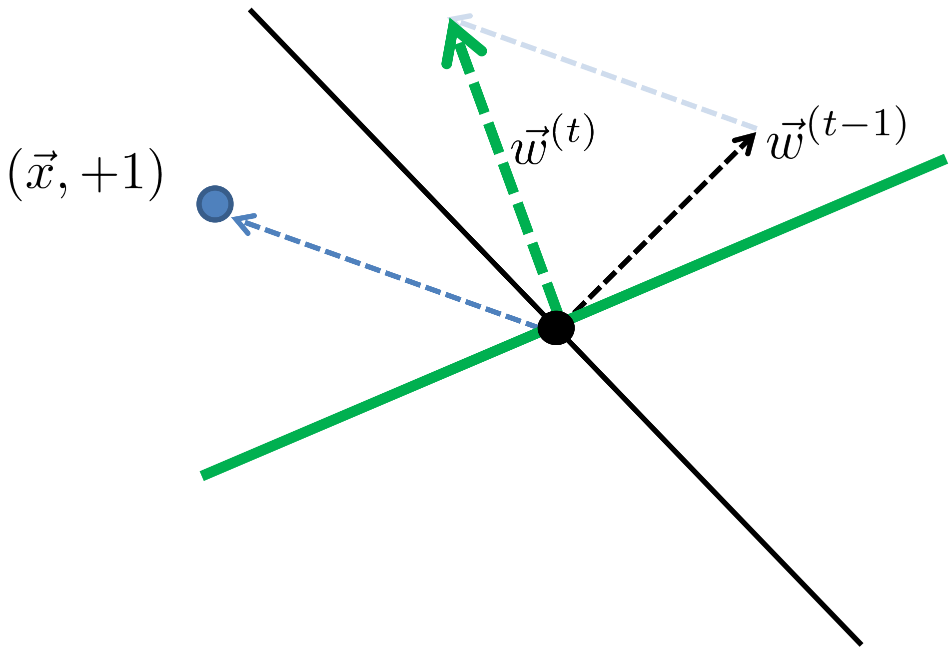
For t = 1,2,3,...

If exists $(\vec{x}, y) \in S$ s.t. $\operatorname{sign}(\vec{w}^{(t-1)} \cdot \vec{x}) \neq y$

$$\vec{w}^{(t)} \leftarrow \begin{cases} \vec{w}^{(t-1)} + \vec{x} & \text{if } y = +1 \\ \vec{w}^{(t-1)} - \vec{x} & \text{if } y = -1 \end{cases} \qquad = \vec{w}^{(t-1)} + y\vec{x}$$

(terminate when no such training sample exists)

