## Algorithmic Game Theory: HW 2

1.

2. (a) Consider the utility maximizing game below starting with the the initial outcome  $(A_1, B_1)$ , the the game cycles forever which best-response dynamics, avoiding the pure Nash of  $(A_3, B_2)$ .

P1
$$A_{1} \quad A_{2} \quad A_{3}$$

$$B_{1} \quad 4,1 \quad 1,2 \quad 0,0$$

$$P2 \quad B_{2} \quad 0,0 \quad 0,0 \quad 5,5$$

$$B_{3} \quad 3,3 \quad 3,2 \quad 0,0$$

(b)

3.

4. Let 
$$f_{\epsilon}(x) = (1 - \epsilon)^x$$
 and  $g_{\epsilon}(x) = 1 + \epsilon x$ , then

$$f_{\epsilon}(0) = 1 = g_{\epsilon}(0)$$

$$f_{\epsilon}(1) = 1 - \epsilon = g_{\epsilon}(1)$$

$$f'_{\epsilon}(x) = (1 - \epsilon)^{x} \ln(1 - \epsilon)$$

$$g'_{\epsilon}(x) = \epsilon$$

$$f'_{\epsilon}(0) = \ln(1 - \epsilon) < 0 = g'_{\epsilon}(0)$$

also  $f_{\epsilon}$  is a convex function as  $f''_{\epsilon}(x) = (1 - \epsilon)^x \left[\ln(1 - \epsilon)\right]^2 > 0$  for  $\epsilon \in (0, 1/2]$ . This this proves  $f_{\epsilon}(x) \leq g_{\epsilon}(x)$  since the initial gradient of  $f_{\epsilon}$  is smaller then  $g_{\epsilon}$