CS221 Fall 2018 Homework [1]

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By turning in this assignment, I agree by the Stanford honor code and declare that all of this is my own work.

Problem 1: Optimization and probability

1.a: What value of θ minimizes $f(\theta)$?

Answer: $\theta = \frac{\sum_{i=1}^{n} x_i}{n}$ In order to get minimized $f(\theta) = \frac{1}{2} \sum_{i=1}^{n} w_i (\theta - x_i)^2$ when w_1, w_n are positive real numbers, we need to find a θ which close to x in average, so we have $\theta = \frac{\sum_{i=1}^{n} x_i}{n}$.

When some w_i is negative, this approach won't work well. ex, For given n = 8, W =mized $f(\theta)$ in this case.

1.b: Does $f(x) \leq (x), f(x) = g(x)$ or $f(x) \geq g(x)$ hold for all x? Prove it.

Proof: We will prove $f(x) \ge g(x)$ for $f(x) = \sum_{i=1}^{d} \max_{s \in \{1,-1\}} sx_i$ and $g(x) = \max_{s \in \{1,-1\}} \sum_{i=1}^{d} sx_i$ Let's convert f(x) and g(x) to following expressions by using s = 1 and s = -1:

$$f(x) = \sum_{i=1}^{d} \max(x_i, -x_i)$$

$$\tag{1}$$

$$g(x) = \max(\sum_{i=1}^{d} x_i, \sum_{i=1}^{d} -x_i)$$
(2)

In order to show $f(x) \geq g(x)$, we have below three cases to consider:

First case, all $x_i \in \mathbf{x}$ are not negative, in this case, we find $f(x) = \sum_{i=1}^d x_i$ and $g(x) = \sum_{i=1}^d x_i$ $\sum_{i=1}^{d} x_i$, we could get f(x) = g(x).

Second case, all $x_i \in \mathbf{x}$ are negative, then we find $f(x) = \sum_{i=1}^d -x_i$ and $g(x) = \sum_{i=1}^d -x_i$, which is f(x) = g(x).

Last case, part of $x \in \mathbf{x}$ are negative and rest of them are not, let's define this set as $\mathbf{x}' = \{x | x < 0, x \in \mathbf{x}\}, \mathbf{x}' \subset \mathbf{x}$, then we could get $f(x) = \sum_{i=1}^{d} |x_i|$ and $g(x) = \sum_{i=1}^{d} |x_i| - \sum_{i=1}^{m} |x_i'|$ where m is the size of \mathbf{x}' , it's clear that f(x) > g(x).

Since f(x) is either equal or greater than g(x) in all condition, we could conclude that $f(x) \geq g(x)$.

1.c What is the expected number of points (as a function of a and b) you will have when you stop.

Answer:

According to probability expectation formula, we could define function f(a,b) as $f(a,b) = \frac{1}{6}b - \frac{1}{6}a + 3 \times \frac{1}{6}f(a,b)$, after keep repeating f(a,b), we could have

$$a = \frac{1}{6}b - \frac{1}{6}a + \frac{1}{2}(\frac{1}{6}b - \frac{1}{6}a + \frac{1}{2}f(a,b))$$
 (3)

$$= \frac{1}{6}b - \frac{1}{6}a + \frac{1}{2}(\frac{1}{6}b - \frac{1}{6}a + \frac{1}{2}(\frac{1}{6}b - \frac{1}{6}a + \frac{1}{2}f(a,b))) \tag{4}$$

$$= \frac{1}{6}(b-a)(1+\frac{1}{2}+\frac{1}{4}+\frac{1}{8}+\ldots+\frac{1}{2^n})+\frac{1}{2^n}f(a,b)$$
 (5)

$$= \frac{1}{6}(b-a)\left(1+\frac{1}{2}+\frac{1}{4}+\frac{1}{8}+\ldots+\frac{1}{2^n}\right) \tag{6}$$

$$= \frac{1}{6}(b-a) \times 2(1-(\frac{1}{2})^n) \tag{7}$$

$$= \frac{1}{3}(b-a) \tag{8}$$

Hence, we could say the expect number of points is $\frac{1}{3}(b-a)$.

1.d what value of p maximizes L(p)? What is an intuitive interpretation of this value of p?

Answer: when $p = \frac{4}{7}$, it will maximize L(p). From value p, we could interpret it as $p = \frac{Count(H)}{TotalDiceTimes}$.

Let's calculate derivative for log(L(p)), since $L(p) = p^4(1-p)^3$, we have log(L(p))'s derivative as:

$$log'(L(p)) = \frac{1}{L(P)ln2}L'(p)$$
 (9)

$$= \frac{1}{\ln 2 \times p^4 (1-p)^3} \times (p^4 \times (1-p)^{3'} + p^{4'} (1-p)^3)$$
 (10)

$$= \frac{1}{\ln 2 \times p^4 (1-p)^3} \times (p^4 \times 3(1-p)^2 \times (-1) + 4p^3 (1-p)^3) \tag{11}$$

$$= \frac{1}{\ln 2 \times p^4 (1-p)^3} \times p^3 \times (1-p)^2 \times (4-7p) \tag{12}$$

$$= \frac{4-7p}{\ln 2 \times p(1-p)} \tag{13}$$

Base on expression (13), when $p = \frac{4}{7}$, $\log'(L(p)) = 0$, which represents $\log(L(p))$'s max value.

