Lecture 2

Hilbert Space Embedding of Probability Measures

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Recap of Lecture 1

Kernel method provides an elegant approach to achieve non-linear algorithms from linear algorithms.

- Input space, $\mathcal{X}$: the space of observed data on which learning is performed.
- Feature map, Φ: defined through a positive definite kernel function, $k : \mathcal{X} \times \mathcal{X} \to \mathbb{R}$

$$x \mapsto \Phi(x), \qquad x \in \mathcal{X}$$

- Constructing linear algorithms in the feature space $\Phi(\mathcal{X})$ translates as non-linear algorithms in $\mathcal{X}$.
- Elegance: No explicit construction of Φ as $\langle \Phi(x), \Phi(y) \rangle = k(x, y)$.
- Function space view: RKHS; smoothness and generalization

Examples

- Ridge regression. In fact many more (Kernel+SVM/PCA/FDA/CCA/Perceptron/logistic regression, ...)

Outline

- Motivating example: Comparing distributions
- Hilbert space embedding of measures
  - Mean element
  - Distance on probabilities (MMD)
  - Characteristic kernels
  - Cross-covariance operator and measure of independence
- Applications
  - Two-sample testing
- Choice of kernel

Motivating Example: Coin Toss

- Toss 1: $T\ H\ H\ H\ T\ T\ H\ T\ T\ H\ H\ T\ H$
- Toss 2: $H\ T\ T\ H\ T\ H\ T\ T\ H\ H\ H\ T\ T$

Are the coins/tosses statistically similar?

Toss 1 is a sample from $\mathbb{P}$:=Bernoulli(p) and Toss 2 is a sample from $\mathbb{Q}$:=Bernoulli(q).

Is $p = q$ or not?, i.e., compare

$$\mathbb{E}_{\mathbb{P}}[X] = \int_{\{0,1\}} x\, d\mathbb{P}(x) \quad \text{and} \quad \mathbb{E}_{\mathbb{Q}}[X] = \int_{\{0,1\}} x\, d\mathbb{Q}(x).$$

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Coin Toss Example

In other words, we compare

$$\int_{\mathbb{R}} \Phi(x)\, d\mathbb{P}(x) \quad \text{and} \quad \int_{\mathbb{R}} \Phi(x)\, d\mathbb{Q}(x)$$

where Φ is an identity map,

$$\Phi(x) = x.$$

A positive definite kernel corresponding to Φ is

$$k(x, y) = \langle \Phi(x), \Phi(y) \rangle_2 = xy,$$

which is a linear kernel on $\{0, 1\}$. Therefore, comparing two Bernoulli is equivalent to

$$\int_{\{0,1\}} k(y, x)\, d\mathbb{P}(x) \stackrel{?}{=} \int_{\{0,1\}} k(y, x)\, d\mathbb{Q}(x)$$

for all $y \in \{0, 1\}$, i.e., compare the expectations of the kernel.

Comparing two Gaussians

$$\mathbb{P} = N(\mu_1, \sigma_1^2) \qquad \text{and} \qquad \mathbb{Q} = N(\mu_2, \sigma_2^2)$$

Comparing $\mathbb{P}$ and $\mathbb{Q}$ is equivalent to comparing μ_1, μ_2 and σ_1^2, σ_2^2, i.e.,

$$\mathbb{E}_{\mathbb{P}}[X] = \int_{\mathbb{R}} x \, d\mathbb{P}(x) \stackrel{?}{=} \int_{\mathbb{R}} x \, d\mathbb{Q}(x) = \mathbb{E}_{\mathbb{Q}}[X]$$

and

$$\mathbb{E}_{\mathbb{P}}[X^2] = \int_{\mathbb{R}} x^2 \, d\mathbb{P}(x) \stackrel{?}{=} \int_{\mathbb{R}} x^2 \, d\mathbb{Q}(x) = \mathbb{E}_{\mathbb{Q}}[X^2].$$

Concisely

$$\int_{\mathbb{R}} \Phi(x) \, d\mathbb{P}(x) \stackrel{?}{=} \int_{\mathbb{R}} \Phi(x) \, d\mathbb{Q}(x)$$

where

$$\Phi(x) = (x, x^2).$$

Compare the first moment of the feature map

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Compare the first moment of the feature map

Comparing two Gaussians

Using the map Φ, we can construct a positive definite kernel as

$$k(x, y) = \langle \Phi(x), \Phi(y) \rangle_{\mathbb{R}^2} = xy + x^2 y^2$$

which is a polynomial kernel of order 2.

Therefore, comparing two Gaussians is equivalent to

$$\int_{\mathbb{R}} k(y, x)\, d\mathbb{P}(x) \stackrel{?}{=} \int_{\mathbb{R}} k(y, x)\, d\mathbb{Q}(x)$$

for all $y \in \mathbb{R}$, i.e., compare the expectations of the kernel.

Comparing general $\mathbb{P}$ and $\mathbb{Q}$

Moment generating function is defined as

$$M_{\mathbb{P}}(y) = \int_{\mathbb{R}} e^{xy} \, d\mathbb{P}(x)$$

and (if it exists) captures the information about a distribution, i.e.,

$$M_{\mathbb{P}} = M_{\mathbb{Q}} \Leftrightarrow \mathbb{P} = \mathbb{Q}.$$

Choosing

$$\Phi(x) = \left(1, x, \frac{x^2}{\sqrt{2!}}, \ldots, \frac{x^i}{\sqrt{i!}}, \ldots\right) \in \ell_2(\mathbb{N}), \forall\, x \in \mathbb{R}$$

it is easy to verify that

$$k(x, y) = \langle \Phi(x), \Phi(y) \rangle_{\ell_2(\mathbb{N})} = e^{xy}$$

and so

$$\int_{\mathbb{R}} k(x, y) \, d\mathbb{P}(x) = \int_{\mathbb{R}} k(x, y) \, d\mathbb{Q}(x), \forall\, y \in \mathbb{R} \Leftrightarrow \mathbb{P} = \mathbb{Q}.$$

Two-Sample Problem

- Given random samples $\{X_1, \ldots, X_m\} \stackrel{i.i.d.}{\sim} \mathbb{P}$ and $\{Y_1, \ldots, Y_n\} \stackrel{i.i.d.}{\sim} \mathbb{Q}$.
- Determine: $\mathbb{P} = \mathbb{Q}$ or $\mathbb{P} \neq \mathbb{Q}$?

Applications:

- Microarray data (aggregation problem)
- Speaker verification
- Independence Testing: Given random samples $\{(X_1, Y_1), \ldots, (X_n, Y_n)\} \stackrel{i.i.d}{\sim} \mathbb{P}_{xy}$. Does $\mathbb{P}_{xy}$ factorize into $\mathbb{P}_x \mathbb{P}_y$?
- Feature selection (microarrays, image and text,...)

Hilbert Space Embedding of Measures

Hilbert Space Embedding of Measures

- Canonical feature map:

$$\Phi(x) = k(\cdot, x) \in \mathcal{H}, \qquad x \in \mathcal{X}$$

where $\mathcal{H}$ is a reproducing kernel Hilbert space (RKHS).

- Generalization to probabilities:

$$x \mapsto k(\cdot, x) \qquad \equiv \qquad \underbrace{\delta_x}_{\text{point mass at } x} \mapsto \underbrace{k(\cdot, x)}_{\int_{\mathcal{X}} k(\cdot, y)\, d\delta_x(y) = \mathbb{E}_{\delta_x}[k(\cdot, Y)]}$$

Based on the above, the map is extended to probability measures as

$$\mathbb{P} \mapsto \mu_{\mathbb{P}} := \int_{\mathcal{X}} \Phi(x)\, d\mathbb{P}(x) = \underbrace{\int_{\mathcal{X}} k(\cdot, x)\, d\mathbb{P}(x)}_{\mathbb{E}_{X \sim \mathbb{P}} k(\cdot, X)}$$

(Smola et al., ALT 2007)

Properties

- $\mu_{\mathbb{P}}$ is the mean of the feature map and is called the kernel mean or mean element of $\mathbb{P}$.

