

## Randomized Complexity Classes

- Let  $N$  be a polynomial-time precise NTM that runs in time  $p(n)$  and has 2 nondeterministic choices at each step.
- $N$  is a **polynomial Monte Carlo Turing machine** for a language  $L$  if the following conditions hold:
  - If  $x \in L$ , then at least half of the  $2^{p(|x|)}$  computation paths of  $N$  on  $x$  halt with “yes.”
  - If  $x \notin L$ , then all computation paths halt with “no.”
- The class of all languages with polynomial Monte Carlo TMs is denoted **RP** for **randomized polynomial time**.

## Comments on RP

- Nondeterministic steps can be seen as fair coin flips.
- There are no false positive answers.
- The probability of false negatives is at most 0.5.
- Any constant  $0 \leq \epsilon \leq 1$  can replace 0.5.
  - By repeating the algorithm  $k$  times, the probability of false negatives can be reduced to  $(1 - \epsilon)^k$ .
  - Now pick  $k = \lceil -\frac{1}{\log_2 1 - \epsilon} \rceil$ .
- In fact,  $\epsilon$  can be arbitrarily close to 0 as long as it is of the order  $1/p(n)$  for some polynomial  $p(n)$ .
  - $-\frac{1}{\log_2 1 - \epsilon} = O\left(\frac{1}{\epsilon}\right) = O(p(n))$ .

## Where RP Fits

- $P \subseteq RP \subseteq NP$ .
  - A polynomial-time deterministic TM is like a polynomial Monte Carlo TM except that all the coin flips are ignored.
  - A polynomial Monte Carlo TM is a polynomial-time NTM with extra demands on the number of accepting paths.
- COMPOSITENESS  $\in RP$ .
- PRIMES  $\in coRP$ .
- $RP \cup coRP$  is a “plausible” notion of efficient computation.

## ZPP<sup>a</sup> (Zero Probabilistic Polynomial)

- The class **ZPP** is defined as  $\text{RP} \cap \text{coRP}$ .
- A language in ZPP has *two* Monte Carlo algorithms, one with no false positives and another with no false negatives.
- If we repeatedly run both Monte Carlo algorithms, *eventually* one definite answer will come (unlike RP).
  - A *positive* answer from the one without false positives.
  - A *negative* answer from the one without false negatives.
- The algorithm is called **Las Vegas**.

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<sup>a</sup>Gill, 1977.

## The ZPP Algorithm

- 1: {Suppose that  $L \in \text{ZPP}$ .}
- 2: { $N_1$  has no false positives, and  $N_2$  has no false negatives.}
- 3: **while true do**
- 4:   **if**  $N_1(x) = \text{“yes”}$  **then**
- 5:     **return** “yes”;
- 6:   **end if**
- 7:   **if**  $N_2(x) = \text{“no”}$  **then**
- 8:     **return** “no”;
- 9:   **end if**
- 10: **end while**

## ZPP (continued)

- The *expected* running time for it to happen is polynomial.
  - The probability that a run of the 2 algorithms does not generate a definite answer is 0.5.
  - Let  $p(n)$  be the running time of each run.
  - The expected running time for a definite answer is thus

$$\sum_{i=1}^{\infty} 0.5^i ip(n) = 2p(n).$$

- PRIMES  $\in$  ZPP (whose proof remains inaccessible).

## Me Too, RP?

- 1: {Suppose that  $L \in \text{RP}$ .}
  - 2: { $N$  decides  $L$  without false positives.}
  - 3: **while true do**
  - 4:   **if**  $N(x) = \text{“yes”}$  **then**
  - 5:     **return** “yes”;
  - 6:   **end if**
  - 7:   {What to do here?}
  - 8: **end while**
- You eventually get a “yes” if  $x \in L$ .
  - But how to get a “no” when  $x \notin L$ ?

