

Calculating algorithm complexity

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with function interpolation

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Abstract

Traditionally, calculating an algorithm's complexity is done by looking at the runtime terminal statements and counting the number of operations. However, algorithms with non-polynomial complexity are particularly hard to estimate this way as one would usually resort to brute-force calculation. Our method proposes a simple way to approximate the actual complexity of an algorithm. First, we make a table with the number of operations that a function makes for a certain input n starting at 1, and with each incrementation of n corresponding to a new value in our table (Ex: $n=1, 2, 3, 4, 5 \Rightarrow f(n)= 1, 2, 4, 7, 11\dots$). Then we made a calculated column with $n-1$ values, where each number is the difference between the upper two complexity values, (1, 2, 3, 4 in this case, since it represents $2-1, 4-2, 7-4, 11-7$). This process was repeated until we got a table with one value, and then treated it as the starting constant for the operation complexity equation (Example: if there were 5 tables, then the lone value at the bottom was the 4th derivative of the operation function). We tested this method with a java program that interpolated the data from the tables into a function that served as a reasonable estimate for what the complexity behaves like for a certain range of data points. For an input of X test data points we can model the operation complexity of a sample size of $2X$ data points with an average accuracy of 70%.

Introduction

The complexity of a given algorithm provides an approximate **estimation of its runtime**, expressed as a function of the input size (n). Such estimation is done **independent of the particular implementation** details. The runtime $T(n)$ is measured as the number of elementary steps of constant duration needed to execute the algorithm.

Goals:

- Predict the behavior and runtime of an algorithm without implementing it
- Compare multiple algorithms in order to select the best one for the considered purpose

Assumptions:

- Determining the algorithm complexity is an approximate evaluation
- Exact behavior and runtime are hard to compute given the large number of influencing factors

In AI, algorithm complexity is crucial. [1] investigates the speed of algorithm improvement and the corresponding complexity.

Background

Usual steps:

1. **Identify time consuming operations:**
 - Evaluate which operations in the given algorithm contribute significantly to the overall runtime
2. **Count operations:**
 - Estimate how many times each key operation is executed as a function of the input size (n)
3. **Expression simplification:**
 - Simplify the expressions from step 2, focusing on the higher powers of (n) that give the largest time contribution (ignore lower order terms in power of (n))
4. **Use Big O notation:**
 - Transform the simplified expression from step 3 in Big O notation, that provides an upper bound for the algorithm runtime growth rate as a function of input size (n)

Issues:

- Takes long time
- Slow



Introducing solution with example

Algorithm:

$R(n) \{$

$T(n)$

$R(n-$

$1)\}$

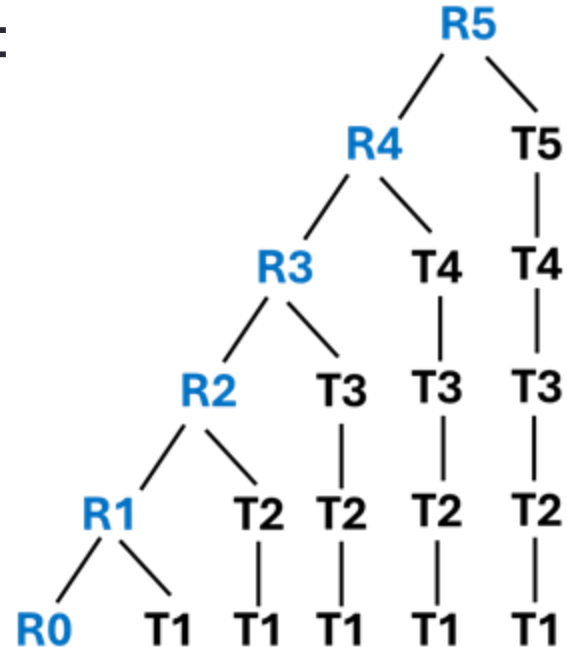
$T(n)\{$

$T(n-$

$1)\}$



Tree calls:



Integration

ValueTable:

N:	0	1	2	3	4	5
calls:	0	2	5	9	14	20
diff:		2	3	4	5	6
diff:		1	1	1	1	

$$f''(n) = 1$$

$$f'(n) = \int 1 dn = n + c$$

$$f(n) = \int n + c dn = \frac{n^2}{2} + cn + d$$

$$O(n) \approx \text{highest power} = \frac{n^2}{2} \approx n^2$$

$$\longrightarrow O(n) = n^2$$

Math - finite differences

Derive difference quotient from Taylor's polynomial [\[edit \]](#)

For a n -times differentiable function, by [Taylor's theorem](#) the [Taylor series](#) expansion is given as

$$f(x_0 + h) = f(x_0) + \frac{f'(x_0)}{1!}h + \frac{f^{(2)}(x_0)}{2!}h^2 + \dots + \frac{f^{(n)}(x_0)}{n!}h^n + R_n(x),$$

Assuming that $R_1(x)$ is sufficiently small, the approximation of the first derivative of f is:

$$f'(x_0) \approx \frac{f(x_0 + h) - f(x_0)}{h}.$$

This is similar to the definition of derivative, which is:

$$f'(x_0) = \lim_{h \rightarrow 0} \frac{f(x_0 + h) - f(x_0)}{h}.$$

except for the limit towards zero (the method is named after this).