- When is $\mu_{\mathbb{P}}$ well defined?

$$\int_{\mathcal{X}} \sqrt{k(x,x)}\, d\mathbb{P}(x) < \infty \quad \Rightarrow \quad \mu_{\mathbb{P}} \in \mathcal{H}$$

Proof:

$$\|\mu_{\mathbb{P}}\|_{\mathcal{H}} = \left\| \int_{\mathcal{X}} k(\cdot,x)\, d\mathbb{P}(x) \right\|_{\mathcal{H}} \stackrel{Jensen's}{\leq} \int_{\mathcal{X}} \|k(\cdot,x)\|_{\mathcal{H}}\, d\mathbb{P}(x).$$

- We know that for any $f \in \mathcal{H}$, $f(x) = \langle f, k(\cdot,x)\rangle_{\mathcal{H}}$. So, for any $f \in \mathcal{H}$,

$$\begin{aligned}\int_{\mathcal{X}} f(x)\, d\mathbb{P}(x) &= \int_{\mathcal{X}} \langle f, k(\cdot,x)\rangle_{\mathcal{H}}\, d\mathbb{P}(x) \stackrel{\bullet}{=} \left\langle f, \int_{\mathcal{X}} k(\cdot,x)\, d\mathbb{P}(x) \right\rangle_{\mathcal{H}} \\ &= \langle f, \mu_{\mathbb{P}} \rangle_{\mathcal{H}}.\end{aligned}$$

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$$= \langle f, \mu_{\mathbb{P}}\rangle_{\mathcal{H}}.$$

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Interpretation (S et al., JMLR 2010)

Suppose k is translation invariant on $\mathbb{R}^d$, i.e., $k(x,y) = \psi(x-y)$, $x, y \in \mathbb{R}^d$. Then

$$\mu_{\mathbb{P}} = \int_{\mathbb{R}^d} \psi(\cdot - x)\, d\mathbb{P}(x) = \psi \star \mathbb{P},$$

where $\star$ is the convolution of ψ and $\mathbb{P}$.

- Convolution is a smoothing operation $\Rightarrow$ $\mu_{\mathbb{P}}$ is a smoothed version of $\mathbb{P}$.
- Example: Suppose $\mathbb{P} = \delta_y$, a point mass at y. Then

$$\mu_{\mathbb{P}} = \psi \star \mathbb{P} = \psi(\cdot - y).$$

- Example: Suppose $\psi \propto N(0, \sigma^2)$ and $\mathbb{P} = N(\mu, \tau^2)$. Then

$$\mu_{\mathbb{P}} = \psi \star \mathbb{P} \propto N(\mu, \sigma^2 + \tau^2).$$

$\mu_{\mathbb{P}}$ is a wider Gaussian than $\mathbb{P}$

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Comparing Kernel Means

Define a distance (maximum mean discrepancy) on probabilities

$$MMD_{\mathcal{H}}(\mathbb{P}, \mathbb{Q}) = \|\mu_{\mathbb{P}} - \mu_{\mathbb{Q}}\|_{\mathcal{H}}$$

(Gretton et al., NIPS 2006; Smola et al., ALT 2007)

$$\begin{aligned}
MMD^2_{\mathcal{H}}(\mathbb{P}, \mathbb{Q}) &= \langle \mu_{\mathbb{P}}, \mu_{\mathbb{P}} \rangle_{\mathcal{H}} + \langle \mu_{\mathbb{Q}}, \mu_{\mathbb{Q}} \rangle_{\mathcal{H}} - 2\langle \mu_{\mathbb{P}}, \mu_{\mathbb{Q}} \rangle_{\mathcal{H}} \\
&= \int_{\mathcal{X}} \mu_{\mathbb{P}}(x)\, d\mathbb{P}(x) + \int_{\mathcal{X}} \mu_{\mathbb{Q}}(x)\, d\mathbb{Q}(x) - 2\int_{\mathcal{X}} \mu_{\mathbb{P}}(x)\, d\mathbb{Q}(x) \\
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Comparing Kernel Means

In the motivating examples, we compare $\mathbb{P}$ and $\mathbb{Q}$ by comparing

$$\mu_{\mathbb{P}}(y) = \int_{\mathcal{X}} k(y,x)\, d\mathbb{P}(x) \quad \text{and} \quad \mu_{\mathbb{Q}}(y) = \int_{\mathcal{X}} k(y,x)\, d\mathbb{Q}(x), \ \forall\, y \in \mathcal{X}.$$

For any $f \in \mathcal{H}$,

$$\|f\|_\infty = \sup_{y\in\mathcal{X}} |f(y)| = \sup_{y\in\mathcal{X}} |\langle f, k(\cdot,y)\rangle_{\mathcal{H}}| \le \sup_{y\in\mathcal{X}} \sqrt{k(y,y)}\|f\|_{\mathcal{H}}.$$

$$\|\mu_{\mathbb{P}} - \mu_{\mathbb{Q}}\|_\infty \le \sup_{y\in\mathcal{X}} \sqrt{k(y,y)}\|\mu_{\mathbb{P}} - \mu_{\mathbb{Q}}\|_{\mathcal{H}}.$$

Does $\|\mu_{\mathbb{P}} - \mu_{\mathbb{Q}}\|_{\mathcal{H}} = 0 \Rightarrow \mathbb{P} = \mathbb{Q}$? (More on this later)

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$$\|\mu_{\mathbb{P}} - \mu_{\mathbb{Q}}\|_\infty \leq \sup_{y\in\mathcal{X}} \sqrt{k(y,y)}\|\mu_{\mathbb{P}} - \mu_{\mathbb{Q}}\|_{\mathcal{H}}.$$

Does $\|\mu_{\mathbb{P}} - \mu_{\mathbb{Q}}\|_{\mathcal{H}} = 0 \Rightarrow \mathbb{P} = \mathbb{Q}$? (More on this later)

Comparing Kernel Means

In the motivating examples, we compare $\mathbb{P}$ and $\mathbb{Q}$ by comparing

$$\mu_{\mathbb{P}}(y) = \int_{\mathcal{X}} k(y,x)\, d\mathbb{P}(x) \quad \text{and} \quad \mu_{\mathbb{Q}}(y) = \int_{\mathcal{X}} k(y,x)\, d\mathbb{Q}(x), \ \forall\, y \in \mathcal{X}.$$

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Integral Probability Metric

The integral probability metric between $\mathbb{P}$ and $\mathbb{Q}$ is defined as

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\begin{aligned}
IPM(\mathbb{P}, \mathbb{Q}, \mathcal{F}) &:= \sup_{f \in \mathcal{F}} \left| \int_{\mathcal{X}} f(x)\, d\mathbb{P}(x) - \int_{\mathcal{X}} f(x)\, d\mathbb{Q}(x) \right| \\
&= \sup_{f \in \mathcal{F}} \left| \mathbb{E}_{\mathbb{P}} f(X) - \mathbb{E}_{\mathbb{Q}} f(X) \right| .
\end{aligned}
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(Müller, 1997)

- $\mathcal{F}$ controls the degree of distinguishability between $\mathbb{P}$ and $\mathbb{Q}$.
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- $\mathcal{F}$ controls the degree of distinguishability between $\mathbb{P}$ and $\mathbb{Q}$.
- Related to the Bayes risk of a certain classification problem (S et al., NIPS 2009; EJS 2012)
- Example: Suppose $\mathcal{F} = \{a \cdot x,\ x \in \mathbb{R} : a \in [-1, 1]\}$. Then

$$IPM(\mathbb{P}, \mathbb{Q}, \mathcal{F}) = \sup_{a \in [-1,1]} |a| \left| \int_{\mathbb{R}} x\, d\mathbb{P}(x) - \int_{\mathbb{R}} x\, d\mathbb{Q}(x) \right|$$

Integral Probability Metric

Example: Suppose $\mathcal{F} = \{a \cdot x + b \cdot x^2,\, x \in \mathbb{R} \,:\, a^2 + b^2 = 1\}$. Then

$$
\begin{aligned}
IPM(\mathbb{P}, \mathbb{Q}, \mathcal{F}) &= \sup_{a^2+b^2=1} \left| a \int_{\mathbb{R}} x \, d(\mathbb{P} - \mathbb{Q}) + b \int_{\mathbb{R}} x^2 \, d(\mathbb{P} - \mathbb{Q}) \right| \\
&= \left[\left(\int_{\mathbb{R}} x \, d(\mathbb{P} - \mathbb{Q}) \right)^2 + \left(\int_{\mathbb{R}} x^2 \, d(\mathbb{P} - \mathbb{Q}) \right)^2 \right]^{\frac{1}{2}}.
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$$

How? Exercise!

- The richer the $\mathcal{F}$ is, the finer is the resolvability of $\mathbb{P}$ and $\mathbb{Q}$.

