

Q3 of HW2

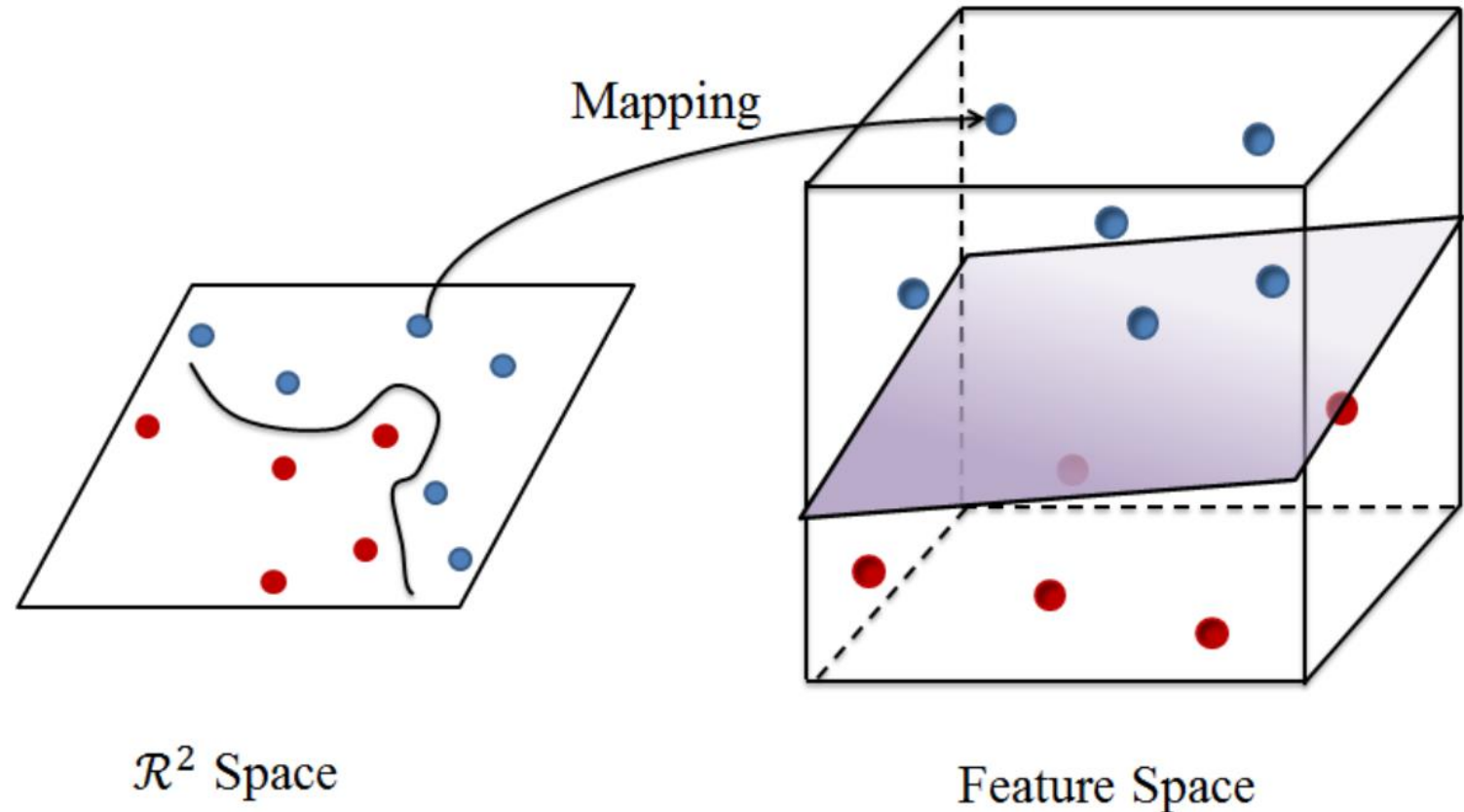
Reference:

“Random Features for Large-Scale Kernel Machines”

Test of Time Award, NeurIPS (NIPS) 2017

High level idea

- Motivation:
Classification easier
- Issue:
Expensive
- Solution:
Linear



Detail

Kernels:

$$, k(\mathbf{x}_1 - \mathbf{x}_2) = e^{-\frac{\|\mathbf{x}_1 - \mathbf{x}_2\|_2^2}{2\sigma^2}} \circ$$

$$\therefore k(\mathbf{x}_1 - \mathbf{x}_2) = e^{-\|\mathbf{x}_1 - \mathbf{x}_2\|_1} \circ$$

$$k(\mathbf{x}_1 - \mathbf{x}_2) = \prod_d \frac{2}{1 + \|\mathbf{x}_1 - \mathbf{x}_2\|_d^2} \circ$$

$$k(\mathbf{x}_1 - \mathbf{x}_2) = \int_{\mathbb{R}^d} p(\mathbf{w}) e^{-j\mathbf{w}^\top (\mathbf{x}_1 - \mathbf{x}_2)} d\mathbf{w}$$

$$= \int_{\mathbb{R}^d} p(\mathbf{w}) \cos(\mathbf{w}^\top (\mathbf{x}_1 - \mathbf{x}_2)) d\mathbf{w}$$

$$= \mathbb{E}_{\mathbf{w} \sim p(\mathbf{w})} [\cos(\mathbf{w}^\top (\mathbf{x}_1 - \mathbf{x}_2))] \circ$$