1.e Compute the gradient of $f(x) = \sum_{i=1}^n \sum_{j=1}^n (a_i^\top w - b_j^\top w)^2 + \lambda \|w\|_2^2$

Answer:

For gradient of f(w), let's calculate partial derivative $\nabla f(w) = \{\frac{\partial f(w)}{\partial w_1}, ..., \frac{\partial f(w)}{\partial w_d}\}$, for w_k where $1 \leq k \leq d$, we have:

$$\frac{\partial f(w)}{\partial w_k} = \sum_{i=1}^n \sum_{j=1}^n 2(a_i^\top w - b_j^\top w) \times (a_k - b_k) + \frac{\partial \lambda \|w\|_2^2}{\partial w_k}$$
(14)

$$= \sum_{i=1}^{n} \sum_{j=1}^{n} 2(a_i^{\top} w - b_j^{\top} w) \times (a_k - b_k) + 2\lambda w_k$$
 (15)

Problem 2

return dp[n-1]

2.a How many possible faces (choice of its component rectangles) are there?

answer: Consider to put an arbitrary organ on face first, it has roughly $n \times n$ choices for its location, and has roughly $n \times n$ choices for its size, then we could see there are nearly n^4 possible approach for the first organ.

According to problem description, requirement for the total 6 organs are the same, so we could see there are $O(n^{24})$ possible face choices.

2.b Give an algorithm for computing the minimum cost in the most efficient way. What is the runtime (just give the big-O)?

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answer: List python code implementation below, algorithm runtime is O(n^2). import sys
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def ComputeMinCost(n, c):
    dp = [sys.maxint for i in range(n)]
    dp[0] = 0

for i in range(n):
    pre = dp[0]
    for j in range(n):
        # cost(i,j) = min (move_from_top, move_from_left) + c(i,j)
        # dp array is used for caching cost of cells in above row.
        # pre is used for caching cost of the left cell
        dp[j] = min(dp[j], pre) + c(i,j)
        pre = dp[j]
```

2.c How many ways are there to reach the top?

answer: according to the problem description, we could find the following expression hold for number of ways to the 'x'th $(1 \le x \le n)$ stair: num[x] = num[x-1] + num[x-2] + ... num[0], num[0] means move cur steps at once, num[x-2] means move 2 steps at once at stair x-2. So we could get below generic expression for f(n):

$$f(n) = f(n-1) + f(n-2) + \dots + f(1) + f(0)$$
(16)

$$= \sum_{i=1}^{n} f(n-i) \tag{17}$$

$$f(0) = 1 \tag{18}$$

2.d Devise a strategy that first does preprocessing in $O(nd^2)$ time, and then for any given vector w, takes $O(d^2)$ time instead to compute f(w).

answer: let's transform $f(x) = \sum_{i=1}^{n} \sum_{j=1}^{n} (a_i^{\top} w - b_j^{\top} w)^2 + \lambda ||w||_2^2$ to separate w out of summation computing, see below expressions:

$$f(n) = \sum_{i=1}^{n} \sum_{j=1}^{n} ((a_i^T w)(a_i^T w) - (a_i^T w)(b_j^T w) - (b_j^T w)(a_i^T w) + (b_j^T w)(b_j^T w)) + \lambda \|w\|_2^2 (19)$$

$$= \sum_{i=1}^{n} \sum_{j=1}^{n} (w^{T}(a_{i}a_{i}^{T})w - 2w^{T}(a_{i}b_{j})w + w^{T}(b_{j}a_{j}^{T})w) + \lambda \|w\|_{2}^{2}$$
(20)

$$= w^{T}w(\sum_{i=1}^{n}(a_{i}^{T}a_{i}) + \sum_{j=1}^{n}(b_{j}^{T}b_{j}) - 2\sum_{i=1}^{n}\sum_{j=1}^{n}(a_{i}b_{j}^{T})) + \lambda \|w\|_{2}^{2}$$
(21)

from expression (21), we could see, if we could pre compute $K = \sum_{i=1}^{n} (a_i^T a_i) + \sum_{j=1}^{n} (b_j^T b_j) - 2\sum_{i=1}^{n} \sum_{j=1}^{n} (a_i b_j^T)$, which takes $O(nd^2)$, then we could have below expression for f(n):

$$f(n) = Kw^T w + \lambda ||w||_2^2$$

, this will take $O(d^2)$ time to compute if k is pre-computed.