# Dijkstra's Algorithm and Divide and Conquer

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- Midterm back soon
- Assignment released Wednesday
- Current plan: Assignments 3 and 5 in groups; Assignment 4 solo
- Today we'll have a fun discussion of how to optimize Kruskal's, then Dijkstra's algorithm, and finally intro divide and conquer
- Hand-multiplying integers?

# **Dijkstra's Algorithm**

• Given a directed graph G with positive edge weights

• Find the *shortest path* from s to t

• Path *p* from s to *t* minimizing  $\sum_{e \in p} w_e$ 



destination t

length of path = 9 + 4 + 1 + 11 = 25



# Shortest Path Applications

- Map routing
- Robot navigation
- Texture mapping
- Latex typesetting
- Traffic Planning
- Scheduling
- Network routing protocols
- We'll revisit later in class as well (to allow for negative weights in the graph)

#### Shortest Path: Plan

- Greedy algorithm much like Prim's
- Find shortest path from s to all vertices of the graph
  - Therefore, we get the shortest path to *t*
  - Assume *G* is connected to keep things simple. (If there is no path from s to *t* we will detect that anyway)
- Each time we add a new vertex, *guarantee* that we've found the shortest distance to that vertex
- Greedily grow the vertices we've found the shortest path to
- Denote the *actual* shortest path d(s, v). We will store the shortest path we find in an array d[]; so our goal is d[v] = d(s, v).
- Let's start building the algorithm [On Board #1]

- Maintain a set S of vertices we have found the shortest path to; array *d* of shortest paths
- Start with  $S \leftarrow \{s\}$ ; d[s] = 0;  $d[v] = \infty$  for all  $v \neq s$
- To add a new vertex to S:
  - Among all cut edges C of S
  - Find the edge  $e = (u, v) \in C$  minimizing  $d[u] + w_e$
  - Set *d*[*v*] = *d*[*u*] + *w*<sub>e</sub>; add *v* to S

How can we prove that this is correct? (Then: how can we implement this?)

# Dijkstra's Proof Intuition



- By induction
- I.H.: for any k, if |S| = k, then for any v ∈ S, d[v] stores the length of the shortest path from s to v.
- Base case?
  - *k* = 1; *d*[s] = ∅
  - We are done because all edge lengths are positive so no path can have length less than 0.

# Dijkstra's Algorithm Inductive Step



- Assume that for some set S of size k, for all  $w \in S$ , d[w] = d(s, w)
- We find cut edge e = (u, v) minimizing d[u] + w<sub>e</sub>; add v to S; set d[v] = d[u] + w<sub>e</sub>. To show: d[v] = d(s, v)
- Claim: for any vertex  $y \notin S$ ,  $d(s, y) \ge d[u] + w_e$ 
  - Idea: If there is a shorter path to *y*, there must be a smaller cut edge [On Board #2]
- Now: there cannot be a path p' to v with length less than  $d[u] + w_e$ 
  - Idea: assume contrary. Let y be the first vertex in p' not in S. Then the length of p' is at least d(s, y) + d(y, v)
  - $d(s, y) \ge d[u] + w_e$  from claim above;  $d(y, v) \ge 0$

#### Implementing Dijkstra's Algorithm

- Dijkstra's is correct by induction (see above)
- How can we find the smallest cut edge?
- Same technique as Prim's algorithm!
- Keep a priority queue Q of cut edges; "priority" of an edge e = (u, v) is  $d[u] + w_e$
- Remove smallest-weight edge e' = (x, y) from Q. If  $y \in S$ , skip it. Otherwise, add y to S, and set  $d[y] = d[x] + w_{e'}$
- Running time?
  - $O(m \log m)$  (each edge is added to the queue only once;  $O(\log m)$  to add it or extract minimum)

# Improving Dijkstra's Algorithm

- We are being wasteful with our edge storage!
- Only need to store one edge to each node in  $V \setminus S$  [On Board #3]
- Only need a priority queue of *n* items!
- But: what happens when we find a new edge to a vertex not in S?
  - Need to update the vertex's weight
  - Must modify the priority queue! How can we update the weight of a vertex in a heap?
- In practice: smaller queue means runs faster
- In theory: using a Fibonnacci heap can insert and decrease key in *O*(1); extract minimum in *O*(log *n*)
  - Gives  $O(m + n \log n)$  running time for Dijkstra's algorithm
  - Can we do better? Open problem.
  - If edge weights are integers can get O(m) running time

