Kernel Methods in Machine Learning - Course Notes

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1 Kernels and RKHS

1.1 Positive Definite Kernels

Definition 1

A kernel K is a comparison function $K : \mathcal{X} \times \mathcal{X} \to \mathbb{R}$.
With n data point $\{x_1, x_2, ..., x_n\}$ a $n \times n$ matrix $\mathbf{K}$ can be defined by $\mathbf{K}_{ij} = K(x_i, x_j)$.
A kernel K is **positive definite** (p.d.) if it is **symmetric** ($K(x, x') = K(x', x)$) and for all sets of a and x

$$\boxed{\sum_i \sum_j a_i a_j K(x_i, x_j) \geq 0}$$

This is equivalent to the kernel matrix being **positive semi-definite**.

Examples:

- Kernel on $\mathbb{R} \times \mathbb{R}$ defined by $K(x, x') = xx'$ is p.d. ($xx' = x'x$ and $\sum_i \sum_j a_i a_j K(x_i, x_j) = \left(\sum_i a_i x_i\right)^2 \geq 0$).
- Linear kernel ($K(x, x') = \langle x, x' \rangle_{\mathbb{R}^d}$) is p.d
- More generally for any set $\mathcal{X}$, and function $\Phi : \mathcal{X} \to \mathbb{R}^d$, the kernel defined by $K(x, x') = \langle \Phi(x), \Phi(x') \rangle_{\mathbb{R}^d}$ is p.d.

Theorem 1 – Aronszajn, 1950

K is a p.d. kernel on the set $\mathcal{X}$ if and only if there exists a **Hilbert space** $\mathcal{H}$ **and a mapping** $\Phi : \mathcal{X} \to \mathcal{H}$ such that, for any x, x' in $\mathcal{X}$:

$$\boxed{K(x, x') = \langle \Phi(x), \Phi(x') \rangle_{\mathcal{H}}}$$

Proof.

(A Hilbert space is a vector space with an inner product and complete for the corresponding norm).

1.2 Reproducing Kernel Hilbert Spaces (RKHS)

Let $\mathcal{X}$ be a set and $\mathcal{H} \subset \mathbb{R}^{\mathcal{X}}$ a class of functions forming a Hilbert space.

Definition 2 – Reproducing kernel

A kernel K is called a **reproducing kernel** (r.k.) of $\mathcal{H}$ if

- $\mathcal{H}$ contains all functions of the form

$$\boxed{\forall x \in \mathcal{X}, K_x : t \to K(x, t)}$$

- For every $x \in \mathcal{X}$ and $f \in \mathcal{H}$, $\boxed{f(x) = \langle f, K_x \rangle_{\mathcal{H}}}$

If there exists a r.k., $\mathcal{H}$ is called a RKHS.

Theorem 2 – Equivalent Definition of RKHS

$\mathcal{H}$ is a RKHS if and only if for any $x \in \mathcal{X}$, the mapping

$$\begin{aligned} F : & \mathcal{H} \to \mathbb{R} \\ & f \mapsto f(x) \end{aligned}$$

is **continuous**.

Proof.

As a corollary, convergence in a RKHS implies point-wise convergence.

Theorem 3 – Uniqueness of RKHS

If $\mathcal{H}$ is a RKHS, it has a **unique r.k.**, and a function K can be **the r.k of at most one RKHS**.

Proof.

Theorem 4

A function $K : \mathcal{X} \times \mathcal{X} \to \mathbb{R}$ is **p.d. if and only if it is a r.k.**.

Proof.

1.3 Examples

1.3.1 Steps for finding the RKHS of a Kernel

1. Look for an **inner product** ($K(x, y) = \langle \Phi(x), \Phi(y) \rangle_{\mathcal{H}}$)
2. Propose a **candidate RKHS** $\mathcal{H}$
3. Check that the candidate $\mathcal{H}$ is a **Hilbert space** (inner product and complete)
4. Check that $\mathcal{H}$ is **the RKHS**
   - $\mathcal{H}$ contains all the functions $K_x : t \mapsto K(x, t)$
   - For all $f \in \mathcal{H}$ and $x \in \mathcal{X}$, $f(x) = \langle f, K_x \rangle_{\mathcal{H}}$.