## PP

- A language  $L$  is in the class **PP** if there is a polynomial-time precise NTM  $N$  such that:
  - For all inputs  $x$ ,  $x \in L$  if and only if more than half of the computations of  $N$  (i.e.,  $2^{p(n)-1} + 1$  or up) on input  $x$  end up with a “yes.”
  - We say that  $N$  decides  $L$  by majority.
- MAJSAT: is it true that the majority of the  $2^n$  truth assignments to  $\phi$ 's  $n$  variables satisfy it?
- MAJSAT is PP-complete.
- PP is closed under complement.



## NP vs. PP

**Theorem 61**  $NP \subseteq PP$ .

- Suppose that  $L \in NP$  is decided by an NTM  $N$ .
- Construct a new NTM  $N'$ :
  - $N'$  has one more extra state  $s$  than  $N$ .
  - $N'$  starts at  $s$  and either branches to  $N$ 's program or simply accepts (after  $p(|x|)$  steps).
- Consider an input  $x$ .
- Suppose that  $N$  on  $x$  computes for  $p(|x|)$  steps and produces  $2^{p(|x|)}$  computation paths.

## The Proof (continued)

- Then  $N'$  has  $2^{p(|x|)+1}$  computation paths.
- Half of these will always halt with “yes.”
- Thus a majority of the paths of  $N'$  accept  $x$  if and only if at least one path of  $N$  accepts  $x$ .
- That is, if and only if  $x \in L$ .
- So  $N'$  accepts  $L$  by majority and  $L \in \text{PP}$ .

## Theory of Large Deviations

- You have a *biased* coin.
- One side has probability  $0.5 + \epsilon$  to appear and the other  $0.5 - \epsilon$ , for some  $0 < \epsilon < 1$ .
- But you do not know which is which.
- How to decide which side is the more likely—with high confidence?
- Answer: Flip the coin many times and pick the side that appeared the most times.
- Question: Can you quantify the confidence?

## The Chernoff Bound

**Theorem 62 (Chernoff, 1952)** *Suppose that  $x_1, x_2, \dots, x_n$  are independent random variables taking the values 1 and 0 with probabilities  $p$  and  $1 - p$ , respectively.*

*Let  $X = \sum_{i=1}^n x_i$ . Then for all  $0 \leq \theta \leq 1$ ,*

$$\text{prob}[X \geq (1 + \theta)pn] \leq e^{-\theta^2 pn/3}.$$

- The probability that the deviate of a **binomial random variable** from its expected value decreases exponentially with the deviation.
- The Chernoff bound is asymptotically optimal.

## The Proof

- Let  $t$  be any positive real number.
- Then

$$\text{prob}[X \geq (1 + \theta)pn] = \text{prob}[e^{tX} \geq e^{t(1+\theta)pn}].$$

- Markov's inequality (p. 282) generalized to real-valued random variables says that

$$\text{prob}[e^{tX} \geq kE[e^{tX}]] \leq 1/k.$$

- With  $k = e^{t(1+\theta)pn} / E[e^{tX}]$ , we have

$$\text{prob}[X \geq (1 + \theta)pn] \leq e^{-t(1+\theta)pn} E[e^{tX}].$$

## The Proof (continued)

- Because  $X = \sum_{i=1}^n x_i$  and  $x_i$ 's are independent,

$$E[e^{tX}] = (E[e^{tx_1}])^n = [1 + p(e^t - 1)]^n.$$

- Substituting, we obtain

$$\begin{aligned} \text{prob}[X \geq (1 + \theta)pn] &\leq e^{-t(1+\theta)pn} [1 + p(e^t - 1)]^n \\ &\leq e^{-t(1+\theta)pn} e^{pn(e^t - 1)} \end{aligned}$$

as  $(1 + a)^n \leq e^{an}$  for all  $a > 0$ .

