

CS 580

ALGORITHM DESIGN AND ANALYSIS

Dynamic Programming

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DYNAMIC PROGRAMMING

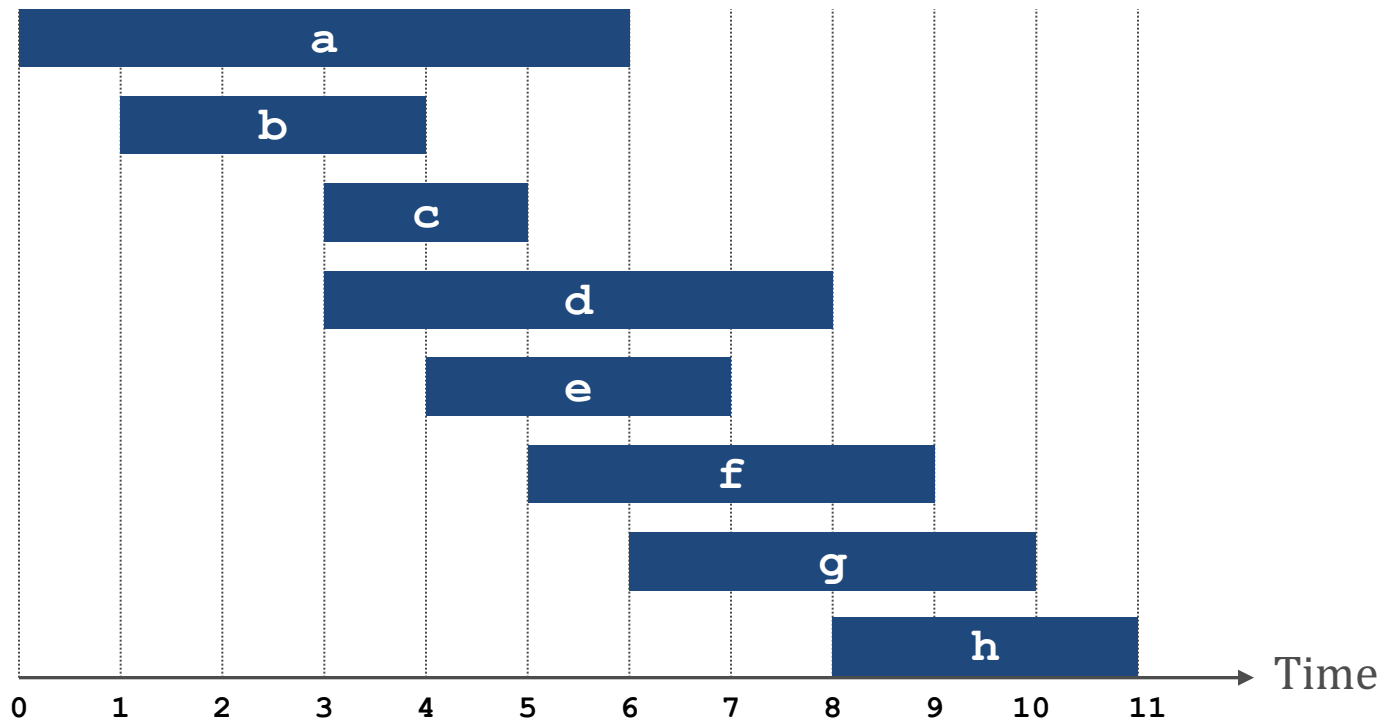
- The algorithmic tools so far:
 - Greedy and D&C
- Great tools
- But useful in very specific types of problems
 - E.g. the problems we talked in the D&C module have obvious poly-time solutions, and the smart D&C solution was faster
 - But we didn't see how to break “exponential barriers”
- Today:
 - Sledgehammer #1: Dynamic programming
- In the future:
 - Sledgehammer #2: Linear programming

DYNAMIC PROGRAMMING

- Greedy:
 - Build a solution incrementally
- D&C:
 - Break problem into smaller sub-problems of the same instance, solve recursively and combine
- Dynamic programming:
 - Break up problem into series of overlapping sub-problems and build up solutions to larger and larger sub-problems

