

Summation: Guess and Test

Technique 1: Guess the solution and use induction to test.

Technique 1a: Guess the form of the solution, and use simultaneous equations to generate constants. Finally, use induction to test.

no notes

Summation Example

$$S(n) = \sum_{i=0}^n i^2.$$

Guess that $S(n)$ is a polynomial $\leq n^3$.
Equivalently, guess that it has the form
 $S(n) = an^3 + bn^2 + cn + d$.

For $n = 0$ we have $S(n) = 0$ so $d = 0$.
For $n = 1$ we have $a + b + c + 0 = 1$.
For $n = 2$ we have $8a + 4b + 2c = 5$.
For $n = 3$ we have $27a + 9b + 3c = 14$.
Solving these equations yields $a = \frac{1}{3}, b = \frac{1}{2}, c = \frac{1}{6}$.
Now, prove the solution with induction.

This is Manber Problem 2.5.

We need to prove by induction since we don't know that the guessed form is correct. All that we **know** without doing the proof is that the form we guessed models some low-order points on the equation properly.

Technique 2: Shifted Sums

Given a sum of many terms, shift and subtract to eliminate intermediate terms.

$$G(n) = \sum_{i=0}^n ar^i = a + ar + ar^2 + \dots + ar^n$$

Shift by multiplying by r .

$$rG(n) = ar + ar^2 + \dots + ar^n + ar^{n+1}$$

Subtract.

$$G(n) - rG(n) = G(n)(1 - r) = a - ar^{n+1}$$

$$G(n) = \frac{a - ar^{n+1}}{1 - r} \quad r \neq 1$$

We often solve summations in this way – by multiplying by something or subtracting something. The big problem is that it can be a bit like finding a needle in a haystack to decide what “move” to make. We need to do something that gives us a new sum that allows us either to cancel all but a constant number of terms, or else converts all the terms into something that forms an easier summation.

Shift by multiplying by r is a reasonable guess in this example since the terms differ by a factor of r .

Example 3.3

$$G(n) = \sum_{i=1}^n i2^i = 1 \times 2 + 2 \times 2^2 + 3 \times 2^3 + \dots + n \times 2^n$$

Multiply by 2.

$$2G(n) = 1 \times 2^2 + 2 \times 2^3 + 3 \times 2^4 + \dots + n \times 2^{n+1}$$

Subtract (Note: $\sum_{i=1}^n 2^i = 2^{n+1} - 2$)

$$2G(n) - G(n) = n2^{n+1} - 2^n \dots 2^2 - 2$$

$$G(n) = n2^{n+1} - 2^{n+1} + 2$$

$$= (n - 1)2^{n+1} + 2$$

no notes

Recurrence Relations

- A (math) function defined in terms of itself.
- Example: Fibonacci numbers:

$$F(n) = F(n-1) + F(n-2) \quad \text{general case}$$

$$F(1) = F(2) = 1 \quad \text{base cases}$$
- There are always one or more general cases and one or more base cases.
- We will use recurrences for time complexity of recursive (computer) functions.
- General format is $T(n) = E(T, n)$ where $E(T, n)$ is an expression in T and n .
 - ▶ $T(n) = 2T(n/2) + n$
- Alternately, an upper bound: $T(n) \leq E(T, n)$.

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- Alternately, an upper bound: $T(n) \leq E(T, n)$.

We won't spend a lot of time on techniques... just enough to be able to use them.

Solving Recurrences

We would like to find a closed form solution for $T(n)$ such that:

$$T(n) = \Theta(f(n))$$

Alternatively, find lower bound

- Not possible for inequalities of form $T(n) \leq E(T, n)$.

Methods:

- Guess (and test) a solution
- Expand recurrence
- Theorems

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- Theorems

Note that "finding a closed form" means that we have $f(n)$ that doesn't include T .

Can't find lower bound for the inequality because you do not know enough... you don't know *how much bigger* $E(T, n)$ is than $T(n)$, so the result might not be $\Omega(T(n))$.

Guessing is useful for finding an asymptotic solution. Use induction to prove the guess correct.

Guessing

$$T(n) = 2T(n/2) + 5n^2 \quad n \geq 2$$

$$T(1) = 7$$

Note that T is defined only for powers of 2.

Guess a solution: $T(n) \leq c_1 n^3 = f(n)$
 $T(1) = 7$ implies that $c_1 \geq 7$

Inductively, assume $T(n/2) \leq f(n/2)$.

$$\begin{aligned} T(n) &= 2T(n/2) + 5n^2 \\ &\leq 2c_1(n/2)^3 + 5n^2 \\ &\leq c_1(n^3/4) + 5n^2 \\ &\leq c_1 n^3 \text{ if } c_1 \geq 20/3. \end{aligned}$$

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For Big-oh, not many choices in what to guess.

$$7 \times 1^3 = 7$$

Because $\frac{20}{3}n^3 + 5n^2 = \frac{20}{3}n^3$ when $n = 1$, and as n grows, the right side grows even faster.

