

02 Basics of Algorithm Analysis

CS216 Algorithm Design and Analysis (H)

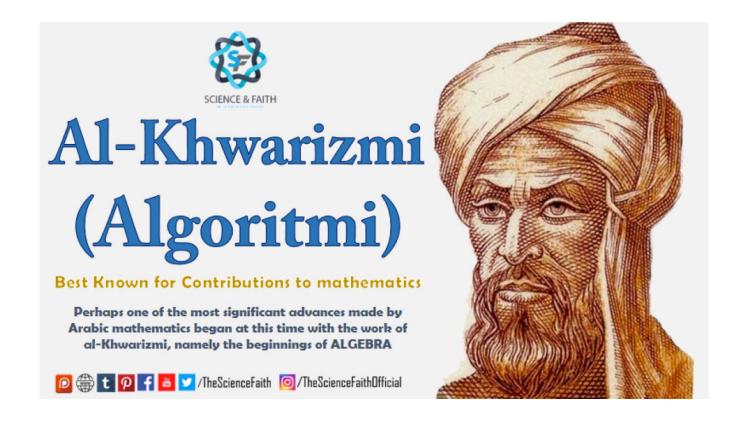
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Algorithms

• An algorithm is a finite sequence of precise instructions for performing a computation or for solving a problem.





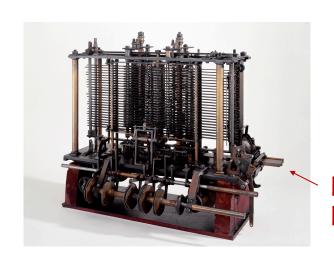
1. Computational Tractability

Computational Tractability (计算可处理性)



A strikingly modern thought...

As soon as an Analytical Engine exists, it will necessarily guide the future course of the science. Whenever any result is sought by its aid, the question will arise - By what course of calculation can these results be arrived at by the machine in the shortest time? - Charles Babbage (1864)



Analytical Engine

how many times do you have to turn the crank?

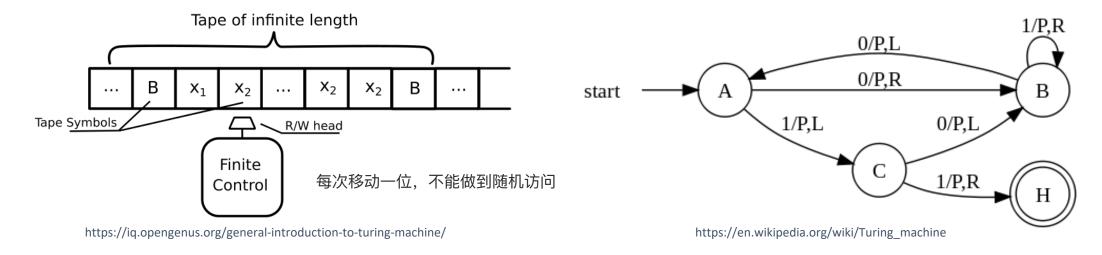


Charles Babbage (1791 - 1871)



Models of Computation: Turing Machines

Deterministic Turing machine. Simple and idealized model.



- Running time. Number of steps. Memory. Number of tape cells utilized.
- Caveat. No random access of memory.
 - \triangleright A single-tape Turing machine requires $\approx n^2$ steps to detect *n*-bit palindromes.
 - \triangleright Easy to detect palindromes in $\approx n$ steps on a real computer.



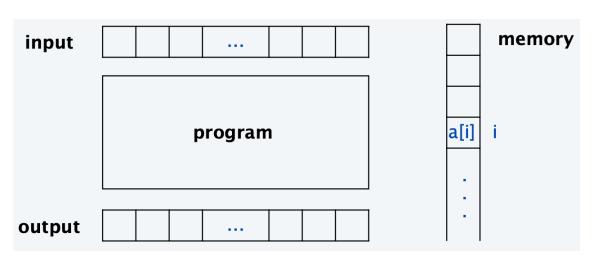


Models of Computation: Word RAM

每个内存位置和输入/输出单元都存储一个 w 位整数/字。这里的 w 是字长,表示每次计算时处理的位数。

• Word random-access machine (RAM).

- w ≥ log₂ n
- Each memory location and input/output cell stores a w-bit integer/word.
- Primitive operations:
 - ✓ arithmetic/logic operations
 - ✓ read/write memory
 - ✓ array indexing
 - ✓ following a pointer
 - ✓ conditional branch...



