

# Randomized Algorithms

Two Types of Randomized Algorithms

and

Some Complexity Classes

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# References

- Professor Hsueh-I Lu's slides.
- *Randomized Algorithms*, Rajeev Motwani and Prabhakar Raghavan.
- *Probability and Computing - Randomized Algorithms and Probabilistic Analysis*, Michael Mitzenmacher and Eli Upfal.



# Outline



- Las Vegas algorithms and Monte Carlo algorithms
- RAMs and Turing machines
- Complexity classes
  - P, NP, RP, ZPP, BPP and their complementary classes
  - Open problems



# Las Vegas vs. Monte Carlo



## ■ Las Vegas algorithms

- Always produces a (correct/optimal) solution.
- Like RandQS.



## ■ Monte Carlo algorithms

- Allow a small probability for outputting an incorrect/non-optimal solution.
- Like RandMC.
- The name is by von Neumann.



# Las Vegas Algorithms

- For example, RandQS is a Las Vegas algorithm.
- A Las Vegas **always** gives the correct solution
- The only variation from one run to another is its **running time**, whose distribution we study.



# Randomized quicksort

```
algorithm RandQS( $X$ ) {  
  if  $X$  is empty then  
    return;
```

randomization

```
  select  $x$  uniformly at random from  $X$ ;
```

```
  let  $Y = \{y \in X \mid y < x\}$ ;
```

```
  let  $Z = \{z \in X \mid z > x\}$ ;
```

```
  call RandQS( $Y$ );
```

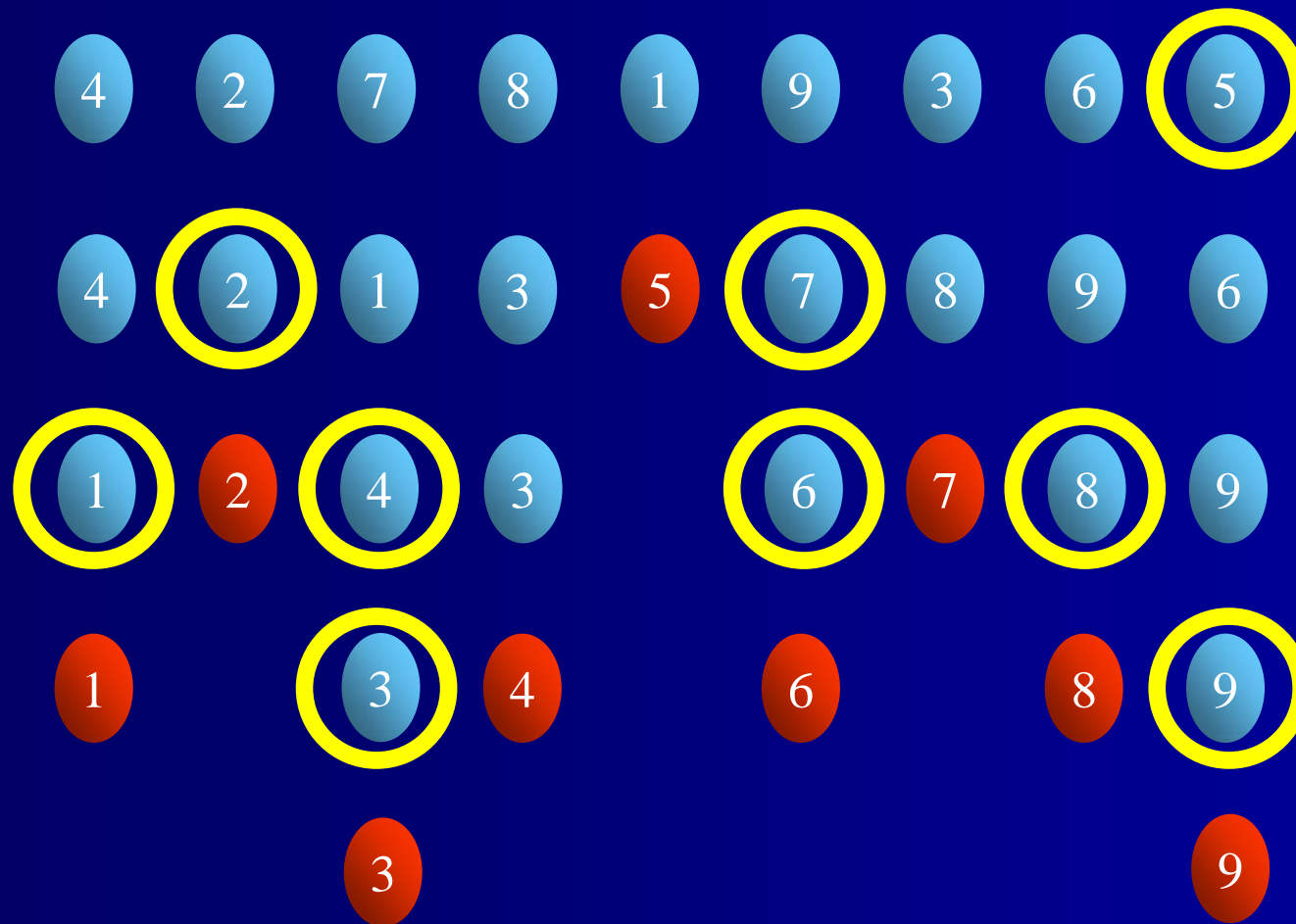
```
  print  $x$ ;
```

```
  call RandQS( $Z$ );
```

```
}
```



