

**CS221 Fall 2015 Homework [foundations]****Problem 1: Optimization and Probability****1a.**

Given:  $f(x) = \frac{1}{2} \sum_{i=1}^n w_i (x - b_i)^2$

Therefore  $f'(x) = \sum_{i=1}^n w_i (x - b_i)$

Furthermore

$$f'(x) = x \sum_{i=1}^n w_i - \sum_{i=1}^n w_i b_i$$

The value of  $x$  that minimizes  $f(x)$  will occur when  $f'(x)$  is equal to zero.

This means that

$$x \sum_{i=1}^n w_i - \sum_{i=1}^n w_i b_i = 0$$

Therefore  $x = \frac{\sum_{i=1}^n w_i b_i}{\sum_{i=1}^n w_i}$  is the answer.

Finally, confirm that  $f''(x)$  is greater than zero with  $f''(x) = \sum_{i=1}^n w_i$  which proves it is a minimum.

**1b.**

Given

$$f(x) = \max_{a \in \{1, -1\}} \sum_{j=1}^d a x_j$$

Therefore  $f(x)$  is only one of two possibilities:

$$f_1(x) = \sum_{j=1}^d x_j \quad \text{or} \quad f_2(x) = - \sum_{j=1}^d x_j$$

And given

$$g(x) = \sum_{j=1}^d \max_{a \in \{1, -1\}} a x_j$$

We can state that  $\max_{a \in \{1, -1\}} a x_j$  is equal to  $|x_j|$

Therefore  $g(x) = \sum_{j=1}^d \max_{a \in \{1, -1\}} a x_j$  is equivalent to:  $g(x) = \sum_{j=1}^d |x_j|$

Thus we know that  $g(x) \geq f_1(x)$  because  $|x_j| \geq x_j$  for any  $x_j$

Similarly we know that  $g(x) \geq f_2(x)$  because  $|x_j| \geq -x_j$  for any  $x_j$

Therefore we have proven that  $f(x) \leq g(x)$  for all of  $x$ .

**1c.**

First, on a roll event, the “terminating event” probability is  $\frac{1}{2}$  or 50% chance that the fair six sided dice will roll a 3, 2 or 1. Conversely, on a single roll, the “continue event” probability, i.e. the probability that the dice will roll a 4, 5, or 6 is also  $\frac{1}{2}$  or 50%.

Second, the probability of achieving a reward  $r$  given that a “continue event” has occurred is  $\frac{1}{3}$

The expected reward for a continue event is therefore  $r \frac{1}{3}$

The probability of terminating on the  $n^{\text{th}}$  throw is  $\frac{1}{2^n}$  and the expected reward in this case is

$\frac{r}{3}(n-1)$  because the first  $n-1$  throws are continue events.

Therefore:

$$f(r) = \frac{r}{3} \sum_{n=1}^{\infty} \frac{(n-1)}{2^n}$$

Now consider the infinite series portion:  $\sum_{n=1}^{\infty} \frac{(n-1)}{2^n}$

Let's assign S equal to the infinite series:  $S = \sum_{n=1}^{\infty} \frac{(n-1)}{2^n}$  (such that  $f(r) = \frac{r}{3} S$  holds true).

This results in:  $S = 0 + \frac{1}{4} + \frac{2}{8} + \frac{3}{16} + \frac{4}{32} \dots$

Then, divide both sides by 2:  $\frac{S}{2} = \frac{1}{8} + \frac{2}{16} + \frac{3}{32} + \frac{4}{64} \dots$

and subtract the two equations  $S - \frac{S}{2} = \frac{1}{4} + \frac{1}{8} + \frac{1}{16} + \frac{1}{32} \dots = \frac{1}{2}$

Thus we determine that  $S=1$  therefore:

$$f(r) = \frac{r}{3} S \text{ is equal to } f(r) = \frac{r}{3} \text{ which is the answer.}$$

**1d.**

Given:  $L(p) = p^3(1-p)^2$

And converting this into

$$\log L(p) = 3 \log p + 2 \log(1-p)$$

The value of  $p$  that maximizes  $\log L(p)$  also maximizes  $L(p)$  because  $\log$  is a monotonic function.

To determine the value of  $p$  that maximizes  $\log L(p)$  we must equate the derivative of  $\log L(p)$  to zero. We can do this using the suggested method of taking the derivative of  $\log L(p)$  as follows:

$$\frac{d(\log L(p))}{dp} = 3 \frac{1}{p} + 2 \frac{1}{(1-p)} * (-1) \text{ which when set to zero implies:}$$

$$\frac{3}{p} - \frac{2}{1-p} = 0 \text{ and therefore: } p = \frac{3}{5} \text{ is the answer.}$$

To ensure this is a maximum, we can check that the second order derivative  $-\frac{3}{p^2} - \frac{2}{(1-p)^2} < 0$

**1e.**

Given

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

Rewritten as:

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

The gradient of  $f(w)$  defined as  $\nabla f(w)$  can be determined by taking the derivative of the function  $f(w)$  with respect to the vector  $w$ :

Therefore:  $\nabla f(w) = \sum_{i=1}^n \sum_{j=1}^n 2(a_i^T w - b_j^T w) * (a_i - b_j) + 2\lambda w$  is the answer.