1.3.2 Linear Kernel

Definition 3 – Linear Kernel

In $\mathbb{R}^d$, the linear kernel is defined by $K(x, y) = \langle x, y \rangle_{\mathbb{R}^d}$

Theorem 5 – RKHS of a linear Kernel

The RKHS of the linear kernel is the set of linear functions of the form $f_w(x) = \langle w, x \rangle_{\mathbb{R}^d}$ for $w \in \mathbb{R}^d$, endowed with the inner product $\langle f_w, f_v \rangle_{\mathcal{H}} = \langle w, v \rangle_{\mathbb{R}^d}$

1.3.3 Polynomial Kernel

Definition 4 – Polynomial Kernel

In $\mathbb{R}^d$, the polynomial kernel is defined by $K(x, y) = \langle x, y\rangle^2_{\mathbb{R}^d}$

Theorem 6 – RKHS of a polynomial Kernel

The RKHS $\mathcal{H}$ of the polynomial kernel is the set of quadratic functions of the form $f_S(x) = x^T S x$ for $S \in \mathcal{S}^{d\times d}$

1.3.4 Properties of kernels

If K_1, K_2 are p.d. kernels,

- $K_1 + K_2$ is a p.d. kernel
- $K_1 \cdot K_2$ is a p.d. kernel
- cK_1 for $c \geq 0$ is a p.d. kernel
- The point-wise limits of a sequence of p.d. kernels is a p.d kernel.
- $\exp(K_1)$ is a p.d. kernel

Small norms in the RKHS space means slow variations in the original space $\mathcal{X}$ with respect to the geometry defined by the kernel.

2 Kernel tricks

2.1 Kernel trick

Statement: All expression of vectors that can be written in terms of pairwise inner products can be transposed to a infinite dimensional space by replacing inner products with kernel evaluations.

2.2 Representer theorem

Theorem 7 – Representer theorem

Let $\mathcal{X}$ a set with a p.d. kernel K and corresponding RKHS $\mathcal{H}$, $S = \{x_1, ..., x_n\} \subset \mathcal{X}$ a set of points of $\mathcal{X}$.
Let $\Phi : \mathbb{R}^{n+1} \to \mathbb{R}$ a function strictly increasing w.r.t. the last variable.
Any solution to the optimization problem

$$\min_{f \in \mathcal{H}} \Phi(f(x_1), ..., f(x_n), \|f\|_{\mathcal{H}})$$

admits a representation in the form

$$\forall x \in \mathcal{X}, f(x) = \sum_{i=1}^{n} \alpha_i K(x_i, x)$$

Proof

One of the main consequences of the theorem is that problems of the form

$$\min_{f \in \mathcal{H}} \Phi(f(x_1), ..., f(x_n), \|f\|_{\mathcal{H}})$$

can be re-written as

$$\min_{\alpha \in \mathbb{R}^n} \Phi([\mathbf{K}\alpha]_1, ..., [\mathbf{K}\alpha]_n, \alpha^T \mathbf{K} \alpha)$$

which is a n-dimensional optimization problem (instead of a possibly infinite dimensional one).

3 Kernel Methods: Supervised Learning

3.1 Kernel Ridge regression

The problem can be described as minimizing a RKHS norm regularized MSE criterion

$$\hat{f} = \arg\min_{f \in \mathcal{H}} \frac{1}{n} \sum_{i=1}^{n} (y_i - f(x_i))^2 + \lambda \|f\|_{\mathcal{H}}^2$$

Effects of regularization:

- **Penalize non smooth functions** (avoid overfitting)
- **Simplify the solution** (representer theorem)

The problem can be re-written

$$\hat{\alpha} = \arg\min_{\alpha \in \mathbb{R}^n} \frac{1}{n} (\mathbf{K}\alpha - y)^T (\mathbf{K}\alpha - y) + \lambda \alpha^T \mathbf{K} \alpha$$

One solution is to take

$$\alpha = (\mathbf{K} + \lambda n \mathbf{I})^{-1} y$$

(Uniqueness: If $\mathbf{K}$ is singular, all $\alpha + \varepsilon$ with $\varepsilon \in \mathrm{Ker}(\mathbf{K})$ are solutions leading to the same function f.)