We will explore the relation of $MMD_{\mathcal{H}}(\mathbb{P}, \mathbb{Q})$ to $IPM(\mathbb{P}, \mathbb{Q}, \mathcal{F})$.

Integral Probability Metric

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Classical results:

- $\mathcal{F} =$ unit Lipschitz ball (Wasserstein distance) (Dudley, 2002)
- $\mathcal{F} =$ unit bounded-Lipschitz ball (Dudley metric) (Dudley, 2002)
- $\mathcal{F} = \{\mathbb{1}_{(-\infty,t]} : t \in \mathbb{R}^d\}$ (Kolmogorov metric) (Müller, 1997)
- $\mathcal{F} =$ unit ball in bounded measurable functions (Total variation distance) (Dudley, 2002)

For all these $\mathcal{F}$, $IPM(\mathbb{P}, \mathbb{Q}, \mathcal{F}) = 0 \Rightarrow \mathbb{P} = \mathbb{Q}$.

(Gretton et al., NIPS 2006, JMLR 2012; S et al., COLT 2008): $\mathcal{F} =$ unit ball in an RKHS, $\mathcal{H}$ with bounded kernel, k. Then

$$MMD_{\mathcal{H}}(\mathbb{P}, \mathbb{Q}) = IPM(\mathbb{P}, \mathbb{Q}, \mathcal{F}).$$

Proof: $\int_{\mathcal{X}} f(x)\, d(\mathbb{P} - \mathbb{Q})(x) = \langle f, \mu_{\mathbb{P}} - \mu_{\mathbb{Q}} \rangle_{\mathcal{H}} \leq \|f\|_{\mathcal{H}} \|\mu_{\mathbb{P}} - \mu_{\mathbb{Q}}\|_{\mathcal{H}}$

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Two-Sample Problem

- Given random samples $\{X_1, \ldots, X_m\} \overset{i.i.d.}{\sim} \mathbb{P}$ and $\{Y_1, \ldots, Y_n\} \overset{i.i.d.}{\sim} \mathbb{Q}$.
- Determine: $\mathbb{P} = \mathbb{Q}$ or $\mathbb{P} \neq \mathbb{Q}$?
- Approach: Define ρ to be a distance on probabilities

$$\begin{matrix} H_0 : \mathbb{P} = \mathbb{Q} \\ \\ H_1 : \mathbb{P} \neq \mathbb{Q} \end{matrix} \quad \equiv \quad \begin{matrix} H_0 : \rho(\mathbb{P}, \mathbb{Q}) = 0 \\ \\ H_1 : \rho(\mathbb{P}, \mathbb{Q}) > 0 \end{matrix}$$

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Why $MMD_{\mathcal{H}}$?

- Related to the estimation of $IPM(\mathbb{P}, \mathbb{Q}, \mathcal{F})$.
- Recall

$$MMD^2_{\mathcal{H}}(\mathbb{P}, \mathbb{Q}) = \left\| \int_{\mathcal{X}} k(\cdot, x)\, d\mathbb{P}(x) - \int_{\mathcal{X}} k(\cdot, x)\, d\mathbb{Q}(x) \right\|^2_{\mathcal{H}}.$$

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  - For $\mathcal{F} =$ Lipschitz and bounded Lipschitz balls,

$$|IPM(\mathbb{P}_m, \mathbb{Q}_m, \mathcal{F}) - IPM(\mathbb{P}, \mathbb{Q}, \mathcal{F})| = O_p\left(m^{-\frac{1}{d+1}}\right), \quad d > 2$$

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Beware of Pitfalls

- There are many other distances on probabilities:
  - Total variation distance
  - Hellinger distance
  - Kullback-Leibler divergence and its variants
  - Fisher divergence ...
- Estimating these distances is both computationally and statistically difficult.
- $MMD_{\mathcal{H}}$ is computationally simpler and appears statistically powerful with no curse of dimensionality. In fact, it is NOT statistically powerful. (Ramdas et al., AAAI 2015; S, Bernoulli, 2016)
- Recall: $MMD_{\mathcal{H}}$ is based on $\mu_{\mathbb{P}}$ which is a smoothed version of $\mathbb{P}$. Even though $\mathbb{P}$ and $\mathbb{Q}$ can be distinguished (coming up!!) based on $\mu_{\mathbb{P}}$ and $\mu_{\mathbb{Q}}$, the distinguishability is weak compared to that of the above distances. (S et al., JMLR 2010; S, Bernoulli, 2016)

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So far . . .

$$\mathbb{P} \mapsto \mu_{\mathbb{P}} := \int_{\mathcal{X}} k(\cdot, x)\, d\mathbb{P}(x)$$

$$MMD_{\mathcal{H}}(\mathbb{P}, \mathbb{Q}) = \|\mu_{\mathbb{P}} - \mu_{\mathbb{Q}}\|_{\mathcal{H}}$$

- Computation
- Estimation

When is $\mathbb{P} \mapsto \mu_{\mathbb{P}}$ one-to-one?, i.e., $MMD_{\mathcal{H}}(\mathbb{P}, \mathbb{Q}) = 0 \quad \Rightarrow \quad \mathbb{P} = \mathbb{Q}$?

Characteristic Kernel

k is said to be characteristic if

$$MMD_{\mathcal{H}}(\mathbb{P},\mathbb{Q}) = 0 \Leftrightarrow \mathbb{P} = \mathbb{Q}$$

for any $\mathbb{P}$ and $\mathbb{Q}$.

Not all kernels are characteristic.

- Example: If $k(x,y) = c > 0, \forall\, x,y \in \mathcal{X}$, then

$$\mu_{\mathbb{P}} = \int_{\mathcal{X}} k(\cdot,x)\,d\mathbb{P}(x) = c, \quad \mu_{\mathbb{Q}} = c$$

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- Example: Let $k(x,y) = xy,\ x,y \in \mathbb{R}$. Then

$$MMD_{\mathcal{H}}(\mathbb{P},\mathbb{Q}) = |\mathbb{E}_{\mathbb{P}}[X] - \mathbb{E}_{\mathbb{Q}}[X]|.$$

  Characteristic for Bernoulli's but not for all $\mathbb{P}$ and $\mathbb{Q}$.

- Example: Let $k(x,y) = (1+xy)^2,\ x,y \in \mathbb{R}$. Then

$$MMD^2_{\mathcal{H}}(\mathbb{P},\mathbb{Q}) = 2(\mathbb{E}_{\mathbb{P}}[X] - \mathbb{E}_{\mathbb{Q}}[X])^2 + (\mathbb{E}_{\mathbb{P}}[X^2] - \mathbb{E}_{\mathbb{Q}}[X^2]).$$

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Characteristic Kernels on $\mathbb{R}^d$

- Translation invariant kernel: $k(x,y) = \psi(x-y)$, $x, y \in \mathbb{R}^d$; bounded and continuous.
- Bochner's theorem:

$$\psi(x) = \int_{\mathbb{R}^d} e^{\sqrt{-1}\langle x,\omega\rangle_2}\, d\Lambda(\omega),\ \ x \in \mathbb{R}^d,$$

  where Λ is a non-negative finite Borel measure on $\mathbb{R}^d$.

Then, k is characteristic $\Leftrightarrow$ $\text{supp}(\Lambda) = \mathbb{R}^d$. (S et al., COLT 2008; JMLR, 2010)

- Corollary: Compactly supported ψ are characteristic (S et al., COLT 2008; JMLR, 2010).

Key Idea: Fourier representation of $MMD_{\mathcal{H}}$

Fourier Representation of $MMD^2_{\mathcal{H}}$

$$MMD^2_{\mathcal{H}}(\mathbb{P},\mathbb{Q}) = \int_{\mathbb{R}^d} |\varphi_{\mathbb{P}}(\omega) - \varphi_{\mathbb{Q}}(\omega)|^2 \, d\Lambda(\omega)$$

where $\varphi_{\mathbb{P}}$ is the characteristic function of $\mathbb{P}$.

