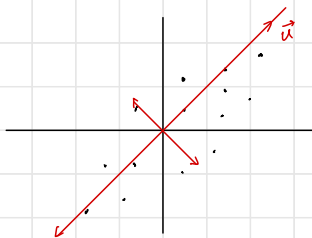


PCA

$$\max_{\|u\|_2=1} \frac{1}{n} \sum_{i=1}^n \left(u^T (x_i - \frac{1}{n} \sum_{i=1}^n x_i) \right)^2$$



kernel PCA: Approach I (makes more sense to me in optimization viewpoint)

$$\max_{\|f\|_{\mathcal{H}} \leq 1} \frac{1}{n} \sum_{i=1}^n \left\langle f, \phi(x_i) - \frac{1}{n} \sum_{i=1}^n \phi(x_i) \right\rangle_{\mathcal{H}}^2$$

$$\Rightarrow \max_{\|f\|_{\mathcal{H}} \leq 1} \frac{1}{n} \sum_{i=1}^n \left\langle \sum_{j=1}^m \alpha_j \phi(x_j), \phi(x_i) - \frac{1}{n} \sum_{i=1}^n \phi(x_i) \right\rangle_{\mathcal{H}}^2$$

$$\Rightarrow \max_{\|f\|_{\mathcal{H}} \leq 1} \frac{1}{n} \sum_{i=1}^n \left[\sum_{j=1}^m \alpha_j \left(K(x_j, x_i) - \frac{1}{n} \sum_{i=1}^n K(x_j, x_i) \right) \right]^2$$

$$\Rightarrow \max_{\|f\|_{\mathcal{H}} \leq 1} \frac{1}{n} \sum_{i=1}^n \left[\alpha^T \tilde{K}_i \right]^2 \quad \tilde{K}_i[j] = K(x_j, x_i) - \frac{1}{n} \sum_{i=1}^n K(x_j, x_i)$$

$$\Rightarrow \max_{\|f\|_{\mathcal{H}} \leq 1} \alpha^T \underbrace{\left(\frac{1}{n} \sum_{i=1}^n \tilde{K}_i \tilde{K}_i^T \right)}_{\tilde{K}} \alpha$$

$$\|f\|_{\mathcal{H}}^2 = \sum_{i,j} \alpha_i \alpha_j K(x_i, x_j) = \alpha^T K \alpha$$

↓

$$\begin{array}{ccc} \max_{\alpha} & \alpha^T \tilde{K} \alpha & \xrightarrow[\alpha = \tilde{K}^{\frac{1}{2}} \beta]{\beta = \tilde{K}^{\frac{1}{2}} \alpha} \max_{\beta} \beta^T \tilde{K}^{\frac{1}{2}} \tilde{K}^{\frac{1}{2}} \beta \\ \text{s.t.} & \alpha^T K \alpha \leq 1 & \text{s.t. } \|\beta\|_2 \leq 1 \end{array}$$

β^* = eigenvector with maximum eigenvalue of $\tilde{K}^{\frac{1}{2}} \tilde{K}^{\frac{1}{2}}$

$$\alpha^* = \tilde{K}^{-\frac{1}{2}} \beta^*$$

remark. if β, β are orthogonal eigenvectors of $\tilde{K}^{\frac{1}{2}} \tilde{K}^{\frac{1}{2}}$

then $\alpha_1 = \tilde{K}^{\frac{1}{2}} \beta_1$ are orthogonal eigenvectors of $\tilde{K}$

then the subspace $\sum \alpha_1 [\cdot] \phi(x_i, \cdot)$ and $\sum \alpha_2 [\cdot] \phi(x_i, \cdot)$ are orthogonal in $\mathcal{H}$

