# ML Written Homework 1

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## 1 Linear Algebra Recap

(a) (i)  $\Rightarrow$  (ii) **A** is positive semi-definite implies **A** is symmetric. Since **A** is symmetric, **A** is diagonalizable. Suppose  $\lambda_1, \lambda_2, ..., \lambda_n$  are the eigenvalues of **A**, there are eigenvectors  $v_1, v_2, ..., v_n$  such that  $\mathbf{A}v_k = \lambda_k v_k$ .

By the definition of positive semi-definite, we have

$$\langle \mathbf{A}v_k, v_k \rangle = \langle \lambda_k v_k, v_k \rangle = \lambda_k \|v_k\|^2 \ge 0$$

Hence, all eigenvalues  $\lambda_k \geq 0$ .

(ii)  $\Rightarrow$  (iii) **A** is symmetric and all of eigenvalues  $\lambda_k$  are non negative. Since **A** is symmetric, **A** is diagonalizable. That is, there are P, D such that  $\mathbf{A} = P^T D P$ , where  $\mathbf{D} = diag(\lambda_1, \lambda_2, ..., \lambda_n)$ .

Since  $\lambda_k \geq 0$ , we can find  $e_k = \sqrt{\lambda_k}$  and  $E = diag(e_1, e_2, ..., e_n)$  so that  $D = E^2$ . Now we have

$$\mathbf{A} = P^T D P = P^T E E P = (P^T E)(EP) = (EP)^T (EP)$$

Hence,  $\mathbf{A} = \mathbf{B}^T \mathbf{B}$  where  $\mathbf{B} = EP$ 

(iii)  $\Rightarrow$  (i)  $\mathbf{A} = \mathbf{B}^T \mathbf{B}$ , then we have

$$u^T \mathbf{A} u = u^T \mathbf{B}^T \mathbf{B} u = (\mathbf{B} u)^T (\mathbf{B} u) = \|\mathbf{B} u\|^2 \ge 0$$

for all  $u \in V$ . Hence, **A** is positive semi-definite.

- (b) Note that  $\langle \mathbf{A}^T \mathbf{A} x, x \rangle = \langle \mathbf{A} x, \mathbf{A} x \rangle = ||\mathbf{A} x||^2 \ge 0$  for all  $x \in V$ . By (a),  $\mathbf{A}^T \mathbf{A}$  is positive semi-definite. Hence the eigenvalues of  $\mathbf{A}^T \mathbf{A}$  are nonnegative.
- (c) For  $x \in Null(\mathbf{A})$ , we have  $\mathbf{A}^T \mathbf{A} x = 0$ , so that  $x \in Null(\mathbf{A}^T \mathbf{A})$ . For  $x \in Null(\mathbf{A}^T \mathbf{A})$ ,

$$\langle \mathbf{A}^T \mathbf{A} x, x \rangle = \langle \mathbf{A} x, \mathbf{A} x \rangle = \| \mathbf{A} x \|^2 = 0$$

which implies  $\mathbf{A}x = 0$ . Hence  $x \in Null(\mathbf{A})$ . By the above, we can find that  $Null(\mathbf{A}) = Null(\mathbf{A}^T\mathbf{A})$ .

- (d)  $\langle \mathbf{A}v_i, \mathbf{A}v_j \rangle = \langle \mathbf{A}^T \mathbf{A}v_i, v_j \rangle = \langle \lambda_i v_i, v_j \rangle = 0$  for any  $i \neq j$ . Hence  $\{\mathbf{A}v_1, ..., \mathbf{A}v_r\}$  is an orthogonal set.
- (e) Suppose V is a  $n \times n$  matrix whose i-th column is  $v_i$ , then V is an orthogonal matrix where  $\mathbf{A}^T \mathbf{A} = VDV^T$ . Let U be a  $m \times m$  matrix with its i-th column  $u_i$ , where  $u_i = \frac{\mathbf{A}v_i}{\sigma_i}$ , and  $\Sigma$  be a  $m \times n$  matrix with its diagonal entries  $\sigma_i$ .