# An illustration



## 2 Questions for RandQS

- Is RandQS correct?
  - That is, does RandQS “**always**” output a sorted list of  $X$ ?
- What is the time complexity of RandQS?
  - Due to the randomization for selecting  $x$ , the running time for RandQS becomes a **random variable**.
  - We are interested in the **expected** time complexity for RandQS.





# Monte Carlo algorithms

- For example, RandEC (the randomized minimum-cut algorithm we have discussed) is a Monte Carlo algorithm.
- A Monte Carlo algorithm may **sometimes** produce a solution that is **incorrect**.
- For decision problems, there are two kinds of Monte Carlo algorithms:
  - those with **one**-sided error
  - those with **two**-sided error



# Which is better?

- The answer depends on the application.
- A Las Vegas algorithm is by definition a Monte Carlo algorithm with error probability 0.
- Actually, we can derive a Las Vegas algorithm **A** from a Monte Carlo algorithm **B** by repeated running **B** until we get a correct answer.



# Computation model

- Throughout this talk, we use the *Turing machine* model to discuss complexity theory issues.
- As is common, we switch to the **RAM** (random access machine) as the model of computation when describing and analyzing algorithms.



# Computation model (cont'd)

- For simplicity, we will work with the general *unit-cost* RAM model.
- In unit-cost RAM model, each instruction can be performed in **one** time step.





# Determinist

You can refer to any computation theory textbook to for more details here.

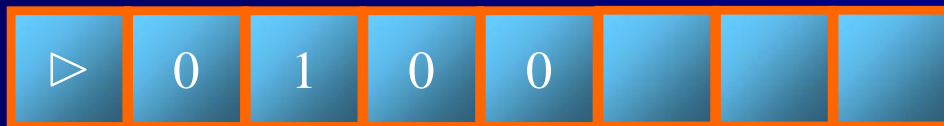
- A deterministic Turing machine is a quadruple  $M = (S, \Sigma, \delta, s)$ .
  - Here  $S$  is a finite set of states, of which  $s \in S$  is the machine's initial state.
  - $\Sigma$  : a finite set of symbols (this set includes special symbols **BLANK** and **FIRST**).
  - $\delta$  : the transition function of the Turing machine, mapping  $S \times \Sigma$  to  $(S \cup \{\text{HALT}, \text{YES}, \text{NO}\}) \times \Sigma \times \{\leftarrow, \rightarrow, \text{STAY}\}$ .
- The machine has three states: **HALT** (the halting state), **YES** (the accepting state), and **NO** (the rejecting state) (these are states, but formally not in  $S$ .)