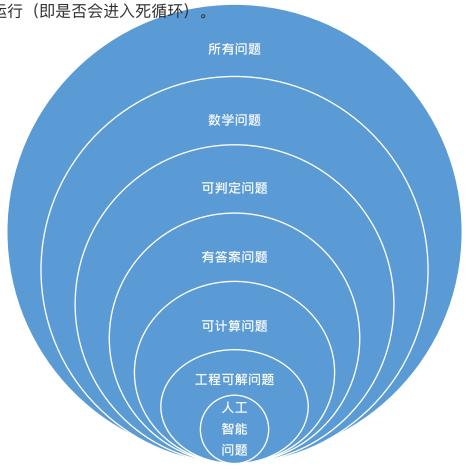
- Running time. Number of primitive operations.
- Memory. Number of memory cells utilized.
- Caveat. At times, need more refined model, e.g., multiply *n*-bit integers.





Limits of Artificial Inteligence

- All problems
- Math problems 能否构造一个算法,决定任何程序和输入对是否会停止运行(即是否会进入死循环)。
 - halting problem is undecidable
- Decidable problems
 - some solutions exist but hard to find
- Solvable problems
 - by any algorithms (e.g., quantum ones)
- Computable problems
 - by Turing machines in finite steps
- Engineering solvabe problems
 - efficiently solvable in practice
- Artificial inteligence problems





Computational Complexity

- Q. How do we measure the efficiency of an algorithm?
 - We human beings are **not** good at perception of numbers.

- A. Computational complexity: measure efficiency as a function of the algorithm's input size.
 - Time complexity: number of primitive computation steps
 - Space complexity: number of memory units



Why It Matters

Table 2.1 The running times (rounded up) of different algorithms on inputs of increasing size, for a processor performing a million high-level instructions per second. In cases where the running time exceeds 10²⁵ years, we simply record the algorithm as taking a very long time.

	n	$n \log_2 n$	n^2	n^3	1.5 ⁿ	2 ⁿ	n!
n = 10	< 1 sec	< 1 sec	< 1 sec	< 1 sec	< 1 sec	< 1 sec	4 sec
n = 30	< 1 sec	< 1 sec	< 1 sec	< 1 sec	< 1 sec	18 min	10 ²⁵ years
n = 50	< 1 sec	< 1 sec	< 1 sec	< 1 sec	11 min	36 years	very long
n = 100	< 1 sec	< 1 sec	< 1 sec	1 sec	12,892 years	10 ¹⁷ years	very long
n = 1,000	< 1 sec	< 1 sec	1 sec	18 min	very long	very long	very long
n = 10,000	< 1 sec	< 1 sec	2 min	12 days	very long	very long	very long
n = 100,000	< 1 sec	2 sec	3 hours	32 years	very long	very long	very long
n = 1,000,000	1 sec	20 sec	12 days	31,710 years	very long	very long	very long





Brute Force vs Polynomial Running Time

- Brute force. For many non-trivial problems, there is a natural brute force search algorithm that checks every possible solution.
 - \triangleright Typically takes 2^n steps (or worse) for inputs of size n.
 - Unacceptable in practice.
- Desirable scaling property. If the input size is increased by a constant factor C_1 , the algorithm should also slow down by a constant factor C_2 .
- Def. An algorithm is polynomial-time if there exist constants a > 0, b > 0 such that the running time of the algorithm is bounded by an^b .
 - \triangleright Note that the above scaling property holds for polynomials, e.g., $C_2 = C_1^b$.





Polynomial Running Time

- We say that an algorithm is efficient if has a polynomial running time.
- Theory. Definition is (relatively) insensitive to models of computation.
- Practice. It really works!
 - The polynomial-time (e.g., an^b) algorithms that people develop almost always have both small constant a and small exponent b.
 - \triangleright Breaking through the exponential barrier (e.g., 2^n) of brute force typically exposes some crucial structure of the problem.

• Exceptions:

- Some polynomial-time algorithms in the wild have galactic constants and/or huge exponents, then useless in practice, e.g., $6.02 \times 10^{23} \times n^{20}$.
- Some exponential-time (or worse) algorithms are widely used because the worst-case instances (i.e., inputs) seem to be rare, e.g., the simplex method.





Worst-Case/Average-Case Analysis

- Worst-case analysis. Worst possible running time on any input of size n.
 - Generally captures efficiency in practice.
 - Draconian view, but hard to find effective alternative.
- Average-case analysis. Average running time on random input of size n.
 - Hard (or impossible) to accurately model real-world instances with random distributions, e.g., the real-world instances may not follow the distribution.
 - Algorithms tuned for a certain distribution of instances may perform poorly on other distributions.





