

CS221 Fall 2018 - 2019 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

(a)

$$\begin{aligned}f'(\theta) &= \sum_{i=1}^n w_i(\theta - x_i) \\&= \theta \sum_{i=1}^n w_i - \sum_{i=1}^n w_i x_i \\f'(\theta) &= 0 \\ \Leftrightarrow \theta &= \frac{\sum_{i=1}^n w_i x_i}{\sum_{i=1}^n w_i}\end{aligned}$$

(b) Let $s' = \operatorname{argmax}_{s \in \{1, -1\}} \sum_{i=1}^d s x_i$. Then we have

$$\max_{s \in \{1, -1\}} \sum_{i=1}^d s x_i = \sum_{i=1}^d s' x_i \leq \sum_{i=1}^d \max_{s \in \{1, -1\}} s x_i$$

(c) Let the expected value be V , the outcome at the i^{th} toss be s_i ($s_i \in \{1, 2, 3, 4, 5, 6\}$) and the point we get at i^{th} toss be $R(s_i)$

$$R(s_i) = \begin{cases} 0 & \text{if } s_i \in \{1, 3, 4, 5\} \\ -a & \text{if } s_i = 2 \\ b & \text{if } s_i = 6 \end{cases}$$

We have

$$\begin{aligned}
V &= \sum_{s_1, s_2, \dots} P(s_1, s_2, \dots)(R(s_1) + R(s_2) + \dots) \\
&= \sum_{s_1} \sum_{s_2, s_3, \dots} P(s_1)P(s_2, s_3, \dots | s_1)(R(s_1) + R(s_2) + \dots) \\
&= \sum_{s_1} \sum_{s_2, s_3, \dots} P(s_1)P(s_2, s_3, \dots | s_1)(R(s_1)) + \sum_{s_1} \sum_{s_2, s_3, \dots} P(s_1)P(s_2, s_3, \dots | s_1)(R(s_2) + R(s_3) + \dots) \\
&= \sum_{s_1} P(s_1)R(s_1) + \sum_{s_1 \in \{2, 3, 4, 5, 6\}} P(s_1)P(s_2, s_3, \dots | s_1)(R(s_2) + R(s_3) + \dots) + \\
&\quad \sum_{s_1=1} P(s_1)P(s_2, s_3, \dots | s_1)(R(s_2) + R(s_3) + \dots) \\
&= \frac{a+b}{6} + \frac{5}{6}V + 0
\end{aligned}$$

Therefore

$$\begin{aligned}
\frac{V}{6} &= \frac{a+b}{6} \\
V &= a+b
\end{aligned}$$

(d)

$$\begin{aligned}
\log L(p) &= \log(p^4(1-p)^3) \\
&= 4\log p + 3\log(1-p)
\end{aligned}$$

So

$$\begin{aligned}
\frac{\partial \log L(p)}{\partial p} &= \frac{4}{p} - \frac{3}{1-p} \\
&= \frac{4-7p}{p(1-p)}
\end{aligned}$$

$$\begin{aligned}
\frac{\partial \log L(p)}{\partial p} &= 0 \\
&\Leftrightarrow p = \frac{4}{7}
\end{aligned}$$

(e)

$$\begin{aligned}
\Delta f(w) &= \sum_{i=1}^n \sum_{j=1}^n 2(\mathbf{a}_i^T \mathbf{w} - \mathbf{b}_j^T \mathbf{w}) \Delta(\mathbf{a}_i^T \mathbf{w} - \mathbf{b}_j^T \mathbf{w}) - 2\lambda w \\
&= \mathbf{w} \sum_{i=1}^n \sum_{j=1}^n 2(\mathbf{a}_i^T - \mathbf{b}_j^T)(\mathbf{a}_i - \mathbf{b}_j) - 2\lambda w
\end{aligned}$$

Problem 2: Complexity

- (a) For each part of the face, we first choose the top left corner then choose the width and height. since there are n^2 way to choose top left corner, up to n way to choose width and height, in total we have up to $n^2nn = n^4$ ways to place a part of the face. because the face has 6 parts, asymptotically we have $(n^4)^6 = n^{24}$ ways to represent the face.
- (b) We will adopt a dynamic programming approach, let $v[i, j]$ be the optimal cost to reach position i, j .

