Lecture Topic: Theoretical Computer Science 101

What is a Classical Computer?

Before we consider quantum computing, it is worthwhile to review classical computing. Modern computers are very complicated.

People hence study many abstractions of the workings of a computer, called "models of computation".

We hence formalise a notion of a problem and a model of computation first.

What is a Classical Computer?

Before we consider quantum computing, it is worthwhile to review classical computing. Modern computers are very complicated.

People hence study many abstractions of the workings of a computer, called “models of computation”.

We hence formalise a notion of a problem and a model of computation first.

What is a Classical Computer?

Before we consider quantum computing, it is worthwhile to review classical computing. Modern computers are very complicated.

People hence study many abstractions of the workings of a computer, called "models of computation".

We hence formalise a notion of a problem and a model of computation first.

Decision Problem

Much of computer science uses a language-inspired definition of a decision problem.

One starts with an finite alphabet A.

By stringing elements of the alphabet one after another, one obtains strings of finite or countably infinite length.

A set of strings is called a language.

A decision problem is defined by a fixed set S, which is a subset of the language U of all possible strings over the alphabet A.

A particular instance of the decision problem is to decide, given an element $u \in U$, whether u is included in S.

Decision Problem

Much of computer science uses a language-inspired definition of a decision problem.

One starts with an finite alphabet A.

By stringing elements of the alphabet one after another, one obtains strings of finite or countably infinite length.

A set of strings is called a language.

A decision problem is defined by a fixed set S, which is a subset of the language U of all possible strings over the alphabet A.

A particular instance of the decision problem is to decide, given an element $u \in U$, whether u is included in S.

Decision Problem

Much of computer science uses a language-inspired definition of a decision problem.

One starts with an finite alphabet A.

By stringing elements of the alphabet one after another, one obtains strings of finite or countably infinite length.

A set of strings is called a language.

A decision problem is defined by a fixed set S, which is a subset of the language U of all possible strings over the alphabet A.

A particular instance of the decision problem is to decide, given an element $u \in U$, whether u is included in S.

Decision Problem

Much of computer science uses a language-inspired definition of a decision problem.

One starts with an finite alphabet A.

By stringing elements of the alphabet one after another, one obtains strings of finite or countably infinite length.

A set of strings is called a language.

A decision problem is defined by a fixed set S, which is a subset of the language U of all possible strings over the alphabet A.

A particular instance of the decision problem is to decide, given an element $u \in U$, whether u is included in S.

Decision Problem

Much of computer science uses a language-inspired definition of a decision problem.

One starts with an finite alphabet A.

By stringing elements of the alphabet one after another, one obtains strings of finite or countably infinite length.

A set of strings is called a language.

A decision problem is defined by a fixed set S, which is a subset of the language U of all possible strings over the alphabet A.

A particular instance of the decision problem is to decide, given an element $u \in U$, whether u is included in S.

Decision Problem

Much of computer science uses a language-inspired definition of a decision problem.

One starts with an finite alphabet A.

By stringing elements of the alphabet one after another, one obtains strings of finite or countably infinite length.

A set of strings is called a language.

A decision problem is defined by a fixed set S, which is a subset of the language U of all possible strings over the alphabet A.

A particular instance of the decision problem is to decide, given an element $u \in U$, whether u is included in S.

Example (Primality testing.)

For example, alphabet could be composed of binary digits $A = \{0, 1\}$, U could be the set of all natural numbers encoded in binary, and set S could be the binary encodings of prime numbers. The decision problem is the inclusion of an arbitrary binary encoding of a natural number in the set of S. $\diamondsuit$

Models of Computation

Several models of computation were devised. Alan Turing introduced a model, where

- characters are stored on an infinitely long tape,
- with a read/write head scanning one square at any given time and having
- very simple rules for changing its internal state based on the symbol read and current state.

Many of these formalisms turn out to be equivalent in computational power, *i.e.*, any computation that can be carried out with one can be carried out with any of the others. As it turns out, quantum computing may be one of the first models, where this is not the case.

Models of Computation

Several models of computation were devised. Alan Turing introduced a model, where

- characters are stored on an infinitely long tape,
- with a read/write head scanning one square at any given time and having
- very simple rules for changing its internal state based on the symbol read and current state.

Many of these formalisms turn out to be equivalent in computational power, *i.e.*, any computation that can be carried out with one can be carried out with any of the others. As it turns out, quantum computing may be one of the first models, where this is not the case.

Turing Machine

Formally, one can define a Turing machine using:

- a finite, non-empty set Q of objects, representing states
- a subset F of Q, corresponding to "accepting" states, where computation halts
- $q_0 \in Q$, the initial state
- a finite, non-empty set Γ of objects, representing the symbols to be used on a tape
- a partial function $\delta : (Q \setminus F) \times \Gamma \to Q \times \Gamma \times \{-1, 0, 1\}$ where for a combination of a state and symbol read from the tape, we get the next state, the symbol to write onto the tape, and an instruction to shift the tape left (-1), right (+1), or keep in its position (0).

Example (There and Back Again.)

Let us, for example, construct a machine, which scans over an integer encoded in binary and delimited by "blank" on the tape from left to right, and back. This is not very useful, but will be easy to understand:

- $Q = \{\text{goingright}, \text{goingleft}, \text{halt}\}$
- $F = \{\text{halt}\}$
- $q_0 = \text{goingright}$
- $\Gamma = \{0, 1, \text{“}blank''\}$
- δ given by the table below:

Current state	Scanned symbol	Print symbol	Move tape	Next state
goingright	0	0	1	goingright
goingright	1	1	1	goingright
goingright	blank	blank	-1	goingleft
goingleft	0	0	-1	goingleft
goingleft	1	1	-1	goingleft
goingleft	blank	blank	0	halt

◇

Exercise 1

Exercise

Consider the following simulator of a Turing machine (TM):

```python
def turing(code, tape, initPos = 0, initState = "1"):
  position = initPos
  state = initState
  while state != "halt":
    print f"{state} : {position} in {tape}"
    symbol = tape[position]
    (symbol, direction, state) = code[state][symbol]
    if symbol != "noWrite": tape[position] = symbol
    position += direction
```

code/ch1/turing.py

Implement a TM, which checks whether an integer, which is encoded on the tape as in binary and delimited by "blank" on both ends of the tape, is odd. If so, it should replace all symbols representing the integer with "1". Otherwise, it should replace all symbols representing the integer with "0".

Exercise

Consider the same simulator of a Turing machine (TM) as in Exercise 0.3. Implement a TM, which adds two integers, which are encoded on the tape in binary and delimited by "blank" on both ends of the tape and between the numbers. Replace both numbers with the result.

Computability

Computability studies these models of computation, and
asks which problems can be proven to be unsolvable by a computers.

Example (The Halting Problem)

Given a program and an input to the program,
will the program eventually stop when given that input? $\diamond$

The Halting Problem

A silly solution would be to just run the program with the given input, for a reasonable amount of time.

If the program stops, we know the program stops.

But if the program doesn't stop in a "reasonable" amount of time, we cannot conclude that it *won't* stop.

Maybe we didn't wait long enough.

Alan Turing proved the Halting problem to be undecidable in 1936.

The Halting Problem

A silly solution would be to just run the program with the given input, for a reasonable amount of time.

If the program stops, we know the program stops.

But if the program doesn't stop in a "reasonable" amount of time, we cannot conclude that it *won't* stop.

Maybe we didn't wait long enough.

Alan Turing proved the Halting problem to be undecidable in 1936.

The Halting Problem

A silly solution would be to just run the program with the given input, for a reasonable amount of time.

If the program stops, we know the program stops.

But if the program doesn't stop in a "reasonable" amount of time, we cannot conclude that it *won't* stop.

Maybe we didn't wait long enough.

Alan Turing proved the Halting problem to be undecidable in 1936.

The Halting Problem

A silly solution would be to just run the program with the given input, for a reasonable amount of time.

If the program stops, we know the program stops.

But if the program doesn't stop in a "reasonable" amount of time, we cannot conclude that it *won't* stop.

Maybe we didn't wait long enough.

Alan Turing proved the Halting problem to be undecidable in 1936.

The Halting Problem

A silly solution would be to just run the program with the given input, for a reasonable amount of time.

