Lecture 3 Overview, greedy algorithms, and graph traversal

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Previously in CSE 421...

Algorithmic complexity

Measuring algorithmic efficiency The RAM model

- RAM Model = "Random Access Machine" Model
- Each simple operation (arithmetic, evaluating if loop criteria, call, increment counter, etc.) takes one time step
- Accessing any one arithmetic number in memory takes one time step
- Measuring algorithm efficiency
 - Let input be (x_1, \ldots, x_n) with each x_i representing one arithmetic number
 - Runtime of algorithm is the number of "simple operations" taken to compute algorithm in RAM model.



Complexity analysis

- Input (x_1, \ldots, x_n) of length n.
- Multiple measures of complexity.
 - Worst-case: maximum # of steps taken on any input of length n
 - Best-case: minimum # of steps taken on any input of length n
 - Average-case: average # of steps taken over all input of length n

Complexity analysis

- The complexity of an alg. is a function T(n) for each input size $n \in \mathbb{N}$. • i.e. $T_{\text{worst}}(n)$ or $T_{\text{avg}}(n)$ could be two different functions.
- $T: \mathbb{N} \to \mathbb{N}$
- We are interested in understanding the overall behavior/shape of T, not the exact function.
- *m* edge graph.

• Sometimes there is more than one size parameter. T(n, m) for a n vertex and

Polynomial time A notion of efficiency

- c, k, d > 0.
 - polynomial.
 - Polynomial time is known as "efficient" in theoretical CS.

• A function T(n) is polynomial time if $T(n) \le cn^k + d$ for some constants

• Let k be the minimal such value. This is the degree of the dominating

Polynomial time A notion of efficiency

- A function T(n) is polynomial time if $T(n) \le cn^k + d$.
- Why **polynomial time**?
 - Scaling the instance by a constant factor so does the runtime.
 - computation can also be computed in polynomial time a *different* physically realizable model.
 - I.e. polynomial-time is a notion independent of model of computation.
 - Ideal for theoretical study of what problems are efficient and which are not.
 - Problem size grows by constant, then running time also grows by constant.
 - If $T(n) = cn^k + d$ then $T(2n) = c(2n)^k + d \le 2^k(cn^k + d) = 2^kT(n)$.

• Church-Turing thesis: Any function computable in polynomial time by a physically realizable model of

• Typically, polynomials for common algorithms are small polynomials cn, cn^2, cn^3, cn^4 . Rarely anything higher.

Big-O notation

Let $T, g : \mathbb{N} \to \mathbb{N}$. Then

- T(n) is o(g(n)) if $\lim_{n \to \infty} \frac{T(n)}{g(n)} = 0.$
- T(n) is $\Theta(g(n))$ if T(n) is O(g(n)) and T(n) is $\Omega(g(n))$.

• T(n) is O(g(n)) if $\exists c, n_0 > 0$ such that $T(n) \leq cg(n)$ when $n \geq n_0$.

• T(n) is $\Omega(g(n))$ if $\exists \epsilon, n_0 > 0$ such that $T(n) \ge \epsilon g(n)$ when $n \ge n_0$.

Big-O notation Cartoon



Big-O notation Cartoon



Measuring algorithmic efficiency The RAM model

- RAM Model = "Random Access Machine" Model
- Each simple operation (arithmetic, evaluating if loop criteria, call, increment counter, etc.) takes one time step
- Accessing any bit of memory takes one time step

Measuring algorithmic efficiency The RAM model, Examples

- Sorting a list of integers $L = (x_1, ..., x_n)$

 - rigorous.

All-pairs shortest path problem: Given a weighte every pair of vertices $u, v \in V$.

- Floyd-Warshall alg. Makes $O(n^3)$ arithmetic comparisons where n = |V|, m = |E|.

• You probably know that sorting can be solved in $\Theta(n \log n)$ time by algorithms such as merge sort. • This is measuring the number of comparisons $x_i < x_j$ that we are making. RAM model makes this

ed graph
$$G = (V, E)$$
 output $d_{uv} = \min_{p:u \sim v} \sum_{(a,b) \in p} w_{ab}$ for

• Requires adjacency matrix access to the graph. Meaning, unit cost to compute w_{ab} for any $a, b \in V$.

