### Problem 1 1

#### 1.1 $\mathbf{a}$

Let  $\theta = 0.5$ , then we need to show that f(1/2x + 1/2y) is not always  $\leq$ 1/2f(x) + 1/2f(y) for  $x = (x_1, x_2), y = (y_1, y_2)$ . f(1/2x + 1/2y) = f(1/2(x + 1/2y)) $(y) = 1/2(x_1 + y_1)(x_2 + y_2)$  and  $1/2f(x) + 1/2f(y) = 1/2x_1x_2 + 1/2y_1y_2$ . For x = (0.5, 1) and y = (1, 0.5), we get f(1/2x + 1/2y) = 1/2 \* 1.5 \* 1.5 =1.1125 and 1/2f(x) + 1/2f(y) = 1/2 \* 1 \* 0.5 + 1/2 \* 1 \* 0.5 = 0.5. Since 1.1125 > 0.5, this does not hold, meaning it is not convex.

#### 1.2 b

For this to be concave, we need to prove the opposite, that f(1/2x + 1/2y)is not always >= 1/2f(x) + 1/2f(y). For  $\theta = 0.1, f(0.1x + 0.9y) = (0.1x_1 + 0.9y)$  $(0.9y_1)(0.1x_2 + 0.9y_2)$  and  $(0.1f(x) + 0.9f(y)) = (0.1x_1x_2 + 0.9y_1y_2)$ . For  $x = 0.9y_1$ (1,1), y = (10,10), f(0.1x + 0.9y) = 82.81 and 0.1f(x) + 0.9f(y) = 90.1. Since 82.81 < 90.1, this does not hold, meaning it is not concave.

### 2 Problem 2

In order to show that this element is concave, we just need to show that the overall set is concave, as partial minimization shows that the minimum element of a concave set is concave.

For two vectors  $x, y \in R^m$ , let f(z) be the weighted least squares problem, then  $f(x) = \sum_{i=1}^n w_i (a_i^T x - b_i)^2$  and  $f(y) = \sum_{i=1}^n w_i (a_i^T y - b_i)^2$ . For  $\lambda = 1/2$ , we need to show that f(1/2x + 1/2y) >= 1/2f(x) + 1/2f(y) always.  $f(1/2x + 1/2y) = \sum_{i=1}^n w_i (a_i^T (1/2x + 1/2y) - b_i)^2 = \sum_{i=1}^n w_i (1/2a_i^T x + 1/2a_i^T y - b_i)^2 = \sum_{i=1}^n 1/4w_i (a_i^T x + a_i^T y - b_i)^2$ .  $1/2f(x) + 1/2f(y) = \sum_{i=1}^n 1/2w_i (a_i^T x - b_i)^2 + \sum_{i=1}^n 1/2w_i (a_i^T x - b_i)^2 = \sum_{i=1}^n 1/2w_i (a_i^T x - b_i)^2 + (a_i^T y - b_i)^2$ . Comparing these are  $\sum_{i=1}^n 1/4$  of  $\sum_{i=1}^n 1/4$  of  $\sum_{i=1}^n 1/2$  and  $\sum_{i=1}^n 1/2$  of  $\sum_{i=1}^n 1/2w_i (a_i^T x - b_i)^2 + (a_i^T y - b_i)^2$ .

Comparing these, we get  $\sum_{i=1}^{n} 1/4w_i(a_i^Tx + a_i^Ty - b_i)^2 > = \sum_{i=1}^{n} 1/2w_i((a_i^Tx - b_i)^2 + (a_i^Ty - b_i)^2)$ , or  $\sum_{i=1}^{n} (a_i^Tx + a_i^Ty - b_i)^2 > = \sum_{i=1}^{n} 2((a_i^Tx - b_i)^2 + (a_i^Ty - b_i)^2)$ . We know this is true, because as we try to minimize the vector in the least squares problem, this will be as close as possible to 0 for  $(a_i^T x - b_i)^2$ and  $(a_i^T y - b_i)^2$ . Therefore, we can say that this is approximately equal to  $\sum_{i=1}^{n} (a_i^T x)^2 > = 0$ , meaning this is concave.

#### 3 Problem 3

## 3.1

For  $\lambda$  between 0 and 1, we need to show that  $f(\lambda x + (1-\lambda)y) \le \lambda f(x) + (1-\lambda)y$  $\lambda f(y)$  for two vectors x and y in  $\mathbb{R}^n$ . If we let  $\lambda = 1/2$ , then we need to show that  $f(1/2x + 1/2y) \le 1/2f(x) + 1/2f(y)$ .

If we let  $x = (x_1, x_2...x_n)$  and  $y = (y_1, y_2...y_n)$ , then  $f(1/2x + 1/2y) = max(x_a, y_b) - min(x_i - y_j)$  where  $x_a, y_b$  are the maximum values and  $x_i, y_j$  are the minimum values in x and y respectively.

 $1/2f(x) + 1/2f(y) = 1/2x_a + 1/2y_b - 1/2x_i - 1/2y_j = 1/2(x_a + y_b - x_i - y_j)$ . This means the function is convex if and only if  $max(x_a, y_b) - min(x_i - y_j) <= 1/2x_a + 1/2y_b - 1/2x_i - 1/2y_j$ . Let us say  $x_a = 1, x_i = 0, y_b = 0, y_j = 0$ , then this yields 1 <= 1/2, which is false. Therefore, this function is not convex.

## 3.2 b

 $f(x) = (1/n\sum_{i=1}^{n}x_{i}^{2} - (1/n\sum_{i=1}^{n}x_{i})^{2})^{1/2}$ . This can be rewritten as  $f(x) = (1/n(x-1/nx^{T}1)^{T}(x-1/n1^{T}x1))^{1/2} = (1/n||(I-1/n11^{T})||^{2})^{1/2} = 1/\sqrt{n}||(I-P)x||$ . We know that vector norms are convex, so this function is also convex as it is a scaled-by-n function of a norm.

## 3.3 c

If we take the space the function covers, the entirety of  $\mathbb{R}^n$  is under this function, since every vector in the space is a possible mapping. Therefore, this function is convex.

# 4 Problem 4

We know that  $g(x) = \sum_{i=1}^{n} x_{[i]}$  is convex, so we know that  $f(x) = \sum_{i=1}^{r} \alpha_i x_{[i]}$  is also convex since it is a nonnegative multiple. Since all the  $\alpha_1...\alpha_r >= 0$  and f(x) is convex,  $\alpha f(x)$  is also convex for all the alpha values.