## The Proof (continued)

- With the choice of  $t = \ln(1 + \theta)$ , the above becomes

$$\text{prob}[X \geq (1 + \theta)pn] \leq e^{pn[\theta - (1 + \theta)\ln(1 + \theta)]}.$$

- The exponent expands to  $-\frac{\theta^2}{2} + \frac{\theta^3}{6} - \frac{\theta^4}{12} + \dots$  for  $0 \leq \theta \leq 1$ , which is less than

$$-\frac{\theta^2}{2} + \frac{\theta^3}{6} \leq \theta^2 \left( -\frac{1}{2} + \frac{\theta}{6} \right) \leq \theta^2 \left( -\frac{1}{2} + \frac{1}{6} \right) = -\frac{\theta^2}{3}.$$

## Effectiveness of the Majority Rule

From  $\text{prob}[X \leq (1 - \theta)pn] \leq e^{-\frac{\theta^2}{2}pn}$  (prove it), it follows that:

**Corollary 63** *If  $p = (1/2) + \epsilon$  for some  $0 \leq \epsilon \leq 1/2$ , then*

$$\text{prob} \left[ \sum_{i=1}^n x_i \leq n/2 \right] \leq e^{-\epsilon^2 n/2}.$$

- The textbook's corollary to Lemma 11.9 seems incorrect.
- Our original problem (p. 329) hence demands  $\approx 1.4k/\epsilon^2$  independent coin flips to guarantee making an error with probability at most  $2^{-k}$  with the majority rule.



## $\text{BPP}^a$ (Bounded Probabilistic Polynomial)

- The class **BPP** contains all languages for which there is a precise polynomial-time NTM  $N$  such that:
  - If  $x \in L$ , then at least  $3/4$  of the computation paths of  $N$  on  $x$  accept, and
  - If  $x \notin L$ , then at least  $3/4$  of the computation paths of  $N$  on  $x$  reject.
- $N$  accepts or rejects by a *clear* majority.

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<sup>a</sup>Gill, 1977.

## Magic 3/4?

- The number  $3/4$  bounds the probability of a right answer away from  $1/2$ .
- Any constant *strictly* between  $1/2$  and  $1$  can be used without affecting the class BPP.
- In fact, any  $0.5$  plus inverse polynomial

$$0.5 + 1/p(n)$$

between  $1/2$  and  $1$  can be used.

## The Majority Vote Algorithm

Suppose that  $L$  is decided by  $N$  by majority  $(1/2) + \epsilon$ .

- 1: **for**  $i = 1, 2, \dots, 2k + 1$  **do**
- 2:   Run  $N$  on input  $x$ ;
- 3: **end for**
- 4: **if** “yes” is the majority answer **then**
- 5:   “yes”;
- 6: **else**
- 7:   “no”;
- 8: **end if**