Perceptron Algorithm: Geometry

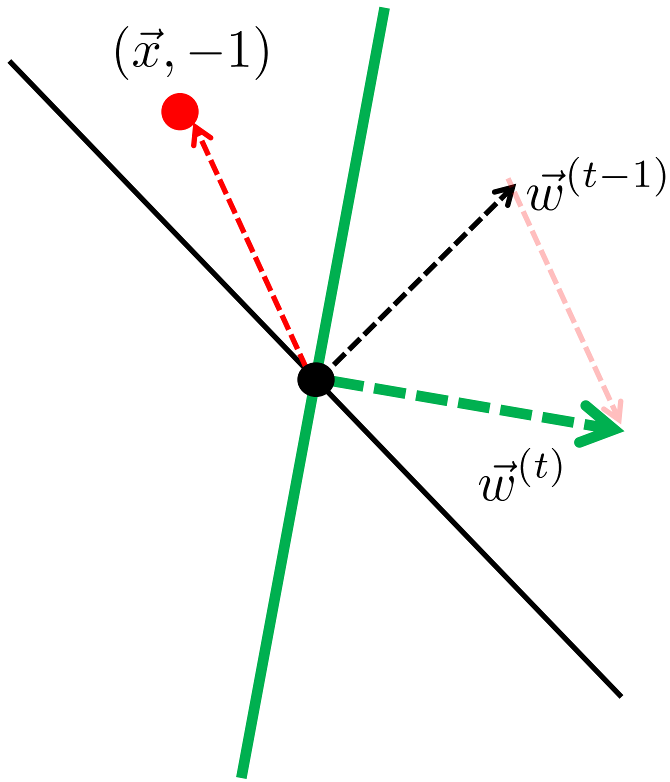


$$\text{sign}(\vec{w}^{(t-1)} \cdot \vec{x}) \neq +1$$

$$\vec{w}^{(t)} \leftarrow \vec{w}^{(t-1)} + \vec{x}$$

$$\text{sign}(\vec{w}^{t} \cdot \vec{x}) = +1$$

Perceptron Algorithm: Geometry



$$\mathrm{sign}(\vec{w}^{(t-1)} \cdot \vec{x}) \neq -1$$

$$\vec{w}^{(t)} \leftarrow \vec{w}^{(t-1)} - \vec{x}$$

$$\mathrm{sign}(\vec{w}^{t} \cdot \vec{x}) = -1$$

The Perceptron Algorithm

Input: labelled training data S = $(\vec{x}_1, y_1), (\vec{x}_2, y_2), \ldots (\vec{x}_n, y_n)$

Initialize $\vec{w}^{(0)}$ = 0

For t = 1,2,3,…

If exists $(\vec{x}, y) \in S$ s.t. $\text{sign}(\vec{w}^{(t-1)} \cdot \vec{x}) \neq y$

$$\vec{w}^{(t)} \leftarrow \begin{cases} \vec{w}^{(t-1)} + \vec{x} & \text{if } y = +1 \\ \vec{w}^{(t-1)} - \vec{x} & \text{if } y = -1 \end{cases} \qquad = \vec{w}^{(t-1)} + y\vec{x}$$

(terminate when no such training sample exists)

What Good is a Mistake Bound?

- It's an upper bound on the number of mistakes made by an ***online algorithm*** on an **arbitrary sequence** of examples

  i.e. no i.i.d. assumption and not loading all the data at once!

- Online algorithms with small mistake bounds can be used to develop classifiers with **good generalization error**!

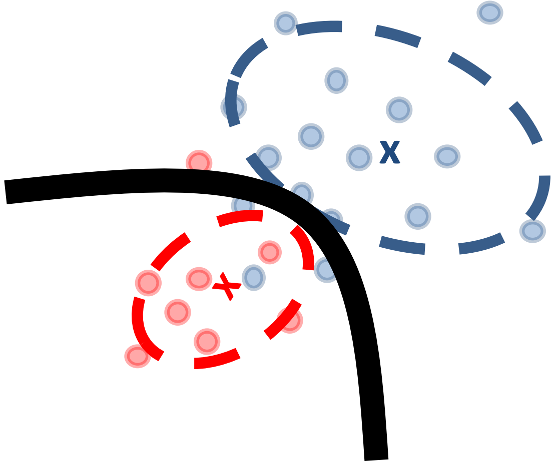
Linear Classification

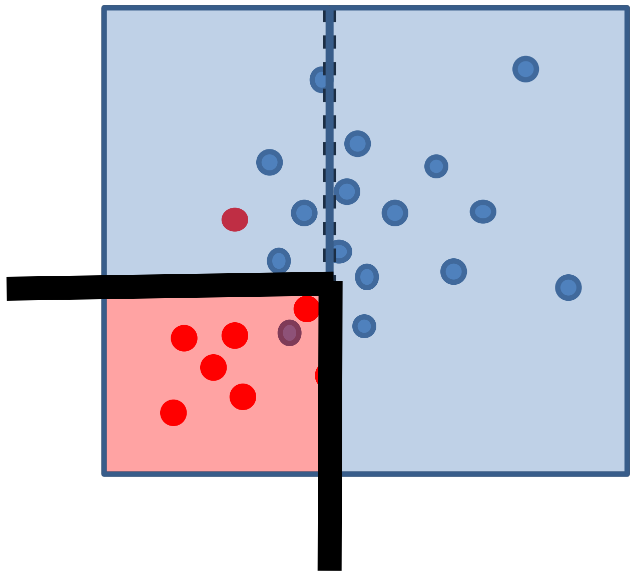
Linear classification simple,

but… *when is real-data (even approximately) linearly separable?*

What about non-linear decision boundaries?