Other Types of Analyses

- Probabilistic. Expected running time of a randomized algorithm.
 - Note that here the algorithm itself is randomized. Shown in later sections
 - E.g., the expected number of compares (i.e., the running time) to quicksort n elements is $\approx 2n \ln n$.
- Amortized analysis. Worst-case running time for any sequence of *n* operations in total.
 - \triangleright E.g., pushing *n* elements to a JAVA ArrayList (dynamic array) takes $\approx 4n$ steps.

will be discussed in our first lab lecture





2. Asymptotic Order of Growth



Notation

- Let function T(n) denote the worse-case running time of an algorithm on any input of size n.
- Upper bounds. T(n) is O(f(n)) if there exist constants c > 0 and $n_0 \ge 0$ such that for all $n \ge n_0$ we have $0 \le T(n) \le c \cdot f(n)$.
- Lower bounds. T(n) is $\Omega(f(n))$ if there exist constants c > 0 and $n_0 \ge 0$ such that for all $n \ge n_0$ we have $T(n) \ge c \cdot f(n) \ge 0$.
- Tight bounds. T(n) is $\Theta(f(n))$ if T(n) is both O(f(n)) and $\Omega(f(n))$.
- Example: $T(n) = 32n^2 + 17n + 32$
 - \succ T(n) is $O(n^2)$, $O(n^3)$, $\Omega(n^2)$, $\Omega(n)$, and $\Theta(n^2)$.
 - \succ T(n) is not O(n), $\Omega(n^3)$, O(n), or $O(n^3)$.





Remark on the Use of Notation

- Slight abuse of notation. T(n) = O(f(n))
 - = is not an equivalence relation:

```
\checkmark f(n) = 5n^3; g(n) = 3n^2
\checkmark f(n) = O(n^3) 后面的  
\checkmark f(n) \neq g(n).
```

- \triangleright better notation: $T(n) \in O(f(n))$
- Vacuous statement example. Any compare-based sorting algorithm requires at least *O(n log n)* compares in the worst case.
 - The statement does not "type-check".
 - \triangleright Should use Ω for lower bounds.





Properties

Reflexivity and constants:

- ightharpoonup f = O(f), f = O(f), f = O(f)
- ightharpoonup If c > 0 is a constant, then cf = O(f), $cf = \Omega(f)$, $cf = \Theta(f)$.

Transitivity:

- \rightarrow If f = O(g) and g = O(h) then f = O(h).
- ightharpoonup If $f = \Omega(g)$ and $g = \Omega(h)$ then $f = \Omega(h)$.
- ightharpoonup If $f = \Theta(g)$ and $g = \Theta(h)$ then $f = \Theta(h)$.

Sums and Products:

- ightharpoonup If f = O(h) and g = O(h), then f + g = O(h) and $f \cdot g = O(h^2)$.
- ightharpoonup If $f = \Omega(h)$ and $g = \Omega(h)$, then $f + g = \Omega(h)$ and $f \cdot g = \Omega(h^2)$.
- ightharpoonup If $f = \Theta(h)$ and $g = \Theta(h)$, then $f + g = \Theta(h)$ and $f \cdot g = \Theta(h^2)$.





Asymptotic Bounds for Some Common Functions

- Polynomials. If $a_d > 0$, then $a_0 + a_1 n + ... + a_d n^d = \Theta(n^d)$.
- Polynomial time. The running time is $O(n^c)$ for some constant c > 0 independent of the input size n.
- Logarithms. $O(\log_a n) = O(\log_b n)$ for any constants a, b > 1.

 no need to specify log base
- Logarithms < polynomials. For every a > 1, c > 0, $log_a n = O(n^c)$.
- Exponentials > polynomials. For every r > 1, c > 0, $n^c = O(r^n)$.
- Factorials. $n! = 2^{\Theta(n \log n)}$, i.e., $\log_2 n! = \Theta(n \log n)$.
 - ightharpoonup Can be proved by Stirling's formula: $n! \approx \sqrt{2\pi n} \left(\frac{n}{e}\right)^n$
- Factorials > exponentials. For every r > 1, $r^n = O(n!)$.





3. A Survey of Common Running Times



Sublinear Time: O(log n)

• Logarithmic time. Running time proportional to logarithm of input size.

- Binary search. Search a given number in a sorted array of size *n*.
 - \triangleright Terminates within $O(\log_2 n)$ steps





Linear Time: O(n)

• Linear time. Running time proportional to input size *n*.