If the program stops, we know the program stops.

But if the program doesn't stop in a "reasonable" amount of time, we cannot conclude that it *won't* stop.

Maybe we didn't wait long enough.

Alan Turing proved the Halting problem to be undecidable in 1936.

The Halting Problem

A silly solution would be to just run the program with the given input, for a reasonable amount of time.

If the program stops, we know the program stops.

But if the program doesn't stop in a "reasonable" amount of time, we cannot conclude that it *won't* stop.

Maybe we didn't wait long enough.

Alan Turing proved the Halting problem to be undecidable in 1936.

Complexity

Some problems are solvable by a computer,
but require such a long time to compute that solution is impractical.

Here, we express the run time as a function from the dimensions of the input to the numbers of steps of a Turing machine (or similar).

Complexity

Some problems are solvable by a computer,
but require such a long time to compute that solution is impractical.

Here, we express the run time as a function from the dimensions of the input to the numbers of steps of a Turing machine (or similar).

Example (Fischer-Rabin Theorem.)

For example, let us have a logic featuring 0, 1, the usual addition, and where the axioms are a closure of the following:

- $\neg(0 = x + 1)$
- $x + 1 = y + 1 \Rightarrow x = y$
- $x + 0 = x$
- $x + (y + 1) = (x + y) + 1$
- For a first-order formula $P(x)$ (i.e., with the universal and existential quantifiers) with a free variable x, $(P(0) \wedge \forall x(P(x) \Rightarrow P(x + 1))) \Rightarrow \forall y P(y)$ ("induction").

This is known as the Presburger arithmetic.

Fischer and Rabin proved in 1974 that every classical algorithm that decides the truth of statement of length n in Presburger arithmetic has a runtime of at least $2^{2^{cn}}$ for some constant c, because it may need to produce output of that size. ◊

Example (Fischer-Rabin Theorem.)

For example, let us have a logic featuring 0, 1, the usual addition, and where the axioms are a closure of the following:

- $\neg(0 = x + 1)$
- $x + 1 = y + 1 \Rightarrow x = y$
- $x + 0 = x$
- $x + (y + 1) = (x + y) + 1$
- For a first-order formula $P(x)$ (i.e., with the universal and existential quantifiers) with a free variable x, $(P(0) \wedge \forall x(P(x) \Rightarrow P(x + 1))) \Rightarrow \forall y P(y)$ ("induction").

This is known as the Presburger arithmetic.

Fischer and Rabin proved in 1974 that every classical algorithm that decides the truth of statement of length n in Presburger arithmetic has a runtime of at least $2^{2^{cn}}$ for some constant c, because it may need to produce output of that size. $\diamondsuit$

Complexity theory

Complexity theory deals with questions concerning the time or space requirements of given problems: the *computational cost*. For algorithms working with finite strings from a finite alphabet, this is often surprisingly easy.

Analysis of algorithms

The term analysis of algorithms is used to describe the study of the performance of computer programs on a scientific basis.

One such approach concentrates on determining the growth of the worst-case performance of the algorithm (an “upper bound”): An algorithm’s “order” suggests asymptotics of the number of operations carried out by the algorithm on a particular input, as a function of the dimensions of the input.

Analysis of algorithms

The term analysis of algorithms is used to describe the study of the performance of computer programs on a scientific basis.

One such approach concentrates on determining the growth of the worst-case performance of the algorithm (an "upper bound"): An algorithm's "order" suggests asymptotics of the number of operations carried out by the algorithm on a particular input, as a function of the dimensions of the input.

O notation in run-time analysis

Example

For example, we might find that a certain algorithm takes time $T(n) = 3n^2 - 2n + 6$ to complete a problem of size n.

If we ignore

- constants (which makes sense because those depend on the particular hardware/virtual machine the program is run on), and
- slower growing terms such as $2n$,

we could say "$T(n)$ grows at the order of n^2".

O notation in run-time analysis

Example

For example, we might find that a certain algorithm takes time $T(n) = 3n^2 - 2n + 6$ to complete a problem of size n.

If we ignore

- constants (which makes sense because those depend on the particular hardware/virtual machine the program is run on), and
- slower growing terms such as $2n$,

we could say "$T(n)$ grows at the order of n^2".

O notation in run-time analysis

Example

For example, we might find that a certain algorithm takes time $T(n) = 3n^2 - 2n + 6$ to complete a problem of size n.

If we ignore

- constants (which makes sense because those depend on the particular hardware/virtual machine the program is run on), and
- slower growing terms such as $2n$,

we could say "$T(n)$ grows at the order of n^2". ◇

Asymptotic behaviour of functions and O notation

Let us introduce a formalisation of the notion of asymptotics.

The formalisation known as "Big O notation" or "Bachmann–Landau notation" goes back at least to 1892 and Paul Gustav Heinrich Bachmann, according to some sources, although it was reinvented many times over.

Suppose our A requires $T(n)$ operations to complete the algorithm in the longest possible case.

Then we may say A is $O(g(n))$ if $|T(n)/g(n)|$ is bounded from above as $n \to \infty$.

The fastest growing term in $T(n)$ dominates all the others as n gets bigger and so is the most significant measure of complexity.

Asymptotic behaviour of functions and O notation

Let us introduce a formalisation of the notion of asymptotics.

The formalisation known as “Big O notation” or “Bachmann–Landau notation” goes back at least to 1892 and Paul Gustav Heinrich Bachmann, according to some sources, although it was reinvented many times over.

Suppose our A requires $T(n)$ operations to complete the algorithm in the longest possible case.

Then we may say A is $O(g(n))$ if $|T(n)/g(n)|$ is bounded from above as $n \to \infty$.

The fastest growing term in $T(n)$ dominates all the others as n gets bigger and so is the most significant measure of complexity.

Asymptotic behaviour of functions and O notation

Let us introduce a formalisation of the notion of asymptotics.

The formalisation known as "Big O notation" or "Bachmann–Landau notation" goes back at least to 1892 and Paul Gustav Heinrich Bachmann, according to some sources, although it was reinvented many times over.

Suppose our A requires $T(n)$ operations to complete the algorithm in the longest possible case.

Then we may say A is $O(g(n))$ if $|T(n)/g(n)|$ is bounded from above as $n \to \infty$.

The fastest growing term in $T(n)$ dominates all the others as n gets bigger and so is the most significant measure of complexity.

Asymptotic behaviour of functions and O notation

Let us introduce a formalisation of the notion of asymptotics.

The formalisation known as "Big O notation" or "Bachmann–Landau notation" goes back at least to 1892 and Paul Gustav Heinrich Bachmann, according to some sources, although it was reinvented many times over.

Suppose our A requires $T(n)$ operations to complete the algorithm in the longest possible case.

Then we may say A is $O(g(n))$ if $|T(n)/g(n)|$ is bounded from above as $n \to \infty$.

The fastest growing term in $T(n)$ dominates all the others as n gets bigger and so is the most significant measure of complexity.

Asymptotic behaviour of functions and O notation

Let us introduce a formalisation of the notion of asymptotics.

The formalisation known as "Big O notation" or "Bachmann–Landau notation" goes back at least to 1892 and Paul Gustav Heinrich Bachmann, according to some sources, although it was reinvented many times over.

Suppose our A requires $T(n)$ operations to complete the algorithm in the longest possible case.

Then we may say A is $O(g(n))$ if $|T(n)/g(n)|$ is bounded from above as $n \to \infty$.

The fastest growing term in $T(n)$ dominates all the others as n gets bigger and so is the most significant measure of complexity.

Asymptotic behaviour of functions and O notation

Let us introduce a formalisation of the notion of asymptotics.

The formalisation known as "Big O notation" or "Bachmann–Landau notation" goes back at least to 1892 and Paul Gustav Heinrich Bachmann, according to some sources, although it was reinvented many times over.

Suppose our A requires $T(n)$ operations to complete the algorithm in the longest possible case.

Then we may say A is $O(g(n))$ if $|T(n)/g(n)|$ is bounded from above as $n \to \infty$.

The fastest growing term in $T(n)$ dominates all the others as n gets bigger and so is the most significant measure of complexity.

Asymptotic behaviour of functions and O notation

Similarly to "Big O", there are 4 more notions, as summarised in Table **??**.