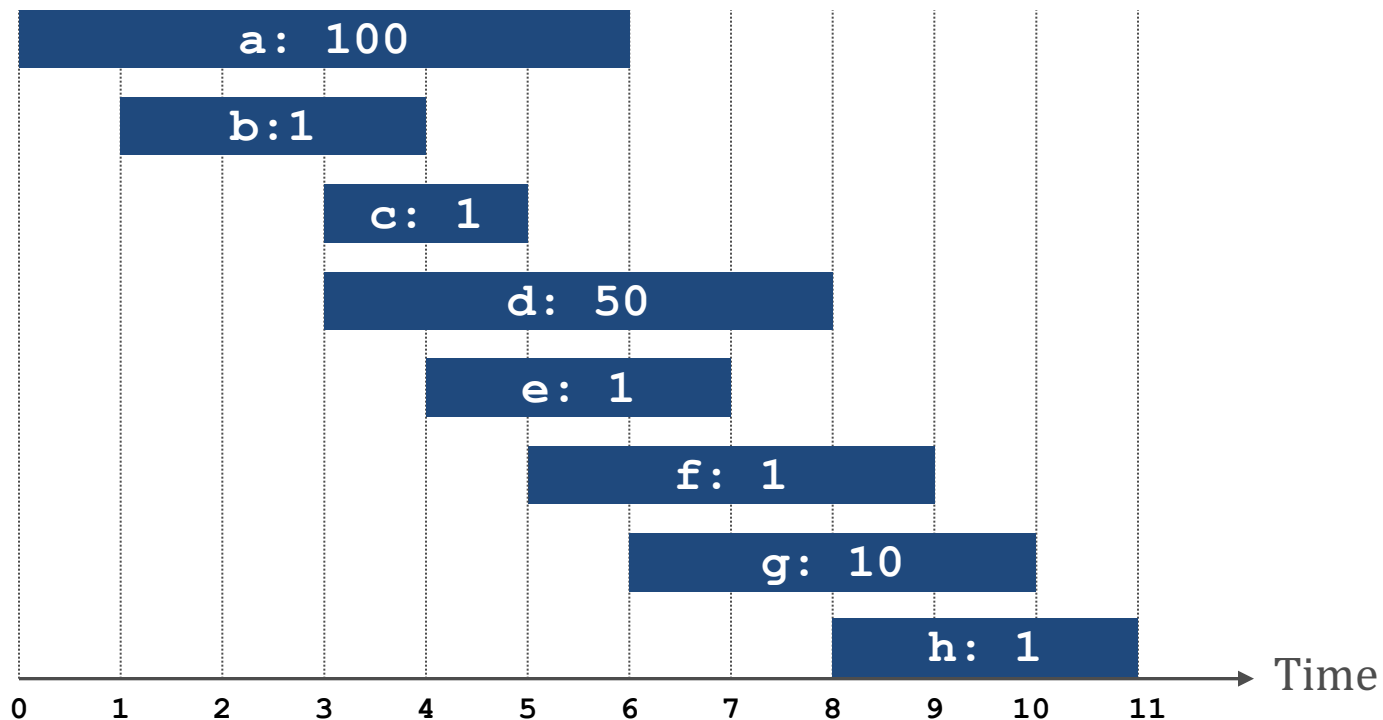
INTERVAL SCHEDULING

- There's an incoming set of jobs $\{1, \dots, n\}$
- The i th job corresponds to an interval $[s_i, t_i]$
- Two jobs are compatible if they don't overlap
- Goal: find maximum subset of compatible jobs



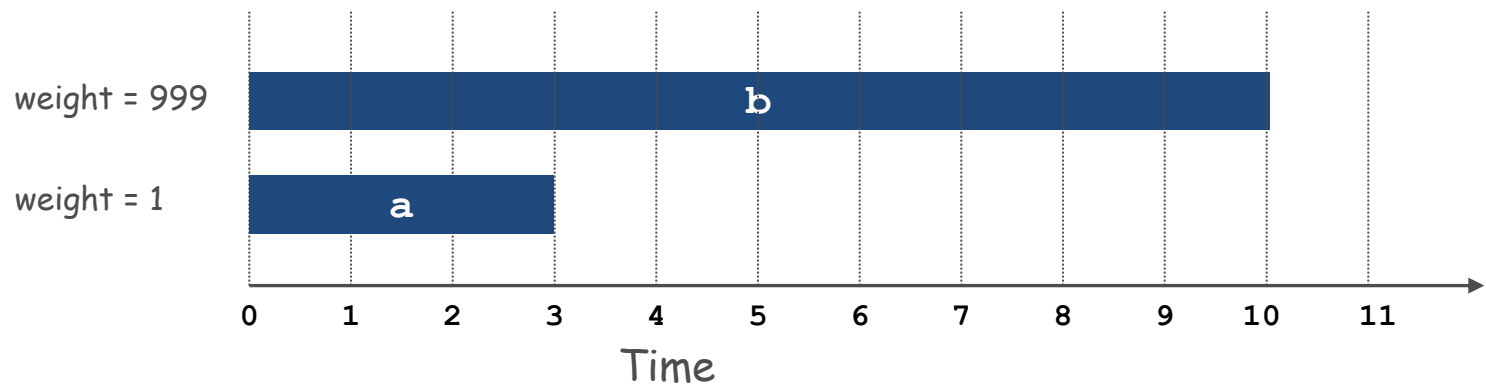
WEIGHTED INTERVAL SCHEDULING

- There's an incoming set of jobs $\{1, \dots, n\}$
- The i th job corresponds to an interval $[s_i, t_i]$ and has weight v_i
- Two jobs are compatible if they don't overlap
- Goal: find maximum weight subset of compatible jobs