## Problem 2: Complexity

**2a.**

Within an  $n \times n$  pixel image, each feature represented as an unconstrained arbitrary axis-aligned rectangle can be uniquely specified using 2 diagonally opposite points to define a feature's bounding box. Therefore, asymptotically the number of ways of choosing a single rectangle is:

$$\binom{n^2}{2}$$

Which is:

$$O(n^4)$$

Thus for three features, the complexity is:

$$O(n^4 * n^4 * n^4)$$

As observed, the answer is in the  $O(n^c)$  form, where  $c = 12$

Thus the asymptotic complexity is  $O(n^{12})$  which is the answer.

**2b.**

Given the following recurrence:  $f(j) = \min_{1 \leq i < j} [c(i, j) + f(i)]$

The algorithm for computing  $f(n)$  using the above recurrence can be implemented using dynamic programming. The dynamic programming algorithm calculates  $f(1), f(2), f(3) \dots f(n)$  in that order.

To compute  $f(j)$  we need to examine all previous terms  $c(i, j) + f(i)$  where  $i$  is less than  $j$ .

Therefore  $j-1$  terms has to be examined for computing  $f(j)$ . The run-time for computing  $f(n)$  is

therefore  $O(\sum_{j=1}^n (j-1))$  which is equal to  $O(n^2)$  which is the answer.

2c.

For any  $n \times n$  grid with moves constrained as specified at each step, the following illustration explains the problem for any number of  $n$  :

	n=1	n=2	n=3	n=4	n=5	n=6	... n=d
n=1	0	1	1	1	1	1	
n=2	1	2 $\frac{(2(n-1))!}{(n-1)! (n-1)!}$	3	4	5	6	
n=3	1	3	6 $\frac{(2(n-1))!}{(n-1)! (n-1)!}$	10	15	21	
n=4	1	4	10	20 $\frac{(2(n-1))!}{(n-1)! (n-1)!}$	35	56	
n=5	1	5	15	35	70 $\frac{(2(n-1))!}{(n-1)! (n-1)!}$	126	
n=6	1	6	21	56	126	252 $\frac{(2(n-1))!}{(n-1)! (n-1)!}$	
...							
n=d							

The number of ways to get from the upper-left corner to the lower-right corner if at each step you are only allowed to move down or right can be determined by computing the total number of moves from  $2(n-1)$  available moves using the binomial coefficient for number of outcomes as follows:

$$\binom{2(n-1)}{(n-1)} = \frac{(2(n-1))!}{(n-1)! (n-1)!}$$

The answer is now given as a function of  $n$ :

$$f(n) = \frac{(2(n-1))!}{(n-1)! (n-1)!}$$

**2d.**

In the equation

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

$\lambda \|w\|_2^2$  is computable in  $O(d)$  time so we can ignore it for this problem.

Now this  $\sum_{i=1}^n \sum_{j=1}^n (a_i^T w - b_j^T w)^2$  can be refactored as  $\sum_{i=1}^n \sum_{j=1}^n (a_i^T w - b_j^T w)^T (a_i^T w - b_j^T w)$

Expanding this we get  $\sum_{i=1}^n \sum_{j=1}^n (w^T a_i a_i^T w + w^T b_j b_j^T w - w^T a_i b_j^T w - w^T b_j a_i^T w)$

Let  $A$  be the  $d \times n$  matrix equal to  $A = (a_1 a_2 a_3 a_4 \dots a_n)$  where each of the columns represents the  $\mathbf{a}$  vectors. Similarly let  $B$  be the  $d \times n$  matrix  $B = (b_1 b_2 b_3 b_4 \dots b_n)$  which represents the  $\mathbf{b}$  vectors.

Now the strategy is to represent the terms from the summation expression as matrix multiplication, such that:  $f(w) = w^T C w$  for some  $d \times d$  matrix  $C$ . This will make run-time computation of  $f(w)$  happen in  $O(d^2)$  time.

Strategically speaking, an example  $A B^T$  has equivalent terms to the expanded form of  $f(w)$ . Therefore computing  $C$  is equivalent to  $A B^T$  in compute time. Computing  $C$  can be done in  $O(nd^2)$  preprocessing time since  $A$  and  $B$  are both  $d \times n$  matrices that yield a  $d \times d$  matrix result similar to  $C$ .