$f(x) = O(g(x))$: f does not grow faster than g

Definition

We write:

$$f(x) = O(g(x)) \qquad \text{(or, to be more precise, } f(x) = O(g(x)) \text{ for } x \to \infty\text{)}$$

if and only if there exist constants N and $C > 0$ such that

$$|f(x)| \leq C|g(x)| \text{ for all } \; x > N \quad \text{or, equivalently, } \frac{|f(x)|}{|g(x)|} \leq C \text{ for all } \; x > N.$$

That is, $|f(x)/g(x)|$ is bounded from above as $x \to \infty$.

Intuitively, this means that f does not grow faster than g.

The letter "O" is read as "order" or just "Oh".

$f(x) = O(g(x))$: f does not grow faster than g

Definition

We write:

$$f(x) = O(g(x)) \qquad \text{(or, to be more precise, } f(x) = O(g(x)) \text{ for } x \to \infty\text{)}$$

if and only if there exist constants N and $C > 0$ such that

$$|f(x)| \leq C|g(x)| \text{ for all } \; x > N \quad \text{or, equivalently, } \frac{|f(x)|}{|g(x)|} \leq C \text{ for all } \; x > N.$$

That is, $|f(x)/g(x)|$ is bounded from above as $x \to \infty$.

Intuitively, this means that f does not grow faster than g.

The letter "O" is read as "order" or just "Oh".

$f(x) = O(g(x))$: f does not grow faster than g

Definition

We write:

$$f(x) = O(g(x)) \qquad \text{(or, to be more precise, } f(x) = O(g(x)) \text{ for } x \to \infty\text{)}$$

if and only if there exist constants N and $C > 0$ such that

$$|f(x)| \leq C|g(x)| \text{ for all } \; x > N \quad \text{or, equivalently, } \frac{|f(x)|}{|g(x)|} \leq C \text{ for all } \; x > N.$$

That is, $|f(x)/g(x)|$ is bounded from above as $x \to \infty$.

Intuitively, this means that f does not grow faster than g.

The letter "O" is read as "order" or just "Oh".

$f(x) = O(g(x))$: f does not grow faster than g

Definition

We write:

$$f(x) = O(g(x)) \qquad \text{(or, to be more precise, } f(x) = O(g(x)) \text{ for } x \to \infty)$$

if and only if there exist constants N and $C > 0$ such that

$$|f(x)| \leq C|g(x)| \text{ for all } \; x > N \quad \text{or, equivalently, } \frac{|f(x)|}{|g(x)|} \leq C \text{ for all } \; x > N.$$

That is, $|f(x)/g(x)|$ is bounded from above as $x \to \infty$.

Intuitively, this means that f does not grow faster than g.

The letter "O" is read as "order" or just "Oh".

$f(x) = \Omega(g(x))$: f does not grow slower than g

Definition

We also write:

$$f(x) = \Omega(g(x)) \qquad\qquad (\text{for } x \to \infty)$$

if and only if there exist constants N and $C > 0$ such that

$$|f(x)| \geq C|g(x)| \text{ for all } x > N \quad \text{or, equivalently, } \frac{|f(x)|}{|g(x)|} \geq C \text{ for all } x > N.$$

That is, $|f(x)/g(x)|$ is bounded from below by a *positive* (*i.e.*, non-zero) number as $x \to \infty$.

Intuitively, this means that f does not grow more slowly than g (*i.e.*, $g(x) = O(f(x))$).

The letter "Ω" is read as "omega" or just "bounded from below by".

$f(x) = \Omega(g(x))$: f does not grow slower than g

Definition

We also write:

$$f(x) = \Omega(g(x)) \qquad\qquad (\text{for } x \to \infty)$$

if and only if there exist constants N and $C > 0$ such that

$$|f(x)| \geq C|g(x)| \text{ for all } x > N \quad \text{or, equivalently, } \frac{|f(x)|}{|g(x)|} \geq C \text{ for all } x > N.$$

That is, $|f(x)/g(x)|$ is bounded from below by a *positive* (*i.e.*, non-zero) number as $x \to \infty$.

Intuitively, this means that f does not grow more slowly than g (*i.e.*, $g(x) = O(f(x))$).

The letter "Ω" is read as "omega" or just "bounded from below by".

$f(x) = \Omega(g(x))$: f does not grow slower than g

Definition

We also write:

$$f(x) = \Omega(g(x)) \qquad \text{(for } x \to \infty\text{)}$$

if and only if there exist constants N and $C > 0$ such that

$$|f(x)| \geq C|g(x)| \text{ for all } x > N \quad \text{or, equivalently, } \frac{|f(x)|}{|g(x)|} \geq C \text{ for all } x > N.$$

That is, $|f(x)/g(x)|$ is bounded from below by a *positive* (*i.e.*, non-zero) number as $x \to \infty$.

Intuitively, this means that f does not grow more slowly than g (*i.e.*, $g(x) = O(f(x))$).

The letter "Ω" is read as "omega" or just "bounded from below by".

$f(x) = \Omega(g(x))$: f does not grow slower than g

Definition

We also write:

$$f(x) = \Omega(g(x)) \qquad \text{(for } x \to \infty\text{)}$$

if and only if there exist constants N and $C > 0$ such that

$$|f(x)| \geq C|g(x)| \text{ for all } x > N \quad \text{or, equivalently, } \frac{|f(x)|}{|g(x)|} \geq C \text{ for all } x > N.$$

That is, $|f(x)/g(x)|$ is bounded from below by a *positive* (*i.e.*, non-zero) number as $x \to \infty$.

Intuitively, this means that f does not grow more slowly than g (*i.e.*, $g(x) = O(f(x))$).

The letter "Ω" is read as "omega" or just "bounded from below by".

$f(x) = \Theta(g(x))$: f grows at the same rate as g

Definition

$$f(x) = \Theta(g(x)) \qquad (\text{for } x \to \infty)$$

if and only if there exist constants N, C and $D > 0$ such that

$$D|g(x)| \leq |f(x)| \leq C|g(x)| \text{ for all } x > N \iff D \leq \frac{|f(x)|}{|g(x)|} \leq C \text{ for all } x > N.$$

That is, $|f(x)/g(x)|$ is bounded from both above and below by positive numbers as $x \to \infty$.

Intuitively, this means that f grows roughly at the same rate as g.

$f(x) = \Theta(g(x))$: f grows at the same rate as g

Definition

$$f(x) = \Theta(g(x)) \qquad (\text{for } x \to \infty)$$

if and only if there exist constants N, C and $D > 0$ such that

$$D|g(x)| \leq |f(x)| \leq C|g(x)| \text{ for all } x > N \iff D \leq \frac{|f(x)|}{|g(x)|} \leq C \text{ for all } x > N.$$

That is, $|f(x)/g(x)|$ is bounded from both above and below by positive numbers as $x \to \infty$.

Intuitively, this means that f grows roughly at the same rate as g.

$f(x) = \Theta(g(x))$: f grows at the same rate as g

Definition

$$f(x) = \Theta(g(x)) \qquad (\text{for } x \to \infty)$$

if and only if there exist constants N, C and $D > 0$ such that

$$D|g(x)| \le |f(x)| \le C|g(x)| \text{ for all } x > N \iff D \le \frac{|f(x)|}{|g(x)|} \le C \text{ for all } x > N.$$

That is, $|f(x)/g(x)|$ is bounded from both above and below by positive numbers as $x \to \infty$.

Intuitively, this means that f grows roughly at the same rate as g.

Polynomial time: order $O(n^k)$

Example

Let us consider algorithm A with parameter n and polynomial run-time $O(n^k)$. By our definition of O, the algorithm is of order $O(n^k)$ if $|T(n)/n^k|$ is bounded from above as $n \to \infty$, or — equivalently — there are real constants $a_0, a_1, \ldots, a_k$ with $a_k > 0$ so that A requires

$$a_k n^k + a_{k-1} n^{k-1} + \cdots + a_1 n + a_0$$

operations to complete in the worst case.

Note k is an integer constant independent of the algorithm input and n. There may be no such polynomial for the number of operations in terms of n.

If there is such a polynomial, A is usually considered "good" as it does not require "very many" operations.