$$= \mathbb{E}_{\mathbf{w} \sim p(\mathbf{w})} [\cos(\mathbf{w}^\top \mathbf{x}_1) \cos(\mathbf{w}^\top \mathbf{x}_2) + \sin(\mathbf{w}^\top \mathbf{x}_1) \sin(\mathbf{w}^\top \mathbf{x}_2)]$$



$$\mathbb{E}_{\mathbf{w} \sim p(\mathbf{w})} [\cos(\mathbf{w}^\top \mathbf{x}_1) \cos(\mathbf{w}^\top \mathbf{x}_2) + \sin(\mathbf{w}^\top \mathbf{x}_1) \sin(\mathbf{w}^\top \mathbf{x}_2)] \approx \frac{1}{n} \sum_{i=1}^n \cos(\mathbf{w}_i^\top \mathbf{x}_1) \cos(\mathbf{w}_i^\top \mathbf{x}_2) + \sin(\mathbf{w}_i^\top \mathbf{x}_1) \sin(\mathbf{w}_i^\top \mathbf{x}_2)$$



$$z(\mathbf{x}_1) = \frac{1}{\sqrt{n}} (\cos(\mathbf{w}_1^\top \mathbf{x}_1), \dots, \cos(\mathbf{w}_D^\top \mathbf{x}_1), \sin(\mathbf{w}_1^\top \mathbf{x}_1), \dots, \sin(\mathbf{w}_n^\top \mathbf{x}_1))$$

$$z(\mathbf{x}_2) = \frac{1}{\sqrt{n}} (\cos(\mathbf{w}_1^\top \mathbf{x}_2), \dots, \cos(\mathbf{w}_D^\top \mathbf{x}_2), \sin(\mathbf{w}_1^\top \mathbf{x}_2), \dots, \sin(\mathbf{w}_n^\top \mathbf{x}_2))$$



$$p(\mathbf{w}) = \frac{1}{(2\pi)^n} \int_{\mathbb{R}^d} e^{j\mathbf{w}^\top (\mathbf{x}_1 - \mathbf{x}_2)} k(\mathbf{x}_1 - \mathbf{x}_2) d(\mathbf{x}_1 - \mathbf{x}_2) \rightarrow p(\mathbf{w}) = e^{-\frac{\|\mathbf{w}\|_2^2 \sigma^2}{2}} \sigma^d (2\pi)^{-\frac{d}{2}} \sim \mathcal{N}(\mathbf{0}, \Sigma)$$

Implementation

- Implement:
 - `theta, Omega, B = random_fourier_features(data_X, data_Y, num_fourier_features=10, alpha=0.1, num_iters=500)`
 - `vis_rff_model(train_X, train_Y, theta, Omega, B)`
- Result
 - 12 Figure with 4 dataset, and each dataset with 3 different `num_fourier_features(K)`

Note: for input `data_X` of `random_fourier_features` has one 1 column appended.

In random_fourier_features

Algorithm 1 Random Fourier Features.

Require: A positive definite shift-invariant kernel $k(\mathbf{x}, \mathbf{y}) = k(\mathbf{x} - \mathbf{y})$.

Ensure: A randomized feature map $\mathbf{z}(\mathbf{x}) : \mathcal{R}^d \rightarrow \mathcal{R}^D$ so that $\mathbf{z}(\mathbf{x})' \mathbf{z}(\mathbf{y}) \approx k(\mathbf{x} - \mathbf{y})$.

Compute the Fourier transform p of the kernel k : $p(\omega) = \frac{1}{2\pi} \int e^{-j\omega' \delta} k(\delta) d\Delta$.

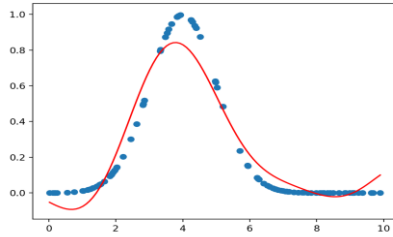
Draw D iid samples $\omega_1, \dots, \omega_D \in \mathcal{R}^d$ from p and D iid samples $b_1, \dots, b_D \in \mathcal{R}$ from the uniform distribution on $[0, 2\pi]$.

Let $\mathbf{z}(\mathbf{x}) \equiv \sqrt{\frac{2}{D}} [\cos(\omega_1' \mathbf{x} + b_1) \dots \cos(\omega_D' \mathbf{x} + b_D)]'$.

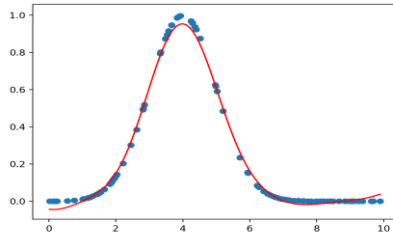
- Only Calculate Omega and B
- What's the Omega?
 - iid samples $\omega_1, \dots, \omega_D \in \mathcal{R}^d$ from p , You can generate Omega using normal random distribution with mean = 0, sigma = 1
- What's the B?
 - $B = b_1, \dots, b_D \in \mathcal{R}$ from the uniform distribution on $[0, 2\pi]$

Example Result for 1D-exp-samp.txt

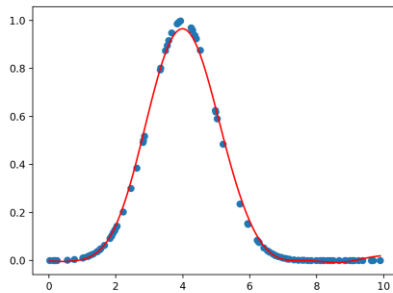
- $K = 10$



- $K = 100$



- $K = 800$



Please also generate the figure for other 3 dataset.

Thanks!

Feel free to email for the additional office hour
for more questions!