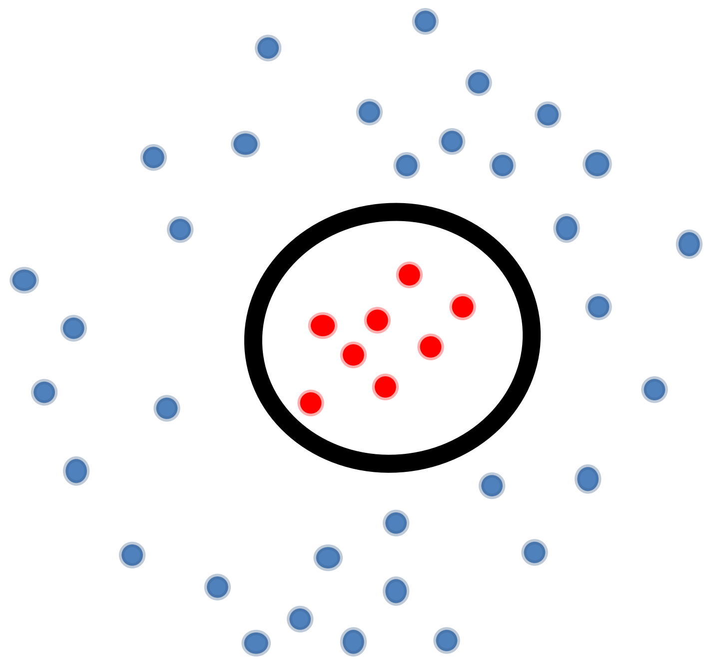
Non linear decision boundaries are common:





Generalizing Linear Classification

Suppose we have the following training data:



d=2 case:

$$g(\vec{x}) = w_1 x_1^2 + w_2 x_2^2 + w_0$$

say, the decision boundary is some sort of ellipse

e.g. circle of radius r:

$$w_1 = 1$$
$$w_2 = 1$$
$$w_0 = -r^2$$

separable via a circular decision boundary

not linear in $\vec{x}$ *!*

But g *is* Linear in *some* Space!

$$g(\vec{x}) = w_1 x_1^2 + w_2 x_2^2 + w_0$$ *non linear in x_1 & x_2*

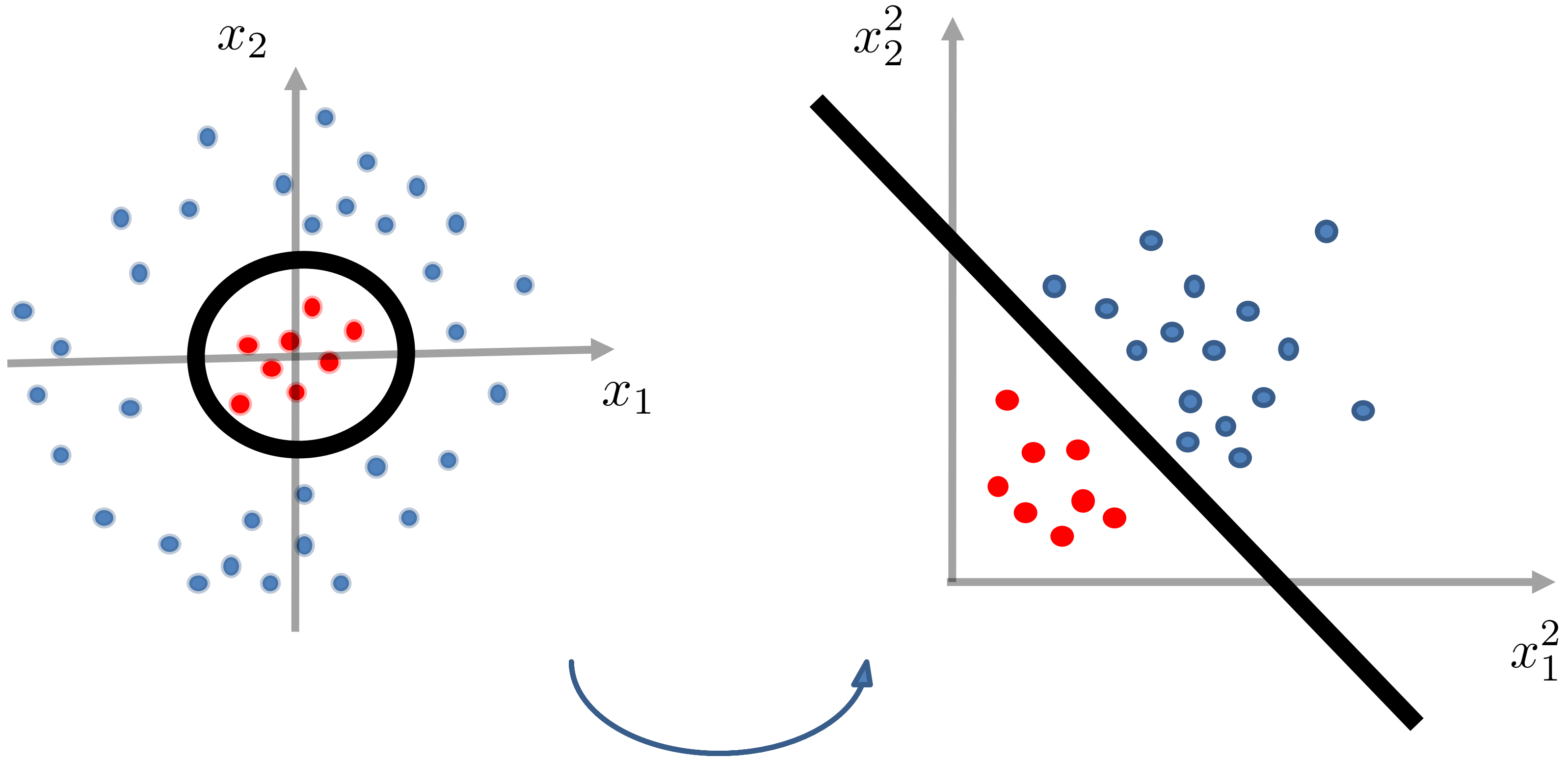
$$= w_1 \chi_1 + w_2 \chi_2 + w_0$$ *non linear in χ_1 & χ_2*

