

## Homework-4

= Given

Design matrix =  $X$

Covariance matrix =  $C = \frac{1}{n} X^T X$

Eigenvectors:  $v_1, v_2, \dots, v_k$

$\tilde{x}_i^o$  is the orthogonal projection of  $x_i^o$ , column vectors representing a data point, orthogonal to  $v_1$

$$\tilde{x}_i^o = (I - v_1 v_1^T) x_i^o$$

$\tilde{X}_T = [\tilde{x}_1, \dots, \tilde{x}_n]$  deflated matrix, lies in the direction of the first principal eigenvector

$$\tilde{X}_T = (I - v_1 v_1^T) X^T$$

$$C = \frac{1}{n} X^T X = V \tilde{\Lambda}_n V^T$$

Let's suppose that the kernel matrix is  $K = X X^T$

$$\text{So, } K = X X^T = U \Lambda_m U^T$$

The columns  $v_i^o$  of the orthonormal matrix  $V$  are the eigenvectors of  $C$  and the columns  $u_i^o$  of the orthonormal

matrix  $U$  are the eigenvectors of  $K$ . Considering an eigen-vector eigen-value pair  $u, \lambda$  of  $K$ .

$$C = \frac{1}{n} (X^T U) = X^T X X^T U = X^T K U = \lambda X^T U$$

$X^T U, \lambda$  is an eigen-vector-eigenvalue pair for  $C$ .

$$\|X^T U\|^2 = U^T X X^T U = \lambda$$

So the normalised eigenvector of  $C$  is  $v_1 = \lambda^{-\frac{1}{2}} X^T U$ .

$$U = \lambda^{-\frac{1}{2}} X v_1$$

Deflating  $X$ ,

$$\tilde{X} = X - U U^T X = X - \lambda^{\frac{1}{2}} U v_1' = X - X v_1 v_1'$$

$$\tilde{C} = \tilde{X}^T \tilde{X} = \frac{1}{n} (X - U U^T X)^T (X - U U^T X)$$

$$= \frac{1}{n} (X^T X - X^T U U^T X)$$

$$\boxed{= \frac{1}{n} (X^T X - \lambda v_1 v_1^T)}$$

$$0) \quad C v_j^0 = \lambda_j^0 v_j^0$$

$$\tilde{C} = C - \lambda_j^0 v_j^0 v_j^{0T}$$

$$(C - \lambda_j^0 v_j^0 v_j^{0T}) v_j^0$$

$$= C v_j^0 - \lambda_j^0 v_j^0 v_j^{0T} v_j^0$$

$$= \lambda_j^0 v_j^0 - \lambda_j^0 v_j^0 (v_j^{0T} v_j^0)$$

$$\text{if } j \neq 1, \text{ then } (C - \lambda_j^0 v_j^0 v_j^{0T}) v_j^0 = \lambda_j^0 v_j^0 - \lambda_j^0 v_j^0 (0) = \lambda_j^0 v_j^0$$

Thus  $(C - \lambda_j^0 v_j^0 v_j^{0T}) = \tilde{C}$  has the same eigenvectors as  $C$  and the same eigenvalues as  $C$  except that the largest one has been replaced by 0.

1) Hotelling deflation assumes that the largest eigenvalue  $\lambda_1$  and an associated eigenvector  $v(1)$  of  $C$  have been obtained from its deflation matrix  $\tilde{C}$ , which has the same eigenvalues  $\lambda_2 \dots \lambda_j^0$  as  $C$  except that  $\tilde{C}$  has eigenvalue 0 with eigenvector  $v(1)$  instead of eigenvalue  $\lambda_1$ .



So if  $u$  be the first principal eigenvector of  $\tilde{C}$   
 $u = v_2$  because the first eigenvector is zero.

(d) After  $k$  iterations,  
 $C^k u_0 = \lambda^k \left[ c_1 u_1 + c_2 \left( \frac{\lambda_2}{\lambda_1} \right)^k u_2 + \dots + c_n \left( \frac{\lambda_n}{\lambda_1} \right)^k u_n \right]$  [ $u_0 = c_1 u_1 + \dots + c_n u_n$ ]  
Since here  $\lambda_1$  dominates, the ratio  $\left( \frac{\lambda_i}{\lambda_1} \right)^k \rightarrow 0$  as  $k \rightarrow \infty$   
for all  $i$ . Therefore,  $C^k u_0 = \lambda_1^k c_1 u_1$  gets better as  $k$   
grows. Here  $c_1, \dots, c_n$  is constant.