3.2 Kernel logistic regression

$$\hat{f} = \arg\min_{f \in \mathcal{H}} \frac{1}{n} \sum_{i=1}^{n} \log\left(1 + \exp(-y_i f(x_i))\right) + \lambda \|f\|_{\mathcal{H}}^2$$

This problem can also be reformulated in terms of the Gram matrix of the kernel and a parameter α

$$\min_{\alpha \in \mathbb{R}^n} J(\alpha) \triangleq \frac{1}{n} \sum_{i=1}^{n} \log\left(1 + \exp(-y_i [\mathbf{K}\alpha]_i)\right) + \frac{\lambda}{2} \alpha^T \mathbf{K} \alpha$$

By writing and computing the terms of the Taylor expansion of J near a point α_0, we can explicitly solve the problem with Newton's method.

$$J_q(\alpha) = J(\alpha_0) + (\alpha - \alpha_0)^T \nabla J(\alpha_0) + \frac{1}{2}(\alpha - \alpha_0)^T \nabla^2 J(\alpha_0)(\alpha - \alpha_0)$$

$$\nabla J(\alpha) = \frac{1}{n}\mathbf{K}\mathbf{P}(\alpha) y + \lambda \mathbf{K}\alpha$$
$$\nabla^2 J(\alpha) = \frac{1}{n}\mathbf{K}\mathbf{W}(\alpha)\mathbf{K} + \lambda \mathbf{K}$$

where $\mathbf{P}(\alpha) = \mathrm{diag}(\ell'_{\mathrm{logistic}}(y_i[\mathbf{K}\alpha]_i))$ and $\mathbf{W}(\alpha) = \mathrm{diag}(\ell''_{\mathrm{logistic}}(y_i[\mathbf{K}\alpha]_i))$. By developing the approximation, we obtain the following equality

$$2J_q(\alpha) = \frac{1}{n}(\mathbf{K}\alpha - z)^T \mathbf{w}(\mathbf{K}\alpha - z) + \lambda \alpha^T \mathbf{K}\alpha + C$$

with $z = (\mathbf{K}\alpha_0 - \mathbf{W^{-1}}\mathbf{P}y)$. This is exactly the formulation of a weighted kernel ridge regression problem. This problem can be iteratively solved by updating W^t and z^t until convergence (kernel IRLS).

3.3 Support vector machines (SVM)

Definition 5 – Hinge loss

The Hinge loss is a function $\mathbb{R} \to \mathbb{R}_+$ defined by

$$\varphi_{\mathrm{hinge}}(u) = \max(0, 1-u) = \begin{cases} 0 & \text{if } u \geq 1 \\ 1-u & \text{otherwise} \end{cases}$$

Definition 6 – SVM problem

SVM is the large margin classifier that solves

$$\min_{f \in \mathcal{H}} \left\{ \frac{1}{n} \sum_{i=1}^{n} \varphi_{\mathrm{hinge}}(y_i f(x_i)) + \lambda \|f\|_{\mathcal{H}}^2 \right\}$$

It can be reformulated by using the Representer theorem as

$$\min_{\alpha \in \mathbb{R}^n} \left\{ \frac{1}{n} \sum_{i=1}^{n} \varphi_{\mathrm{hinge}}(y_i [\mathbf{K}\alpha]_i) + \lambda \alpha^T \mathbf{K}\alpha \right\}$$

Then, by introducing slack variables and using the definition of the Hinge loss, the following formulation is obtained

$$\hat{f}(x) = \sum_{i=1}^{n} \hat{\alpha}_i K(x_i, x)$$

where $\hat{\alpha}$ solves

$$\begin{aligned} \min_{\alpha \in \mathbb{R}^n, \xi \in \mathbb{R}^n} \quad & \frac{1}{n} \sum_{i=1}^{n} \xi_i + \lambda \alpha^T \mathbf{K} \alpha \\ \text{s.t.} \quad & y_i [\mathbf{K}\alpha]_i + \xi_i - 1 \geq 0, \quad \forall i \\ & \xi_i \geq 0, \quad \forall i \end{aligned}$$

4 Kernel Methods: Unsupervised Learning

4.1 Kernel K-means and spectral clustering

The objective is similar to K-means, but transposed in the RKHS. Given data points $x_1, ..., x_n$ and a p.d. kernel K and RKHS $\mathcal{H}$ the objective reads

$$\min_{\substack{\mu_j \in \mathcal{H} \quad \forall j \leq k \\ s_i \in \{1, ...k\} \quad \forall i \leq n}} \sum_{i=1}^{n} \|\varphi(x_i) - \mu_{s_i}\|_{\mathcal{H}}^2$$

.