Polynomial time: order $O(n^k)$

Example

Let us consider algorithm A with parameter n and polynomial run-time $O(n^k)$. By our definition of O, the algorithm is of order $O(n^k)$ if $|T(n)/n^k|$ is bounded from above as $n \to \infty$, or — equivalently — there are real constants $a_0, a_1, \ldots, a_k$ with $a_k > 0$ so that A requires

$$a_k n^k + a_{k-1} n^{k-1} + \cdots + a_1 n + a_0$$

operations to complete in the worst case.
Note k is an integer constant independent of the algorithm input and n. There may be no such polynomial for the number of operations in terms of n.
If there is such a polynomial, A is usually considered "good" as it does not require "very many" operations.

Polynomial time: order $O(n^k)$

Example

Let us consider algorithm A with parameter n and polynomial run-time $O(n^k)$. By our definition of O, the algorithm is of order $O(n^k)$ if $|T(n)/n^k|$ is bounded from above as $n \to \infty$, or — equivalently — there are real constants $a_0, a_1, \ldots, a_k$ with $a_k > 0$ so that A requires

$$a_k n^k + a_{k-1} n^{k-1} + \cdots + a_1 n + a_0$$

operations to complete in the worst case.
Note k is an integer constant independent of the algorithm input and n. There may be no such polynomial for the number of operations in terms of n.
If there is such a polynomial, A is usually considered "good" as it does not require "very many" operations. $\diamondsuit$

Multiple parameters

This notation can also be used with multiple parameters and with other expressions on the right side of the equal sign. The notation:

$$f(n, m) = n^2 + m^3 + O(n + m)$$

represents the statement:

there exist C, N such that, for all $n, m > N : f(n, m) \leq n^2 + m^3 + C(n + m)$.

Similarly, $O(mn^2)$ would mean the number of operations the algorithm carries out is a polynomial in two indeterminates n and m, with the highest degree term being mn^2, *e.g.*, $2mn^2 + 4mn - 6n^2 - 2n + 7$. This is most useful if we can relate m and n
(*e.g.*, in dense graphs $m = O(n^2)$, so $O(mn^2)$ would mean $O(n^4)$ there).

Multiple parameters

This notation can also be used with multiple parameters and with other expressions on the right side of the equal sign. The notation:

$$f(n, m) = n^2 + m^3 + O(n + m)$$

represents the statement:

there exist C, N such that, for all $n, m > N : f(n, m) \leq n^2 + m^3 + C(n + m)$.

Similarly, $O(mn^2)$ would mean the number of operations the algorithm carries out is a polynomial in two indeterminates n and m, with the highest degree term being mn^2, *e.g.*, $2mn^2 + 4mn - 6n^2 - 2n + 7$. This is most useful if we can relate m and n
(*e.g.*, in dense graphs $m = O(n^2)$, so $O(mn^2)$ would mean $O(n^4)$ there).

Multiple parameters

This notation can also be used with multiple parameters and with other expressions on the right side of the equal sign. The notation:

$$f(n, m) = n^2 + m^3 + O(n + m)$$

represents the statement:

there exist C, N such that, for all $n, m > N : f(n, m) \leq n^2 + m^3 + C(n + m)$.

Similarly, $O(mn^2)$ would mean the number of operations the algorithm carries out is a polynomial in two indeterminates n and m, with the highest degree term being mn^2, *e.g.*, $2mn^2 + 4mn - 6n^2 - 2n + 7$. This is most useful if we can relate m and n
(*e.g.*, in dense graphs $m = O(n^2)$, so $O(mn^2)$ would mean $O(n^4)$ there).

Classes of functions commonly met in algorithm analysis

Notation	*Name*
$O(1)$	constant
$O(\log(n))$	logarithmic
$O((\log(n))^c)$	polylogarithmic
$O(n)$	linear
$O(n^2)$	quadratic
$O(n^c)$	polynomial
$O(c^n)$	exponential
$O(n!)$	factorial

Here, $c > 0$ is a constant. Once again, if a function $f(n)$ is a sum of functions, the fastest growing one determines the order of $f(n)$.

E.g.: If $f(n) = 10\log(n) + 5(\log(n))^3 + 7n + 3n^2 + 6n^3$, then $f(n) = O(n^3)$.

Caveat: the number of summands must be constant and not depend on n.

Classes of functions commonly met in algorithm analysis

Notation	*Name*
$O(1)$	constant
$O(\log(n))$	logarithmic
$O((\log(n))^c)$	polylogarithmic
$O(n)$	linear
$O(n^2)$	quadratic
$O(n^c)$	polynomial
$O(c^n)$	exponential
$O(n!)$	factorial

Here, $c > 0$ is a constant. Once again, if a function $f(n)$ is a sum of functions, the fastest growing one determines the order of $f(n)$.

E.g.: If $f(n) = 10\log(n) + 5(\log(n))^3 + 7n + 3n^2 + 6n^3$, then $f(n) = O(n^3)$.

Caveat: the number of summands must be constant and not depend on n.

Classes of functions commonly met in algorithm analysis

Notation	*Name*
$O(1)$	constant
$O(\log(n))$	logarithmic
$O((\log(n))^c)$	polylogarithmic
$O(n)$	linear
$O(n^2)$	quadratic
$O(n^c)$	polynomial
$O(c^n)$	exponential
$O(n!)$	factorial

Here, $c > 0$ is a constant. Once again, if a function $f(n)$ is a sum of functions, the fastest growing one determines the order of $f(n)$.

E.g.: If $f(n) = 10\log(n) + 5(\log(n))^3 + 7n + 3n^2 + 6n^3$, then $f(n) = O(n^3)$.

Caveat: the number of summands must be constant and not depend on n.

Classes of functions commonly met in algorithm analysis

Notation	*Name*
$O(1)$	constant
$O(\log(n))$	logarithmic
$O((\log(n))^c)$	polylogarithmic
$O(n)$	linear
$O(n^2)$	quadratic
$O(n^c)$	polynomial
$O(c^n)$	exponential
$O(n!)$	factorial

Here, $c > 0$ is a constant. Once again, if a function $f(n)$ is a sum of functions, the fastest growing one determines the order of $f(n)$.

E.g.: If $f(n) = 10\log(n) + 5(\log(n))^3 + 7n + 3n^2 + 6n^3$, then $f(n) = O(n^3)$.

Caveat: the number of summands must be constant and not depend on n.

Notes on growth of functions

$O(n^c)$ and $O(c^n)$ are very different.

The former is polynomial, the latter is exponential and grows much, much faster, no matter how big the constant c is.

A function that grows faster than $O(n^c)$ is called superpolynomial. One that grows slower than $O(c^n)$ is called subexponential.

An algorithm can require time that is both superpolynomial and subexponential.

$O(\log n)$ is exactly the same as $O(\log(n^c))$.

The logarithms differ only by a constant factor,
and the big O notation ignores that.

Similarly, logs with different constant bases are equivalent.

Notes on growth of functions

$O(n^c)$ and $O(c^n)$ are very different.

The former is polynomial, the latter is exponential and grows much, much faster, no matter how big the constant c is.

A function that grows faster than $O(n^c)$ is called superpolynomial. One that grows slower than $O(c^n)$ is called subexponential.

An algorithm can require time that is both superpolynomial and subexponential.

$O(\log n)$ is exactly the same as $O(\log(n^c))$.

The logarithms differ only by a constant factor,
and the big O notation ignores that.

Similarly, logs with different constant bases are equivalent.

Notes on growth of functions

$O(n^c)$ and $O(c^n)$ are very different.

The former is polynomial, the latter is exponential and grows much, much faster, no matter how big the constant c is.

A function that grows faster than $O(n^c)$ is called superpolynomial. One that grows slower than $O(c^n)$ is called subexponential.

An algorithm can require time that is both superpolynomial and subexponential.

$O(\log n)$ is exactly the same as $O(\log(n^c))$.

The logarithms differ only by a constant factor,
and the big O notation ignores that.

Similarly, logs with different constant bases are equivalent.

Notes on growth of functions

$O(n^c)$ and $O(c^n)$ are very different.

The former is polynomial, the latter is exponential and grows much, much faster, no matter how big the constant c is.

A function that grows faster than $O(n^c)$ is called superpolynomial. One that grows slower than $O(c^n)$ is called subexponential.