# **Divide and Conquer Algorithms**

# Algorithmic Design Paradigms

- Greedy Algorithms
  - Gas-filling; maximum interval scheduling
  - Prim's, Kruskal's, Dijkstra's
  - Idea: we choose an item to add *permanently* to the solution
  - Proof that each item we have is correct
- Divide and Conquer  $\leftarrow$  we are here!
  - Divide problem into multiple parts
  - Combine solutions into a new correct solution
- Dynamic Programming
- Network Flow

- Selection sort: take largest item; place it in last slot; repeat
- Can be viewed as "greedy:" once we place an item, we have proven that it stays there irrevocably
- $\Theta(n^2)$  time (requires  $\Omega(i)$  time to find largest of *i* items)
- Can we do better with divide and conquer?
- Let's revisit Merge Sort, and talk about how to analyze it

Goal: sort an array A of size n (Assume |A| is a power of 2 for simplicity)

- If  $|A| \leq 1$  return A
- Otherwise, sort the left half of A and the right half of A using Merge Sort
- "Merge" the two halves together to create a sorted array

Let's look at how to merge efficiently [On Board #4]

Running time? O(n)

- Classic divide and conquer algorithm; need:
  - A base case
  - A way to divide into smaller instances
  - A way to combine the solution for smaller instances into an overall solution
- What do we need for correctness?
  - Combining smaller solutions must give correct solution for overall instance
  - Base case must be correct
  - Must *reach* the base case!

- Analyzing D & C algorithms can be initially confusing
- Challenge: the algorithm "jumps" all over the place due to the recursive structure
- Today: *group/categorize* costs to allow us to analyze divide and conquer more effectively

## Merge Sort Running Time

What is the running time of Merge Sort on an array of size n?

One answer:

- running time of Merge Sort on an array of size n/2, plus
- running time of Merge Sort on a second array of size n/2, plus
- O(n) to merge.
- Or, if n = 1, then the cost is 1.

Let T(n) be the *exact* cost of Merge Sort on an array of size *n*. Then:

$$T(n) = 2 \cdot T(n/2) + O(n), \qquad T(1) = 1$$

**Recurrences** 

- To find the running time of a divide and conquer algorithm, we write a *recurrence*
- Let T(n) be the cost of the algorithm on a problem of size *n*. Can write T(n) as:

- A base case for small *n* (oftentimes T(1) = 1)
- A sum of the "divide" recursive calls which can be written in terms of *T* (e.g. T(n/2)), plus the cost to "conquer"
- A solution to this recurrence gives our total running time!

• 
$$T(n) = 2T(n/2) + O(n); T(1) = 1$$

- First: set constants
- For some *c*,  $T(n) \le 2T(n/2) + cn$ ;  $T(1) \le c$
- How can we solve this?

- Let's draw the recurrence as a tree [On Board #5]
- Idea: this drawing will help us group together the costs of the algorithm
- How does Merge Sort actually run?
- But: can we bound the cost of a given level of the tree?
  - Yes: each level costs cn in total
  - Specifically: level *i* has  $2^i$  subproblems, each with cost  $\leq cn/2^i$
- How many levels are there?
- What is the total cost of Merge Sort?

#### Recurrence Tree Analysis: Merge Sort

- What is this level-by-level analysis saying about Merge Sort?
- Look at all work we do across all subproblems of size  $n/2^i$
- Answer: *cn* total work
- So we do *cn* total work on the subproblem of size *n*; *cn* total work on the 2 subproblems of size *n*/2; *cn* on the four subproblems of size *n*/4, . . . , *n* on the *n* subproblems of size 1
- That's  $\leq cn(\log_2 n + 1)$  total work!