Proposition 1

The center of mass $\varphi_n = \frac{1}{n} \sum_{i=1}^{n} \varphi(x_i)$ solves the optimization problem

$$\min_{\mu \in \mathcal{H}} \sum_{i=1}^{n} \|\varphi(x_i) - \mu\|_{\mathcal{H}}^2$$

Proof.

Greedy (K-means) approach:

Centroid update Given a centroid assignment, update the centroids

$$\forall j, \quad \mu_j = \frac{1}{|C_j|} \sum_{i \in C_j} \varphi(x_i)$$

Cluster assignment For $\mu_1, ..., \mu_k$ centers of mass assign each x_i to the closest centroid.

$$s_i \in \arg \min_{s \in \{1, ..., k\}} \|\varphi(x_i) - \mu_s\|_{\mathcal{H}}^2$$

Proposition 2

The equivalent objective to the kernel k-means algorithm is

$$\max_{s_i \in 1,\dots,k \forall i} \sum_{l=1}^{k} \frac{1}{|C_l|} \sum_{i,j \in C_l} K(x_i, x_j)$$

The above problem is a combinatorial optimization problem. The greedy algorithm (kernel K-means) approximates its solution but spectral clustering can also be used.

Idea: Introduce $\mathbf{A} \in \{0,1\}^{n \times k}$ the binary assignment matrix and $\mathbf{D} \in \mathbb{R}^k$ a diagonal matrix with diagonal elements the inverse of cardinality of corresponding cluster. The objective becomes

$$\max_{\mathbf{A},\mathbf{D}} \operatorname{tr}(\mathbf{D}^{1/2}\mathbf{A}^T\mathbf{K}\mathbf{A}\mathbf{D}^{1/2})$$

such that the two matrices verify the properties implied by their definition. One can define $\mathbf{Z} = \mathbf{A}\mathbf{D}^{1/2}$ and the objective becomes

$$\max_{\mathbf{Z}} \operatorname{tr}(\mathbf{Z}^T\mathbf{K}\mathbf{Z}) \quad \text{s.t.} \quad \mathbf{Z}^T\mathbf{Z} = \mathbf{I}$$

This can be solved by finding the eigenvectors of $\mathbf{K}$ with k largest eigenvalues. Then, $\mathbf{Z}^*$ is used to find the best cluster assignment.

4.2 Kernel PCA

Assumption: data are centered w.r.t the kernel, i.e $\frac{1}{n}\sum_{i=1}^{n} \varphi(x_i) = 0$. The orthogonal projection onto a direction f in $\mathcal{H}$ is written $h_f(x) = \left\langle \varphi(x), \frac{f}{\|f\|_{\mathcal{H}}} \right\rangle_{\mathcal{H}}$

The empirical variance captured by a direction f is

$$\operatorname{Var}(h_f) = \frac{1}{n}\sum_{i=1}^{n} \frac{\langle \varphi(x_i), f\rangle_{\mathcal{H}}^2}{\|f\|_{\mathcal{H}}^2} = \frac{1}{n}\sum_{i=1}^{n} \frac{f(x_i)^2}{\|f\|_{\mathcal{H}}^2}$$

and the i-th principal direction is

$$f_i = \arg \max_{f \perp f_1,\dots,f_{i-1}} \operatorname{Var}(h_f) = \sum f(x_i)^2 \quad \text{s.t.} \quad \|f\|_{\mathcal{H}} = 1$$

In practice:

1. Center the Gram matrix
2. Compute the required number of eigenvectors/values (u_i, Δ_i)
3. Normalize $\alpha_i = \frac{u_i}{\sqrt{\Delta_i}}$
4. Project onto the i-th eigenvectors by computing $\mathbf{K}\alpha_i$

5 The Kernel Jungle

5.1 Green, Mercer, Herglotz, Bochner and friends

5.1.1 Green Kernel

Theorem 8 – Green Kernel in dimension 1

The set defined by

$$\mathcal{H} = \left\{ f : [0,1] \to \mathbb{R}, \text{absolutely continuous}, f' \in L^2([0,1]), f(0) = 0 \right\}$$

endowed with the inner product $\forall (f,g) \in \mathcal{F}^2 \langle f,g \rangle = \int_0^1 f'(u)g'(u)du$, is a RKHS with with r.k.

$$\forall (x,y) \in [0,1]^2, K(x,y) = \min(x,y)$$

.