Then we have the relation:

$$U\Sigma = \mathbf{A}V \Rightarrow \mathbf{A} = U\Sigma V^T$$

By (d),  $\{\mathbf{A}v_1, ..., \mathbf{A}v_r\}$  is an orthogonal set, we have  $\{\mathbf{u}_1, ..., \mathbf{u}_r\}$  is also an orthogonal set. Hence U is also an orthogonal matrix.

## 2 Definition of Derivative as Linear Operator

Assume f(n), g(n), h(n) are all positive function.

(a)  $f(n) \in O(g(n))$  and  $g(n) \in O(h(n))$  gives us  $f(n) \le c_1 g(n), g(n) \le c_2 h(n)$ . Hence we have

$$f(n) \le c_1 g(n) \le c_1 c_2 h(n) \le c h(n)$$

This gives us  $f(n) \in O(h(n))$ 

(b)  $f(n) \in O(g(n))$  means  $f(n) \le c_1 g(n)$ . Since f(n), g(n) are positive, we have  $c_1$  also be positive. Hence we have

$$g(n) \ge \frac{1}{c_1} f(n)$$

This gives us  $g(n) \in \Omega(f(n))$ 

(c)  $f(n) \in \omega(g(n))$  means for all constants c > 0, there exists an  $n_0$  such that f(n) > cg(n) when  $n \ge n_0$ .

Then we have for all constants c > 0, there exists an  $n_0$  such that  $g(n) < \frac{1}{c}f(n)$  when  $n \ge n_0$ . This gives us  $g(n) \in o(f(n))$ .

#### 3 Matrix Calculus

(a) Here we use limit supremum to prove.

$$\limsup_{n \to \infty} \frac{2^{2n}}{2^{2n+1024}} = \limsup_{n \to \infty} \frac{1}{2^{1024}} = \frac{1}{2^{1024}} < \infty$$

Hence  $2^{2n} \in O(2^{2n+1024})$ 

(b) Note that  $\log_{1024} n^2 = 2 \log_{1024} n = 2 \frac{\log n}{\log 1024}$ ,  $\log_2 n^{1024} = 1024 \log_2 n = 1024 \frac{\log n}{\log 2}$ . Then we have

$$\limsup_{n \to \infty} \frac{\log_{1024} n^2}{\log_2 n^{1024}} = \limsup_{n \to \infty} \frac{\frac{2 \log n}{\log 1024}}{\frac{1024 \log n}{\log 2}} = \limsup_{n \to \infty} \frac{2 \log 2}{1024 \log 1024} = \frac{1}{5120} \neq 0$$

Hence  $\log_{1024} n^2 \notin o(\log_2 n^{1024})$ 

(c) From the Stirling's approximation, we have  $n! \sim \sqrt{2\pi n} \left(\frac{n}{e}\right)^n$  when n is large enough. Then we get

$$\log(n!) \sim \log\left(\sqrt{2\pi n} \left(\frac{n}{e}\right)^n\right) = n(\log n - \log e) + 0.5(\log n + \log 2\pi)$$

$$\log(n!) \qquad \log e \qquad 1 \qquad \log 2\pi$$

$$\frac{\log(n!)}{n\log n} = 1 - \frac{\log e}{\log n} + \frac{1}{2n} + \frac{\log 2\pi}{2n\log n}$$

Hence, we have  $\lim_{n\to\infty}\frac{\log(n!)}{n\log n}=1$ . By the result of 1.(c), we have

$$\log(n!) \in \Theta(n \log n)$$

(d)  $x^{2.5} = \lfloor x^{2.5} \rfloor + \{x^{2.5}\}$ , where  $\{x^{2.5}\}$  is the fraction part of  $x^{2.5}$ . Then we have

$$\lim_{x \to \infty} \frac{\lfloor x^{2.5} \rfloor}{x^{2.5}} = \lim_{x \to \infty} \frac{x^{2.5} - \{x^{2.5}\}}{x^{2.5}} = 1$$

By the result of 1.(c), we have  $\lfloor x^{2.5} \rfloor \in \Theta(x^{2.5}) \Rightarrow \lfloor x^{2.5} \rfloor \in \Omega(x^{2.5})$ 

