Time and Space complexity

Agenda

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Overview and notations

Overview

 Computational complexity theory aims to categorize different algorithmic problems according to their difficulty

 Uses mathematical models to provide estimates in terms of resources needed to solve a particular problem such as:

time: the predicted execution time

space: the predicted memory required by the problem

Overview

 In practice complexity theory can be used to statically determine what is the required execution time or memory for a piece of code

 Applies for pretty much any programming language and program logic (not only complex algorithms)

Overview

 To provide those estimates complexity theory uses several notations used to predict:

- worst case
- best case
- average case

Complexity

- Complexity is expressed as a function of the inputs
- For an algorithm depending on input n, complexity might be expressed a function f(n) of that input

$$n \rightarrow f(n)$$

 For multiple inputs complexity might a function of multiple parameters

```
n, m \rightarrow f(n, m)
```

Notations

- Theta notation measures average case complexity
- It is measured by a function f(n) such that there are two constants c1 and c2, which for sufficiently large n (n0) can bound f(n) by g(n)

```
\Theta(g(n)) = \{ f(n) \mid \exists c1, c2 > 0, \exists n0 : \forall n \ge n0, \\ 0 \le c1.g(n) \le f(n) \le c2.g(n) \}
```

Notations

- O notation (big or small) measures worst case complexity
- Big-O is measured by a function f(n) such that there is a constant c which for sufficiently large n (n0) can upperbound f(n) by g(n)

```
O(g(n)) = \{ f(n) \mid \exists c > 0, \exists n0 : \forall n \ge n0, \\ 0 \le f(n) \le c.g(n) \}
```

 For small-o there is any constant c > 0 for sufficiently large n(n0)

```
o(g(n)) = \{ f(n) | \forall c > 0, \exists n0 : \forall n \ge n0, \\ 0 \le f(n) < c.g(n)
```

Notations

- Omega notation (big or small) measures best case complexity
- Big-omega is measured by a function f(n) such that there is a constant c which for sufficiently large n (n0) can lowerbound f(n) by g(n)

```
\Omega(g(n)) = \{ f(n) \mid \exists c > 0, \exists n0 : \forall n \ge n0, \\ 0 \le c.g(n) \le f(n) \}
```

 For small-omega there is any constant c > 0 for sufficiently large n(n0)

```
\omega(g(n)) = \{ f(n) \mid \forall c > 0, \exists n0 : \forall n \ge n0, \\ 0 \le c.g(n) < f(n)
```

Basic terminology

O(1)	constant
O(log(n))	logarithmic
O(n)	linear
O(n ²)	quadratic
O(n ^c)	polynomial
O(c ⁿ)	exponential
O(n!)	factorial

Big-O notation is most widely used in practice

Amortized complexity

 Complexity might not be very precise in many cases as it depends on the operations and not on the algorithm itself

 That is why amortized analysis tries to provide a more accurate measure for time and space complexity

 The general idea is that we first determine the total cost of a sequence operations and divide the results by the number of these operations

Amortized complexity

Example (amortized complexity is O(n)):

```
public double f(double[] prices,
              double[] discounts) {
       double result = 0;
       for (int i = 0; i < n; i++) {
              result+= prices[i];
              // if there are 10 items or more
              // then discounts apply
              if(i == 10) {
                     for (int j = 0; j < n; j++) {
                            result -= discounts[j];
       return result;
```

Algorithm complexity

Algorithm complexity

- We will define how to weight each type of construct in the Java programming language in order to measure properly time complexity:
 - simple operations like variable assignment, expressions, if/swtich statements etc. are considered constant
 - loops (for/while) take linear time if number of iterations is linear on an input parameter
 - recursive calls add another method invocation, hence multiply to the complexity of the method (without the recursive calls)

Constant complexity

```
public int f(int x, int y) {
    return x + y;
}
```

Linear complexity

```
public int f(int n, int[] numbers) {
    int result = 0;
    for(int number : numbers) {
        result += number;
    }
    return result;
}
```