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let v[0, j] = 0 for all j and v[i, 0] = 0 for all i
for i = 1 to n
  for j = 1 to n
    v[i, j] = c(i, j) + max(v[i - 1, j], v[i, j - 1])
return v[n, n]

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the running time of the above algorithm is $O(n^2)$

- (c) From step 1 to step $n - 1$, at each step we have 2 choices of actions i) stop at this step to prepare for the next move or ii) continue this step as a step of the current move. when we reach step n we are done so we do not need to choose actions. therefore there are 2^{n-1} ways to reach the top.
- (d) We have

$$\begin{aligned}
f(\mathbf{w}) &= \sum_{i=1}^n \sum_{j=1}^n (\mathbf{a}_i^T \mathbf{w} - \mathbf{b}_j^T \mathbf{w})^2 + \lambda \|\mathbf{w}\|_2^2 \\
&= \sum_{i=1}^n \sum_{j=1}^n (\mathbf{w}^T \mathbf{a}_i - \mathbf{w}^T \mathbf{b}_j)(\mathbf{a}_i^T \mathbf{w} - \mathbf{b}_j^T \mathbf{w}) + \lambda \|\mathbf{w}\|_2^2 \\
&= \sum_{i=1}^n \sum_{j=1}^n (\mathbf{w}^T \mathbf{a}_i \mathbf{a}_i^T \mathbf{w} - \mathbf{w}^T \mathbf{a}_i \mathbf{b}_j^T \mathbf{w} - \mathbf{w}^T \mathbf{b}_j \mathbf{a}_i^T \mathbf{w} + \mathbf{w}^T \mathbf{b}_j \mathbf{b}_j^T \mathbf{w}) + \lambda \|\mathbf{w}\|_2^2 \\
&= \sum_{i=1}^n \sum_{j=1}^n \mathbf{w}^T (\mathbf{a}_i \mathbf{a}_i^T - 2\mathbf{a}_i \mathbf{b}_j^T + \mathbf{b}_j \mathbf{b}_j^T) \mathbf{w} + \lambda \|\mathbf{w}\|_2^2 \\
&= \mathbf{w}^T \left(\sum_{i=1}^n \sum_{j=1}^n (\mathbf{a}_i \mathbf{a}_i^T - 2\mathbf{a}_i \mathbf{b}_j^T + \mathbf{b}_j \mathbf{b}_j^T) \right) \mathbf{w} + \lambda \|\mathbf{w}\|_2^2 \\
&= \mathbf{w}^T \left(\sum_{i=1}^n n \mathbf{a}_i \mathbf{a}_i^T - 2 \sum_{i=1}^n \mathbf{a}_i \sum_{j=1}^n \mathbf{b}_j^T + \sum_{j=1}^n n \mathbf{b}_j \mathbf{b}_j^T \right) \mathbf{w} + \lambda \|\mathbf{w}\|_2^2
\end{aligned}$$

In the processing step we will calculate

$$A = \left(\sum_{i=1}^n n \mathbf{a}_i \mathbf{a}_i^T - 2 \sum_{i=1}^n \mathbf{a}_i \sum_{j=1}^n \mathbf{b}_j^T + \sum_{j=1}^n n \mathbf{b}_j \mathbf{b}_j^T \right)$$

Because $\sum_{i=1}^n n \mathbf{a}_i \mathbf{a}_i^T$ takes $O(nd^2)$, $2 \sum_{i=1}^n \mathbf{a}_i \sum_{j=1}^n \mathbf{b}_j^T$ takes $O(nd)$ and $\sum_{j=1}^n n \mathbf{b}_j \mathbf{b}_j^T$ takes $O(nd^2)$, the processing step takes time $O(nd^2)$.

For any given \mathbf{w} we compute $\mathbf{w}^T A \mathbf{w}$ which takes time $O(d^2)$ and $\lambda \|\mathbf{w}\|_2^2$ which also takes time $O(d^2)$.