Proof:

$$\begin{aligned}
MMD^2_{\mathcal{H}}(\mathbb{P},\mathbb{Q}) &= \int_{\mathbb{R}^d}\int_{\mathbb{R}^d} \psi(x-y)\, d(\mathbb{P}-\mathbb{Q})(x)\, d(\mathbb{P}-\mathbb{Q})(y) \\
&\overset{(*)}{=} \int_{\mathbb{R}^d}\int_{\mathbb{R}^d}\int_{\mathbb{R}^d} e^{-\sqrt{-1}\langle x-y,\omega\rangle}\, d\Lambda(\omega)\, d(\mathbb{P}-\mathbb{Q})(x)\, d(\mathbb{P}-\mathbb{Q})(y) \\
&\overset{(\dagger)}{=} \int_{\mathbb{R}^d}\int_{\mathbb{R}^d} e^{-\sqrt{-1}\langle x,\omega\rangle}\, d(\mathbb{P}-\mathbb{Q})(x) \int_{\mathbb{R}^d} e^{\sqrt{-1}\langle y,\omega\rangle}\, d(\mathbb{P}-\mathbb{Q})(y)\, d\Lambda(\omega) \\
&= \int_{\mathbb{R}^d} |\varphi_{\mathbb{P}}(\omega) - \varphi_{\mathbb{Q}}(\omega)|^2 \, d\Lambda(\omega),
\end{aligned}$$

where Bochner's theorem is used in $(*)$ and Fubini's theorem in $(\dagger)$.

- Suppose $\Lambda = 1$, i.e., uniform on $\mathbb{R}^d$ (!!). Then $MMD_{\mathcal{H}}(\mathbb{P},\mathbb{Q})$ is the L^2 distance between the densities (if they exist) of $\mathbb{P}$ and $\mathbb{Q}$.

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Proof:

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Characteristic Kernels on $\mathbb{R}^d$

Proof:

- Suppose $\text{supp}(\Lambda) = \mathbb{R}^d$. Then

$$MMD^2_{\mathcal{H}}(\mathbb{P}, \mathbb{Q}) = 0 \Rightarrow \int_{\mathbb{R}^d} \left|\varphi_{\mathbb{P}}(\omega) - \varphi_{\mathbb{Q}}(\omega)\right|^2 \, d\Lambda(\omega) = 0 \Rightarrow \varphi_{\mathbb{P}} = \varphi_{\mathbb{Q}} \text{ a.e.}$$

  But characteristic functions are uniformly continuous and so $\varphi_{\mathbb{P}} = \varphi_{\mathbb{Q}}$ which implies $\mathbb{P} = \mathbb{Q}$.

- Suppose $\text{supp}(\Lambda) \subsetneq \mathbb{R}^d$. Then there exists an open set $U \subsetneq \mathbb{R}^d$ such that $\Lambda(U) = 0$. Construct $\mathbb{P}$ and $\mathbb{Q}$ such that $\varphi_{\mathbb{P}}$ and $\varphi_{\mathbb{Q}}$ differ only in U, i.e., $MMD_{\mathcal{H}}(\mathbb{P}, \mathbb{Q}) > 0$.

- If ψ is compactly supported, its Fourier transform is analytic, i.e., cannot vanish on an interval.

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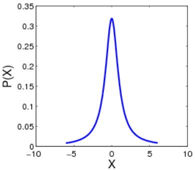
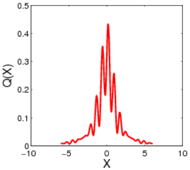
Translation Invariant Kernels on $\mathbb{R}^d$

$$MMD_{\mathcal{H}}(\mathbb{P}, \mathbb{Q}) = \|\varphi_{\mathbb{P}} - \varphi_{\mathbb{Q}}\|_{L^2(\mathbb{R}^d, \Lambda)}$$

- Example: $\mathbb{P}$ differs from $\mathbb{Q}$ at (roughly) one frequency





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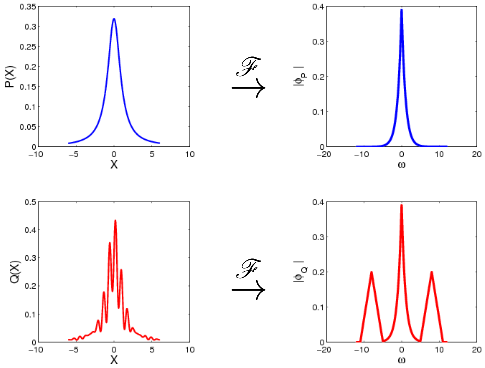

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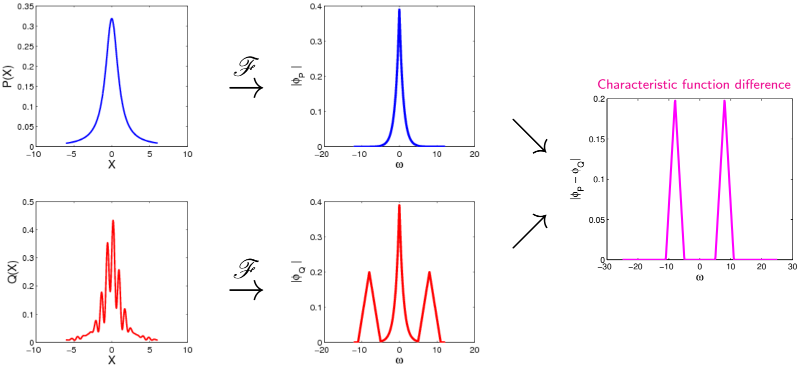

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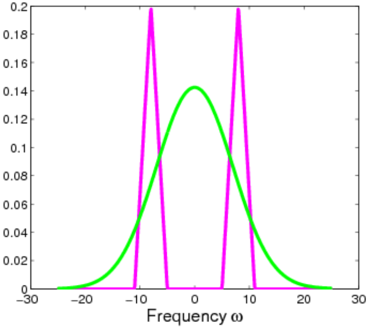
Gaussian kernel

$|\varphi_{\mathbb{P}} - \varphi_{\mathbb{Q}}|$



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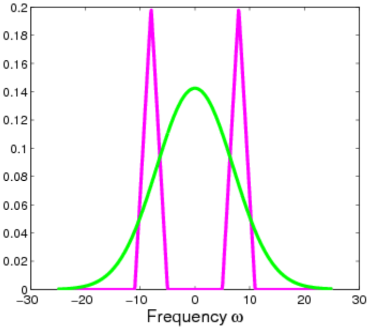
Characteristic



Picture credit: A. Gretton

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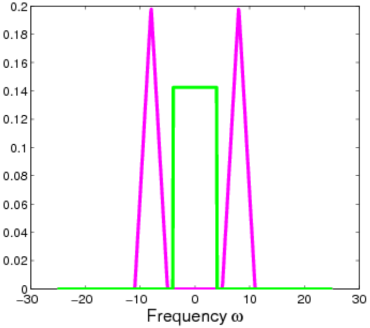
Sinc kernel

$|\varphi_{\mathbb{P}} - \varphi_{\mathbb{Q}}|$



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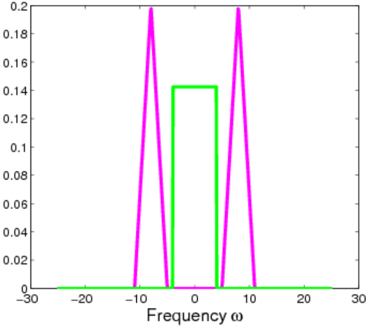

Picture credit: A. Gretton

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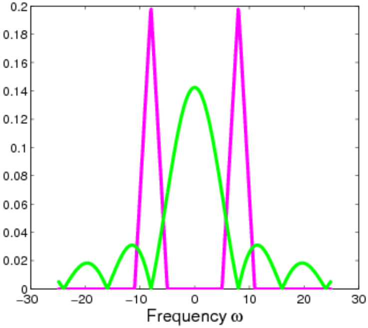
B-Spline kernel

$|\varphi_{\mathbb{P}} - \varphi_{\mathbb{Q}}|$



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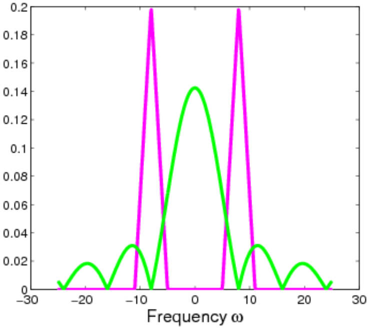
???