Brook Taylor(1685 -1731)



Algorithm

```

/**
 * Method that takes an ArrayList of numbers and returns an ArrayList of number that are the distances between each of the terms
 * Exe: Takes [0, 1, 3, 6, 10, 15], and returns [1, 2, 3, 4, 5], since those are the distance between 0 and 1, 1 and 3, 3 and 6, etc
 * @param prevArrayList the original ArrayList from which to find the distances
 * @return An ArrayList of the distances between each of the terms in the og AL
 */
public ArrayList<Integer> arrDeriv(ArrayList<Integer> prevArrayList)
{
    ArrayList<Integer> derived = new ArrayList<Integer>();
    for(int i = 0; i < prevArrayList.size()-1; i++)
    {
        derived.add(prevArrayList.get(i+1) - prevArrayList.get(i));
    }

    return derived;
}

```



```

+1.0x^(0)
1 , 2 , 4 , 8 , 16 ,
1 , 2 , 4 , 8 ,
1 , 2 , 4 ,
1 , 2 ,
1 ,

```

PREDICTED FUNCTION: $+0.04166666666666664x^4 - 0.08333333333333333x^3 + 0.5x^2 + 0.41666666666666669x^1 + 1.0x^0$

PREDICTED COMPLEXITY: 57.5

REAL COMPLEXITY: 64.0

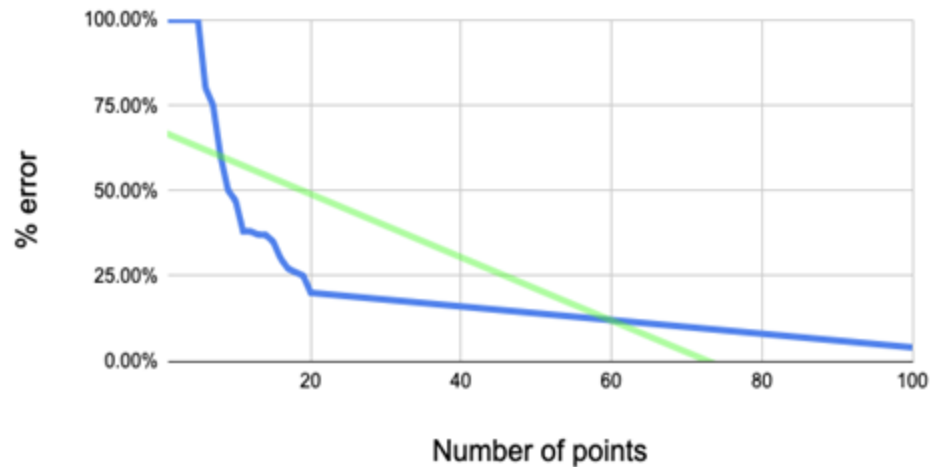
THE ERROR PERCENT IS: 10.15625%

Results

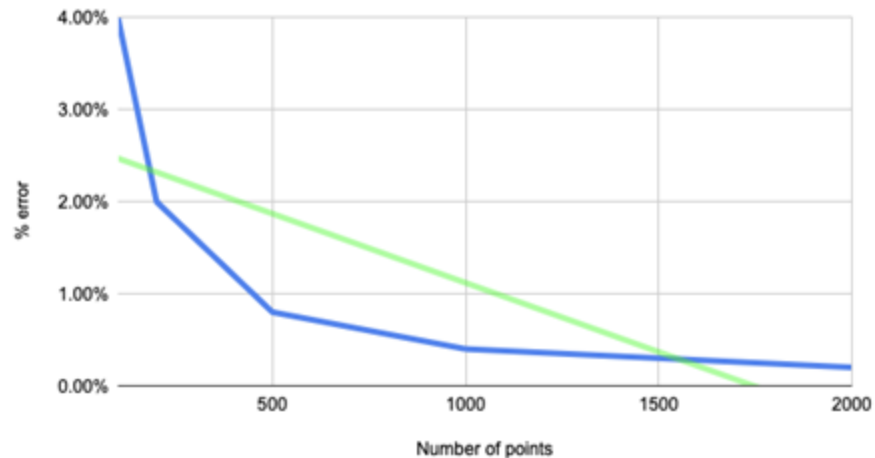
Polynomial function of grade 4



% average gap actual complexity vs our method



