

COMPLEXITY THEORY

Lecture 21: Probabilistic Turing Machines

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Knowledge-Based Systems

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Randomness in Computation

Random number generators are an important tool in programming

- Many known algorithms use randomness
- DTMs are fully deterministic without random choices
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Could a Turing machine benefit from having access to (truly) random numbers?

Example: Finding the Median

It is of interest to select the k -th smallest element of a set of numbers.

For example, the **median** of a set of numbers $\{a_1, \dots, a_n\}$ is the $\lceil \frac{n}{2} \rceil$ -th smallest number.

(Note: we restrict to odd n and disallow repeated numbers for simplicity)

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(Note: we restrict to odd n and disallow repeated numbers for simplicity)

The following simple algorithm selects the k -th smallest element:

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01 SELECTKTHELEMENT( $k, a_1, \dots, a_n$ ) :  
02   pick some  $p \in \{1, \dots, n\}$  // select pivot element  
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04   if  $c == k$  :  
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06   else if  $c > k$  :  
07      $L :=$  list of all  $a_i$  with  $a_i < a_p$   
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- The considered set shrinks by at least one element per iteration: $O(n)$ iterations

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So it would be faster to sort the list in $O(n \log n)$ and look up the k -th smallest element directly!

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However, what if we pick pivot elements at random with uniform probability?

- then it is extremely unlikely that the worst case occurs
- one can show that the expected runtime is linear [Arora & Barak, Section 7.2.1]
- worse than linear runtimes can occur, but the total probability of such runs is 0

The algorithm runs in almost certain linear time.

A refined implementation that works with repeated numbers is [Quickselect](#).

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- PTMs therefore are very similar to NTMs with (at most) two options per step
- We think of transitions as being selected randomly, with equal probability of 0.5: the PTM flips a fair coin in each step
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Example 21.2: The task of picking a random pivot element $p \in \{1, \dots, n\}$ with uniform probability can be achieved by a PTM:

- (1) Perform ℓ coin flips, where ℓ is the least number with $2^\ell \geq n$
- (2) Each outcome $\{1, \dots, n\}$ corresponds to one combination of the ℓ flips
- (3) For any other combination (if $n \neq 2^\ell$): goto (1) Note that the probability of infinite repetition is 0.

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- (1) it is possible that it will halt and accept
- (2) it is more likely than not that it will halt and accept
- (3) it is more likely than, say, 0.75 that it will halt and accept
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↪ Definitions do not seem to capture practical & efficient probabilistic algorithms yet

Random numbers as witnesses

Towards efficient probabilistic algorithms, we can restrict to PTMs where any run is guaranteed to be of **polynomial length**.

A useful alternative view on such PTMs is as follows:

Definition 21.3 (Polytime PTM, alternative definition): A **polynomially time-bounded PTM** is a polynomially time-bounded deterministic TM that receives inputs of the form $w\#r$, where $w \in \Sigma^*$ is an input word, and $r \in \{0, 1\}^*$ is a sequence of random numbers of length polynomial in $|w|$. If $w\#r$ is accepted, we may call r a **witness** for w .

Note the similarity to the notion of polynomial verifiers used for NP.

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The prior definition is closely related to the alternative version:

- Every run of a PTM corresponds to a sequence of results of coin flips
- Polytime PTMs only perform a polynomially bounded number of coin flips
- A DTM can simulate the same computation when given the outcome of the coin flips as part of the input

(Note: the polynomial bound comes from a fixed polynomial for the given TM, of course)

PP: Polynomial Probabilistic Time

Polynomial Probabilistic Time

The challenge of defining practical algorithms is illustrated by a basic class of PTM languages based on polynomial time bounds:

Definition 21.4: A language \mathbf{L} is in **Polynomial Probabilistic Time (PP)** if there is a PTM \mathcal{M} such that:

- there is a polynomial function f such that \mathcal{M} will always halt after $f(|w|)$ steps on all input words w ,
- if $w \in \mathbf{L}$, then $\Pr[\mathcal{M} \text{ accepts } w] > \frac{1}{2}$,
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Polynomial Probabilistic Time

The challenge of defining practical algorithms is illustrated by a basic class of PTM languages based on polynomial time bounds:

Definition 21.4: A language L is in **Polynomial Probabilistic Time (PP)** if there is a PTM M such that:

- there is a polynomial function f such that M will always halt after $f(|w|)$ steps on all input words w ,
- if $w \in L$, then $\Pr[M \text{ accepts } w] > \frac{1}{2}$,
- if $w \notin L$, then $\Pr[M \text{ accepts } w] \leq \frac{1}{2}$.

Alternative view: We could also say that M is a polynomially time-bounded PTM that accepts any word that is accepted in the majority of runs (or: the majority of witnesses)

\leadsto PP is sometimes called **Majority-P** (which would indeed be a better name)

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It turns out that PP is far from capturing the idea of “practically efficient”:

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The following PP algorithm \mathcal{M} solves **SAT** on input formula φ :

- (1) Randomly guess an assignment for φ .
- (2) If the assignment satisfies φ , accept.
- (3) If the assignment does not satisfy φ , randomly accept or reject with equal probability.