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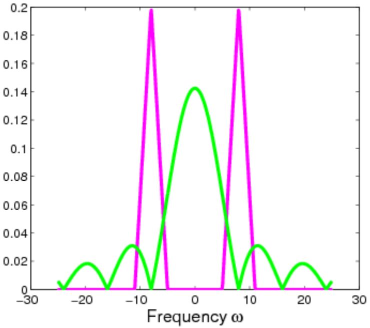
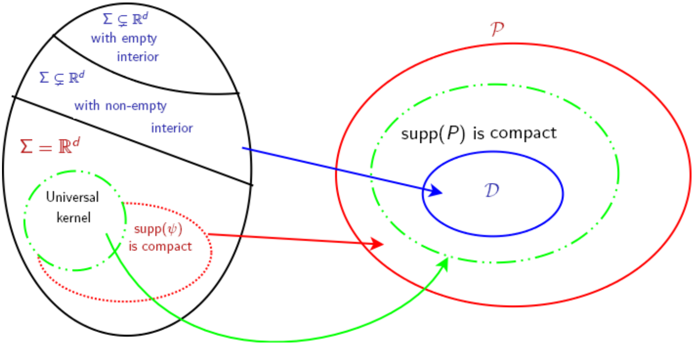


Picture credit: A. Gretton

Caution

Chararacteristic property relates class of kernels and class of probabilities.



$$\Sigma := \text{supp}(\Lambda)$$

(S et al., COLT 2008; JMLR 2010)

Characteristic Kernels

Similar reasoning hold wherever extensions of Bochner's theorem exist (Fukumizu et al., NIPS 2009):

- Locally compact Abelian groups (periodic domains, e.g., circle, d-Torus)
- Compact, non-Abelian groups (Orthogonal matrices)
  - Represent and compare distributions over matrices
- The semigroup $\mathbb{R}_+^d$ (histograms)
  - Compare distributions over distributions

- Characteristic property is related to the richness of $\mathcal{H}$ in approximating certain class of functions. Characteristic property is in general a weaker notion than universality. But for translation invariant kernels on $\mathbb{R}^d$, these notions are equivalent. (Gretton et al., NIPS 2006; Fukumizu et al., NIPS 2008, 2009; Steinwart and Christmann, 2008; S et al., JMLR 2010, JMLR 2011; Simon-Gabriel and Schölkopf, 2016)

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So far . . .

$$\mathbb{P} \mapsto \mu_{\mathbb{P}} := \int_{\mathcal{X}} k(\cdot, x)\, d\mathbb{P}(x)$$

$$MMD_{\mathcal{H}}(\mathbb{P}, \mathbb{Q}) = \|\mu_{\mathbb{P}} - \mu_{\mathbb{Q}}\|_{\mathcal{H}}$$

- Computation
- Estimation
- $MMD_{\mathcal{H}}(\mathbb{P}, \mathbb{Q}) = 0 \quad \Rightarrow \quad \mathbb{P} = \mathbb{Q}$ for characteristic kernels.

Measuring (In)Dependence

- X and Y are random variables taking values in $\mathcal{X}$ and $\mathcal{Y}$.
- $(X, Y) \sim \mathbb{P}_{XY}$ with marginals $X \sim \mathbb{P}_X$ and $Y \sim \mathbb{P}_Y$.
- Dependency measure using MMD: Using k_X and k_Y defined on $\mathcal{X}$ and $\mathcal{Y}$,

$$MMD_{\mathcal{H}}(\mathbb{P}_{XY}, \mathbb{P}_X \times \mathbb{P}_Y) := \left\| \int \underbrace{k_X(\cdot, x) k_Y(\cdot, y)}_{k(\cdot,(x,y))} \, d(\mathbb{P}_{XY} - \mathbb{P}_X \times \mathbb{P}_Y)(x, y) \right\|_{\mathcal{H}}$$

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- If k is characteristic on $\mathcal{X} \times \mathcal{Y}$, then $MMD_{\mathcal{H}}$ captures independence.

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Measuring (In)Dependence

- Let X and Y be Gaussian random variables on $\mathbb{R}$. Then

  X and Y are independent $\Leftrightarrow \text{Cov}(X, Y) = \mathbb{E}(XY) - \mathbb{E}(X)\mathbb{E}(Y) = 0$

- In general, $\text{Cov}(X, Y) = 0 \not\Rightarrow X \perp Y$.
- Covariance captures the linear relationship between X and Y.
- Feature space view point: How about $\text{Cov}(\Phi(X), \Psi(Y))$?
- Suppose

  $$\Phi(X) = (1, X, X^2) \text{ and } \Psi(Y) = (1, Y, Y^2, Y^3).$$

  Then $\text{Cov}(\Phi(X), \Phi(Y))$ captures $\text{Cov}(X^i, Y^j)$ for $i \in \{0, 1, 2\}$ and $j \in \{0, 1, 2, 3\}$.

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Measuring (In)Dependence

- Characterization of independence:

$$X \perp Y \Leftrightarrow \text{Cov}(f(X), g(Y)) = 0, \forall \text{ measurable functions } f \text{ and } g.$$

- Dependence measure:

$$\sup_{f,g} |\text{Cov}(f(X), g(Y))| = \sup_{f,g} |\mathbb{E}[f(X)g(Y)] - \mathbb{E}[f(X)]\mathbb{E}[g(Y)]|$$

Similar to the IPM between $\mathbb{P}_{XY}$ and $\mathbb{P}_X\mathbb{P}_Y$.

- Restricting functions in RKHS: (constrained covariance)

$$COCO(\mathbb{P}_{XY}; \mathcal{H}_X, \mathcal{H}_Y) := \sup_{\substack{\|f\|_{\mathcal{H}_X}=1 \\ \|g\|_{\mathcal{H}_Y}=1}} |\mathbb{E}[f(X)g(Y)] - \mathbb{E}[f(X)]\mathbb{E}[g(Y)]|.$$

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Covariance Operator

Let k_X and k_Y be the r.k.'s of $\mathcal{H}_X$ and $\mathcal{H}_Y$ respectively. Then

- $\mathbb{E}[f(X)] = \langle f, \mu_{\mathbb{P}_X} \rangle_{\mathcal{H}_X}$ and $\mathbb{E}[g(Y)] = \langle g, \mu_{\mathbb{P}_Y} \rangle_{\mathcal{H}_Y}$
- $$\begin{aligned} \mathbb{E}[f(X)]\mathbb{E}[g(Y)] &= \langle f, \mu_{\mathbb{P}_X} \rangle_{\mathcal{H}_X} \langle g, \mu_{\mathbb{P}_Y} \rangle_{\mathcal{H}_Y} \\ &= \langle f \otimes g, \mu_{\mathbb{P}_X} \otimes \mu_{\mathbb{P}_Y} \rangle_{\mathcal{H}_X \otimes \mathcal{H}_Y} \\ &= \langle f, (\mu_{\mathbb{P}_X} \otimes \mu_{\mathbb{P}_Y}) g \rangle_{\mathcal{H}_X} \\ &= \langle g, (\mu_{\mathbb{P}_Y} \otimes \mu_{\mathbb{P}_X}) f \rangle_{\mathcal{H}_Y} \end{aligned}$$
- $$\begin{aligned} \mathbb{E}[f(X)g(Y)] &= \mathbb{E}[\langle f, k_X(\cdot, X) \rangle_{\mathcal{H}_X} \langle g, k_Y(\cdot, Y) \rangle_{\mathcal{H}_Y}] \\ &= \mathbb{E}[\langle f \otimes g, k_X(\cdot, X) \otimes k_Y(\cdot, Y) \rangle_{\mathcal{H}_X \otimes \mathcal{H}_Y}] \\ &= \mathbb{E}[\langle f, (k_X(\cdot, X) \otimes k_Y(\cdot, Y)) g \rangle_{\mathcal{H}_X}] \\ &= \mathbb{E}[\langle g, (k_Y(\cdot, Y) \otimes k_X(\cdot, X)) f \rangle_{\mathcal{H}_Y}] \end{aligned}$$

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Covariance Operator

- Assuming $\mathbb{E}\sqrt{k_X(X,X)k_Y(Y,Y)} < \infty$, we obtain

$$\begin{aligned}\mathbb{E}[f(X)g(Y)] &= \langle f, \mathbb{E}[k_X(\cdot,X) \otimes k_Y(\cdot,Y)]g\rangle_{\mathcal{H}_X} \\ &= \langle g, \mathbb{E}[k_Y(\cdot,Y) \otimes k_X(\cdot,X)]f\rangle_{\mathcal{H}_Y}\end{aligned}$$

-

$$\mathrm{Cov}(f(X), g(Y)) = \langle f, C_{XY} g\rangle_{\mathcal{H}_X} = \langle g, C_{YX} f\rangle_{\mathcal{H}_Y}$$

where

$$C_{XY} := \mathbb{E}[k_X(\cdot,X) \otimes k_Y(\cdot,Y)] - \mu_{\mathbb{P}_X} \otimes \mu_{\mathbb{P}_Y}$$

is a cross-covariance operator from $\mathcal{H}_Y$ to $\mathcal{H}_X$ and $C_{YX} = C^*_{XY}$.