An algorithm can require time that is both superpolynomial and subexponential.

$O(\log n)$ is exactly the same as $O(\log(n^c))$.

The logarithms differ only by a constant factor,
and the big O notation ignores that.

Similarly, logs with different constant bases are equivalent.

Notes on growth of functions

$O(n^c)$ and $O(c^n)$ are very different.

The former is polynomial, the latter is exponential and grows much, much faster, no matter how big the constant c is.

A function that grows faster than $O(n^c)$ is called superpolynomial. One that grows slower than $O(c^n)$ is called subexponential.

An algorithm can require time that is both superpolynomial and subexponential.

$O(\log n)$ is exactly the same as $O(\log(n^c))$.

The logarithms differ only by a constant factor,
and the big O notation ignores that.

Similarly, logs with different constant bases are equivalent.

Notes on growth of functions

$O(n^c)$ and $O(c^n)$ are very different.

The former is polynomial, the latter is exponential and grows much, much faster, no matter how big the constant c is.

A function that grows faster than $O(n^c)$ is called superpolynomial. One that grows slower than $O(c^n)$ is called subexponential.

An algorithm can require time that is both superpolynomial and subexponential.

$O(\log n)$ is exactly the same as $O(\log(n^c))$.

The logarithms differ only by a constant factor,
and the big O notation ignores that.

Similarly, logs with different constant bases are equivalent.

Notes on growth of functions

$O(n^c)$ and $O(c^n)$ are very different.

The former is polynomial, the latter is exponential and grows much, much faster, no matter how big the constant c is.

A function that grows faster than $O(n^c)$ is called superpolynomial. One that grows slower than $O(c^n)$ is called subexponential.

An algorithm can require time that is both superpolynomial and subexponential.

$O(\log n)$ is exactly the same as $O(\log(n^c))$.

The logarithms differ only by a constant factor,
and the big O notation ignores that.

Similarly, logs with different constant bases are equivalent.

Exercise

Prove that any later function in the above table grows faster than any earlier function.

Hint: you need several small proofs. Also, each function is differentiable.

Exercise

Prove that any later function in the above table grows faster than any earlier function.

Hint: you need several small proofs. Also, each function is differentiable.

P and **NP**

In complexity theory there are two commonly used classes of (decision) problems:

- The class **P** consists of all those decision problems that can be solved on a deterministic Turing machine in an amount of time that is polynomial in the size of the input, *i.e.*, $O(n^k)$ for some constant k. Intuitively, we think of the problems in **P** as those that can be solved "reasonably fast".
- The class **NP** consists of all those decision problems whose *solutions* (called witnesses) can be verified in polynomial time on a Turing machine. That is, given a proposed solution to the problem, we can check it really *is* a solution in polynomial time.

Defining NP

A language $L \subset \{0,1\}^*$ is in **NP**, if there exists a deterministic Turing machine M and a polynomial p such that upon receipt of:

- an input string x, e.g., $x \in \{0,1\}^*$,
- a witness of length $p(|x|)$

M runs in time polynomial in $|x|$ and

- for all $x \in L$, there exists y such that M accepts (x, y) ("completeness"),
- for all $x \notin L$, for all y, (x, y) is rejected ("soundness").

Randomized complexity classes

It seems quite unlikely that the Turing machine can produce a truly random number.

But would the availability of a source of randomness make a Turing machine more powerful?

We will formalise the question using the classes of Probabilistic Polynomial Time (PP) and Bounded-Error Probabilistic Polynomial Time (BPP), where BPP $\subset$ PP.

It is not known whether BPP is equal to P or NP, i.e., whether the source of randomness helps at all or whether having access to a source of randomness makes a deterministic Turing machine as powerful as a non-deterministic Turing machine, despite much attention paid to the questions over the past couple of decades.

On the other hand, it is known NP $\subset$ PP and, in a somewhat different formalisation of Bennett and Gill, we will see that the source of randomness does render many classes of computation (LOGSPACE^A, P^A, NP^A, PP^A, and PSPACE^A) properly contained in this order, with probability 1 with respect to random oracles A.

Randomized complexity classes

It seems quite unlikely that the Turing machine can produce a truly random number.

But would the availability of a source of randomness make a Turing machine more powerful?

We will formalise the question using the classes of Probabilistic Polynomial Time (PP) and Bounded-Error Probabilistic Polynomial Time (BPP), where BPP $\subset$ PP.

It is not known whether BPP is equal to P or NP, i.e., whether the source of randomness helps at all or whether having access to a source of randomness makes a deterministic Turing machine as powerful as a non-deterministic Turing machine, despite much attention paid to the questions over the past couple of decades.

On the other hand, it is known NP $\subset$ PP and, in a somewhat different formalisation of Bennett and Gill, we will see that the source of randomness does render many classes of computation (LOGSPACE^A, P^A, NP^A, PP^A, and PSPACE^A) properly contained in this order, with probability 1 with respect to random oracles A.

Randomized complexity classes

It seems quite unlikely that the Turing machine can produce a truly random number.

But would the availability of a source of randomness make a Turing machine more powerful?

We will formalise the question using the classes of Probabilistic Polynomial Time (PP) and Bounded-Error Probabilistic Polynomial Time (BPP), where BPP $\subset$ PP.

It is not known whether BPP is equal to P or NP, i.e., whether the source of randomness helps at all or whether having access to a source of randomness makes a deterministic Turing machine as powerful as a non-deterministic Turing machine, despite much attention paid to the questions over the past couple of decades.

On the other hand, it is known NP $\subset$ PP and, in a somewhat different formalisation of Bennett and Gill, we will see that the source of randomness does render many classes of computation (LOGSPACE^A, P^A, NP^A, PP^A, and PSPACE^A) properly contained in this order, with probability 1 with respect to random oracles A.

Randomized complexity classes

It seems quite unlikely that the Turing machine can produce a truly random number.

But would the availability of a source of randomness make a Turing machine more powerful?

We will formalise the question using the classes of Probabilistic Polynomial Time (PP) and Bounded-Error Probabilistic Polynomial Time (BPP), where BPP $\subset$ PP.

It is not known whether BPP is equal to P or NP, i.e., whether the source of randomness helps at all or whether having access to a source of randomness makes a deterministic Turing machine as powerful as a non-deterministic Turing machine, despite much attention paid to the questions over the past couple of decades.

On the other hand, it is known NP $\subset$ PP and, in a somewhat different formalisation of Bennett and Gill, we will see that the source of randomness does render many classes of computation (LOGSPACE^A, P^A, NP^A, PP^A, and PSPACE^A) properly contained in this order, with probability 1 with respect to random oracles A.

Randomized complexity classes

It seems quite unlikely that the Turing machine can produce a truly random number.

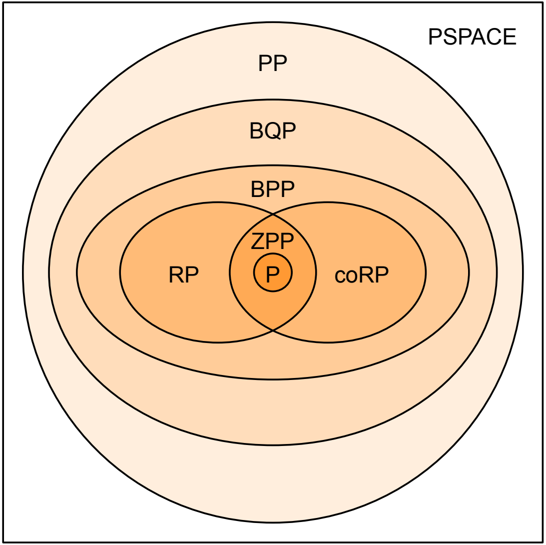
But would the availability of a source of randomness make a Turing machine more powerful?

We will formalise the question using the classes of Probabilistic Polynomial Time (PP) and Bounded-Error Probabilistic Polynomial Time (BPP), where BPP $\subset$ PP.

It is not known whether BPP is equal to P or NP, i.e., whether the source of randomness helps at all or whether having access to a source of randomness makes a deterministic Turing machine as powerful as a non-deterministic Turing machine, despite much attention paid to the questions over the past couple of decades.