Proof.

Definition 7 – Green functions

Consider the differential equation $f = Dg$ (D differential operator).
Solutions of the form $g(x) = \int_{\mathcal{X}} k(x,y)f(y)\mathrm{d}y$ for some function k that must satisfy

$$\forall x \in \mathcal{X}, \quad f(x) = Dg(x) = \langle Dk_x, f \rangle_{L^2(\mathcal{X})}$$

If k exists, it is called the Green function of the operator D.

Theorem 9 – General Green Kernel

If D is a differential operator on a class of functions of $\mathcal{H}$ such that the inner product $\langle f,g \rangle_{\mathcal{H}} = \langle Df, Dg \rangle_{L^2(\mathcal{X})}$ make $\mathcal{H}$ a Hilbert space
Then $\mathcal{H}$ is a RKHS and admits for r.k. the Green function of the operator D^*D

5.1.2 Mercer Kernels

Definition 8 – Mercer Kernels

A kernel K on a set $\mathcal{X}$ is called a Mercer kernel if:

- $\mathcal{X}$ is a compact metric space (typically, a closed bounded subset of $\mathbb{R}^d$)
- $K : \mathcal{X} \times \mathcal{X} \to \mathbb{R}$ is a continuous p.d kernel (w.r.t the Borel topology)

5.1.3 Shift invariant Kernels

Definition 9 – Fourier-Stieltjes coefficients

For a measure $\mu \in M(\mathbb{T})$ the set of the finite complex Borel measures of the torus $[0, 2\pi]$, the Fourier-Stieltjes coefficients of μ is the sequence

$$\forall n \in \mathbb{Z}, \quad \hat{\mu}(n) = \frac{1}{2\pi} \int_{\mathbb{T}} e^{-int} \mathrm{d}\mu(t)$$

(It is an extension of Fourier transform for integrable functions to measures)

Definition 10 – Shift invariant kernels on $\mathbb{Z}$

kernel $K : \mathbb{Z} \times \mathbb{Z} \to \mathbb{R}$ is called shift invariant (or translation invariant, t.i.) if it only depends on the difference between its arguments, i.e.

$$\forall x, y \in \mathbb{Z}, \quad K(x, y) = a_{x-y}$$

For a sequence $(a_n)_{n\in\mathbb{Z}}$. The sequence is called p.d. if the corresponding kernel is p.d..

Theorem 10 – Herglotz

A sequence $(a_n)_{n\in\mathbb{Z}}$ is p.d. iff it is the Fourier-Stieltjes transform of a positive measure $\mu \in M(\mathbb{T})$

Examples:

- Diagonal kernel:

$$\mu = \mathrm{d}t, \quad a_n = \hat{\mu}(n) = \frac{1}{2\pi} \int_{\mathbb{T}} e^{-int} \mathrm{d}t = \begin{cases} 1 & \text{if } n = 0, \\ 0 & \text{otherwise} \end{cases}$$

  The kernel is $K(x, t) = \mathbb{1}(x = t)$

- Constant kernel: for $C \geq 0$

$$\mu = 2\pi C \delta_0, \quad a_n = \hat{\mu}(n) = C \int_{\mathbb{T}} e^{-int} \delta_0(t) = C$$

  resulting in $K(x, t) = C$

Definition 11 – Fourier transform on $\mathbb{R}^d$

For any $f \in L^1(\mathbb{R}^d)$ the Fourier transform of f is

$$\forall \omega \in \mathbb{R}^d, \quad \hat{f}(\omega) = \int_{\mathbb{R}^d} e^{-ix^\top \omega} f(x) \mathrm{d}x$$

