Kernels Methods in Machine Learning

- Perceptron. Geometric Margins.
- Kernels
- Kernelized Perceptron

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Quick Recap about Perceptron and Margins
**The Online Learning Model**

- Example arrive *sequentially*.
- We need to make a prediction. Afterwards observe the outcome.

For $i=1, 2, \ldots,$ :

- **Phase i:**
  - Online Algorithm
  - Example $x_i$
  - Prediction $h(x_i)$
  - Observe $c^*(x_i)$

**Mistake bound model**

- Analysis wise, make **no distributional assumptions**.
- **Goal:** Minimize the number of **mistakes**.
Perceptron Algorithm in Online Model

WLOG homogeneous linear separators \([w_0 = 0]\).

- Set \(t=1\), start with the all zero vector \(w_1\).
- Given example \(x\), predict + iff \(w_t \cdot x \geq 0\)
- On a mistake, update as follows:
  - Mistake on positive, \(w_{t+1} \leftarrow w_t + x\)
  - Mistake on negative, \(w_{t+1} \leftarrow w_t - x\)

**Note 1:** \(w_t\) is weighted sum of incorrectly classified examples
\[
w_t = a_{i_1} x_{i_1} + \cdots + a_{i_k} x_{i_k}
\]
So, \(w_t \cdot x = a_{i_1} x_{i_1} \cdot x + \cdots + a_{i_k} x_{i_k} \cdot x\)

**Note 2:** Number of mistakes ever made depends only on the geometric margin of examples seen.
  - No matter how long the sequence is or how high dimension \(d\) is!
**Geometric Margin**

**Definition:** The *margin* of example $x$ w.r.t. a linear sep. $w$ is the distance from $x$ to the plane $w \cdot x = 0$.

If $||w|| = 1$, margin of $x$ w.r.t. $w$ is $|x \cdot w|$.
Geometric Margin

Definition: The margin of example $x$ w.r.t. a linear sep. $w$ is the distance from $x$ to the plane $w \cdot x = 0$.

Definition: The margin $\gamma_w$ of a set of examples $S$ wrt a linear separator $w$ is the smallest margin over points $x \in S$.

Definition: The margin $\gamma$ of a set of examples $S$ is the maximum $\gamma_w$ over all linear separators $w$. 
Perceptron: Mistake Bound

**Theorem:** If data linearly separable by margin $\gamma$ and points inside a ball of radius $R$, then Perceptron makes $\leq (R/\gamma)^2$ mistakes.

- No matter how long the sequence is how high dimension $n$ is!

*Margin: the amount of wiggle-room available for a solution.*

(Normalized margin: multiplying all points by 100, or dividing all points by 100, doesn’t change the number of mistakes; algo is invariant to scaling.)
**Margin Important Theme in ML**

- If **large** margin, # mistakes Peceptron makes is small *(independent on the dim of the ambient space)!*

- **Large** margin can help prevent **overfitting**.
  - If **large** margin $\gamma$ and if alg. produces a large margin classifier, then amount of data needed depends only on $R/\gamma$ [Bartlett & Shawe-Taylor ’99].
So far, talked about margins in the context of (nearly) linearly separable datasets
Problem: data not linearly separable in the most natural feature representation.

Example: No good linear separator in pixel representation.

Solutions:

• “Learn a more complex class of functions”
  • (e.g., decision trees, neural networks, boosting).

• “Use a Kernel” (a neat solution that attracted a lot of attention)
  • “Use a Deep Network”
  • “Combine Kernels and Deep Networks”
Overview of Kernel Methods

What is a Kernel?

A kernel $K$ is a legal def of dot-product: i.e. there exists an implicit mapping $\Phi$ s.t. $K(x, y) = \Phi(x) \cdot \Phi(y)$

\[ E.g., K(x, y) = (x \cdot y + 1)^d \]

$\phi$: (n-dimensional space) $\rightarrow$ $n^d$-dimensional space

Why Kernels matter?

- Many algorithms interact with data only via dot-products.
- So, if replace $x \cdot z$ with $K(x, z)$ they act implicitly as if data was in the higher-dimensional $\Phi$-space.
- If data is linearly separable by large margin in the $\Phi$-space, then good sample complexity.
Kernels

Definition

\( K(\cdot,\cdot) \) is a kernel if it can be viewed as a legal definition of inner product:

- \( \exists \phi: X \rightarrow \mathbb{R}^N \) s.t. \( K(x, z) = \phi(x) \cdot \phi(z) \)
  - Range of \( \phi \) is called the \( \Phi \)-space.
  - \( N \) can be very large.