So if we apply a feature transformation on our data:

$$\phi(x_1, x_2) \mapsto (x_1^2, x_2^2)$$

Then *g* becomes linear in ϕ - transformed feature space!

Feature Transformation Geometrically



$$\phi(x_1, x_2) \mapsto (x_1^2, x_2^2)$$

Feature Transform for Quadratic Boundaries

R^2 *case: (generic quadratic boundary)*

$$g(\vec{x}) = w_1 x_1^2 + w_2 x_2^2 + w_3 x_1 x_2 + w_4 x_1 + w_5 x_2 + w_0$$

$$= \sum_{p+q \leq 2} w_{p,q} \; x_1^p x_2^q$$

feature transformation:

$$\phi(x_1, x_2) \mapsto (x_1^2, x_2^2, x_1 x_2, x_1, x_2, 1)$$

R^d *case: (generic quadratic boundary)*

This captures all pairwise interactions between variables

$$g(\vec{x}) = \sum_{p+q \leq d} w_{p,q} \; x_1^p x_2^q$$

feature transformation:

$$\phi(x_1, x_2) \mapsto (x_1^2, x_2^2, \ldots, x_d^2, x_1 x_2, \ldots, x_{d-1} x_d, x_1, x_2, 1)$$

Data is Linearly Separable in some Space!

Theorem:

Given n labeled points $(\vec{x}_1, y_1), (\vec{x}_2, y_2), \ldots (\vec{x}_n, y_n)$ y_i = {*-1*,*+1*},

there exists a feature transform where the data points are linearly separable.

(this feature transform is sometimes called the Kernel transform)

the proof is almost trivial!

Proof

Given n points, consider the mapping into $\mathbf{R}^n$:

$$\phi(\vec{x}_i) \mapsto \begin{bmatrix} 0 \\ \vdots \\ 0 \\ y_i \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

(zero in all coordinates except in coordinate i)

Then, the decision boundary induced by linear weighting $\vec{w}^* = \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix}$ perfectly separates the input data!

∎

Transforming the Data into Kernel Space

Pros:

Any problem becomes **linearly separable**!

Cons:

What about computation? Generic kernel transform is $\Omega(n)$

Some useful kernel transforms map the input space into ***infinite dimensional space****!*

What about model complexity?

Generalization performance typically degrades with model complexity

The Kernel Trick (to Deal with Computation)

Explicitly working in generic Kernel space $\phi(\vec{x}_i)$ takes time Ω(n)

But the dot product between two data points in kernel space can be computed relatively quickly

$$\phi(\vec{x}_i) \cdot \phi(\vec{x}_j)$$ *can compute fast*

Example: quadratic kernel transform for data in $\mathbf{R}^d$

explicit transform *O*(d²) $(x_1^2, \ldots, x_d^2, x_1 x_2, \ldots, x_{d-1} x_d, x_1, x_2, 1)$

dot products *O(d)* $(1 + \vec{x}_i \cdot \vec{x}_j)^2$

RBF (radial basis function) kernel transform for data in $\mathbf{R}^d$

explicit transform infinite dimension!

dot products *O(d)*

The Kernel Trick

The trick is to perform classification in such a way that it **only accesses the data** in terms of dot products (so it can be done quicker)