Quadratic complexity

```
public int f(int n, int[] numbers) {
    int result = 0;
    for(int n1 : numbers) {
        for(int n2 : numbers) {
            result += n1 + n2;
        }
    }
    return result;
}
```

Polynomial complexity

Logarithmic complexity

Example:

```
int indexedBinarySearch(List<? extends Comparable<? super T>>
             list, T key) {
      int low = 0;
      int high = list.size()-1;
       while (low <= high) {
            int mid = (low + high) >>> 1;
            Comparable<? super T> midVal = list.get(mid);
            int cmp = midVal.compareTo(key);
            if (cmp < 0) low = mid + 1;
            else if (cmp > 0) high = mid - 1;
            else return mid; // key found
      return -(low + 1); // key not found
```

Above method is called from java.util.Collections#binarySearch

Exponential complexity

```
public int f(int n, int c) {
    int result = 0;
    for(int i = 2; i <= n; i++) {
        result += Math.log(i);
    }
    if(c > 1) {
        result += f(n, c - 1);
    }
    return result;
}
```

Factorial complexity

```
public int f(int n) {
    int result = 0;
    for(int i = 2; i <= n; i++) {
        result += Math.log(i);
    }

    if(n > 1) {
        result += f(n - 1);
    }

    return result;
}
```

Exercises

```
public double f(int n) {
    double a = 0;
    for(int i = 0; i < n; i++) {
        for(int j = i; j < n; j++) {
            for (int k = n + i + j - 3; k < n; k++) {
                a = a + Math.log(k);
            }
        }
    }
    return a;
}</pre>
```

```
public double f(int n) {
    double a = 0;
    for(int i = 0; i < n; i++) {
        for(int j = i; j < n; j++) {
            for (int k = n + i + j - 3; k < n; k++) {
                a = a + Math.log(k);
            }
        }
    }
    return a;
}</pre>
```

Answer: O(n²)

Answer: O(n)

```
public int f(int n) {
    int result = 0;
    for(int i = 1; i <= n; i++) {
        result += Math.cos(i);
    }

    if(n > 1) {
        result += f(n/2);
    }

    return result;
}
```

```
public int f(int n) {
    int result = 0;
    for(int i = 1; i <= n; i++) {
        result += Math.cos(i);
    }

    if(n > 1) {
        result += f(n/2);
    }

    return result;
}
```

Answer: O(n log(n))

```
// mergeSort(n, 0, n.length - 1);
public void mergeSort(Comparable [ ] a,
    int left, int right) {
    if( left < right )
    {
        int center = (left + right) / 2;
        mergeSort(a, left, center);
        mergeSort(a, center + 1, right);
        // merge is O(n)
        merge(a, tmp, left, center + 1, right);
    }
}</pre>
```

```
// mergeSort(n, 0, n.length - 1);
public void mergeSort(Comparable [ ] a,
    int left, int right) {
    if( left < right )
    {
        int center = (left + right) / 2;
        mergeSort(a, left, center);
        mergeSort(a, center + 1, right);
        // merge is O(n)
        merge(a, tmp, left, center + 1, right);
    }
}</pre>
```

Answer: O(n log(n))

Answer: O(n²)

```
public double f(int n, int[] numbers) {
    double a = 0;
    for(int i = n; i > 0; i/=2) {
        for(int j = i; j < n; j*=2) {
            for (int k = 0; k < n; k+=2) {
                a = a + numbers[i];
            }
        }
     }
    return a;
}</pre>
```

```
public double f(int n, int[] numbers) {
    double a = 0;
    for(int i = n; i > 0; i/=2) {
        for(int j = i; j < n; j*=2) {
            for (int k = 0; k < n; k+=2) {
                a = a + numbers[i];
            }
        }
        return a;
}</pre>
```

Answer: O(n log(n)²)

Questions?