- But think of \( \phi \) as implicit, not explicit!!!!
Example

For \( n=2, \ d=2 \), the kernel \( K(x, z) = (x \cdot z)^d \) corresponds to

\[
(x_1, x_2) \rightarrow \Phi(x) = (x_1^2, x_2^2, \sqrt{2}x_1x_2)
\]
Example

\[ \phi: \mathbb{R}^2 \to \mathbb{R}^3, (x_1, x_2) \to \Phi(x) = (x_1^2, x_2^2, \sqrt{2}x_1x_2) \]

\[ \phi(x) \cdot \phi(z) = (x_1^2, x_2^2, \sqrt{2}x_1x_2) \cdot (z_1^2, z_2^2, \sqrt{2}z_1z_2) \]

\[ = (x_1z_1 + x_2z_2)^2 = (x \cdot z)^2 = K(x, z) \]
Kernels

Definition

$K(\cdot, \cdot)$ is a kernel if it can be viewed as a legal definition of inner product:

- $\exists \phi: X \to \mathbb{R}^N$ s.t. $K(x, z) = \phi(x) \cdot \phi(z)$
  - Range of $\phi$ is called the $\Phi$-space.
  - $N$ can be very large.
- But think of $\phi$ as implicit, not explicit!!!!
Example

**Note:** feature space might not be unique.

\[
\phi: \mathbb{R}^2 \rightarrow \mathbb{R}^3, \ (x_1, x_2) \rightarrow \Phi(x) = (x_1^2, x_2^2, \sqrt{2}x_1x_2)
\]

\[
\phi(x) \cdot \phi(z) = (x_1^2, x_2^2, \sqrt{2}x_1x_2) \cdot (z_1^2, z_2^2, \sqrt{2}z_1z_2)
\]

\[
= (x_1z_1 + x_2z_2)^2 = (x \cdot z)^2 = K(x, z)
\]

\[
\phi: \mathbb{R}^2 \rightarrow \mathbb{R}^4, \ (x_1, x_2) \rightarrow \Phi(x) = (x_1^2, x_2^2, x_1x_2, x_2x_1)
\]

\[
\phi(x) \cdot \phi(z) = (x_1^2, x_2^2, x_1x_2, x_2x_1) \cdot (z_1^2, z_2^2, z_1z_2, z_2z_1)
\]

\[
= (x \cdot z)^2 = K(x, z)
\]
Avoid explicitly expanding the features

Feature space can grow really large and really quickly....

Crucial to think of $\phi$ as implicit, not explicit!!!!

- Polynomial kernel degree $d$, $k(x, z) = (x^\top z)^d = \phi(x) \cdot \phi(z)$
  - $x_1^d$, $x_1 x_2 ... x_d$, $x_1^2 x_2 ... x_{d-1}$
  - Total number of such feature is
    $\binom{d + n - 1}{d} = \frac{(d + n - 1)!}{d! (n - 1)!}$
  - $d = 6$, $n = 100$, there are 1.6 billion terms

$k(x, z) = (x^\top z)^d = \phi(x) \cdot \phi(z)$
Kernelizing a learning algorithm

• If all computations involving instances are in terms of inner products then:
  - Conceptually, work in a very high diml space and the alg’s performance depends only on linear separability in that extended space.
  - Computationally, only need to modify the algo by replacing each $x \cdot z$ with a $K(x, z)$.

• Examples of kernalizable algos:
  - classification: Perceptron, SVM.
  - regression: linear, ridge regression.
  - clustering: k-means.
Kernelizing the Perceptron Algorithm

- Set $t=1$, start with the all zero vector $w_1$.
- Given example $x$, predict $+$ iff $w_t \cdot x \geq 0$
- On a mistake, update as follows:
  - Mistake on positive, $w_{t+1} \leftarrow w_t + x$
  - Mistake on negative, $w_{t+1} \leftarrow w_t - x$

Easy to kernelize since $w_t$ is weighted sum of incorrectly classified examples

$$w_t = a_{i_1}x_{i_1} + \cdots + a_{i_k}x_{i_k}$$

Replace

$$w_t \cdot x = a_{i_1}x_{i_1} \cdot x + \cdots + a_{i_k}x_{i_k} \cdot x$$

with

$$a_{i_1}K(x_{i_1}, x) + \cdots + a_{i_k}K(x_{i_k}, x)$$

Note: need to store all the mistakes so far.
Kernelizing the Perceptron Algorithm

- **Given** \( x \), predict + iff
  \[ \phi(x_i_{t-1}) \cdot \phi(x) \geq 0 \]

- **On the** \( t \) **th mistake**, update as follows:
  - **Mistake on positive**, set \( a_{i_t} \leftarrow 1 \); store \( x_{i_t} \)
  - **Mistake on negative**, \( a_{i_t} \leftarrow -1 \); store \( x_{i_t} \)

\[
\text{Perceptron } w_t = a_{i_1} x_{i_1} + \cdots + a_{i_k} x_{i_k}
\]
\[
w_t \cdot x = a_{i_1} x_{i_1} \cdot x + \cdots + a_{i_k} x_{i_k} \cdot x \rightarrow a_{i_1} K(x_{i_1}, x) + \cdots + a_{i_k} K(x_{i_k}, x)
\]

Exact same behavior/prediction rule as if mapped data in the \( \phi \)-space and ran Perceptron there!