(e)  $\left\lceil \frac{x}{2} \right\rceil = \frac{x}{2} + 1 - \left\{ \frac{x}{2} \right\}$ , where  $\left\{ \frac{x}{2} \right\}$  is the fraction part of  $\frac{x}{2}$ .

$$\frac{x\left[\frac{x}{2}\right]}{x^2} = \frac{x\left(\frac{x}{2} + 1 - \left\{\frac{x}{2}\right\}\right)}{x^2} = \frac{1}{2} + \frac{1}{x} - \frac{\left\{\frac{x}{2}\right\}}{x}$$

Then we have

$$x\left\lceil \frac{x}{2} \right\rceil = 2x^2 + \left(1 - \left\{ \frac{x}{2} \right\} \right) x$$

When x > 1, we know that  $x < x^2$ , hence the  $\left(1 - \left\{\frac{x}{2}\right\}\right)x$  part has the upper-bound  $x^2$ . So that we finally get the result

$$x \left\lceil \frac{x}{2} \right\rceil \le 3x^2$$

for x > 1. This gives us  $x \left\lceil \frac{x}{2} \right\rceil \in O(x^2)$ 

## 4 Closed-Form Linear Regression Solution

$$f_{10}(n) \succ f_{9}(n) \succ f_{4}(n) \succ f_{12}(n) \succ f_{2}(n) \succ f_{3}(n)$$
  
 $f_{3}(n) \sim f_{13}(n) \succ f_{1}(n) \succ f_{5}(n) \succ f_{11}(n) \succ f_{7}(n) \succ f_{6}(n)$ 

 $f_{10} \succ f_9$ :

$$\lim_{n\to\infty}\frac{\log\log n}{10^{10^10}}=\infty$$

 $f_9 \succ f_4$ :

$$\lim_{n \to \infty} \frac{\sqrt{\log n}}{\log \log n} = \lim_{n \to \infty} \frac{\frac{1}{2x\sqrt{\log x}}}{\frac{1}{x \log x}} = \lim_{n \to \infty} \frac{\sqrt{\log x}}{2} = \infty$$

$$f_4 \succ f_{12}$$
:

$$\lim_{n\to\infty}\frac{(\log n)^{1.5}}{\sqrt{\log n}}=\lim_{n\to\infty}\log n=\infty$$

 $f_{12} \succ f_2$ :

$$10^{\log n^2} = (e^{\log 10})^{2\log n} = (e^{\log n})^{2\log 10} = n^{2\log 10}$$

$$\lim_{n \to \infty} \frac{n^{2\log 10}}{(\log n)^{1.5}} = \lim_{n \to \infty} \frac{(2\log 10)n^{(2\log 10)-1}}{\frac{1.5(\log n)^{0.5}}{n}} = \lim_{n \to \infty} \frac{(2\log 10)n^{2\log 10}}{1.5(\log n)^{0.5}} = \infty$$

 $f_2 \succ f_3$ :

$$\lim_{n \to \infty} \frac{n^6}{n^{2\log 10}} = \infty \text{ since } 6 > 2\log 10$$

 $f_3 \sim f_{13}$ :

$$\sum_{k=1}^{n} k^{5} = \frac{1}{12}n^{2}(n+1)^{2}(2n^{2}+2n-1) = \frac{1}{6}n^{6} + \frac{1}{2}n^{5} + \frac{5}{12}n^{4} - \frac{1}{12}n^{2}$$

$$\lim_{n \to \infty} \frac{\sum_{k=1}^{n} k^{5}}{n^{6}} = \frac{1}{6}$$

 $f_{13} \succ f_8$ : Suppose d is a constant, we have

$$d\log n < (\log\log n)(\log n) \Rightarrow n^d < n^{\log\log n}$$

$$\lim_{n \to \infty} \frac{n^{\log \log n}}{\sum_{k=1}^{n} k^5} = \lim_{n \to \infty} \frac{n^{\log \log n}}{\frac{1}{6}n^5 + \frac{1}{2}n^4 + \frac{5}{12}n^3 - \frac{1}{12}n} = \infty$$

