## 15-251: Great Theoretical Ideas In Computer Science

## Recitation 12 : Randomized Algorithms

## Lecture Review

- A randomized algorithm is an algorithm that has access to random bits, i.e. it can flip a coin. In this class we will allow randomized algorithms to call Randlnt(n) and Bernoulli(p).
- Here are two interesting classes of randomized algorithms:
- An algorithm $A$ is a $T(n)$-time Las Vegas algorithm if
* $A$ always outputs the right answer, and
* for every input $x \in \Sigma^{*}, \mathbf{E}[$ number of steps $A(x)$ takes $] \leq T(|x|)$.
- An algorithm $A$ is a $T(n)$-time Monte Carlo algorithm with error probability $\varepsilon$ if
* for every input $x \in \Sigma^{*}, A(x)$ gives the wrong answer with probability at most $\varepsilon$, and
* for every input $x \in \Sigma^{*}, A(x)$ has a worst-case running-time of at most $T(|x|)$.
- We can use boosting to improve the success probability of Monte Carlo algorithms via repeated trials.


## A Hard Exam

(a) Suppose that the average score on the latest $15-150$ exam was 10 points out of 100 and that 200 students took the exam. What's an upper bound on the number of students who received a perfect score? Assume that the 150 TAs are kind enough to not assign negative scores to students.
(b) Markov's inequality: Let $\boldsymbol{X}$ be a non-negative random variable with non-zero expectation. For any $c>0$,

$$
\operatorname{Pr}[\boldsymbol{X} \geq c \mathbf{E}[\boldsymbol{X}]] \leq \frac{1}{c}
$$

(No need to prove this - refer to the course notes to see the proof. But note that the proof is similar to the reasoning in part (a).)

## What happens in Las Vegas doesn't stay in Monte Carlo

The expected number of comparisons that the Quicksort algorithm makes is at most $2 n \ln n$ (which you can cite without proof - you might see a proof of this fact if you take 15-210). Describe how to convert this Las Vegas algorithm into a Monte Carlo algorithm with the worst-case number of comparisons being $1000 n \ln n$. Give an upper bound on the error probability of the Monte Carlo algorithm.

## Randomization Meets Approximation

3SAT is a hard problem to solve exactly, but is it hard to find a decent approximation algorithm for? (Maybe not!)

Consider the MAX-3SAT problem where, given a CNF formula in which every clause has exactly 3 literals (with distinct variables), we want to find a truth assignment to the variables in the formula so that we maximize the number of clauses that evaluate to True.

Describe a polynomial-time randomized algorithm with the property that, given a 3CNF formula with $m$ clauses, it outputs a truth assignment to the variables such that the expected number of clauses that evaluate to True is $\frac{7}{8} m$ (i.e., in expectation, the algorithm is a $\frac{7}{8}$-approximation algorithm).

## (Extra) (Brain Teaser) Passive-Aggressive Passengers

Consider a plane with $n$ seats $s_{1}, s_{2}, \ldots, s_{n}$. There are $n$ passengers, $p_{1}, p_{2}, \ldots, p_{n}$ and they are randomly assigned unique seat numbers. The passengers enter the plane one by one in the order $p_{1}, p_{2}, \ldots p_{n}$. The first passenger $p_{1}$ does not look at their assigned seat and instead picks a uniformly random seat to sit in. All the other passengers, $p_{2}, p_{3}, \ldots, p_{n}$, use the following strategy. If the seat assigned to them is available, they sit in that seat. Otherwise they pick a seat uniformly at random among the available seats, and they sit there. What is the probability that the last passenger, $p_{n}$, will end up sitting in their assigned seat?