Definition 12 – Fourier-Stieltjes transform

For any $\mu \in M(\mathbb{R}^d)$, the Fourier-Stieltjes transform of μ is the function:

$$\forall \omega \in \mathbb{R}^d, \quad \hat{\mu}(\omega) = \int_{\mathbb{R}^d} e^{-ix^\top \omega} \mathrm{d}\mu(x)$$

Definition 13 – Shift invariant kernels on $\mathbb{R}^d$

A kernel $K : \mathbb{R}^d \times \mathbb{R}^d \to \mathbb{R}$ is called shift invariant (or translation invariant, t.i.) if it only depends on the difference between its arguments, i.e.

$$\forall x, y \in \mathbb{R}^d, \quad K(x, y) = \varphi(x - y)$$

for some function $\varphi : \mathbb{R}^d \to \mathbb{R}$. Such a function φ is called positive definite if the corresponding kernel K is p.d.

Theorem 11 – Bochner

A continuous function $\varphi : \mathbb{R}^d \to \mathbb{R}$ is p.d. iff it is the Fourier-Stieltjes transform of a symmetric and positive finite Borel measure $\mu \in M(\mathbb{T})$

Theorem 12 – RKHS of translation invariant kernels

Let $K(x,t) = \varphi(x-t)$ be a translation invariant p.d. kernel such that φ is integrable on $\mathbb{R}^d$ as well as its Fourier transform $\hat{\varphi}$. The subset $\mathcal{H}$ of $L^2(\mathbb{R})$ that consists of integrable and continuous functions f such that

$$\|f\|_K^2 \triangleq \frac{1}{(2\pi)^d} \int_{\mathbb{R}^d} \frac{\left|\hat{f}(\omega)\right|^2}{\hat{\varphi}(\omega)} \mathrm{d}\omega < +\infty$$

endowed with the inner product

$$\langle f, g \rangle \triangleq \frac{1}{(2\pi)^d} \int_{\mathbb{R}^d} \frac{\hat{f}(\omega)\overline{\hat{g}(\omega)}}{\hat{\varphi}(\omega)} \mathrm{d}\omega$$

is a RKHS with K as r.k.

Examples:

- Gaussian kernel:
$$K(x,y) = e^{-\frac{(x-y)^2}{2\sigma^2}}$$
corresponds to $\hat{\varphi}(\omega) = e^{-\frac{\sigma^2\omega^2}{2}}$ and
$$\mathcal{H} = \left\{ f : \int \left|\hat{f}(\omega)\right|^2 e^{\frac{\sigma^2\omega^2}{2}} \mathrm{d}\omega < \infty \right\}$$
In particular, all functions in $\mathcal{H}$ are infinitely differentiable with all derivatives in L^2.
- Laplace kernel:
$$K(x,y) = \frac{1}{2} e^{-\gamma|x-y|}$$
corresponds to $\hat{\varphi}(\omega) = \frac{\gamma}{\gamma^2+\omega^2}$ and
$$\mathcal{H} = \left\{ f : \int \left|\hat{f}(\omega)\right|^2 \frac{\gamma}{\gamma^2+\omega^2} \mathrm{d}\omega < \infty \right\}$$
the set of functions L^2 differentiable with derivatives in L^2 (Sobolev norm).
- Low frequency filter:
$$K(x,y) = \frac{\sin(\Omega(x-y))}{\pi(x-y)}$$
corresponds to $\hat{\varphi}(\omega) = U(\omega+\Omega) - U(\omega-\Omega)$ and
$$\mathcal{H} = \left\{ f : \int_{|\omega|>\Omega} \left|\hat{f}(\omega)\right|^2 \mathrm{d}\omega = 0 \right\}$$
the set of functions whose spectrum is in $[-\Omega, \Omega]$.

5.1.4 Generalization to semigroups

Definition 14

- A semigroup $(S, \circ)$ is a nonempty set S equipped with an associative composition $\circ$ and a neutral element e.
- A semigroup with involution $(S, \circ, *)$ is a semigroup $(S, \circ)$ together with a mapping $* : S \to S$ called involution satisfying:
  1. $(s \circ t)^* = t^* \circ s^*$ for $s, t \in S$.
  2. $(s^*)^* = s$ for $s \in S$.