On the other hand, it is known NP $\subset$ PP and, in a somewhat different formalisation of Bennett and Gill, we will see that the source of randomness does render many classes of computation (LOGSPACE^A, P^A, NP^A, PP^A, and PSPACE^A) properly contained in this order, with probability 1 with respect to random oracles A.

Randomized complexity classes



Defining randomised computation

In two important definitions of randomise computation, one considers a deterministic Turing machine M, which receives:

- an input string x, e.g., $x \in \{0, 1\}^*$,
- a realisation y, e.g., $y \in \{0, 1\}^*$, of a random variable Y

and

- accepts the input (x, y) for all x that we would like to be accepted with a certain probability,
- rejects (x, y) for all x we would like to be rejected with a certain probability,

where the probability is with respect to Y.

Defining PP

A language $L \subset \{0,1\}^*$ is in PP, if there exists a deterministic Turing machine M and a polynomial p such that upon receipt of:

- an input string x, e.g., $x \in \{0,1\}^*$,
- a realisation y of length $p(|x|)$, e.g., $y \in \{0,1\}^{p(|x|)}$, of a random variable Y

M runs in time polynomial in $|x|$ and

- for all $x \in L$, (x, y) is accepted with a probability strictly greater than $1/2$,
- for all $x \notin L$, (x, y) is accepted with a probability less than or equal than $1/2$,

where the probability is with respect to Y.

Explaining PP

In PP, we hence ask only for some "distinguishability".

The "distinguishing" can, however, take arbitrarily long.

Consider, for instance, a Turing machine M of the definition, that

- for all $x \in L$, (x, y) is accepted with probability $1/2 + 1/2|x|$
- for all $x \notin L$, (x, y) is accepted with probability $1/2 - 1/2|x|$.

For any number of trials, there is an $|x|$ that makes those necessary to achieve a fixed probability of the answer being correct.

Notice that the number of trials grows expoentnially with $|x|$.

Explaining PP

In PP, we hence ask only for some "distinguishability".

The "distinguishing" can, however, take arbitrarily long.

Consider, for instance, a Turing machine M of the definition, that

- for all $x \in L$, (x, y) is accepted with probability $1/2 + 1/2|x|$
- for all $x \notin L$, (x, y) is accepted with probability $1/2 - 1/2|x|$.

For any number of trials, there is an $|x|$ that makes those necessary to achieve a fixed probability of the answer being correct.

Notice that the number of trials grows expoentnially with $|x|$.

Explaining PP

In PP, we hence ask only for some "distinguishability".

The "distinguishing" can, however, take arbitrarily long.

Consider, for instance, a Turing machine M of the definition, that

- for all $x \in L$, (x, y) is accepted with probability $1/2 + 1/2|x|$
- for all $x \notin L$, (x, y) is accepted with probability $1/2 - 1/2|x|$.

For any number of trials, there is an $|x|$ that makes those necessary to achieve a fixed probability of the answer being correct.

Notice that the number of trials grows expoentnially with $|x|$.

Explaining PP

In PP, we hence ask only for some “distinguishability”.

The “distinguishing” can, however, take arbitrarily long.

Consider, for instance, a Turing machine M of the definition, that

- for all $x \in L$, (x, y) is accepted with probability $1/2 + 1/2|x|$
- for all $x \notin L$, (x, y) is accepted with probability $1/2 - 1/2|x|$.

For any number of trials, there is an $|x|$ that makes those necessary to achieve a fixed probability of the answer being correct.

Notice that the number of trials grows expoentnially with $|x|$.

Explaining PP

In PP, we hence ask only for some “distinguishability”.

The “distinguishing” can, however, take arbitrarily long.

Consider, for instance, a Turing machine M of the definition, that

- for all $x \in L$, (x, y) is accepted with probability $1/2 + 1/2|x|$
- for all $x \notin L$, (x, y) is accepted with probability $1/2 - 1/2|x|$.

For any number of trials, there is an $|x|$ that makes those necessary to achieve a fixed probability of the answer being correct.

Notice that the number of trials grows expoentnially with $|x|$.

An Alternative Definition of PP

Alternatively, PP is the set of languages, for which there is a variant of a non-deterministic Turing machine that stops in polynomial time with the acceptance condition being that more than one half of computational paths accept.

One hence sometimes refers to PP as Majority-P.

It is hence clear that NP $\subseteq$ PP.

An Alternative Definition of PP

Alternatively, PP is the set of languages, for which there is a variant of a non-deterministic Turing machine that stops in polynomial time with the acceptance condition being that more than one half of computational paths accept.

One hence sometimes refers to PP as Majority-P.

It is hence clear that NP $\subseteq$ PP.

An Alternative Definition of PP

Alternatively, PP is the set of languages, for which there is a variant of a non-deterministic Turing machine that stops in polynomial time with the acceptance condition being that more than one half of computational paths accept.

One hence sometimes refers to PP as Majority-P.

It is hence clear that NP $\subseteq$ PP.

A Complete Problem for PP

PP is a often thought of as a counting class.

Recall that the permanent of an $n \times n$ matrix $A = (a_{ij})$ is

$$\mathrm{perm}(A) = \sum_{\sigma \in S_n} \prod_{i=1}^{n} a_{i,\sigma(i)}. \tag{1.1}$$

Valiant showed that computing permanents is at least as hard as many so-called counting problems (#P-hard), and it is hard (#P-complete) even for matrices with entries 0 or 1.

The language $\{(A, k) |$ the permanent of A is at least $k\}$ is complete for PP, but it is believed to be outside of P.

Alternatively, in terms of the number of accepting and rejecting paths, PP can be seen as computing the high-order bit of a #P function.

A Complete Problem for PP

PP is a often thought of as a counting class.

Recall that the permanent of an $n \times n$ matrix $A = (a_{ij})$ is

$$\mathrm{perm}(A) = \sum_{\sigma \in S_n} \prod_{i=1}^{n} a_{i,\sigma(i)}. \tag{1.1}$$

Valiant showed that computing permanents is at least as hard as many so-called counting problems (#P-hard), and it is hard (#P-complete) even for matrices with entries 0 or 1.

The language $\{(A, k) |$ the permanent of A is at least $k\}$ is complete for PP, but it is believed to be outside of P.

Alternatively, in terms of the number of accepting and rejecting paths, PP can be seen as computing the high-order bit of a #P function.

A Complete Problem for PP

PP is a often thought of as a counting class.

Recall that the permanent of an $n \times n$ matrix $A = (a_{ij})$ is

$$\mathrm{perm}(A) = \sum_{\sigma \in S_n} \prod_{i=1}^{n} a_{i,\sigma(i)}. \tag{1.1}$$

Valiant showed that computing permanents is at least as hard as many so-called counting problems (#P-hard), and it is hard (#P-complete) even for matrices with entries 0 or 1.

The language $\{(A, k)|$ the permanent of A is at least $k\}$ is complete for PP, but it is believed to be outside of P.

Alternatively, in terms of the number of accepting and rejecting paths, PP can be seen as computing the high-order bit of a #P function.

A Complete Problem for PP

PP is a often thought of as a counting class.

Recall that the permanent of an $n \times n$ matrix $A = (a_{ij})$ is

$$\mathrm{perm}(A) = \sum_{\sigma \in S_n} \prod_{i=1}^{n} a_{i,\sigma(i)}. \tag{1.1}$$

Valiant showed that computing permanents is at least as hard as many so-called counting problems (#P-hard), and it is hard (#P-complete) even for matrices with entries 0 or 1.

The language $\{(A, k) |$ the permanent of A is at least $k\}$ is complete for PP, but it is believed to be outside of P.

Alternatively, in terms of the number of accepting and rejecting paths, PP can be seen as computing the high-order bit of a #P function.

Defining BPP

Let ϵ be a constant $0 < \epsilon < 1/2$. A language $L \subset \{0,1\}^*$ is in BPP, if there exists a deterministic Turing machine M and a polynomial p such that upon receipt of:

- an input string x, e.g., $x \in \{0,1\}^*$,
- a realisation y, e.g., $y \in \{0,1\}^{p(|x|)}$, of a random variable Y in dimension $p(|x|)$

M runs in time polynomial in $|x|$ and

- for all $x \in L$, (x, y) is accepted with a probability strictly greater than $1 - \epsilon$,
- for all $x \notin L$, (x, y) is accepted with a probability less than or equal than ϵ,

where the probability is with respect to Y.