Compare to the feature space view point with canonical feature maps

Dependence Measures

- $$COCO(\mathbb{P}_{XY}; \mathcal{H}_X, \mathcal{H}_Y) = \sup_{\substack{\|f\|_{\mathcal{H}_X}=1 \\ \|g\|_{\mathcal{H}_Y}=1}} |\langle f, C_{XY} g\rangle_{\mathcal{H}_X}|$$
  $$= \|C_{XY}\|_{\text{op}} = \|C_{YX}\|_{\text{op}},$$
  which is the maximum singular value of C_{XY}.
- Choosing $k_X(\cdot, X) = \langle \cdot, X\rangle_2$ and $k_Y(\cdot, Y) = \langle \cdot, Y\rangle_2$, for Gaussian distributions,
  $$X \perp Y \Leftrightarrow C_{YX} = 0$$
- In general,
  $$X \perp Y \overset{?}{\Leftrightarrow} C_{YX} = 0.$$

Dependence Measures

- $$COCO(\mathbb{P}_{XY}; \mathcal{H}_X, \mathcal{H}_Y) = \sup_{\substack{\|f\|_{\mathcal{H}_X}=1 \\ \|g\|_{\mathcal{H}_Y}=1}} |\langle f, C_{XY} g\rangle_{\mathcal{H}_X}| = \|C_{XY}\|_{op} = \|C_{YX}\|_{op},$$

  which is the maximum singular value of C_{XY}.

- Choosing $k_X(\cdot, X) = \langle \cdot, X\rangle_2$ and $k_Y(\cdot, Y) = \langle \cdot, Y\rangle_2$, for Gaussian distributions,

  $$X \perp Y \Leftrightarrow C_{YX} = 0$$

- In general,

  $$X \perp Y \overset{?}{\Leftrightarrow} C_{YX} = 0.$$

Dependence Measures

- How about we consider other singular values?
- How about $\|C_{YX}\|^2_{HS}$, which is the sum of squared singular values of C_{YX}?

  Hilbert-Schmidt Independence Criterion (HSIC) (Gretton et al., ALT 2005, JMLR 2005)
- $\|C_{YX}\|_{\text{op}} \leq \|C_{YX}\|_{HS}$

Dependence Measures

- $$COCO(\mathbb{P}_{XY}; \mathcal{H}_X, \mathcal{H}_Y) := \sup_{\substack{\|f\|_{\mathcal{H}_X}=1 \\ \|g\|_{\mathcal{H}_Y}=1}} \left|\mathbb{E}[f(X)g(Y)] - \mathbb{E}[f(X)]\mathbb{E}[g(Y)]\right|.$$

- How about we use different constraint, i.e., $\|f \otimes g\|_{\mathcal{H}_X \otimes \mathcal{H}_Y} \leq 1$?

$$\begin{aligned}
\sup_{\|f\otimes g\|_{\mathcal{H}_X\otimes\mathcal{H}_Y}\leq 1} \mathrm{Cov}(f(X), g(Y)) &= \sup_{\|f\otimes g\|_{\mathcal{H}_X\otimes\mathcal{H}_Y}\leq 1} \langle f, C_{XY} g\rangle_{\mathcal{H}_X} \\
&= \sup_{\|f\otimes g\|_{\mathcal{H}_X\otimes\mathcal{H}_Y}\leq 1} \langle f \otimes g, C_{XY}\rangle_{\mathcal{H}_X\otimes\mathcal{H}_Y} \\
&= \|C_{XY}\|_{\mathcal{H}_X\otimes\mathcal{H}_Y} = \|C_{XY}\|_{HS}
\end{aligned}$$

- $$\begin{aligned}
\|C_{XY}\|_{\mathcal{H}_X\otimes\mathcal{H}_Y} &= \|\mathbb{E}[k_X(\cdot, X) \otimes k_Y(\cdot, Y)] - \mu_{\mathbb{P}_X} \otimes \mu_{\mathbb{P}_X}\|_{\mathcal{H}_X\otimes\mathcal{H}_Y} \\
&= \left\| \int k_X(\cdot, X) \otimes k_Y(\cdot, Y)\, d(\mathbb{P}_{XY} - \mathbb{P}_X \times \mathbb{P}_Y) \right\|_{\mathcal{H}_X\otimes\mathcal{H}_Y} \\
&= MMD_{\mathcal{H}_X\otimes\mathcal{H}_Y}(\mathbb{P}_{XY}, \mathbb{P}_X \times \mathbb{P}_Y)
\end{aligned}$$

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Dependence Measures

- $\mathcal{H}_X \otimes \mathcal{H}_Y$ is an RKHS with kernel $k_X k_Y$.
- If $k_X k_Y$ is characteristic, then

$$\|C_{XY}\|_{\mathcal{H}_X \otimes \mathcal{H}_Y} = 0 \Leftrightarrow \mathbb{P}_{XY} = \mathbb{P}_X \times \mathbb{P}_Y \Leftrightarrow X \perp Y$$

- If k_X and k_Y are characteristic, then

$$\|C_{XY}\|_{HS} = 0 \Leftrightarrow X \perp Y.$$

(Zoltan & S., 2018)

- Using the reproducing property,

$$\begin{aligned}\|C_{XY}\|_{HS}^2 = \mathbb{E}_{XY}\mathbb{E}_{X'Y'} k_X(X,X') k_Y(Y,Y') \\ + \mathbb{E}_{XX'} k_X(X,X') \mathbb{E}_{YY'} k_Y(Y,Y') \\ -2 \cdot \mathbb{E}_{X'Y'} \left[\mathbb{E}_X k_X(X,X') \mathbb{E}_Y k_Y(Y,Y')\right]\end{aligned}$$

- Can be estimated using a V-statistic (empirical sums).

Applications

- Two-sample testing (Gretton et al., NIPS 2006, JMLR 2012; Harchaoui et al., NIPS 2008)
- Goodness-of-fit testing (Balasubramanian et al., 2017)
- Independence testing (Gretton et al., NIPS 2008)
- Conditional independence testing (Fukumizu et al., NIPS 2008)
- Supervised dimensionality reduction (Fukumizu et al., JMLR 2004)
- Kernel Bayes rule (filtering, prediction and smoothing) (Fukumizu et al., JMLR 2013)
- Distribution regression (Szabó et al., JMLR 2016)
- Kernel CCA (Fukumizu et al., JMLR 2007),....

Review paper (Muandet et al., 2017)

Application: Two-Sample Testing

Two-Sample Problem

- Given random samples $\{X_1, \ldots, X_m\} \stackrel{i.i.d.}{\sim} \mathbb{P}$ and $\{Y_1, \ldots, Y_n\} \stackrel{i.i.d.}{\sim} \mathbb{Q}$.
- Determine: $\mathbb{P} = \mathbb{Q}$ or $\mathbb{P} \neq \mathbb{Q}$?
- Approach:

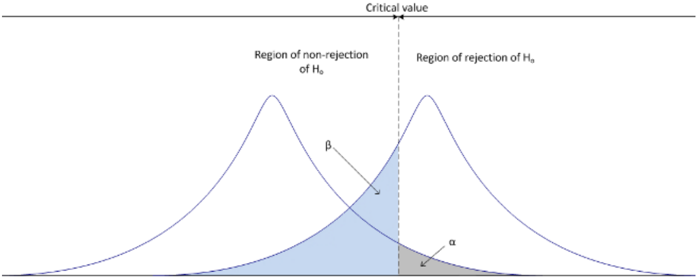
$$\begin{array}{c} H_0 : \mathbb{P} = \mathbb{Q} \\ H_1 : \mathbb{P} \neq \mathbb{Q} \end{array} \equiv \begin{array}{c} H_0 : MMD_{\mathcal{H}}(\mathbb{P}, \mathbb{Q}) = 0 \\ H_1 : MMD_{\mathcal{H}}(\mathbb{P}, \mathbb{Q}) > 0 \end{array}$$

- If $MMD^2_{\mathcal{H}}(\mathbb{P}_m, \mathbb{Q}_n)$ is
  - far from zero: reject H_0
  - close to zero: accept H_0

Type-I and Type-II Errors

Statistical decision	Truth: Null hypothesis true	Truth: Null hypothesis false
Reject null hypothesis	Type I error	Correct (power)
Do not reject null hypothesis	Correct	Type II error

- Given $\mathbb{P} = \mathbb{Q}$, want threshold or critical value $t_{1-\alpha}$ such that $\Pr_{H_0}(MMD^2_{\mathcal{H}}(\mathbb{P}_m, \mathbb{Q}_n) > t_{1-\alpha}) \leq \alpha$.