So, For large powers of  $k$  we will obtain a good  
approximation of the dominant eigenvector.

For  $k$  iteration, the computational complexity is  
 $O(k^2)$ .

In each iteration if we do  $u_i^0 = \frac{C u_{i-1}^0}{\|C u_{i-1}^0\|_2}$ ,

this can be a better approach because the

Power method tends to produce approximations with large entries. In practice it is best to 'scale down' each approximation before proceeding to the next iteration.

The way to accomplish this scaling is to determine the component of  $Cv_i$  that has the largest absolute value.

e) The computational complexity is:  $O(Km^2)$

(See code)



## Problem 2

a) We have to set  $\epsilon$  and  $c$  such that  $\min_i \|q - x_i\| \leq \epsilon$  and  $\|q - x'_i\| \leq c\epsilon$ . More specifically, an  $\epsilon$ -near query with constant factor  $c$  will return a  $j$  such that  $\|q - x'_j\| \leq c\epsilon$  if there is some  $i$  so that  $\min_i \|q - x_i\| \leq \epsilon$ .

We can do this by solving nearest neighbor checking  $\epsilon$  with  $\epsilon = 1, 2, 4, 8, \dots, R$

We only need to give output if there is a point within  $\epsilon$ , even if something within  $c\epsilon$ .

b) Given,

$$h(x_i^0) = x_i^0[a]$$

For each point  $x_i^0, x_j^0 \in \{0,1\}^d$

$$* \Pr(h(x_i^0) = h(x_j^0)) \geq P_1$$

where  $P_1 = 1 - \frac{r_0}{d} \approx e^{-r_0/d}$  if  $\text{dist}(x_i^0, x_j^0) \leq r_0$

$$* \Pr(h(x_i^0) = h(x_j^0)) \leq P_2$$

where  $P_2 = 1 - \frac{cr_0}{d} \approx e^{-cr_0/d}$  if  $\text{dist}(x_i^0, x_j^0) \geq cr_0$

Here  $\boxed{P_1 > P_2}$

$$c) \Pr(g(x_i^0) = g(x_j^0)) \geq P_1^K \text{ [lower bound] } [d(x_i^0, x_j^0) \leq r_0]$$

$$\Pr(g(x_i^0) = g(x_j^0)) \leq P_2^K \text{ [upper bound] } [d(x_i^0, x_j^0) \geq cr_0]$$

$$d) \Pr(g_b(x_i^0) = g_b(x_j^0)) \geq 1 - \frac{1}{n} \text{ [LB] } [d(x_i^0, x_j^0) \leq r_0]$$

$$\Pr(g_b(x_i^0) = g_b(x_j^0)) \leq \frac{1}{n} \text{ [UB] } [d(x_i^0, x_j^0) \geq cr_0]$$



$$e) k = \frac{\ln(n)}{\ln(1/P_2)}$$

This implies that for fixed  $b$ , the expected numbers of  $x'$  that map to the same bucket as  $q$  is at most  $n \times \frac{1}{n} = 1$ .

Applying linearity of expectation over all  $l$  buckets, the expected number of false positive is at most  $l$ .

By Markov's inequality the probability there are more than  $4l$  false positives is therefore at most  $\frac{1}{4}$  and at least  $\boxed{\frac{3}{4}}$ .

According to first event, for any  $b$

$$\Pr[g_b(x^*) \neq g_b(q)] \leq 1 - P_1^k = 1 - n^{-\rho} = 1 - \frac{1}{n^\rho} \quad \left[ k = \frac{\ln(n)}{\ln(1/P_2)} \right]$$

$$\rho = \frac{\ln(P_1)}{\ln(P_2)}$$

$$\text{As } l = n^\rho,$$

$$\Pr[g_b(x^*) \neq g_b(q) \forall i] \leq \left(1 - \frac{1}{n^\rho}\right)^{n^\rho} \leq \frac{1}{e}$$

So, the first event holds with probability at least  $\boxed{1 - \frac{1}{e}}$



With union bound the probability of both event holding at least:

$$1 - \frac{1}{4} - 1/e \geq \frac{1}{3}$$

2f) In expectation, there are  $O(d)$  points in the data set which map to same hash functions as  $q$  for some  $k$ . We need to examine these points to check if any of them within distance  $\epsilon_0$  from  $q$ .

No, it is not guaranteed that there is a point with distance at most  $\epsilon_0$  because the probability of upper bound is very low (only  $1/n$ ).