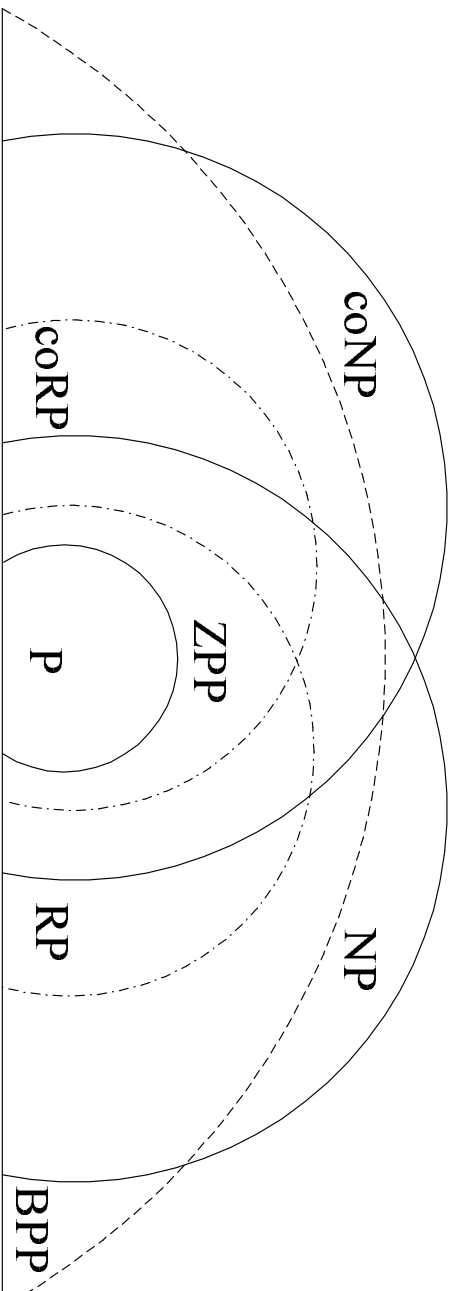
## Analysis

- The running time remains polynomial, being  $2k + 1$  times  $N$ 's running time.
- By Corollary 63 (p. 334), the probability of a false answer is at most  $e^{-\epsilon^2 k}$ .
- By taking  $k = \lceil 2/\epsilon^2 \rceil$ , the error probability is at most  $1/4$ .
- As with the RP case,  $\epsilon$  can be any inverse polynomial, because  $k$  remains polynomial in  $n$ .

## Aspects of BPP

- BPP is the most comprehensive yet plausible notion of efficient computation.
  - If a problem is in BPP, we take it to mean that the problem can be solved efficiently.
- $(\text{RP} \cup \text{coRP}) \subseteq (\text{NP} \cup \text{coNP})$  and  $(\text{RP} \cup \text{coRP}) \subseteq \text{BPP}$ .
- Whether  $\text{BPP} \subseteq (\text{NP} \cup \text{coNP})$  is unknown.