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Therefore:

- if φ is unsatisfiable, $\Pr[\mathcal{M} \text{ accepts } \varphi] = \frac{1}{2}$: the input is rejected;
- if φ is satisfiable, $\Pr[\mathcal{M} \text{ accepts } \varphi] > \frac{1}{2}$: the input is accepted. □

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Proof: Let $L \in \text{PP}$ be accepted by PTM \mathcal{M} , time-bounded by the polynomial $p(n)$. We therefore know:

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We first ensure that, in the second case, no word is accepted with probability $\frac{1}{2}$.

We construct an PTM \mathcal{M}' that first executes \mathcal{M} , and then:

- if \mathcal{M} rejects: \mathcal{M}' rejects
- if \mathcal{M} accepts: \mathcal{M}' flips coins for $p(n) + 1$ steps, rejects if they all of these coins are heads, and accepts otherwise.

This gives us $\Pr[\mathcal{M}' \text{ accepts } w] = \Pr[\mathcal{M} \text{ accepts } w] - (\frac{1}{2})^{p(n)+1}$ for all $w \in \Sigma^*$.

We will show that \mathcal{M}' still describes the language \mathbf{L} .

Complementing PP (2)

Theorem 21.7: PP is closed under complement.

Proof (continued): $\Pr[\mathcal{M}' \text{ accepts } w] = \Pr[\mathcal{M} \text{ accepts } w] - (\frac{1}{2})^{p(n)+1}$. We claim:

- If $w \in \mathbf{L}$, then $\Pr[\mathcal{M}' \text{ accepts } w] > \frac{1}{2}$
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The second inequality is clear (we subtract a non-zero number from $\leq \frac{1}{2}$).

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The first inequality follows since the probability of any run of \mathcal{M} on inputs of length n is an integer multiple of $(\frac{1}{2})^{p(n)}$. The same holds for sums of probabilities of runs, hence, if $w \in \mathbf{L}$, then $\Pr[\mathcal{M} \text{ accepts } w] \geq \frac{1}{2} + (\frac{1}{2})^{p(n)}$. The claim follows since $(\frac{1}{2})^{p(n)} > (\frac{1}{2})^{p(n)+1}$.

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To finish the proof, we construct the complement $\overline{\mathcal{M}'}$ of \mathcal{M}' by exchanging accepting and non-accepting states in \mathcal{M}' . Then:

- If $w \in \mathbf{L}$, then $\Pr[\overline{\mathcal{M}'} \text{ accepts } w] < \frac{1}{2}$
- If $w \notin \mathbf{L}$, then $\Pr[\overline{\mathcal{M}'} \text{ accepts } w] > \frac{1}{2}$

as required. □

PP is hard (2)

Since $\text{NP} \subseteq \text{PP}$ (Theorem 21.5), we also get:

Corollary 21.8: $\text{coNP} \subseteq \text{PP}$

PP therefore appears to be strictly harder than NP or coNP.

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Since $NP \subseteq PP$ (Theorem 21.5), we also get:

Corollary 21.8: $coNP \subseteq PP$

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The following strong result also hints in this direction:

Theorem 21.9: $PH \subseteq P^{PP}$

Note: The proof is based on a non-trivial result known as Toda's Theorem, which is about complexity classes where one can count satisfying assignments of propositional formulae ("**#SAT**"), together with the insight that this count can be computed in polynomial time using a PP oracle.

An upper bound for PP

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Proof: Consider a PTM \mathcal{M} that runs in time bounded by the polynomial $p(n)$.

We can decide if \mathcal{M} accepts input w as follows:

- (1) for each word $r \in \{0, 1\}^{p(|w|)}$:
- (2) decide if \mathcal{M} has an accepting run on w for the sequence r of random numbers;
- (3) accept if the total number of accepting runs is greater than $2^{p(|w|)-1}$, else reject.

This algorithm runs in polynomial space, as each iteration only needs to store r and the tape of the simulated polynomial TM computation. □

Complete problems for PP

We can define PP-hardness and PP-completeness using polynomial many-one reductions as before.

Using the similarity with NP, it is not hard to find a PP-complete problem:

MAJSAT

Input: A propositional logic formula φ .

Problem: Is φ satisfied by more than half of its assignments?

It is not hard to reduce the question whether a PTMs accepts an input to **MAJSAT**:

- Describe the behaviour of the PTM in logic, as in the proof of the Cook-Levin Theorem
- Each satisfying assignment then corresponds to one run

BPP: A practical probabilistic class

How to use PTMs in practice

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Problem: The acceptance probability for words in languages in PP can be arbitrarily close to $\frac{1}{2}$:

- It is enough if $2^{m-1} + 1$ runs accept out of 2^m runs overall
- So one would need an exponential number of repetitions to become reasonably certain

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We would rather like PTMs to accept with a fixed probability that does not converge to $\frac{1}{2}$.