Example: the `kernel Perceptron'

Recall: $\vec{w}^{(t)} \leftarrow \vec{w}^{(t-1)} + y\vec{x}$

Equivalently $\vec{w} = \sum_{k=1}^{n} \alpha_k y_k \vec{x}_k$ *α_i = # of time mistake was made on x_k*

Thus, classification becomes

$$f(\vec{x}) := \text{sign}(\vec{w} \cdot \vec{x}) \quad = \vec{x} \cdot \sum_{k=1}^{n} \alpha_k y_k \vec{x}_k \quad = \sum_{k=1}^{n} \alpha_k y_k \left(\vec{x}_k \cdot \vec{x}\right)$$

Only accessing data in terms of dot products!

The Kernel Trick: for Perceptron

classification in original space:

$$f(\vec{x}) = \sum_{k=1}^{n} \alpha_k y_k \left(\vec{x}_k \cdot \vec{x}\right)$$

If we were working in the transformed Kernel space, it would have been

$$f(\phi(\vec{x})) = \sum_{k=1}^{n} \alpha_k y_k \left(\phi(\vec{x}_k) \cdot \phi(\vec{x})\right)$$

Algorithm:

Initialize $\vec{\alpha}$ = 0

For t = 1,2,3,…, T

If exists $(\vec{x}_i, y_i) \in S$ s.t. $\mathrm{sign}\left(\sum_{k=1}^{n} \alpha_k y_k \left(\phi(\vec{x}_k) \cdot \phi(\vec{x}_i)\right)\right) \neq y_i$

$\alpha_i \leftarrow \alpha_i + 1$

implicitly working in non-linear kernel space!

The Kernel Trick: Significance

$$\sum_{k=1}^{n} \alpha_k y_k \left(\phi(\vec{x}_k) \cdot \phi(\vec{x})\right)$$

dot products are a measure of similarity

Can be replaced by any user-defined measure of similarity!

So, we can work in any user-defined non-linear space ***implicitly*** ***without*** *the potentially heavy computational cost*

What We Learned…

- Decision boundaries for classification
- Linear decision boundary (linear classification)
- The Perceptron algorithm
- Mistake bound for the perceptron
- Generalizing to non-linear boundaries (via Kernel space)
- Problems become linear in Kernel space
- The Kernel trick to speed up computation

Questions?

Perceptron Algorithm: Guarantee

Theorem (Perceptron mistake bound):

Assume there is a (unit length) $\vec{w}^*$ that can separate the training sample S with margin γ

Let R = $\max_{\vec{x} \in S} \|\vec{x}\|$

Then, the perceptron algorithm will make at most $T := \left(\frac{R}{\gamma}\right)^2$ mistakes.

Thus, the algorithm will terminate in T rounds!

umm… but what about the generalization or the test error?

Proof

Key quantity to analyze:

How far is $\vec{w}^{(t)}$ from $\vec{w}^*$?

Suppose the perceptron algorithm makes a mistake in iteration *t*, then

$$
\begin{aligned}
\vec{w}^{(t)} \cdot \vec{w}^* &= (\vec{w}^{(t-1)} + y\vec{x}) \cdot \vec{w}^* \\
&= (\vec{w}^{(t-1)} + y\vec{x}) \cdot \vec{w}^* \\
&\geq \vec{w}^{(t-1)} \cdot \vec{w}^* + \gamma
\end{aligned}
$$

$$
\begin{aligned}
\|\vec{w}^{(t)}\|^2 &= \|\vec{w}^{(t-1)} + y\vec{x}\|^2 \\
&= \|\vec{w}^{(t-1)}\|^2 + 2y(\vec{w}^{(t-1)} \cdot \vec{x}) + \|y\vec{x}\|^2 \\
&\leq \|\vec{w}^{(t-1)}\|^2 + R^2
\end{aligned}
$$

Proof (contd.)

for all iterations *t*

$$\vec{w}^{(t)} \cdot \vec{w}^* \geq \vec{w}^{(t-1)} \cdot \vec{w}^* + \gamma$$

$$\|\vec{w}^{(t)}\|^2 \leq \|\vec{w}^{(t-1)}\|^2 + R^2$$

So, after T rounds

$$T\gamma \leq \vec{w}^{(T)} \cdot \vec{w}^* \leq \|\vec{w}^{(T)}\|\|\vec{w}^*\| \leq R\sqrt{T}$$

Therefore: $T \leq \left(\frac{R}{\gamma}\right)^2$

■