An introduction to algorithms

An introduction to algorithms

- Goal is to understand how to analyze and design algorithms
 - To understand how small changes have big effects on outcomes
 - Build a repertoire of techniques for designing algorithms
 - Identifying when to use which family of algorithms
- Course is structured by teaching various families of algorithms
 - Section and problem sets will cover example instantiations pertinent to that week
 - Midterms and finals will have problems but won't say which family of algorithms to use

- Input: start and end times (s_i, t_i) for i = 1, ..., n for n "jobs"
- Output: A maximal set of mutually compatible jobs



r i = 1, ..., n for n "jobs' compatible jobs

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- Input: start and end times (s_i, t_i) for i = 1, ..., n for n "jobs" **Output:** A maximal set of mutually compatible jobs
- Algorithm:
 - **Brute-force:** Iterate through all 2^n possible selections. Check in O(n) time if selection is (a) feasible and (b) maximal.
 - Greedy: Decide a selection criteria and select jobs accordingly.

- Algorithm: Select the job with earliest start time s_i of jobs not selected.
- Counterexample:



what gets salected by this strategy. MMMMM



- Algorithm: Select the job with earliest start time s_i of jobs not selected.
- Counterexample:



the optimal strategy.



- Counterexample:





• Algorithm: Select the job with shortest duration $t_i - s_i$ of jobs not selected.

- Counterexample:



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- Algorithm: Select the job with earliest ending t_i of jobs not selected.
- **Example:**



- Algorithm: Select the job with earliest ending t_i of jobs not selected.
- Proof of correctness:
 - other *feasible* set of jobs.
 - Claim: The *j*-th job in \mathscr{E} ends at least before the *j*-th job in \mathscr{F} ends.

• Let $\mathscr{E} \subseteq [n]$ be the set of jobs selected by algorithm and $\mathscr{F} \subseteq [n]$ be any

- Claim: The *j*-th job in \mathscr{E} ends at least before the *j*-th job in \mathscr{F} ends.
- **Proof:**

Assume (for contradiction

Smallest conterexample Ejobs -> [j-1 Fjobs C Contradicts the def. of E as job D isn't selected but ends before job B.



- Algorithm: Select the job with earliest ending t_i of jobs not selected.
- Proof of correctness:
 - Let *E* ⊆ [n] be the set of jobs selected by algorithm and *F* ⊆ [n] be any other *feasible* set of jobs.
 - Claim: The *j*-th job in \mathscr{E} ends at least before the *j*-th job in \mathscr{F} ends.
 - If \mathscr{F} had more jobs than \mathscr{E} , we could have added the final job of \mathscr{F} to \mathscr{E} , a contradiction to the def. of \mathscr{E} .
 - So, $\mathscr E$ has at least as many jobs as $\mathscr F.$ True for all feasible $\mathscr F,$ proving optimality.

- Input: start and end times (s_i, t_i) for i = 1, ..., n for n "jobs"
- Output: A maximal set of mutually compatible jobs
- Algorithm: Select the job with earliest ending t_i of jobs not selected.
 - **Details:** Sort the jobs by earliest end time t_i . Keep track of current end time of selected jobs T. Add new job (s_i, t_i) if $s_i \ge T$ and update $T \leftarrow t_i$.
 - **Runtime:** Sorting + linear time to create list of jobs. $O(n \log n) + O(n) = O(n \log n).$

Greedy algorithms

- Myopic style of argument that makes decisions based on current information.
 Does not "look ahead".
- Greedy algorithms tend to only work when there is some kind of special structure to the problem.
- When they do work, they are very efficient.
- When they don't work, they often give very good approximation algorithms!

Weighted interval scheduling

- Same problem as interval scheduling except each job has a value w_i. Want to
 optimize sum of weights of jobs selected.
 - Example: Scheduling rooms for a conference except some speeches pay more.
 - Example: $w_i = t_i s_i$. The value is the length of the job.

Weighted interval scheduling

- Input: start and end times (s_i, t_i) and weights w_i for i = 1, ..., n for n "jobs" **Output:** A set of mutually compatible jobs of maximal weight sum



Weighted interval scheduling

- Input: start and end times (s_i, t_i) and weights w_i for i = 1, ..., n for n "jobs"
- Output: A set of mutually compatible jobs of maximal weight sum
- If all weights $w_i = 1$, then this is regular interval scheduling
- In general, we need a different technique: Dynamic Programming
 - Build up solution from a table of precomputed solutions to smaller problems

Dynamic programming Principal properties

- Optimal substructure:
 - of subproblems.
 - if we could just skip the recursive steps.
- Overlapping subproblems:
 - The subproblems share sub-subproblems.
 - lot of time solving the same problems over and over again.