Statistical Test: Large Deviation Bounds

- Given $\mathbb{P} = \mathbb{Q}$, want threshold t such that $\Pr_{H_0}(MMD^2_{\mathcal{H}}(\mathbb{P}_m, \mathbb{Q}_n) > t) \leq \alpha$.
- We showed that (S et al., EJS 2012)

$$\Pr\Big(\big|MMD^2_{\mathcal{H}}(\mathbb{P}_m, \mathbb{Q}_n) - MMD^2_{\mathcal{H}}(\mathbb{P}, \mathbb{Q})\big| \geq \sqrt{\tfrac{2(m+n)}{mn}}\Big(1 + \sqrt{2\log\tfrac{1}{\alpha}}\Big)\Big) \leq \alpha.$$

- α-level test: Accept H_0 if

$$MMD^2_{\mathcal{H}}(\mathbb{P}_m, \mathbb{Q}_n) < \sqrt{\frac{2(m+n)}{mn}}\left(1 + \sqrt{2\log\frac{1}{\alpha}}\right)$$

Otherwise reject.

Too conservative!!

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Statistical Test: Asymptotic Distribution (Gretton et al., NIPS 2006, JMLR 2012)

Unbiased estimator of $MMD^2_{\mathcal{H}}(\mathbb{P},\mathbb{Q})$: U-statistic

$$\widehat{MMD}^2_{\mathcal{H}} := \frac{1}{m(m-1)} \sum_{i \neq j}^{m} \underbrace{k(X_i, X_j) + k(Y_i, Y_j) - k(X_i, Y_j) - k(X_j, Y_i)}_{h((X_i,Y_i),(X_j,Y_j))}$$

- Under H_0,

$$m\,\widehat{MMD}^2_{\mathcal{H}} \xrightarrow{w} \sum_{i=1}^{\infty} \lambda_i \left(\theta_i^2 - 2\right) \quad \text{as } n \to \infty,$$

where $\theta_i \sim \mathcal{N}(0,2)$ i.i.d., and λ_i are solutions to

$$\int_{\mathcal{X}} \underbrace{\widetilde{k}(x,y)}_{\text{centered}} \psi_i(x)\, d\mathbb{P}(x) = \lambda_i \psi_i(y)$$

- Consistent (Type-II error goes to zero): Under H_1,

$$\sqrt{m}\left(\widehat{MMD}^2_{\mathcal{H}} - MMD^2_{\mathcal{H}}(\mathbb{P},\mathbb{Q})\right) \xrightarrow{w} \mathcal{N}(0, \sigma_h^2) \quad \text{as } n \to \infty.$$

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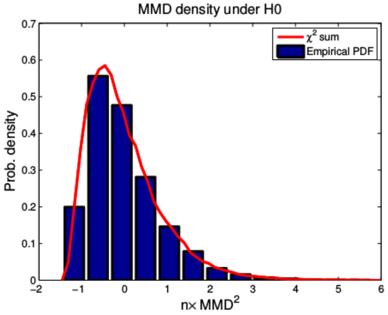
Statistical Test: Asymptotic Distribution (Gretton et al., NIPS 2006, JMLR 2012)

- α-level test: Estimate $1 - \alpha$ quantile of the null distribution using bootstrap.



Computationally intensive!!

Picture credit: A. Gretton

Statistical Test Without Bootstrap (Gretton et al., NIPS 2009)

- Estimate the eigenvalues, λ_i from combined samples
  - Define $Z := (X_1, \ldots, X_m, Y_1, \ldots, Y_m)$
  - $K_{ij} := k(Z_i, Z_j)$
  - Compute the eigenvalues, $\widehat{\lambda}_i$ of

$$\widetilde{K} = HKH$$

  where $H = I - \frac{1}{2m} 1_{2m} 1_{2m}^T$

- α-level test: Compute the $1 - \alpha$ quantile of the distribution associated with

$$\sum_{i=1}^{2m} \widehat{\lambda}_i \left(\theta_i^2 - 2\right)$$

- Test is asymptotically α-level consistent

Experiments (Gretton et al., NIPS 2009)

- Comparison example: Canadian Hansard corpus (agriculture, fisheries and immigration)
- Samples: 5-line extracts
- Kernel: k-spectrum kernel with $k = 10$
- Sample size: 10
- Repetitions: 300
- Compute $\widehat{MMD}^2_{\mathcal{H}}$

k-spectrum kernel: average Type II error 0 ($\alpha = 0.05$)

Bag of words kernel: average Type II error 0.18

First ever test on structured data

Choice of Characteristic Kernel

Choice of Characteristic Kernels

Let $\mathcal{X} = \mathbb{R}^d$. Suppose k is a Gaussian kernel, $k_\sigma(x, y) = e^{-\frac{\|x-y\|_2^2}{2\sigma^2}}$.

- $MMD_{\mathcal{H}_\sigma}$ is a function of σ.
- So $MMD_{\mathcal{H}_\sigma}$ is a family of metrics. Which one should we use in practice?
- Note that $MMD_{\mathcal{H}_\sigma} \to 0$ as $\sigma \to 0$ or $\sigma \to \infty$.

Therefore, the kernel choice is very critical in applications.

Heuristics:

- Median: $\sigma = \text{median}\left(\|X_i^* - X_j^*\|_2 : i \neq j,\ i, j = 1, \ldots, m\right)$ where $X^* = ((X_i)_i, (Y_i)_i)$ (Gretton et al., NIPS 2006, NIPS 2009, JMLR 2012).
- Choose the test statistic to be $MMD_{\mathcal{H}_{\sigma^*}}(\mathbb{P}_m, \mathbb{Q}_m)$ where

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Classes of Characteristic Kernels (S et al., NIPS 2009)

More generally, we use

$$MMD(\mathbb{P},\mathbb{Q}) := \sup_{k\in\mathcal{K}} MMD_{\mathcal{H}_k}(\mathbb{P},\mathbb{Q}).$$

Examples for $\mathcal{K}$:

- $\mathcal{K}_g := \{e^{-\sigma\|x-y\|_2^2}, x,y\in\mathbb{R}^d \,:\, \sigma\in\mathbb{R}_+\}$.
- $\mathcal{K}_{lin} := \{k_\lambda = \sum_{i=1}^{\ell}\lambda_i k_i | k_\lambda \text{ is pd}, \sum_{i=1}^{\ell}\lambda_i = 1\}$.
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Test:

- α-level test: Estimate $1-\alpha$ quantile of the null distribution of $MMD(\mathbb{P}_m,\mathbb{Q}_m)$ using bootstrap.
- Test consistency: Based on the functional central limit theorem for U-processes indexed by VC-subgraph $\mathcal{K}$.

Computational disadvantage!!

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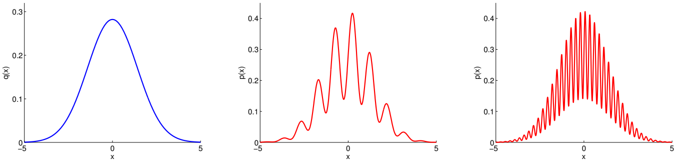
Experiments

- $q = \mathcal{N}(0, \sigma_q^2)$.
- $p(x) = q(x)(1 + \sin \nu x)$.

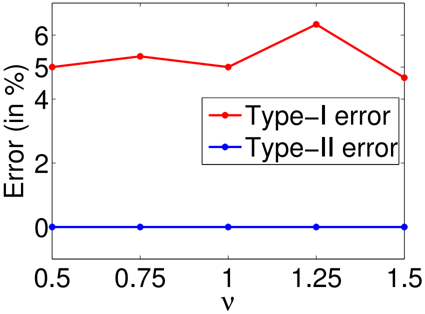


$\nu = 0$ $\quad$ $\nu = 2$ $\quad$ $\nu = 7.5$

- $k(x, y) = \exp(-(x - y)^2/\sigma)$.
- Test statistics: $MMD(\mathbb{P}_m, \mathbb{Q}_m)$ and $MMD_{\mathcal{H}_\sigma}(\mathbb{P}_m, \mathbb{Q}_m)$ for various σ.