# A Turing machine with one tape


state \ symbol	0	1	$\sqcup$	$\triangleright$
$s$	$(s, 0, \rightarrow)$	$(s, 1, \rightarrow)$	$(q, \sqcup, \leftarrow)$	$(s, \triangleright, \rightarrow)$
$q$	$(q_0, \sqcup, \rightarrow)$	$(q_1, \sqcup, \rightarrow)$	$(q, \sqcup, -)$	$(h, \triangleright, \rightarrow)$
$q_0$	$(s, 0, \leftarrow)$	$(s, 0, \leftarrow)$	$(s, 0, \leftarrow)$	$(h, \triangleright, \rightarrow)$
$q_1$	$(s, 1, \leftarrow)$	$(s, 1, \leftarrow)$	$(s, 1, \leftarrow)$	$(h, \triangleright, \rightarrow)$
$h$	$\times$	$\times$	$\times$	$\times$



Q: What does this Turing machine do?



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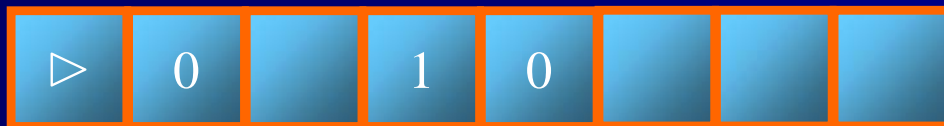

Q: What does this Turing machine do?





# A Turing machine with one tape

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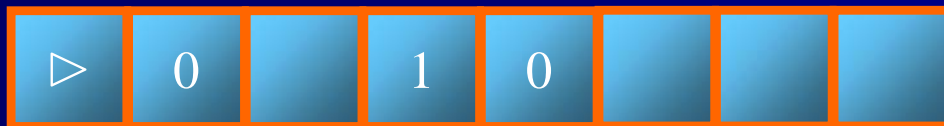
Q: What does this Turing machine do?



# A Turing machine with one tape

↓


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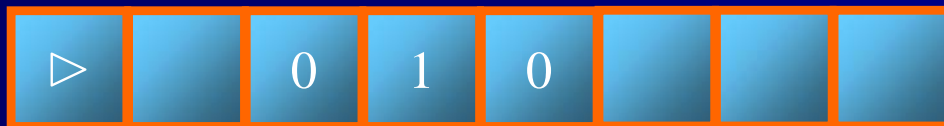
Q: What does this Turing machine do?



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# A Turing machine with one tape

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Q: What does this Turing machine do?



# A probabilistic TM

- A *probabilistic Turing machine* is a (nondeterministic) Turing machine augmented with the ability to generate an unbiased coin flip in one step.
- It corresponds to a randomized algorithm.



# A probabilistic TM (cont'd)

- On any input  $x$ , a probabilistic Turing machine accepts  $x$  with some probability, and we study this probability.



# Language recognition problem

- Any decision problem can be treated as a language recognition problem.
- Let  $\Sigma^*$  be the set of all possible strings over  $\Sigma$ .
- A language  $L \subseteq \Sigma^*$  is a collection of strings over  $\Sigma$ .



# Language recognition problem (cont'd)

- The corresponding language recognition problem is to decide whether a given string  $x \in \Sigma^*$  belongs to  $L$ .
- An algorithm solves a language recognition problem for a specific language  $L$  by *accepting* (output YES) any input string contained in  $L$ , and *rejecting* (output NO) any input string not contained in  $L$ .





# Complexity Classes

- A complexity class is a collection of languages all of whose recognition problem can be solved under prescribed bounds on the computational resources.
- We are primarily interested the classes in which algorithms is *polynomial-time* bounded.



# The Class: **P**

- The class **P** consists of all languages  $L$  that have a polynomial time algorithm  $A$  such that for any input  $x \in \Sigma^*$ ,
  - $x \in L \Rightarrow A(x)$  accepts
  - $x \notin L \Rightarrow A(x)$  rejects



# The Class: **NP**

Here  $y$  can be regarded as a “certificate”

- The class **NP** consists of all languages  $L$  that have a polynomial time algorithm  $A$  such that for any input  $x \in \Sigma^*$ ,
  - $x \in L \Rightarrow \exists y \in \Sigma^*$ ,  $A(x, y)$  accepts, where  $|y|$  is bounded by a polynomial in  $|x|$ .
  - $x \notin L \Rightarrow \forall y \in \Sigma^*$ ,  $A(x, y)$  rejects



# A useful view of **P** and **NP**

- The class **P** consists of all languages  $L$  such that for any  $x$  in  $L$ , a proof (certificate) of the membership  $x$  in  $L$  (represented by the string  $y$ ) can be *found* and *verified* efficiently.
- The class **NP** consists of all languages  $L$  such that for any  $x$  in  $L$ , a proof (certificate) of the membership of  $x$  in  $L$  can be *verified* efficiently.