#### Double-Checking our Work

• We wanted a solution to:

$$T(n) = 2 \cdot T(n/2) + cn, \qquad T(1) = c$$

- Does  $cn(\log_2 n + 1)$  satisfy this?
  - Yes.

$$cn(\log_2 n + 1) \le 2\left(\frac{cn}{2}\left(\log_2 \frac{n}{2} + 1\right)\right) + cn$$
$$= cn\left(\log_2 \frac{n}{2} + 1\right) + cn$$
$$= cn\left(\log_2 n - \log_2 2 + 1\right) + cn$$
$$= cn\left(\log_2 n\right) + cn$$

- Merge Sort divides the array into halves, sorts each half, and then recombines them in O(n) time
- Running time is initially difficult to see
- We wrote the running time as a recurrence
- To solve the recurrence, we drew a tree, which helped us group the costs
- $\log_2 n$  levels, each of cost O(n), means  $O(n \log n)$  total cost!

- Let's say we want to multiply two *n*-digit numbers *a* × *b* (let's assubase 10, but the same idea holds for binary numbers)
  - Let's say *n* is much larger than 64, so our CPU
- What is the running time of the algorithm you learned in school?
  - For each digit of *b*, multiply with each digit of *a*; carry as necessary
  - O(n) time for each digit of b
  - $O(n^2)$  time overall
- Addition is only O(n) however
- Can we do multiplication more efficiently? In 1960, Kolmogorov *conjectured* no; any algorithm takes  $\Omega(n^2)$  worst-case time



Assume n is a power of 2 for the moment for simplicity.

- Let's write *a* as the sum of two n/2-bit numbers:  $a = 10^{n/2}a_{\ell} + a_r$
- Let's write *b* as the sum of two n/2-bit numbers:  $b = 10^{n/2}b_{\ell} + b_r$

• Then 
$$a \times b = (10^{n/2}a_{\ell} + a_r)(10^{n/2}b_{\ell} + b_r)$$

• Using algebra, 
$$a \times b = 10^n (a_\ell + b_\ell) + 10^{n/2} (a_\ell b_r + b_\ell a_r) + a_r b_r$$
.

$$a imes b=$$
 10 $^n(a_\ell b_\ell)+$  10 $^{n/2}(a_\ell b_r+b_\ell a_r)+a_r b_r$ 

- So we can use divide and conquer! To multiply two *n*-digit numbers, we first perform four recursive multiplications:
  - $a_{\ell} \times b_{\ell}$ ,  $a_{\ell} \times b_r$ ,  $b_{\ell} \times a_r$ , and  $a_r \times b_r$
- And then we add them together in O(n) time.
- Recurrence?
- T(n) = 4T(n/2) + O(n); T(1) = 1
- Let's solve this recurrence together on the board!
- Get  $\Theta(n^2)$  time, same as before (for now...)

# Divide and Conquer: A Very Clever Algorithm (Karatsuba's Algorithm)

$$a \times b = 10^n (a_\ell b_\ell) + 10^{n/2} (a_\ell b_r + b_\ell a_r) + a_r b_r$$

- Consider the following three recursive multiplications
  - $a_\ell \times b_\ell$ ,  $a_r \times b_r$ , and  $(a_\ell + a_r) \times (b_\ell + b_r)$
- I claim this is enough! Why?
- $a_\ell b_r + b_\ell a_r = (a_\ell + a_r) \times (b_\ell + b_r) a_\ell \times b_\ell a_r \times b_r$
- So after *three* recursive calls of size n/2 I can calculate a × b. I used O(n) total time other than the recursive calls
- T(n) = 3T(n/2) + O(n); T(1) = 1

$$T(n) = 3T(n/2) + O(n)$$
  $T(1) = 1$ 

- Let's solve this recurrence [On Board #6]
- We want to ask ourselves: What is the height of the tree? What is the cost of each level?
- Solution:  $O(n^{\log_2 3}) = O(n^{1.58})$  time
- Much better than  $n^2$ !
- Reflect: why did changing a *constant* from 3 to 4 have such an impact on the running time?

# Multiplying Numbers Efficiently

- Kolmogorov conjectured that  $\Omega(n^2)$  time is needed; stated this conjecture in a seminar at Moscow State University in 1960
- Karatsuba, a student figured out this  $O(n^{\log_2 3})$  time algorithm in the next week
- Kolmogorov cancelled the whole seminar and then published the result on Karatsuba's behalf without telling him
- Can we do better?
- Best known:  $O(n \log n)$  [Harvey, van der Hoeven 2019]
- Are these speedups useful in practice?
  - Sometimes! Karatsuba's is used in some libraries