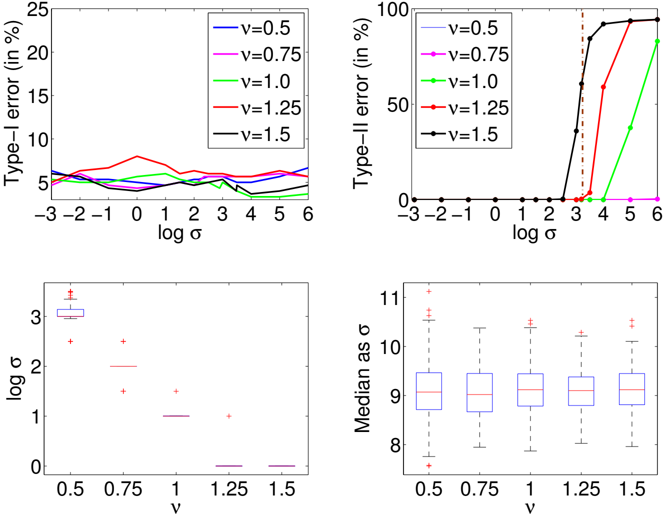
Experiments

$MMD(\mathbb{P}, \mathbb{Q})$



Experiments

$$MMD_{\mathcal{H}_\sigma}(\mathbb{P}, \mathbb{Q})$$



Choice of Characteristic Kernels (Gretton et al., NIPS 2012)

- Choose a kernel that minimizes the Type-II error for a given Type-I error:

$$k^* \in \arg \inf_{k \in \mathcal{K}:\, Type_I(k) \leq \alpha} Type_{II}(k).$$

- Not easy to compute with the asymptotic distributions of the U-statistic, $\widehat{MMD}^2_{\mathcal{H}_k}(\mathbb{P}_m, \mathbb{Q}_m)$.

- Modified statistic: Average of U-statistics computed on independent blocks of size 2.

$$\widetilde{MMD}^2_{\mathcal{H}_k}(\mathbb{P}_m, \mathbb{Q}_m) = \frac{2}{m} \sum_{i=1}^{m/2} \underbrace{k(X_{2i-1}, X_{2i}) + k(Y_{2i-1}, Y_{2i}) - k(X_{2i-1}, Y_{2i}) - k(Y_{2i-1}, X_{2i})}_{h_k(Z_i)},$$

where $Z_i = (X_{2i-1}, X_{2i}, Y_{2i-1}, Y_{2i})$.

- Recall

$$\widehat{MMD}^2_{\mathcal{H}} := \frac{1}{m(m-1)} \sum_{i \neq j}^{m} \underbrace{k(X_i, X_j) + k(Y_i, Y_j) - k(X_i, Y_j) - k(X_j, Y_i)}_{h((X_i, Y_i), (X_j, Y_j))}$$

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- Not easy to compute with the asymptotic distributions of the U-statistic, $\widehat{MMD}^2_{\mathcal{H}_k}(\mathbb{P}_m, \mathbb{Q}_m)$.

- Modified statistic: Average of U-statistics computed on independent blocks of size 2.

$$\widetilde{MMD}^2_{\mathcal{H}_k}(\mathbb{P}_m, \mathbb{Q}_m) = \frac{2}{m} \sum_{i=1}^{m/2} \underbrace{k(X_{2i-1}, X_{2i}) + k(Y_{2i-1}, Y_{2i}) - k(X_{2i-1}, Y_{2i}) - k(Y_{2i-1}, X_{2i})}_{h_k(Z_i)},$$

where $Z_i = (X_{2i-1}, X_{2i}, Y_{2i-1}, Y_{2i})$.

- Recall

$$\widehat{MMD}^2_{\mathcal{H}} := \frac{1}{m(m-1)} \sum_{i \neq j}^{m} \underbrace{k(X_i, X_j) + k(Y_i, Y_j) - k(X_i, Y_j) - k(X_j, Y_i)}_{h((X_i, Y_i), (X_j, Y_j))}$$

Modified Statistic

Advantages:

- $\widetilde{MMD}^2_{\mathcal{H}}$ is computable in $O(m)$ while $\widehat{MMD}^2_{\mathcal{H}}$ requires $O(m^2)$ computations.
- Under H_0,
$$\sqrt{m}\,\widetilde{MMD}^2_{\mathcal{H}_k}(\mathbb{P}_m, \mathbb{Q}_m) \xrightarrow{w} \mathcal{N}(0, 2\sigma^2_{h_k}),$$
where $\sigma^2_{h_k} = \mathbb{E}_Z h^2_k(Z) - (\mathbb{E}_Z h_k(Z))^2$ assuming $0 < \mathbb{E}_Z h^2_k(Z) < \infty$.
- The asymptotic distribution is normal as against weighted sum of infinite χ^2. Therefore, the test threshold is easy to compute.

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- Larger variance
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Type-I and Type-II Errors

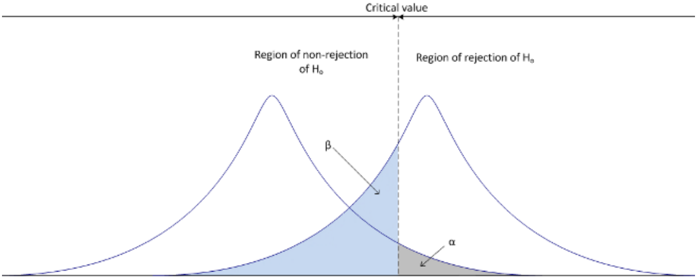
- Test threshold: For a given k and α,

$$t_{k,1-\alpha} = \sqrt{2}\sigma_{h_k}\Phi_N^{-1}(1-\alpha)$$

where Φ_N is the cdf of $\mathcal{N}(0,1)$.

- Type-II error:

$$\Phi_N\left(\Phi_N^{-1}(1-\alpha) - \frac{MMD^2_{\mathcal{H}_k}(\mathbb{P},\mathbb{Q})\sqrt{m}}{\sqrt{2}\sigma_{h_k}}\right)$$



Best Kernel: Minimizes Type-II Error

- Since Φ_N is a strictly increasing function, the Type-II error is minimized by maximizing $\frac{MMD^2_{\mathcal{H}_k}(\mathbb{P},\mathbb{Q})}{\sigma_{h_k}}$.
- Optimal kernel:

$$k^* \in \arg\sup_{k \in \mathcal{K}} \frac{MMD^2_{\mathcal{H}_k}(\mathbb{P},\mathbb{Q})}{\sigma_{h_k}}.$$

- Since $MMD^2_{\mathcal{H}_k}$ and σ_{h_k} depend on unknown $\mathbb{P}$ and $\mathbb{Q}$, we split the data into train and test data to estimate k^* on the train data as $\hat{k}^*$ and evaluate the threshold $t_{\hat{k}^*,1-\alpha}$ on the test data.

Data-Dependent Kernel

- Train data: $\widetilde{MMD}^2_{\mathcal{H}_k}$ and $\hat{\sigma}_{h_k}$.
- Define

$$\hat{k}^* \in \arg\sup_{k \in \mathcal{K}} \frac{\widetilde{MMD}^2_{\mathcal{H}_k}}{\hat{\sigma}_{h_k} + \lambda_m}$$

  for some $\lambda_m \to 0$ as $m \to \infty$.
- Test data: $\widetilde{MMD}^2_{\mathcal{H}_{\hat{k}^*}}$, $\hat{\sigma}_{h_{\hat{k}^*}}$ and $t_{\hat{k}^*, 1-\alpha}$.
- If $\widetilde{MMD}^2_{\mathcal{H}_{\hat{k}^*}} > t_{\hat{k}^*, 1-\alpha}$, reject H_0, else accept.

Similar results are recently obtained for $\widehat{MMD}^2_{\mathcal{H}_k}$ (Sutherland et al., ICLR 2017)

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Advanced Topics

- Consistency of kernel CCA (Fukumizu et al., JMLR 2007)
- Convergence rates for kernel-based hypothesis tests (Balasubramanian et al., 2017)
- Conditional covariance operators and applications

Questions

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