# A useful view of **P** and **NP** (cont'd)

- Obviously  $P \subseteq NP$ , but it is not known whether  $P = NP$ .
- If  $P = NP$ , the existence of an efficiently verifiable proof (certificate) implies that it is possible to **actually find such a proof** (certificate) efficiently.



- When randomized algorithms are allowed, we have some basic classes as follows.



# The Class: **RP**

Actually, the choice of the bound on the error probability  $1/2$  can be arbitrary.

- The class **RP** (for **R**andomized **P**olynomial time) consists of all languages  $L$  that have a *randomized* algorithm  $A$  running in worst-case polynomial time such that for any input  $x \in \Sigma^*$ .
  - $x \in L \Rightarrow \Pr[A(x) \text{ accepts}] \geq 1/2$ .
  - $x \notin L \Rightarrow \Pr[A(x) \text{ accepts}] = 0$ .

One-sided error



# One-sided error vs. two-sided error

- A randomized algorithm  $A$  for recognizing a language  $L$  is of *one-sided error* if for any input  $x \in \Sigma^*$ ,

- $x \in L \Rightarrow \Pr[A(x) \text{ accepts}] \neq 1$

- $x \notin L \Rightarrow \Pr[A(x) \text{ accepts}] = 0.$

or

- $x \in L \Rightarrow \Pr[A(x) \text{ accepts}] = 1.$

- $x \notin L \Rightarrow \Pr[A(x) \text{ accepts}] \neq 0.$





# One-sided error vs. two-sided error (cont'd)

- A randomized algorithm  $A$  for recognizing a language  $L$  is of *two-sided error* if for any input  $x \in \Sigma^*$ ,
  - $x \in L \Rightarrow \Pr[A(x) \text{ accepts}] \neq 1.$
  - $x \notin L \Rightarrow \Pr[A(x) \text{ accepts}] \neq 0.$



# The Class: **ZPP**

- The class **ZPP** (for zero-error Probabilistic Polynomial time) is the class of languages that has Las Vegas algorithms running in expected polynomial time.



# The Class: **ZPP** (cont'd)

- For example,  
RandQS is a **ZPP** algorithm.



# The Class: **PP**

- The class **PP** (for Probabilistic Polynomial time) consists of all languages  $L$  that have a randomized algorithm  $A$  running in worst-case polynomial time that for any input  $x \in \Sigma^*$ ,
  - $x \in L \Rightarrow \Pr[A(x) \text{ accepts}] > 1/2$ .
  - $x \notin L \Rightarrow \Pr[A(x) \text{ accepts}] < 1/2$ .



# Exercise 1.10

- Consider a randomized algorithm with two-sided error probabilities as in the definition of **PP**. Show that a polynomial number of independent repetitions of this algorithm need not suffice to reduce the error probability to  $\frac{1}{4}$ .
  - Consider the case where the error probability is

$$\frac{1}{2} + \left(\frac{1}{2^n}\right)$$



# The Class: **PP** (cont'd)

- The definition of **PP** is weak.
  - It can be proved that it may not be possible to use a small number of repetitions of an algorithm  $A$  with such two-sided error probability to obtain an algorithm with “significantly smaller” error probability. (proved by using the Chernoff bound)
- Compared to the class **BPP**!



# The Class: **PP** (cont'd)

## ■ Note:

- To reduce the error probability of a two-sided error algorithm, we can perform several independent iterations on the same input and produce the output that occurs in the majority of these iterations.
- This can be done by using the Chernoff bound.