Exemples:

- A group $(G, \circ)$ is a semigroup with involution with $s^* = s^{-1}$.
- Any abelian semigroup $(S, +)$ is a semigroup with involution with identity as involution.

5.2 Kernels for probabilistic models

5.2.1 Fisher kernel

Definition 15 – Fisher kernel

Fix a parameter $\theta_0 \in \Theta$ (obtained for instance by maximum likelihood over a training set).
For each sequence x, compute the Fisher score vector

$$\Phi_{\theta_0}(x) = \nabla_\theta \log P_\theta(x)|_{\theta=\theta_0}$$

which can be interpreted as the local contribution of each parameter.
Form the kernel

$$K(x, x') = \Phi_{\theta_0}(x)^\top I(\theta_0)^{-1} \Phi_{\theta_0}(x')$$

where $I(\theta_0) = \mathbb{E}[\Phi_{\theta_0}(x)\Phi_{\theta_0}(x)^\top]$ is the Fisher information matrix.

- Describes how each parameter contributes to generating an example
- Invariant under change of parametrization

In practice,

- $\Phi_{\theta_0}(x)$ can be computed explicitly for many models (HMMs) estimated from data.
- $I(\theta_0)$ is often replaced by the identity matrix.
- Several different models (i.e., different θ_0) can be trained and combined.
- Fisher vectors $\varphi_{\theta_0}(x) = I(\theta_0)^{-1/2}\Phi_{\theta_0}(x)$ and correspond to the explicit embedding

$$K(x, x') = \varphi_{\theta_0}(x)^\top \varphi_{\theta_0}(x') \tag{1}$$

Example: Gaussian model

5.3 Kernels for biological sequences

5.4 Kernels for graphs

5.5 Kernels on graphs

6 Open Problems and Research Topics

A Proofs

A.1 Kernels and RKHS

Proof of Theorem 2

($\Rightarrow$) If a r.k. exists in $\mathcal{H}$ then for any $(x, f) \in \mathcal{X} \times \mathcal{H}$:

$$\begin{aligned}|f(x)| &= |\langle f, K_x\rangle_{\mathcal{H}}| \\ &\leq \|f\|_{\mathcal{H}} \cdot \|K_x\|_{\mathcal{H}} && \text{(Cauchy-Schwarz)} \\ &\leq \|f\|_{\mathcal{H}} \cdot K(x,x)^{\frac{1}{2}}\end{aligned}$$

Therefore, $f \in \mathcal{H} \to f(x) \in \mathbb{R}$ is a linear continuous mapping because F is linear and $\lim_{f\to 0} F(f) = 0$

($\Leftarrow$) F is continuous, by the Riesz representation theorem: there exists a unique $g_x \in \mathcal{H}$ such that $f(x) = \langle f, g_x\rangle_{\mathcal{H}}$.
The function $K : (x, y) \mapsto g_x(y)$ is then a r.k. for $\mathcal{H}$

Proof of Theorem 3

(Uniqueness) If K and K' are two r.k. of a RKHS, then for any x

$$\|K_x - K'_x\|^2 = K_x(x) - K'_x(x) - K_x(x) + K'_x(x) = 0$$

So $K_x = K'_X$

Proof of Theorem 4

($\Leftarrow$) A r.k. is symmetric, and $\sum_{i,j} a_i a_j K(x_i, x_j) = \|\sum_i a_i K_{x_i}\|^2_{\mathcal{H}} \geq 0$

($\Rightarrow$) Let $\mathcal{H}_0$ be the subspace spanned by the functions $(K_x)_{x\in\mathcal{X}}$. If $f = \sum_i a_i K_{x_i}$ and $g = \sum_j b_j K_{y_j}$.
Let (not an inner product yet)

$$\begin{aligned}\langle f, g\rangle_{\mathcal{H}_0} &= \sum_{i,j} a_i b_j K(x_i, y_j) \\ &= \sum_i a_i g(x_i) \\ &= \sum_j b_j f(y_j)\end{aligned}$$

($\langle f, g\rangle_{\mathcal{H}_0}$ does not depend on the expansion of f or g) For any $x \in \mathcal{X}$ and $f \in \mathcal{H}_0$, $\langle f, K_x\rangle_{\mathcal{H}_0} = f(x)$.

