## EE 325: Probability and Random Processes

## Assignment 3

Due: 1159pm on Monday, 03 October

There are three biased coins, named A, B, and C, with unknown biases designated, respectively,  $p_A$ ,  $p_B$ , and  $p_C$ . You are allowed N tosses and you have to maximise the total number of heads in the N tosses. If you you knew the p, then the best thing to do would be to toss the coin with the highest p, say  $p^*$ , and obtain an expected reward of  $Np^*$  heads. Since you do not know the p, let us explore two algorithms to use in maximising the expected reward. Evaluate for the following choices of the  $p_S$ . (i)  $p_A = 0.2$ ,  $p_B = 0.4$ ,  $p_C = 0.7$  (ii)  $p_A = 0.45$ ,  $p_B = 0.5$ ,  $p_C = 0.58$ . We will use N = 20, 100, 1000, 5000.

- 1. **Algorithm A:** Fix  $N_1 < N$  and toss each coin  $N_1/3$  times. Let  $n_A$ ,  $n_B$ , and  $n_C$  be the number of heads obtained for coins A, B, and C. For the remaining  $N N_1$  toss the one with the highest n. The issue here is what is the best  $N_1$ .
  - (a) If  $N_1$  is small then, intuitively, the wrong coin may be chosen with higher probability. In fact, conditioned on  $N_1$  and  $(p_A, p_B, p_C)$ , the probability of choosing the wrong coin after  $N_1$  samples can be determined. Determine that expression.
  - (b) If  $N_1$  is large then there is not enough time to use the more reliable information collected in the first  $N_1$  times. Let  $R(N_1)$  be the expected number of heads in the N tosses for a choice of  $N_1$ . Of course, this also depends on the p and N.

Peform the following computation experiment. For each of the eight cases, simulate the above algorithm for every  $N_1 < N$  1000 times and find the sample average for  $R(N_1)$ .

- (a) Plot the sample average  $R(N_1)$  vs  $N_1$  for the 8 cases and point out the optimum  $N_1$ .
- (b) For each of the cases, compute the (theoretical) probability that the wrong coin will be picked after  $N_1$  tosses. Plot the theoretical and the empirical probabilities as a function of  $N_1$ .
- (c) Submit all the programs.
- 2. **Algorithm B:** We will use Hoeffding's inequality as follows. After k tosses let  $n_A(k)$ ,  $n_B(k)$ , and  $n_C(k)$  be the number of times coins A, B, and C were used and let  $k_A(k)$ ,  $k_B(k)$ , and  $k_C(k)$  be the number of times the corresponding coins tossed heads;  $n_A(k) + n_B(k) + n_C(k) = k$ .

Consider coin A. Although we do not know  $p_A$ , we can use  $n_A(k)$  and  $k_A(k)$  in Hoeffding's inequality to determine at any time k, we can obtain an upper bound on  $p_A$  with a reasonable amount of confidence. Denote this upper bound by  $UCB_A(k)$ . Specifically, use Hoeffding's inequality to calculate  $UCB_A(k) = \frac{k_A(k)}{n_A(k)} + X_A$  such that  $\Pr(p_A \leq UCB_A|n_A, k_A) \geq (1-\alpha)$ . Similarly, calculate  $UCB_B(k)$  and  $UCB_C(k)$ . For the (k+1)-th toss choose the coin with the highest UCB(k). If there is a tie, break it randomly. This is an elementary learning algorithm where you adaptively learn to use the best coin. This algorithm also has many nice properties that a more full fledged course will explore in detail.

Write a program to implement this algorithm. For  $\alpha = 0.1, 0.05$  and  $\alpha = 0.01$  and the values p and N as in the previous algorithm, submit the following plots.

- (a) Plot the sample average of  $k_A(k)/k$ ,  $k_B(k)/k$  and  $k_C(k)/k$  as a function of k for N = 5000 for each combination of the parameter values.
- (b) For each combination of the parameter values, tabulate the sample average of the total reward over the N trials and compare with the best expected value.
- (c) Submit the numerical results and a discussion on the effect of  $\alpha$ , N, and the p.