Guessing (cont)

Therefore, if $c_1 = 7$, a proof by induction yields:
 $T(n) \leq 7n^3$
 $T(n) \in O(n^3)$

Is this the best possible solution?

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 $T(n) \leq 7n^3$
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Is this the best possible solution?

No - try something tighter.

Guessing (cont)

Guess again.

$$T(n) \leq c_2 n^2 = g(n)$$

$T(1) = 7$ implies $c_2 \geq 7$.

Inductively, assume $T(n/2) \leq g(n/2)$.

$$\begin{aligned} T(n) &= 2T(n/2) + 5n^2 \\ &\leq 2c_2(n/2)^2 + 5n^2 \\ &= c_2(n^2/2) + 5n^2 \\ &\leq c_2 n^2 \text{ if } c_2 \geq 10 \end{aligned}$$

Therefore, if $c_2 = 10$, $T(n) \leq 10n^2$. $T(n) = O(n^2)$.

Is this the best possible upper bound?

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 $T(1) = 7$ implies $c_2 \geq 7$.
 Inductively, assume $T(n/2) \leq g(n/2)$.
 $T(n) = 2T(n/2) + 5n^2$
 $\leq 2c_2(n/2)^2 + 5n^2$
 $= c_2(n^2/2) + 5n^2$
 $\leq c_2 n^2$ if $c_2 \geq 10$
 Therefore, if $c_2 = 10$, $T(n) \leq 10n^2$. $T(n) = O(n^2)$.
 Is this the best possible upper bound?

Because $\frac{10}{2}n^2 + 5n^2 = 10n^2$ for $n = 1$, and the right hand side grows faster.

Yes this is best, since $T(n)$ can be as bad as $5n^2$.

Guessing (cont)

Now, reshape the recurrence so that T is defined for all values of n .

$$T(n) \leq 2T(\lfloor n/2 \rfloor) + 5n^2 \quad n \geq 2$$

For arbitrary n , let $2^{k-1} < n \leq 2^k$.

We have already shown that $T(2^k) \leq 10(2^k)^2$.

$$\begin{aligned} T(n) &\leq T(2^k) \leq 10(2^k)^2 \\ &= 10(2^k/n)^2 n^2 \leq 10(2)^2 n^2 \\ &\leq 40n^2 \end{aligned}$$

Hence, $T(n) = O(n^2)$ for all values of n .

Typically, the bound for powers of two generalizes to all n .

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 $T(n) \leq T(2^k) \leq 10(2^k)^2$
 $= 10(2^k/n)^2 n^2 \leq 10(2)^2 n^2$
 $= 40n^2$
 Hence, $T(n) = O(n^2)$ for all values of n .
 Typically, the bound for powers of two generalizes to all n .

no notes

Expanding Recurrences

Usually, start with equality version of recurrence.

$$\begin{aligned} T(n) &= 2T(n/2) + 5n^2 \\ T(1) &= 7 \end{aligned}$$

Assume n is a power of 2; $n = 2^k$.

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no notes

Expanding Recurrences (cont)

$$\begin{aligned} T(n) &= 2T(n/2) + 5n^2 \\ &= 2(2T(n/4) + 5(n/2)^2) + 5n^2 \\ &= 2(2(2T(n/8) + 5(n/4)^2) + 5(n/2)^2) + 5n^2 \\ &= 2^k T(1) + 2^{k-1} \cdot 5(n/2^{k-1})^2 + 2^{k-2} \cdot 5(n/2^{k-2})^2 \\ &\quad + \dots + 2 \cdot 5(n/2)^2 + 5n^2 \\ &= 7n + 5 \sum_{i=0}^{k-1} n^2/2^i = 7n + 5n^2 \sum_{i=0}^{k-1} 1/2^i \\ &= 7n + 5n^2(2 - 1/2^{k-1}) \\ &= 7n + 5n^2(2 - 2/n). \end{aligned}$$

This is the **exact** solution for powers of 2. $T(n) = \Theta(n^2)$.

Expanding Recurrences (cont)

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 $T(n) = 2T(n/2) + 5n^2$
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 $= 2^k T(1) + 2^{k-1} \cdot 5(n/2^{k-1})^2 + 2^{k-2} \cdot 5(n/2^{k-2})^2 + \dots + 2 \cdot 5(n/2)^2 + 5n^2$
 $= 7n + 5 \sum_{i=0}^{k-1} n^2/2^i = 7n + 5n^2 \sum_{i=0}^{k-1} 1/2^i$
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Divide and Conquer Recurrences

These have the form:

$$T(n) = aT(n/b) + cn^k$$

$$T(1) = c$$

... where a, b, c, k are constants.

A problem of size n is divided into a subproblems of size n/b , while cn^k is the amount of work needed to combine the solutions.

Divide and Conquer Recurrences (cont)

Expand the sum; $n = b^m$.

$$T(n) = a(aT(n/b^2) + c(n/b)^k) + cn^k$$

$$= a^m T(1) + a^{m-1} c(n/b^{m-1})^k + \dots + ac(n/b)^k + cn^k$$

$$= ca^m \sum_{i=0}^m (b^k/a)^i$$

$$a^m = a^{\log_b n} = n^{\log_b a}$$

The summation is a geometric series whose sum depends on the ratio

$$r = b^k/a.$$

There are 3 cases.