Explaining BPP

BPP can be seen as a subset of PP, for which there are efficient probabilistic algorithms.

Because the constant ϵ is independent of the dimension $|x|$, we can achieve any desired probability of correctness with the number of trials independent of $|x|$ by the so-called *amplification of probability*.

The majority vote of k trials will be wrong with probability:

$$\sum_{S\subseteq\{1,2,\ldots,k\},|S|\leq k/2} (1-\epsilon)^{|S|}\epsilon^{k-|S|} \tag{1.2}$$

$$= ((1-\epsilon)\epsilon)^{k/2} \sum_{S\subseteq\{1,2,\ldots,k\},|S|\leq k/2} \left(\frac{\epsilon}{1-\epsilon}\right)^{k/2-|S|} \tag{1.3}$$

$$< 2^k(\sqrt{(1-\epsilon)\epsilon})^k = \lambda^k \tag{1.4}$$

for some $\lambda = 2\sqrt{\epsilon(1-\epsilon)} < 1$.

How large is this class within PP?

Explaining BPP

BPP can be seen as a subset of PP, for which there are efficient probabilistic algorithms.

Because the constant ϵ is independent of the dimension $|x|$, we can achieve any desired probability of correctness with the number of trials independent of $|x|$ by the so-called *amplification of probability*.

The majority vote of k trials will be wrong with probability:

$$\sum_{S\subseteq\{1,2,\ldots,k\},|S|\leq k/2} (1-\epsilon)^{|S|}\epsilon^{k-|S|} \tag{1.2}$$

$$= ((1-\epsilon)\epsilon)^{k/2} \sum_{S\subseteq\{1,2,\ldots,k\},|S|\leq k/2} \left(\frac{\epsilon}{1-\epsilon}\right)^{k/2-|S|} \tag{1.3}$$

$$< 2^k(\sqrt{(1-\epsilon)\epsilon})^k = \lambda^k \tag{1.4}$$

for some $\lambda = 2\sqrt{\epsilon(1-\epsilon)} < 1$.

How large is this class within PP?

Explaining BPP

BPP can be seen as a subset of PP, for which there are efficient probabilistic algorithms.

Because the constant ϵ is independent of the dimension $|x|$, we can achieve any desired probability of correctness with the number of trials independent of $|x|$ by the so-called *amplification of probability*.

The majority vote of k trials will be wrong with probability:

$$\sum_{S\subseteq\{1,2,\dots,k\},|S|\leq k/2} (1-\epsilon)^{|S|}\epsilon^{k-|S|} \tag{1.2}$$

$$= ((1-\epsilon)\epsilon)^{k/2} \sum_{S\subseteq\{1,2,\dots,k\},|S|\leq k/2} \left(\frac{\epsilon}{1-\epsilon}\right)^{k/2-|S|} \tag{1.3}$$

$$< 2^k(\sqrt{(1-\epsilon)\epsilon})^k = \lambda^k \tag{1.4}$$

for some $\lambda = 2\sqrt{\epsilon(1-\epsilon)} < 1$.

How large is this class within PP?

Explaining BPP

BPP can be seen as a subset of PP, for which there are efficient probabilistic algorithms.

Because the constant ϵ is independent of the dimension $|x|$, we can achieve any desired probability of correctness with the number of trials independent of $|x|$ by the so-called *amplification of probability*.

The majority vote of k trials will be wrong with probability:

$$\sum_{S\subseteq\{1,2,\ldots,k\},|S|\leq k/2} (1-\epsilon)^{|S|}\epsilon^{k-|S|} \tag{1.2}$$

$$= ((1-\epsilon)\epsilon)^{k/2} \sum_{S\subseteq\{1,2,\ldots,k\},|S|\leq k/2} \left(\frac{\epsilon}{1-\epsilon}\right)^{k/2-|S|} \tag{1.3}$$

$$< 2^k(\sqrt{(1-\epsilon)\epsilon})^k = \lambda^k \tag{1.4}$$

for some $\lambda = 2\sqrt{\epsilon(1-\epsilon)} < 1$.

How large is this class within PP?

An Alternative Definition of BPP, due to Bennett

It turns out that BPP is a substantial subset of PP.

Bennett and Gill have shown that for a language $L \subset \{0,1\}^*$, the following are equivalent:

- $L \in$ BPP.
- For almost all oracles A, $L \in P^A$, wherein the almost all is with respect to a particular measure over the oracles.

An Alternative Definition of BPP, due to Bennett

It turns out that BPP is a substantial subset of PP.

Bennett and Gill have shown that for a language $L \subset \{0,1\}^*$, the following are equivalent:

- $L \in$ BPP.
- For almost all oracles A, $L \in P^A$, wherein the almost all is with respect to a particular measure over the oracles.

Probabilistic Computation of Arora and Barak

It turns out that BPP has yet another definition, due to Arora and Barak, which is very instructive.

It uses a seemingly different model of computation.

There, one works with 2^N-dimensional vector $v \in [0,1]^{2^N}$, which we index with values from $\{0,1\}^N$, and which satisfies $\sum_{i \in \{0,1\}^N} v_i = 1$.

This vector should be seen as a representation of a probability mass function of a random variable over $\{0,1\}^N$.

One cannot access the values of v directly; rather, one obtains $i \in \{0,1\}^N$ with probability v_i, when one attempts to access v.

Probabilistic Computation of Arora and Barak

It turns out that BPP has yet another definition, due to Arora and Barak, which is very instructive.

It uses a seemingly different model of computation.

There, one works with 2^N-dimensional vector $v \in [0,1]^{2^N}$, which we index with values from $\{0,1\}^N$, and which satisfies $\sum_{i \in \{0,1\}^N} v_i = 1$.

This vector should be seen as a representation of a probability mass function of a random variable over $\{0,1\}^N$.

One cannot access the values of v directly; rather, one obtains $i \in \{0,1\}^N$ with probability v_i, when one attempts to access v.

Probabilistic Computation of Arora and Barak

It turns out that BPP has yet another definition, due to Arora and Barak, which is very instructive.

It uses a seemingly different model of computation.

There, one works with 2^N-dimensional vector $v \in [0,1]^{2^N}$, which we index with values from $\{0,1\}^N$, and which satisfies $\sum_{i \in \{0,1\}^N} v_i = 1$.

This vector should be seen as a representation of a probability mass function of a random variable over $\{0,1\}^N$.

One cannot access the values of v directly; rather, one obtains $i \in \{0,1\}^N$ with probability v_i, when one attempts to access v.

Probabilistic Computation of Arora and Barak

It turns out that BPP has yet another definition, due to Arora and Barak, which is very instructive.

It uses a seemingly different model of computation.

There, one works with 2^N-dimensional vector $v \in [0,1]^{2^N}$, which we index with values from $\{0,1\}^N$, and which satisfies $\sum_{i \in \{0,1\}^N} v_i = 1$.

This vector should be seen as a representation of a probability mass function of a random variable over $\{0,1\}^N$.

One cannot access the values of v directly; rather, one obtains $i \in \{0,1\}^N$ with probability v_i, when one attempts to access v.

Probabilistic Computation of Arora and Barak

It turns out that BPP has yet another definition, due to Arora and Barak, which is very instructive.

It uses a seemingly different model of computation.

There, one works with 2^N-dimensional vector $v \in [0,1]^{2^N}$, which we index with values from $\{0,1\}^N$, and which satisfies $\sum_{i \in \{0,1\}^N} v_i = 1$.

This vector should be seen as a representation of a probability mass function of a random variable over $\{0,1\}^N$.

One cannot access the values of v directly; rather, one obtains $i \in \{0,1\}^N$ with probability v_i, when one attempts to access v.

Probabilistic Computation of Arora and Barak

Let us introduce a special notation $|i\rangle$ for the representation of (so-called degenerate) distributions, where all the mass is concentrated in $v_i = 1$ for some $i \in \{0,1\}^N$.

Because $|i\rangle_{i\in\{0,1\}^N}$ is a basis for $\mathbb{R}^{2^N}$, any v can be represented as $\sum_{i\in\{0,1\}^N} v_i|i\rangle$. For the example of $N = 1$, we have $v = v_0|0\rangle + v_1|1\rangle$.