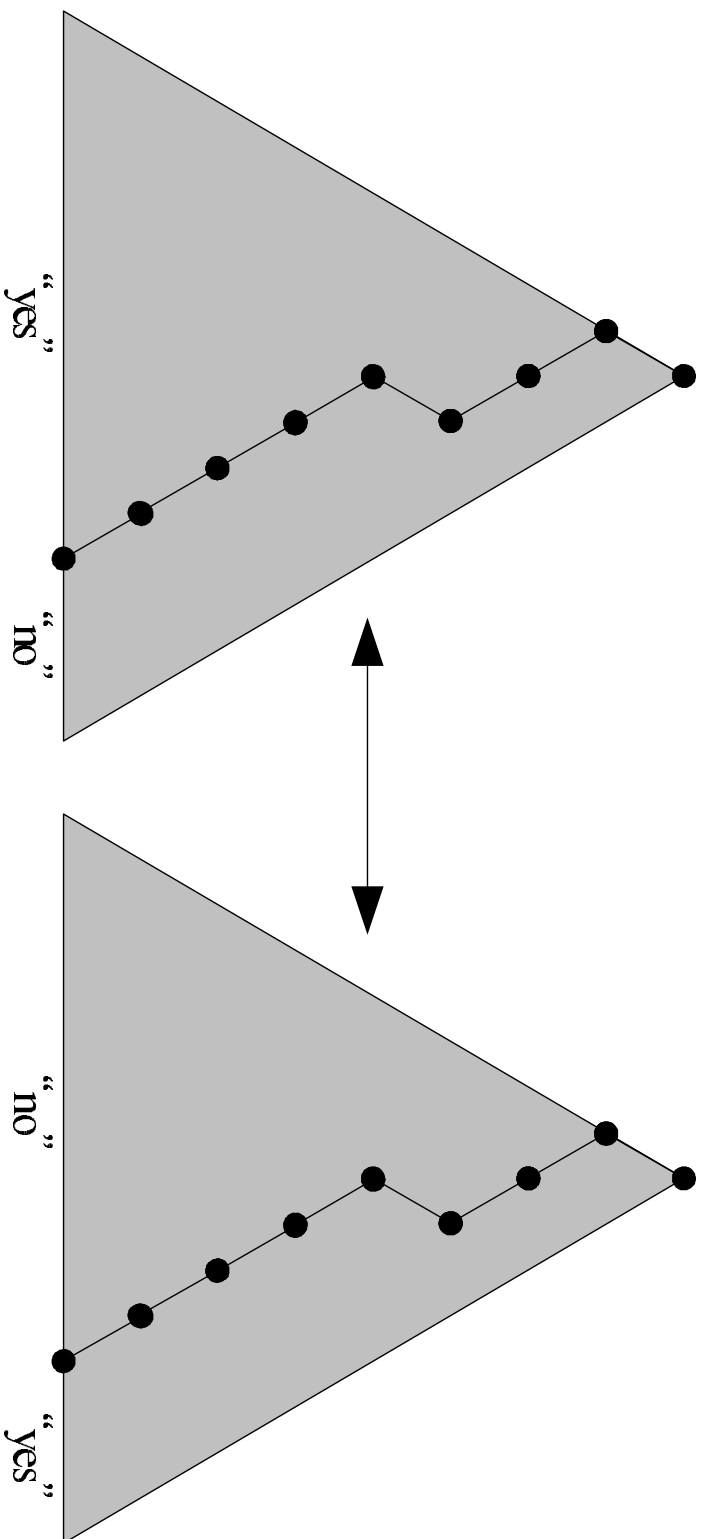
## A Review of Classes



## coBPP

- The definition of BPP is symmetric: acceptance by clear majority and rejection by clear majority.
- An algorithm for  $L \in \text{BPP}$  becomes one for  $\bar{L} \in \text{coBPP}$  by reversing the answer.
- Hence  $\text{BPP} = \text{coBPP}$ .
- This approach does not work for RP (it did not work for NP either).

# BPP and coBPP





## Circuit Complexity

- Circuit complexity is based on boolean circuits instead of Turing machines.
- A boolean circuit with  $n$  inputs computes a boolean function of  $n$  variables.
- By identify true with 1 and false with 0, a boolean circuit with  $n$  inputs accepts certain strings in  $\{0, 1\}^n$ .
- To relate circuits with arbitrary languages, we need one circuit for each possible input length  $n$ .

## Formal Definitions

- The **size** of a circuit is the number of *gates* in it.
- A **family of circuits** is an infinite sequence  $\mathcal{C} = (C_0, C_1, \dots)$  of boolean circuits, where  $C_n$  has  $n$  boolean inputs.
- $L \subseteq \{0, 1\}^*$  has **polynomial circuits** if there is a family of circuits  $\mathcal{C}$  such that:
  - The size of  $C_n$  is at most  $p(n)$  for some fixed polynomial  $p$ .
  - For input  $x \in \{0, 1\}^*$ ,  $C_{|x|}$  outputs 1 if and only if  $x \in L$ .
- \*  $C_n$  accepts  $L \cap \{0, 1\}^n$ .

## The Circuit Complexity of P

**Proposition 64** *All languages in P have polynomial circuits.*

- Let  $L \in P$  be decided by a TM in time  $p(n)$ .
- The construction in the proof of Theorem 25 (p. 169) gives, for any input of size  $n$ , a circuit with  $O(p(n)^2)$  gates that accepts  $L \cap \{0, 1\}^n$ .
- The size of the circuit depends only on  $L$  and the length of the input.
- The size of the circuit is polynomial in  $n$ .

## Languages That Polynomial Circuits Accept

- It is untrue that polynomial circuits accept only languages in P.
- There are *undecidable* languages that have polynomial circuits.
  - Let  $L \subseteq \{0, 1\}^*$  be an undecidable language.
  - Let  $U = \{1^n : \text{the binary expansion of } n \text{ is in } L\}$ .
  - $U$  must be undecidable.
  - $U \cap \{1\}^n$  can be accepted by  $C_n$  that is trivially false if  $1^n \notin U$  and trivially true if  $1^n \in U$ .
  - The family of circuits  $(C_0, C_1, \dots)$  is polynomial in size.

## A Patch

- Despite their simplicity,
  - Circuits are *not* a realistic model of computation.
  - Polynomial circuits are *not* a plausible notion of efficient computation.
- What gives?
- The *effective and efficient constructibility* of  $C_0, C_1, \dots$

## Uniformity

- A family  $(C_0, C_1, \dots)$  of circuits is **uniform** if there is a  $\log n$ -space bounded TM which on input  $1^n$  outputs  $C_n$ .
  - Circuits now cannot accept undecidable languages.
- A language has **uniformly polynomial circuits** if there is a *uniform* family of polynomial circuits that decides it.