# The Class: **BPP**

Actually, we only have to make sure that the difference between the “green one” and the “red one” is only polynomially small.

- The class **BPP** (for Bounded-error Probabilistic Polynomial time) consists of all languages  $L$  that have a randomized algorithm  $A$  running in worst-case polynomial time that for any input  $x \in \Sigma^*$ ,

- $x \in L \Rightarrow \Pr[A(x) \text{ accepts}] \geq \frac{3}{4}$ .

- $x \notin L \Rightarrow \Pr[A(x) \text{ accepts}] \leq \frac{1}{4}$ .





# Note

- Exponentially small
  - $1/2^n, 1/3^n, \dots$
- Polynomially small
  - $1/n^2, 1 / \log n, \dots$



# The Class: **BPP** (cont'd)

- One can show that for this class of algorithms, the error probability can be reduced to  $1/2^n$  with only a polynomial number of iterations.

**Problem 4.8:** Consider a **BPP** algorithm that has an error probability of  $\frac{1}{2} - \frac{1}{p(n)}$ , for some polynomially bounded function  $p(n)$  of the input size  $n$ . Using the Chernoff bound on the tail of the binomial distribution, show that a polynomial number of independent repetitions of this algorithm suffice to reduce the error probability to  $\frac{1}{2^n}$ .



# The Class: **BPP** (cont'd)

- Consider the decision version of the min-cut problem:
  - Given a graph  $G$  and an integer  $K$ , verify that the min-cut size in  $G$  equals  $K$ .
- Assume that we have modified the Monte Carlo algorithm RandEC to reduce its error probability to be less than  $1/4$  (by sufficiently many repetitions).
  - We then get a **BPP** algorithm.



# The Class: **BPP** (cont'd)

- In the case where  $K$  is **indeed the min-cut value**, the algorithm may not come up with the right value and, hence, may reject the input .
- If the min-cut value is **smaller than  $K$** , the algorithm may only find cuts of size  $K$ , and hence, accept the input.
- If the min-cut value is **larger than  $K$** , the algorithm will never find any cut of size  $K$ , and hence, reject the input.



# Note

- Consider another decision version of the min-cut problem:
  - Given a graph  $G$  and an integer  $K$ , verify that the min-cut size in  $G$  is **at most  $K$** .
- Assume again that we have modified the Monte Carlo algorithm RandEC to reduce its error probability to be less than  $\frac{1}{4}$  (by sufficiently many repetitions).
  - We then get a **RP** algorithm for this problem.



# Note (cont'd)

- In the case where the actual min-cut size  $C$  is **larger than  $K$** , the algorithm will never accept the input.
- If the min-cut value is **at most  $K$** , the algorithm may find cuts of size at most  $K$ , and hence, accept the input.

**One-sided error!**



# Complement Classes

- For any complexity class  $C$ , we define the complementary class  $\text{co-}C$  as the set of languages whose complement is in the class  $C$ .

– That is,

$$\text{co-}C = \{L \mid \bar{L} \in C\}$$



# Complement Classes (cont'd)

- Then we have  $\text{co-P}$ ,  $\text{co-NP}$ ,  $\text{co-RP}$ ,  $\text{co-PP}$ ,  $\text{co-ZPP}$ ,  $\text{co-BPP}$ , ...
- For example,





# The Class: **co-RP**

- The class **co-RP** consists of all languages  $L$  that have a *randomized* algorithm  $A$  running in worst-case polynomial time such that for any input  $x \in \Sigma^*$ ,
  - $x \in L \Rightarrow \Pr[A(x) \text{ accepts}] = 1.$
  - $x \notin L \Rightarrow \Pr[A(x) \text{ accepts}] \leq 1/2.$



# Exercise

- Show that  $ZPP = RP \cap \text{co-RP}$ .



# Open problems

- Is  $\text{NP} = \text{P}$ ?
- Is  $\text{RP} = \text{co-RP}$ ?
- Is  $\text{RP} \subseteq \text{NP} \cap \text{co-NP}$ ?
- Is  $\text{BPP} \subseteq \text{NP}$ ?
- Is  $\text{BPP} = \text{P}$ ?
- .....



*Thank you.*

