COMP 3711H

Lecture 1: Introduction

Computational Problems and Algorithms

- A computational problem is a specification of the desired input-output relationship.
- An instance of a problem is all the inputs needed to compute a solution to the problem.
- An algorithm is a well defined computational procedure that transforms inputs into outputs, achieving the desired input-output relationship.
- A correct algorithm halts with the correct output for every input instance. We then say that the algorithm solves the problem.

Example of a Problem and an Instance

Computational Problem: Sorting

- **Input:** Sequence of n numbers $\langle a_1, \dots, a_n \rangle$.
- Output: Permutation (reordering)

$$\langle a_1', a_2', \cdots, a_n' \rangle$$

such that $a_1' \leq a_2' \leq \cdots \leq a_n'$.

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Instance of Problem Sorting

• **Input:** Permutation

$$\langle 8, 3, 6, 7, 1, 2, 9 \rangle$$

• Output: Permutation (reordering)

$$\langle 1, 2, 3, 6, 7, 8, 9 \rangle$$

Example of Algorithm: Insertion Sort

In-Place Sort: uses only a fixed amount of storage beyond that needed for the data.

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Pseudocode:

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A is an array of numbers
for j=2 to length(A)
\{ \text{ key} = A[j];
   i = i - 1:
   while (i \geq 1 \text{ and } A[i] > \text{key})
    \{ A[i+1] = A[i];
       i = i - 1:
   A[i+1] = \text{key};
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Pause:

How does it work?

To sort an array of length n: n steps ith step sorts the array of the first i items by inserting ith item properly into sorted array of the first i-1 items (created in previous step)

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Step 2: (3, 6, 2, 4) Step 4: (2, 3, 4, 6)

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Predict resource utilization

- 1. **Memory** (space complexity)
- 2. Running time (time complexity)

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- 1. **Memory** (space complexity)
- 2. Running time (time complexity)

Remark: Depends on model of computation, e.g.,

sequential vs. parallel or internal memory vs. external memory.

In this class we usually assume sequential and internal memory.

Running time: the number of primitive operations used to solve the problem.

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Input size: rigorous definition given later.

- 1. **Sorting:** number of items to be sorted
- 2. Multiplication: number of bits, number of digits.
- 3. Graphs: number of vertices and edges.

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Average Case: average running time over every possible type of input (usually involve probabilities of different types of input).

Example. In average case *Quicksort* runs in $\Theta(n \log n)$ time on an input of n keys. All n! inputs of n keys are considered equally likely.

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Remark: All cases are relative to the algorithm under consideration.

Best Case:
$$A[1] \leq A[2] \leq A[3] \leq \cdots \leq A[n]$$
.

The number of comparisons needed is equal to

$$\underbrace{1 + 1 + 1 + \dots + 1}_{n-1} = n - 1 = \Theta(n).$$

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The number of comparisons needed is equal to

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Average Case: $\Theta(n^2)$ assuming that each of the n! instances are equally likely.

Further thoughts on algorithm design

- Algorithm Design, as taught in this class, is mainly about designing algorithms that have small big O() running times.
- "All other things being equal", $O(n\log n)$ algorithms will run more quickly than $O(n^2)$ ones and O(n) algorithms will beat $O(n\log n)$ ones.
- Being able to do good algorithm design lets you identify the hard parts of your problem and deal with them effectively.
- Too often, programmers try to solve problems using brute force techniques and end up with slow complicated code! A few hours of abstract thought devoted to algorithm design could have speeded up the solution substantially and simplified it.

Final Note

Note: After algorithm design one can continue on to *Algorithm tuning* which would further concentrate on improving algorithms by cutting cut down on the *constants* in the big O() bounds. This needs a good understanding of both algorithm design principles and efficient use of data structures.

In this course we will not go further into algorithm tuning. For a good introduction, see Chapter 9 in *Programming Pearls*, 2nd ed by Jon Bentley.