D & C Recurrences (cont)

(1) $r < 1$.

$$\sum_{i=0}^m r^i < 1/(1-r), \quad a \text{ constant.}$$

$$T(n) = \Theta(a^m) = \Theta(n^{\log_b a}).$$

(2) $r = 1$.

$$\sum_{i=0}^m r^i = m + 1 = \log_b n + 1$$

$$T(n) = \Theta(n^{\log_b a} \log n) = \Theta(n^k \log n)$$

D & C Recurrences (Case 3)

(3) $r > 1$.

$$\sum_{i=0}^m r^i = \frac{r^{m+1} - 1}{r - 1} = \Theta(r^m)$$

So, from $T(n) = ca^m \sum r^i$,

$$T(n) = \Theta(a^m r^m)$$

$$= \Theta(a^m (b^k/a)^m)$$

$$= \Theta(b^{km})$$

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The summation is a geometric series whose sum depends on the ratio

$$r = b^k/a.$$

There are 3 cases.

$$n = b^m \Rightarrow m = \log_b n.$$

Set $a = b^{\log_b a}$. Switch order of logs, giving $(b^{\log_b n})^{\log_b a} = n^{\log_b a}$.

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$$\sum_{i=0}^m r^i = m + 1 = \log_b n + 1$$

$$T(n) = \Theta(n^{\log_b a} \log n) = \Theta(n^k \log n)$$

When $r = 1$, since $r = b^k/a = 1$, we get $a = b^k$. Recall that $k = \log_b a$.

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So, from $T(n) = ca^m \sum r^i$,

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Summary

Theorem 3.4:

$$T(n) = \begin{cases} \Theta(n^{\log_b a}) & \text{if } a > b^k \\ \Theta(n^k \log n) & \text{if } a = b^k \\ \Theta(n^k) & \text{if } a < b^k \end{cases}$$

Apply the theorem:

$$T(n) = 3T(n/5) + 8n^2.$$

$$a = 3, b = 5, c = 8, k = 2.$$

$$b^k/a = 25/3.$$

Case (3) holds: $T(n) = \Theta(n^2)$.

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Case (3) holds: $T(n) = \Theta(n^2)$

We simplify by approximating summations.

Examples

- Mergesort: $T(n) = 2T(n/2) + n$.
 $2^1/2 = 1$, so $T(n) = \Theta(n \log n)$.
- Binary search: $T(n) = T(n/2) + 2$.
 $2^0/1 = 1$, so $T(n) = \Theta(\log n)$.
- Insertion sort: $T(n) = T(n-1) + n$.
 Can't apply the theorem. Sorry!
- Standard Matrix Multiply (recursively):
 $T(n) = 8T(n/2) + n^2$.
 $2^2/8 = 1/2$ so $T(n) = \Theta(n^{\log_2 8}) = \Theta(n^3)$.

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$$\begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$$

In the straightforward implementation, 2×2 case is:

$$\begin{aligned} c_{11} &= a_{11}b_{11} + a_{12}b_{21} \\ c_{12} &= a_{11}b_{12} + a_{12}b_{22} \\ c_{21} &= a_{21}b_{11} + a_{22}b_{21} \\ c_{22} &= a_{21}b_{12} + a_{22}b_{22} \end{aligned}$$

So the recursion is 8 calls of half size, and the additions take $\Theta(n^2)$ work.

Useful log Notation

- If you want to take the log of $(\log n)$, it is written $\log \log n$.
- $(\log n)^2$ can be written $\log^2 n$.
- Don't get these confused!
- $\log^* n$ means "the number of times that the log of n must be taken before $n \leq 1$ ".
 ▶ For example, $65536 = 2^{16}$ so $\log^* 65536 = 4$ since $\log 65536 = 16, \log 16 = 4, \log 4 = 2, \log 2 = 1$.

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Amortized Analysis

Consider this variation on STACK:

```
void init(STACK S);
element examineTop(STACK S);
void push(element x, STACK S);
void pop(int k, STACK S);
```

... where pop removes k entries from the stack.

"Local" worst case analysis for pop:
 $O(n)$ for n elements on the stack.

Given m_1 calls to push, m_2 calls to pop:
 Naive worst case: $m_1 + m_2 \cdot n = m_1 + m_2 \cdot m_1$.

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Alternate Analysis

Use amortized analysis on multiple calls to `push`, `pop`:

Cannot pop more elements than get pushed onto the stack.

After many pushes, a single pop has high **potential**.

Once that potential has been expended, it is not available for future `pop` operations.

The cost for m_1 pushes and m_2 pops:

$$m_1 + (m_2 + m_1) = O(m_1 + m_2)$$

Actual number of (constant time) push calls + (Actual number of pop calls + Total potential for the pops)

CLR has an entire chapter on this – we won't go into this much, but we use Amortized Analysis implicitly sometimes.