The only operations permitted are linear stochastic functions $U : \mathbb{R}^{2^N} \rightarrow \mathbb{R}^{2^N}$ applied to the vector v, where linearity suggests $U(v) = \sum_{i\in\{0,1\}^N} v_i U(|i\rangle)$ and stochasticity suggests $\sum_{i\in\{0,1\}^N} U(v)_i = 1$ for all v satisfying $\sum_{i\in\{0,1\}^N} v_i = 1$.

Notice that U can be represented by a matrix with non-negative entries, wherein each column sums up to 1.

U can be a composition of multiple linear stochastic functions $U = U_L, U_{L-1}, \cdots U_2, U_1, U_i : \mathbb{R}^{2^N} \rightarrow \mathbb{R}^{2^N}$, where each U_i will represent the so-called gate and L will be the known as the depth of the circuit.

Probabilistic Computation of Arora and Barak

Let us introduce a special notation $|i\rangle$ for the representation of (so-called degenerate) distributions, where all the mass is concentrated in $v_i = 1$ for some $i \in \{0,1\}^N$.

Because $|i\rangle_{i\in\{0,1\}^N}$ is a basis for $\mathbb{R}^{2^N}$, any v can be represented as $\sum_{i\in\{0,1\}^N} v_i|i\rangle$. For the example of $N = 1$, we have $v = v_0|0\rangle + v_1|1\rangle$.

The only operations permitted are linear stochastic functions $U : \mathbb{R}^{2^N} \to \mathbb{R}^{2^N}$ applied to the vector v, where linearity suggests $U(v) = \sum_{i\in\{0,1\}^N} v_i U(|i\rangle)$ and stochasticity suggests $\sum_{i\in\{0,1\}^N} U(v)_i = 1$ for all v satisfying $\sum_{i\in\{0,1\}^N} v_i = 1$.

Notice that U can be represented by a matrix with non-negative entries, wherein each column sums up to 1.

U can be a composition of multiple linear stochastic functions $U = U_L, U_{L-1}, \cdots U_2, U_1, U_i : \mathbb{R}^{2^N} \to \mathbb{R}^{2^N}$, where each U_i will represent the so-called gate and L will be the known as the depth of the circuit.

Probabilistic Computation of Arora and Barak

Let us introduce a special notation $|i\rangle$ for the representation of (so-called degenerate) distributions, where all the mass is concentrated in $v_i = 1$ for some $i \in \{0,1\}^N$.

Because $|i\rangle_{i \in \{0,1\}^N}$ is a basis for $\mathbb{R}^{2^N}$, any v can be represented as $\sum_{i \in \{0,1\}^N} v_i |i\rangle$. For the example of $N = 1$, we have $v = v_0|0\rangle + v_1|1\rangle$.

The only operations permitted are linear stochastic functions $U : \mathbb{R}^{2^N} \to \mathbb{R}^{2^N}$ applied to the vector v, where linearity suggests $U(v) = \sum_{i \in \{0,1\}^N} v_i U(|i\rangle)$ and stochasticity suggests $\sum_{i \in \{0,1\}^N} U(v)_i = 1$ for all v satisfying $\sum_{i \in \{0,1\}^N} v_i = 1$.

Notice that U can be represented by a matrix with non-negative entries, wherein each column sums up to 1.

U can be a composition of multiple linear stochastic functions $U = U_L, U_{L-1}, \cdots U_2, U_1, U_i : \mathbb{R}^{2^N} \to \mathbb{R}^{2^N}$, where each U_i will represent the so-called gate and L will be the known as the depth of the circuit.

Probabilistic Computation of Arora and Barak

Let us introduce a special notation $|i\rangle$ for the representation of (so-called degenerate) distributions, where all the mass is concentrated in $v_i = 1$ for some $i \in \{0,1\}^N$.

Because $|i\rangle_{i\in\{0,1\}^N}$ is a basis for $\mathbb{R}^{2^N}$, any v can be represented as $\sum_{i\in\{0,1\}^N} v_i|i\rangle$. For the example of $N = 1$, we have $v = v_0|0\rangle + v_1|1\rangle$.

The only operations permitted are linear stochastic functions $U : \mathbb{R}^{2^N} \to \mathbb{R}^{2^N}$ applied to the vector v, where linearity suggests $U(v) = \sum_{i\in\{0,1\}^N} v_i U(|i\rangle)$ and stochasticity suggests $\sum_{i\in\{0,1\}^N} U(v)_i = 1$ for all v satisfying $\sum_{i\in\{0,1\}^N} v_i = 1$.

Notice that U can be represented by a matrix with non-negative entries, wherein each column sums up to 1.

U can be a composition of multiple linear stochastic functions $U = U_L, U_{L-1}, \cdots U_2, U_1, U_i : \mathbb{R}^{2^N} \to \mathbb{R}^{2^N}$, where each U_i will represent the so-called gate and L will be the known as the depth of the circuit.

Probabilistic Computation of Arora and Barak

Let us introduce a special notation $|i\rangle$ for the representation of (so-called degenerate) distributions, where all the mass is concentrated in $v_i = 1$ for some $i \in \{0,1\}^N$.

Because $|i\rangle_{i\in\{0,1\}^N}$ is a basis for $\mathbb{R}^{2^N}$, any v can be represented as $\sum_{i\in\{0,1\}^N} v_i|i\rangle$. For the example of $N = 1$, we have $v = v_0|0\rangle + v_1|1\rangle$.

The only operations permitted are linear stochastic functions $U : \mathbb{R}^{2^N} \to \mathbb{R}^{2^N}$ applied to the vector v, where linearity suggests $U(v) = \sum_{i\in\{0,1\}^N} v_i U(|i\rangle)$ and stochasticity suggests $\sum_{i\in\{0,1\}^N} U(v)_i = 1$ for all v satisfying $\sum_{i\in\{0,1\}^N} v_i = 1$.

Notice that U can be represented by a matrix with non-negative entries, wherein each column sums up to 1.

U can be a composition of multiple linear stochastic functions $U = U_L, U_{L-1}, \cdots U_2, U_1, U_i : \mathbb{R}^{2^N} \to \mathbb{R}^{2^N}$, where each U_i will represent the so-called gate and L will be the known as the depth of the circuit.

An Alternative Definition of BPP, due to Arora and Barak

Let a probability threshold be a constant strictly larger than $1/2$. A language $L \subset \{0,1\}^n$ is in BPP, if and only if its corresponding indicator function $F(x) : \{0,1\}^n \to \{0,1\}$ can be computed probabilistically in polynomial time such that:

1. one starts with $v \in [0,1]^{2^N}$, for some $N \geq n$ dependent on F, with an initial state $|x, 0^{N-n}\rangle$ consisting of the input padded to length N by zeros;
2. applies a linear stochastic function $U : \mathbb{R}^{2^N} \to \mathbb{R}^{2^N}$ to v, whose matrix representation can be computed in a sparse format by a Turing machine from all-ones input in time polynomial in n
3. obtains a random variable Y, wherein $F(x)$ is followed by $N-1$ arbitrary subsequent symbols with probability at least as high as the probability threshold, wherein the random variable Y has value y with probability v_y for the value v of some final register.

An Alternative Definition of BQP, due to Arora and Barak

Let a probability threshold be a constant strictly larger than $1/2$. A language $L \subset \{0,1\}^n$ is in BQP, if and only if its corresponding indicator function $F(x) : \{0,1\}^n \to \{0,1\}$ can be computed probabilistically such that:

1. one starts with an N-qubit register, for some $N \geq n$ dependent on F, with an initial state $|x, 0^{N-n}\rangle$ consisting of the input padded to length N by zeros;
2. applies a linear function $U : \mathbb{C}^{2^N} \to \mathbb{C}^{2^N}$ to v, whose matrix representation (a unitary matrix in $\mathbb{C}^{2^N \times 2^N}$) can be computed in a sparse format by a Turing machine from all-ones input in time polynomial in n
3. obtains a random variable Y, wherein $F(x)$ is followed by $N-1$ arbitrary subsequent symbols with probability at least as high as the probability threshold, wherein the random variable Y has value y with probability $|v_y|^2$ for the value v of some final register.