• The optimal value of the problem can easily be obtained given the optimal values

• In other words, there is a recursive algorithm for the problem which would be fast

• In other words, if you actually ran that naïve recursive algorithm, it would waste a

- A graph G = (V, E) is bipartite iff

 - V, the vertices, have two disjoint parts $V = X \sqcup Y$. • Every edge $e \in E$ connects a vertex $x \in X$ and a $y \in Y$.
- A set $M \subseteq E$ is a matching if no two edges in M share a vertex.
- Goal: Find a matching of maximal size given input bipartite G.
- B (2)(c)(3) (\mathfrak{D}) $(\dot{4})$ (E)

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- Goal: Find a matching of maximal size given input bipartite G.
- Differences from stable matching:
 - Limited set of possible partners for each vertex.
 - Sides may not be the same size.
 - No notion of stability, matching everything may be impossible.



- Applications:
 - X represent visitors to websites, Y represent servers they access
 - X represents professors, Y represents courses
 - X represents taxi riders, Y represents taxis
- If |X| = |Y| = n, then G has a "perfect matching" if the matching is size n
- Finding bipartite matchings:
 - Polynomial-time algorithm using "augumentation" technique
 - Solved via general class of network flow problems and algorithms

Independent set

- Given a graph G = (V, E), a subset $I \subseteq V$ is independent if there are no edges between vertices of I
- Input: graph G = (V, E)
- **Output:** Find an independent set of maximal size.
- Models selecting set of non-conflicting scenarios.
 - Example: Assigning frequencies in radio networks lacksquare
 - Example: Scheduling exams with edges represent classes that share a student.



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Independent set **Generalizes many problems**

- Generalizes Interval Scheduling and Bipartite Matching
- Interval Scheduling
 - Vertices correspond to the jobs
 - Edges between jobs that overlap
- **Bipartite matching**
 - Given graph G create a new graph L_G called the line-graph
 - Independent set in L_G corresponds to a bipartite matching in G





Line Graph Construction

- From a graph G = (V, E) to a new graph G' = (V', E') where V' = E
- **Picture:**



• An edge exists in E' if two vertex/edges $e_1, e_2 \in E = V'$ share a vertex in V.



Line Graph Construction

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- **Picture:**



• An edge exists in E' if two vertex/edges $e_1, e_2 \in E = V'$ share a vertex in V.



Hardness of independent set

- There is no known polynomial-time algorithm for independent set (even decision)
 - Input: Graph G and integer $k \ge 0$
 - Output: If there exists $I \subseteq V$ independent set such that $|I| \geq k$
- Easy to check in poly time if a solution I is both (a) valid and (b) at least size k
- Therefore the problem is in NP non-deterministic polynomial time.
- Independent set is NP-complete, the hardest problem in NP.

Graph traversal

Graph search and traversal





Graph search and traversal

- Used to discover the structure of a graph
- "Walk" from a fixed starting vertex s ("the source") to find all the vertices reachable from s

- Generic traversal algorithm.
 - Input: Graph G and vertex $s \in V$
 - Find: set $R \subseteq V$ reachable from s

Reachable(s):

$$R \leftarrow \{s\}$$

While there exists a $(u, v) \in R \times (V)$
Add v to $R: R \leftarrow R \cup \{v\}$.
return R



Generic graph traver

- Claim: R is exactly the set of reachable vert
- - traversal algorithm: If we added v by edge $(u, v) \in R \times (V \setminus R)$ then $s \prec u \to v$.
 - **Direction 2**. Assume (for \perp), there is a vertex v that is reachable but not $v \notin R$.
 - Let p = the path $s \sim v$ and let v' be the **first** vertex on p such that $v' \notin R$.
 - Then u, the predecessor of v', satisfies $u \in R$ and $(u, v') \in R \times (V \setminus R)$.
 - Contradicts the definition of the generic graph traversal.

	Reachable(s):
Sa	$R \leftarrow \{s\}$ While there exists a $(u, v) \in R \times (V)$
ticas	Add v to $R: R \leftarrow R \cup \{v\}$. return R

• **Proof:** We show both directions. (1): every vertex in R is reachable. (2): every reachable is in R.

• Direction 1. For $v \in R$, there is a path $s \sim v$. Proved by induction on the generic graph





• 2

- Used to explore the vertices in R according to their distance from s.
- Implemented using the *queue* data structure.
- Assign a bit to every vertex as visited/not visited.
- Algorithm:
 - Initialize set $R \leftarrow \{s\}$ and queue $Q \leftarrow \{s\}$.
 - Set all vertices to not visited. Set s as visited.
 - While Q isn't empty, pop v off the queue.
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