• Computing the maximum. Compute maximum of n numbers $a_1, ..., a_n$.

```
max = a<sub>1</sub>
for i = 2 to n {
   if (a<sub>i</sub> > max)
      max = a<sub>i</sub>
}
```





Linear Time: O(n) — Another Example

• Merge. Combine two sorted lists $A = a_1, a_2, ..., a_n$ and $B = b_1, b_2, ..., b_n$ into one sorted list.

 $//////|a_i|$

```
i = 1, j = 1
while (both lists are nonempty) {
   if (a<sub>i</sub> ≤ b<sub>j</sub>) append a<sub>i</sub> to output list and increment i
   else append b<sub>j</sub> to output list and increment j
}
append remainder of the nonempty list to output list
```

• Claim. Merging two lists of size n takes O(n) time.

Merged result

• Pf. After each comparison, the length of output list increases by 1.





Linearithmic Time: O(n log n)

• Linearithmic time. Arises in divide-and-conquer algorithms.

• Sorting. Mergesort and Heapsort are sorting algorithms that perform $O(n \log n)$ comparisons.





Quadratic Time: $O(n^2)$

- Quadratic time. Enumerate all pairs of elements.
- Closest pair of points. Given n points in the plane $(x_1, y_1), ..., (x_n, y_n)$, find the pair that is the closest.
 - \triangleright $O(n^2)$ solution: try all pairs of points.

```
 \begin{aligned} & \min = (\mathbf{x}_1 - \mathbf{x}_2)^2 + (\mathbf{y}_1 - \mathbf{y}_2)^2 \\ & \text{for } i = 1 \text{ to } n \text{ } \\ & \text{ for } j = i+1 \text{ to } n \text{ } \\ & d = (\mathbf{x}_i - \mathbf{x}_j)^2 + (\mathbf{y}_i - \mathbf{y}_j)^2 & \longleftarrow \text{ no need to take square roots} \\ & \text{ if } (d < \min) \\ & \text{ min } = d \end{aligned}  better solution in later sections }
```

• Remark. $\Omega(n^2)$ seems inevitable, but this is just an illusion.





Cubic Time: $O(n^3)$

- Cubic time. Enumerate all triples of elements.
- Set disjointness. Given n sets S_1 , ..., S_n , each of which is a subset of 1, 2, ..., n, is there some disjoint pair of these sets?
 - \triangleright $O(n^3)$ solution: for each pairs of sets, check if they are disjoint.

```
foreach set S<sub>i</sub> {
    foreach other set S<sub>j</sub> {
        foreach element p of S<sub>i</sub> {
            determine whether p also belongs to S<sub>j</sub>
        }
        if (no element of S<sub>i</sub> belongs to S<sub>j</sub>)
            report that S<sub>i</sub> and S<sub>j</sub> are disjoint
    }
}
```





Polynomial Time: $O(n^k)$

- Independent set of size k. Given a graph and a constant k, are there k nodes such that no two nodes are joined by an edge?
 - \triangleright $O(n^k)$ solution: enumerate all subsets S of k nodes.

```
foreach subset S of k nodes {
   check whether S in an independent set
   if (S is an independent set)
     report S is an independent set
}
```

- Check whether S is an independent set is $O(k^2)$
- Number of k element subsets is $O(n^k / k!)$
- Overall: $O(k^2 n^k / k!) = O(n^k)$

still polynomial time for k = 17, but not practical





Exponential Time: $O(c^n)$

- Independent set of maximum size. Given a graph, what is maximum size of an independent set?
 - \triangleright $O(n^2 2^n)$ solution: Enumerate all subsets.

```
S* = empty set
foreach subset S of nodes {
   check whether S in an independent set
   if (S is largest independent set seen so far)
      update S* = S
}
```





Factorial Time: *O(n!)*

• Factorial time. Enumerate all permutations of length *n*.

- Traveling salesman problem (TSP). Given a set of *n* cities, with distances between all pairs, what is the shortest tour that visits all cities?
 - \triangleright O(n!) solution: search all (n 1)! tours (salesman starts and ends at the same city)