% error vs. Number of points for large data



Results

Polynomial function of grade 2 with only 3 input points

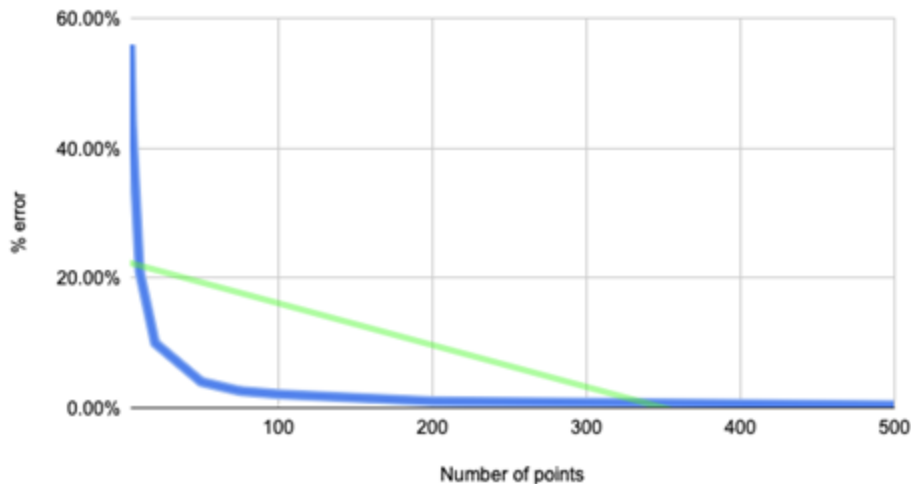
Sample pyramid with 10 points

```

1 , 4 , 9 , 16 , 25 , 36 , 49 , 64 , 81 , 100 ,
3 , 5 , 7 , 9 , 11 , 13 , 15 , 17 , 19 ,
2 , 2 , 2 , 2 , 2 , 2 , 2 , 2 , 2 ,
0 , 0 , 0 , 0 , 0 , 0 , 0 ,
0 , 0 , 0 , 0 , 0 , 0 ,
0 , 0 , 0 , 0 , 0 ,
0 , 0 , 0 , 0 ,
0 , 0 , 0 ,
0 , 0 ,
0 ,

```

% error vs. Number of points



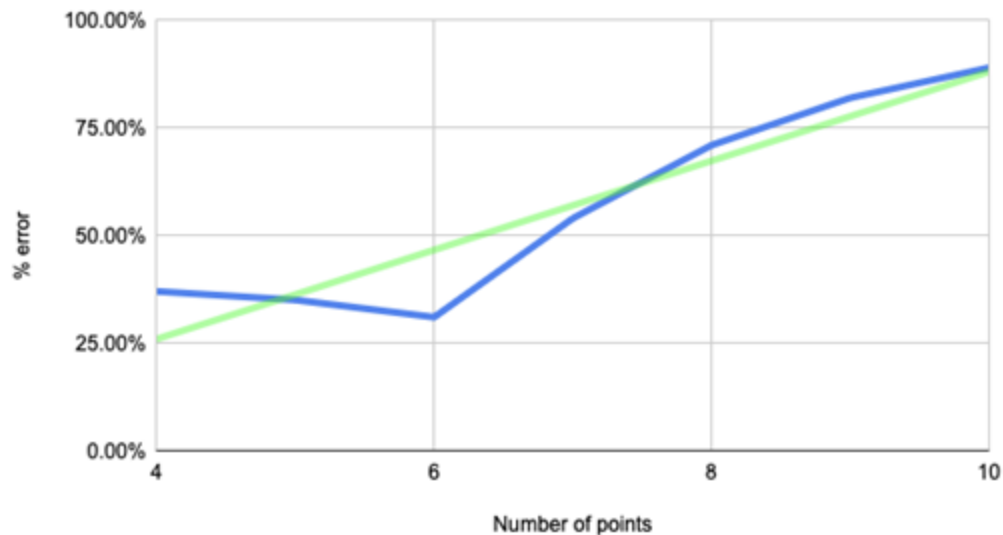
Results

2^n function with only 3 points

Sample pyramid with 3 points

```
2 , 4 , 8 ,  
2 , 4 ,  
2 ,
```

% error vs. Number of points



Conclusion & Further Research

- The computational complexity of algorithms \Rightarrow performance impact
 - speed, efficiency, and resource utilization
 - Polynomials are easier to estimate even at high order
 - Finite differences is a very useful method to evaluate derivatives
- The 2^n and log algorithms need an adjusted approach

Future work

- Math proof for the proposed solution
- Determine the error rate in many more classes of functions
 - $n \log n$
 - binary



Thanks!

References

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