$$\|f\|_{\mathcal{H}_0}^2 = \sum_{i,j} a_i a_j K(x_i, x_j) \geq 0$$

And since Cauchy-Schwarz is valid,

$$|f(x)| = |\langle f, K_x \rangle_{\mathcal{H}_0}| \leq \|f\|_{\mathcal{H}_0} \cdot K(x,x)^{\frac{1}{2}}$$

Therefore $\|f\|_{\mathcal{H}_0} = 0 \implies f = 0$. $\langle ., . \rangle$ is an inner product on $\mathcal{H}_0$.
For a Cauchy sequence $(f_n)_{n \geq 0}$,

$$|f_m(x) - f_n(x)| \leq \|f_m - f_n\|_{\mathcal{H}_0} \cdot K(x,x)^{\frac{1}{2}}$$

For any x the sequence $(f_n(x))$ is Cauchy in $\mathbb{R}$ and therefore converges.
If the functions defined as the point-wise limits of Cauchy sequences are added $\mathcal{H}_0$, it becomes a Hilbert space with K as r.k..

Proof of Aronszajn's theorem

If K is p.d. over a set $\mathcal{X}$, it is the r.k. of a Hilbert space $\mathcal{H}$. The mapping Φ is defined by $\forall x \in \mathcal{X}, \quad \Phi(x) = K_x$.
By the reproducing property

$$\forall (x,y) \in \mathcal{X}^2, \quad \langle \Phi(x), \Phi(y) \rangle_{\mathcal{X}} = \langle K_x, K_y \rangle_{\mathcal{X}} = K(x,y)$$

A.2 Kernels Tricks

Proof of the Representer theorem

Let $\xi(f)$ the functional that is minimized in the optimization problem of the theorem, and $\mathcal{H}_{\mathcal{S}}$ the linear span of all the K_{x_i} functions.
Since $\mathcal{H}_{\mathcal{S}}$ is a finite dimensional space, every function $f \in \mathcal{H}$ can be decomposed as $f = f_{\mathcal{S}} + f_{\perp}$, with f_S the orthogonal projection of f on $\mathcal{H}_{\mathcal{S}}$.
Because $\mathcal{H}$ is a RKHS,

$$\forall i \leq n, \quad f_{\perp}(x_i) = \langle f_{\perp}, K_{x_i} \rangle_{\mathcal{H}} = 0$$

Therefore

$$\forall i \leq n, \quad f(x_i) = f_{\mathcal{S}}(x_i)$$

From Pythagora's theorem in $\mathcal{H}$, $\|f\|_{\mathcal{H}}^2 = \|f_{\mathcal{S}}\|_{\mathcal{H}}^2 + \|f_{\perp}\|_{\mathcal{H}}^2$.
We therefore have $\xi(f) \geq \xi(f_{\mathcal{S}})$ with equality if and only if $\|f_{\perp}\|_{\mathcal{H}}^2 = 0$, the minimum belongs to $\mathcal{H}_{\mathcal{S}}$.

A.3 Kernel Methods: Unsupervised Learning

Proof of Proposition 1

$$\begin{aligned}\frac{1}{n}\sum_{i=1}^{n}\|\varphi(x_i)-\mu\|_{\mathcal{H}}^2 &= \frac{1}{n}\sum_{i=1}^{n}\|\varphi(x_i)\|_{\mathcal{H}}^2 - \left\langle \frac{2}{n}\sum_{i=1}^{n}\varphi(x_i), \mu \right\rangle_{\mathcal{H}} + \|\mu\|_{\mathcal{H}}^2 \\ &= \frac{1}{n}\sum_{i=1}^{n}\|\varphi(x_i)\|_{\mathcal{H}}^2 - 2\langle \varphi_n, \mu\rangle_{\mathcal{H}} + \|\mu\|_{\mathcal{H}}^2 \\ &= \frac{1}{n}\sum_{i=1}^{n}\|\varphi(x_i)\|_{\mathcal{H}}^2 - \|\varphi_n\|_{\mathcal{H}}^2 + \|\varphi_n - \mu\|_{\mathcal{H}}^2\end{aligned}$$

which is minimum for $\varphi_n = \mu$.

A.4 The Kernel Jungle

Proof of Theorem 8