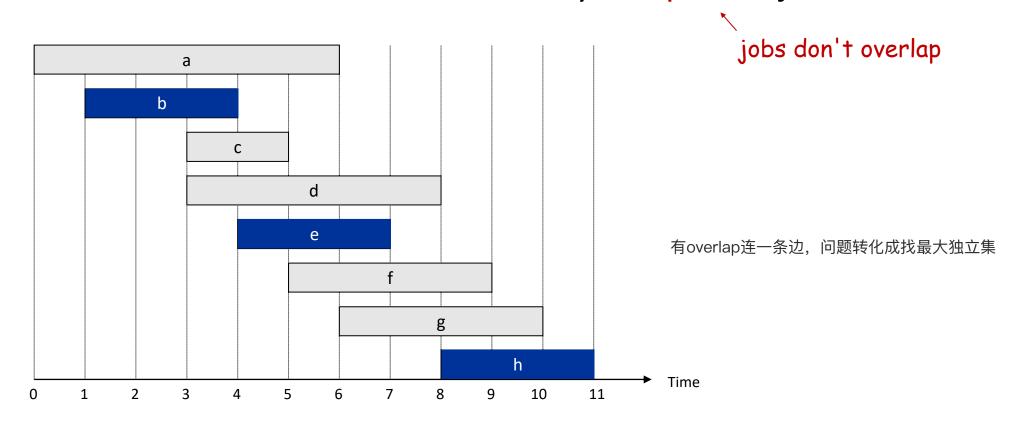


4. Five Representative Problems on Independent Set



Interval Scheduling

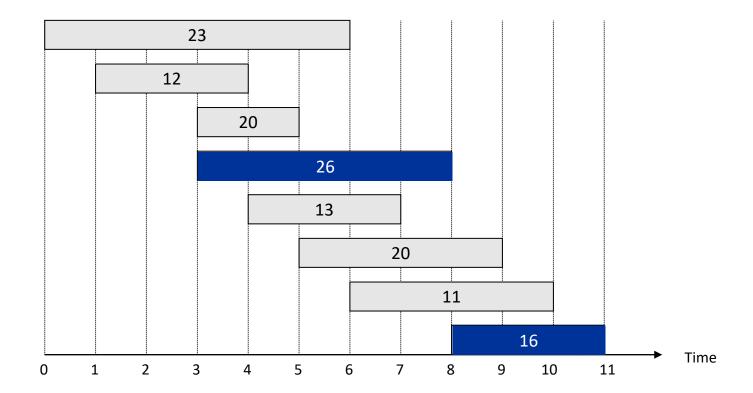
- Input. Set of jobs with start times and finish times.
- Goal. Find maximum-size subset of mutually compatible jobs.





Weighted Interval Scheduling

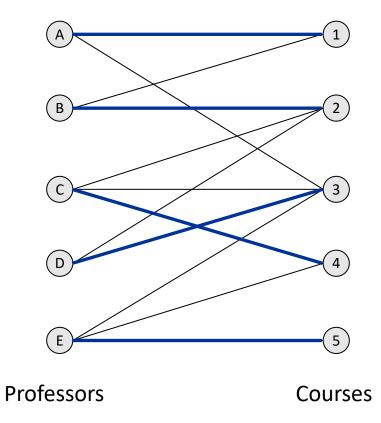
- Input. Set of jobs with start times, finish times, and weights.
- Goal. Find maximum-weight subset of mutually compatible jobs.





Bipartite Matching

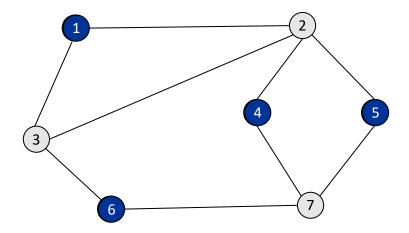
- Input. Bipartite graph.
- Goal. Find maximum-size matching.





Independent Set

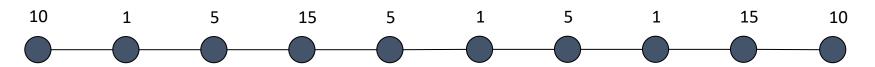
- Input. Graph.
- Goal. Find maximum-size independent set.





Competitive Facility Location

- Input. Graph with weight on each node.
- Game. Two competing players alternately select nodes (facility locations). Not allowed to select a node if any of its neighbors has been selected.
- Goal. Select a maximum-weight subset of nodes.
- Q. Given a bound B, can the second player P_2 get B no matter how the first player P_1 plays?
 - It is hard to determine if P_2 's winning strategy exists; it would even be hard to convince people some strategy is indeed a winning strategy.



 P_2 can guarantee 20, but not 25.



Five Representative Problems: Summary

- Interval scheduling: O(n log n) greedy algorithm.
- Weighted interval scheduling: $O(n \log n)$ dynamic programming algorithm.
- Bipartite matching: $O(n^k)$ max-flow based algorithm.
- Independent set: NP-complete. we will learn this in later sections
- Competitive facility location: *PSPACE*-complete.

we may not capture this more advanced notion but see the textbook if you are interested

All the above are variations on the same theme: independent set



Announcements

 We will learn amortized analysis and some basic lab techniques in our first lab class tonight.

• Lab 1 will be released today and the deadline is Mar 4.