 $f_8 \succ f_1$ :

$$(\log \log n)(\log n) < \log n \log n < n < n \log \frac{3}{2} \Rightarrow n^{\log \log n} < (\frac{3}{2})^n$$

$$\lim_{n \to \infty} \frac{n(\frac{3}{2})^n}{n^{\log \log n}} = \infty$$

 $f_1 \succ f_5$ :

$$\lim_{n \to \infty} \frac{3^n}{n(\frac{3}{2})^n} = \lim_{n \to \infty} \frac{2^n}{n} = \infty$$

 $f_5 \succ f_{11}$ 

$$\lim_{n \to \infty} \frac{n!}{3^n} = \lim_{n \to \infty} \frac{\sqrt{2\pi n} \left(\frac{n}{e}\right)^n}{3^n} = \lim_{n \to \infty} \sqrt{2\pi n} \left(\frac{n}{3e}\right)^n = \infty$$

 $f_{11} \succ f_7$ 

$$\lim_{n \to \infty} \frac{n^n}{n!} = \lim_{n \to \infty} \frac{n^n}{\sqrt{2\pi n} \left(\frac{n}{e}\right)^n} = \lim_{n \to \infty} \frac{e^n}{\sqrt{2\pi n}} = \infty$$

 $f_7 \succ f_6$ 

$$6^n \log 6 > n \log n \Rightarrow 6^{6^n} > n^n$$

## 5 Noise and Regularization

(a) Suppose  $c_1, c_2$  are two constants such that  $f(n) \leq c_1 h(n), g(n) \leq c_2 h(n)$ , then we have

$$f(n) + g(n) \le (c_1 + c_2)h(n) = ch(n)$$

Hence,  $f(n) + g(n) \in O(h(n))$ 

- (b) Since f, g are positive, we have  $|f(n) g(n)| \le \max(f(n), g(n))$ . Then either  $|f(n) g(n)| \in O(f(n))$  or  $|f(n) g(n)| \in O(g(n))$  would be satisfied. This results that  $|f(n) g(n)| \in O(h(n))$  because  $f(n), g(n) \in O(h(n))$
- (c) Since f, g are positive, suppose  $c_1$  is a constant that  $f(n) \leq c_1 g(n)$ . Square both sides of the inequation, we have  $(f(n))^2 \leq (c_1)^2 (g(n))^2$ . Hence,  $(f(n))^2 \in O((g(n))^2)$
- (d) Counterexample:  $f(n) = n, g(n) = \frac{n}{2}$ , then we have  $2^{f(n)} = 2^n, 2^{g(n)} = (\sqrt{2})^n$ .

$$\lim_{n \to \infty} \frac{2^n}{(\sqrt{2})^n} = \lim_{n \to \infty} (\sqrt{2})^n = \infty$$

Hence,  $2^{f(n)} \notin O(2^{g(n)})$ 

(e) Counterexample: Suppose  $f(n) = \log n$ , g(n) = n,  $h(n) = n^2$ , we have  $f(g(n)) = \log n$ ,  $f(h(n)) = 2 \log n$ . Then  $f(g(n)) \notin o(f(h(n)))$ .

#### Problem 6

(a) The loop from line 4 to line 7 runs n times, and for each loop, the line 6 runs k times. Hence the time complexity is

$$\sum_{k=1}^{n} k\Theta(1) = \Theta(n^2)$$

(b) The loop from line 4 to line 7 runs n times, and for each loop, the line 6 runs k times. When the line 6 runs the first time of the loop, the time complexity is  $\Theta(\min(x,k)) = \Theta(1)$ . After the first time of the loop, the time complexity is  $\Theta(\min(x,k)) = \Theta(k)$  Sum up the complexity and we have the total time complexity of the  $k_{th}$  loop be  $(k-1)\Theta(k) + \Theta(1) = \Theta(k^2)$ . Now compute n times, we get the time complexity

$$\sum_{k=1}^{n} \Theta(k^2) = \Theta(k^3)$$