Do this implicitly, so computational savings!!!!!
Generalize Well if Good Margin

• If data is linearly separable by margin in the $\phi$-space, then small mistake bound.

• If margin $\gamma$ in $\phi$-space, then Perceptron makes $\left(\frac{R}{\gamma}\right)^2$ mistakes.
Kernels: More Examples

- **Linear:** $K(x, z) = x \cdot z$

- **Polynomial:** $K(x, z) = (x \cdot z)^d$ or $K(x, z) = (1 + x \cdot z)^d$

- **Gaussian:** $K(x, z) = \exp \left[-\frac{|x-z|^2}{2 \sigma^2}\right]$

- **Laplace Kernel:** $K(x, z) = \exp \left[-\frac{|x-z|}{2 \sigma^2}\right]$

- Kernel for non-vectorial data, e.g., measuring similarity between sequences.
Properties of Kernels

**Theorem (Mercer)**

- $K$ is a kernel if and only if:
  - $K$ is symmetric
  - For any set of training points $x_1, x_2, ..., x_m$ and for any $a_1, a_2, ..., a_m \in \mathbb{R}$, we have:
    \[
    \sum_{i,j} a_i a_j K(x_i, x_j) \geq 0
    \]
    \[
    a^T K a \geq 0
    \]

I.e., $K = (K(x_i, x_j))_{i,j=1,...,n}$ is positive semi-definite.
Kernel Methods

• Offer great modularity.

• No need to change the underlying learning algorithm to accommodate a particular choice of kernel function.

• Also, we can substitute a different algorithm while maintaining the same kernel.
Kernel, Closure Properties

Easily create new kernels using basic ones!

Fact: If $K_1(\cdot;\cdot)$ and $K_2(\cdot;\cdot)$ are kernels $c_1 \geq 0, c_2 \geq 0$, then $K(x, z) = c_1 K_1(x, z) + c_2 K_2(x, z)$ is a kernel.

Key idea: concatenate the $\phi$ spaces.

$$\phi(x) = (\sqrt{c_1} \phi_1(x), \sqrt{c_2} \phi_2(x))$$

$$\phi(x) \cdot \phi(z) = c_1 \phi_1(x) \cdot \phi_1(z) + c_2 \phi_2(x) \cdot \phi_2(z)$$

$K_1(x, z)$  $K_2(x, z)$
Kernel, Closure Properties

Easily create new kernels using basic ones!

**Fact:** If $K_1(\cdot, \cdot)$ and $K_2(\cdot, \cdot)$ are kernels,

then $K(x, z) = K_1(x, z)K_2(x, z)$ is a kernel.

**Key idea:**

$$
\phi(x) = \left( \phi_{1,i}(x) \phi_{2,j}(x) \right)_{i \in \{1, \ldots, n\}, j \in \{1, \ldots, m\}}
$$

$$
\phi(x) \cdot \phi(z) = \sum_{i,j} \phi_{1,i}(x) \phi_{2,j}(x) \phi_{1,i}(z) \phi_{2,j}(z)
$$

$$
= \sum_i \phi_{1,i}(x) \phi_{1,i}(z) \left( \sum_j \phi_{2,j}(x) \phi_{2,j}(z) \right)
$$

$$
= \sum_i \phi_{1,i}(x) \phi_{1,i}(z) K_2(x, z) = K_1(x, z) K_2(x, z)
$$
Kernels, Discussion

- If all computations involving instances are in terms of inner products then:
  - Conceptually, work in a very high diml space and the alg’s performance depends only on linear separability in that extended space.
  - Computationally, only need to modify the algo by replacing each $x \cdot z$ with a $K(x, z)$.

- Lots of Machine Learning algorithms are kernalizable:
  - classification: Perceptron, SVM.
  - regression: linear regression.
  - clustering: k-means.
Kernels, Discussion

• If all computations involving instances are in terms of inner products then:
  ▪ Conceptually, work in a very high diml space and the alg's performance depends only on linear separability in that extended space.
  ▪ Computationally, only need to modify the algo by replacing each $x \cdot z$ with a $K(x, z)$.

How to choose a kernel:

• Kernels often encode domain knowledge (e.g., string kernels)

• Use Cross-Validation to choose the parameters, e.g., $\sigma$ for Gaussian Kernel $K(x, z) = \exp \left[ -\frac{|x-z|^2}{2 \sigma^2} \right]$

• **Learn** a good kernel; e.g., [Lanckriet-Cristianini-Bartlett-El Ghaoui-Jordan’04]