A practical probabilistic class

The following way of deciding languages is based on a more easily detectable difference in acceptance probabilities:

Definition 21.11: A language \mathbf{L} is in **Bounded-Error Polynomial Probabilistic Time (BPP)** if there is a PTM \mathcal{M} such that:

- there is a polynomial function f such that \mathcal{M} will always halt after $f(|w|)$ steps on all input words w ,
- if $w \in \mathbf{L}$, then $\Pr[\mathcal{M} \text{ accepts } w] \geq \frac{2}{3}$,
- if $w \notin \mathbf{L}$, then $\Pr[\mathcal{M} \text{ accepts } w] \leq \frac{1}{3}$.

In other words: Languages in BPP are decided by polynomially time-bounded PTMs with **error probability** $\leq \frac{1}{3}$.

Note that the bound on the error probability is uniform across all inputs:

- For any given input, the probability for a correct answer is at least $\frac{2}{3}$
- It would be weaker to require that the probability of a correct answer is at least $\frac{2}{3}$ over the space of all possible inputs (this would allow worse probabilities on some inputs)

Better error bounds

Intuition suggests: If we run an PTM for a BPP language multiple times, then we can increase our certainty of a particular outcome.

Approach:

- Given input w , run \mathcal{M} for k times
- Accept if the majority of these runs accepts, and reject otherwise.

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Approach:

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What is the probability that we see some significant deviation from this expectation?

- It is still possible that only less than half of the runs return the correct result anyway
- How likely is this, depending on the number of repetitions k ?

Chernoff bounds

Chernoff bounds are a general type of result for estimating the probability of a certain deviation from the expectation when repeating a random experiment.

There are many such bounds – some more accurate, some more usable. We merely give the following simplified special case:

Theorem 21.12: Let X_1, \dots, X_k be mutually independent random variables that can take values from $\{0, 1\}$, and let $\mu = \sum_{i=1}^k E[X_i]$ be the sum of their expected values. Then, for every constant $0 < \delta < 1$:

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Example 21.13: Consider $k = 1000$ tosses of fair coins, X_1, \dots, X_{1000} , with heads corresponding to result 1 and tails corresponding to 0. We expect $\mu = \sum_{i=1}^n E[X_i] = 500$ to be the sum of these experiments. By the above bound, the probability of seeing $600 = 500 + 0.2 \cdot 500$ or more heads is

$$\Pr \left[\left| \sum_{i=1}^k X_i - 500 \right| \geq 100 \right] \leq e^{-0.2^2 \cdot 500 / 4} \leq 0.0068.$$

Much better error bounds

We can now show that even a small, input-dependent probability of finding correct answers is enough to construct an algorithm whose certainty is exponentially close to 1:

Theorem 21.14: Consider a language L and a polynomially time-bounded PTM \mathcal{M} for which there is a constant $c > 0$ such that, for every word $w \in \Sigma^*$, $\Pr[\mathcal{M} \text{ classifies } w \text{ correctly}] \geq \frac{1}{2} + |w|^{-c}$.

Then, for every constant $d > 0$, there is a polynomially time-bounded PTM \mathcal{M}' such that $\Pr[\mathcal{M}' \text{ classifies } w \text{ correctly}] \geq 1 - 2^{-|w|^d}$.

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Proof: We construct \mathcal{M}' as before by running \mathcal{M} for k times, where we set $k = 8|w|^{2c+d}$. Note that this is number of repetitions is polynomial in $|w|$.

To use our Chernoff bound, define k random variables X_i with $X_i = 1$ if the i th run of \mathcal{M} returns the correct result:

- Set p to be $\Pr[X_i = 1] \geq \frac{1}{2} + |w|^{-c}$
- Then $E[\sum_{i=1}^k X_i] = pk$

Much better error bounds (continued)

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Proof (continued): We are interested in the probability that at least half of the runs are correct. This can be achieved by setting $\delta = \frac{1}{2} \cdot |w|^{-c}$.

Our Chernoff bound then yields:

$$\Pr \left[\left| \sum_{i=1}^k X_i - pk \right| \geq \delta pk \right] \leq e^{-\delta^2 pk/4} = e^{-(\frac{1}{2} \cdot |w|^{-c})^2 pk/4} \leq e^{-\frac{1}{4|w|^{2c}} \cdot \frac{1}{2} \cdot 8|w|^{2c+d}} \leq e^{-|w|^d} \leq 2^{-|w|^d}$$

(where the estimations are dropping some higher-order terms for simplification).

BPP is robust

Theorem 21.14 gives a massive improvement in certainty at only polynomial cost. As a special case, we can apply this to BPP (where probabilities are fixed):

Corollary 21.15: Defining the class BPP with any bounded error probability $< \frac{1}{2}$ instead of $\frac{1}{3}$ leads to the same class of languages.

Corollary 21.16: For any language in BPP, there is a polynomial time algorithm with exponentially low probability of error.

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Corollary 21.16: For any language in BPP, there is a polynomial time algorithm with exponentially low probability of error.

BPP might be better than P for describing what is “tractable in practice.”

Summary and Outlook

Probabilistic TMs can be used to randomness in computation

PP defines a simple “probabilistic” class, but is too powerful in practice.

BPP provides a better definition of practical probabilistic algorithm

What's next?

- More probabilistic classes
- Quantum Computing
- Examinations