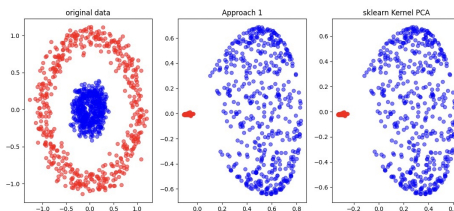
$$\left\langle \sum \alpha_1 [\cdot] \phi(x_i, \cdot), \sum \alpha_2 [\cdot] \phi(x_i, \cdot) \right\rangle_{\mathcal{H}}$$

$$= \alpha_1^T \tilde{K} \alpha_2$$

$$= 0$$

$$\phi(x_i) = \phi(x_i) - \frac{1}{n} \sum_{i=1}^n \phi(x_i)$$

projection: $\langle \phi(z), \sum \alpha_i \phi(x_i) \rangle = \sum \alpha_i K(x_i, z)$



• Kernel PCA : Approach II (most online resource follows this approach)

$$\tilde{\phi}(x_i) = \phi(x_i) - \frac{1}{n} \sum_{j=1}^n \phi(x_j)$$

$$\tilde{K}(x_i, x_j) = \langle \tilde{\phi}(x_i), \tilde{\phi}(x_j) \rangle$$

$$= \langle \phi(x_i) - \frac{1}{n} \sum_{k=1}^n \phi(x_k), \phi(x_j) - \frac{1}{n} \sum_{k=1}^n \phi(x_k) \rangle$$

$$= K(x_i, x_j) - \frac{1}{n} \sum_{k=1}^n K(x_k, x_j) - \frac{1}{n} \sum_{k=1}^n K(x_k, x_i) + \frac{1}{n} \sum_{k=1}^n \sum_{l=1}^n K(x_k, x_l) \quad \left. \vphantom{\sum_{k=1}^n \sum_{l=1}^n K(x_k, x_l)} \right\} \text{ is this a valid kernel?}$$

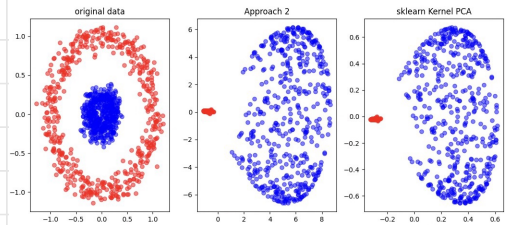
$$\max_{\|\alpha\| \leq 1} \frac{1}{n} \left\langle \sum_{j=1}^n \alpha_j \tilde{\phi}(x_j), \tilde{\phi}(x_i) \right\rangle^2$$

$$\Rightarrow \max_{\|\alpha\| \leq 1} \frac{1}{n} \sum_{j=1}^n \left(\sum_{i=1}^n \alpha_i \tilde{K}(x_i, x_j) \right)^2$$

$$\Rightarrow \max_{\|\alpha\| \leq 1} \frac{1}{n} \sum_{j=1}^n \left(\alpha^T \tilde{E}_j \right) \quad \tilde{E}_i[j] = \tilde{K}(x_i, x_j)$$

$$\Rightarrow \max_{\|\alpha\| \leq 1} \alpha^T \left(\frac{1}{n} \sum_{j=1}^n \tilde{E}_j \tilde{E}_j^T \right) \alpha$$

$$\Rightarrow \max_{\|\alpha\| \leq 1} \alpha^T \tilde{K} \alpha \quad \tilde{K}_{ij} = \tilde{K}(x_i, x_j)$$



different scale than sklearn

$$\|\tilde{f}\|^2 = \sum_i \alpha_i \alpha_j \tilde{K}(x_i, x_j) = \alpha^T \tilde{K} \alpha$$

↓

$$\left. \begin{array}{l} \max_{\alpha} \quad \alpha^T \tilde{K} \alpha \\ \text{s.t.} \quad \alpha^T \tilde{K} \alpha \leq 1 \end{array} \right\} \alpha^* \text{ is the eigenvector with maximum eigenvalue}$$

$$\text{projection: } \langle \tilde{\phi}(z), \sum_i \alpha_i \tilde{\phi}(x_i) \rangle = \sum_i \alpha_i \tilde{K}(x_i, z)$$

can we do this for $x \neq z$?

Anyway, I give more trust to Approach 1.

even if it needs 2 eigenvalue decompositions :)