WEIGHTED INTERVAL SCHEDULING

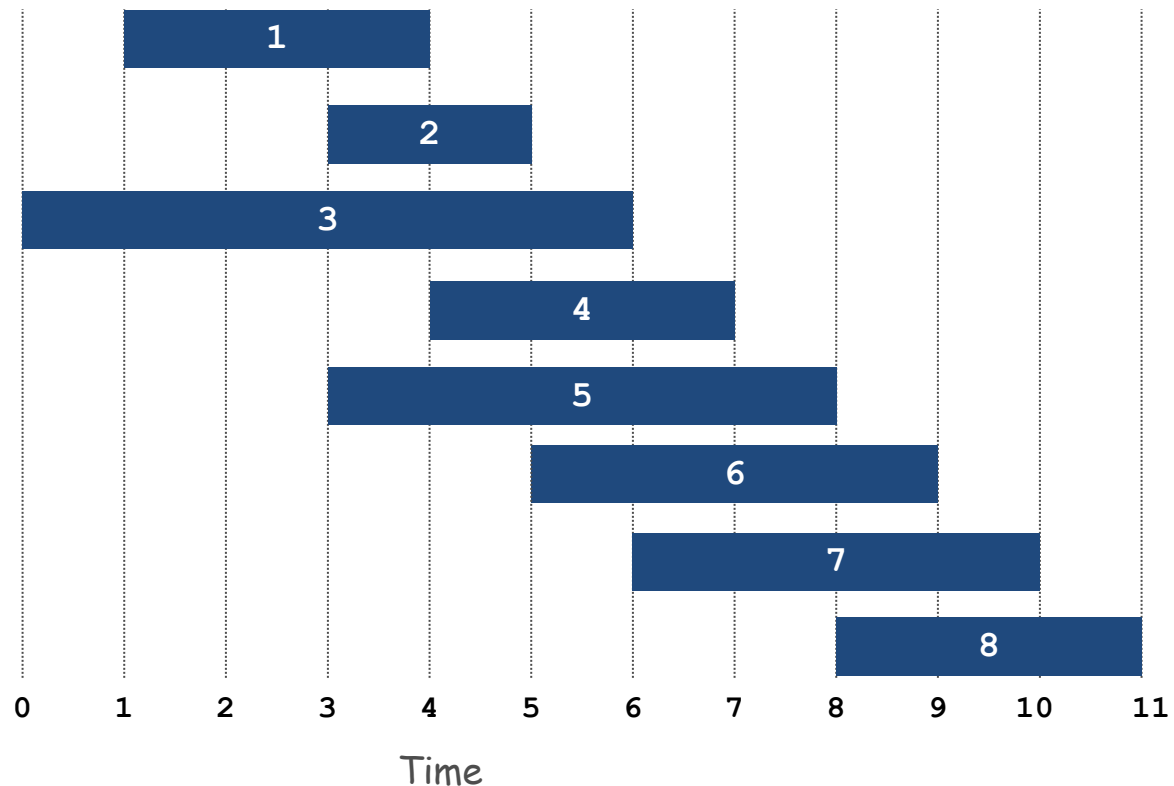
- Observation: Greedy can fail (spectacularly) if arbitrary weights are allowed



WEIGHTED INTERVAL SCHEDULING

- Sort in non decreasing finish time and re-name the jobs so that $f_1 \leq f_2 \leq \dots \leq f_n$
- For job j let $p(j)$ = largest index $i < j$ such that job i is compatible with job j

- $p(2) = 0$
- $p(4) = 1$
- $p(7) = 3$
- $p(8) = 5$



WEIGHTED INTERVAL SCHEDULING

- $OPT(j) :=$ value of optimal solution to the problem with requests $1, \dots, j$
 - Typical dynamic programming formulation
- Case 1: $OPT(j)$ doesn't select job j
 - Easy observation: Then it's just the same as $OPT(j - 1)$
- Case 2: $OPT(j)$ selects job j
 - Then it can't select all the jobs that are incompatible with j
 - Those are exactly $p(j) + 1, \dots, j - 1$
 - Therefore, $OPT(j)$ in this case should just be the same as $OPT(p(j))$ plus job j

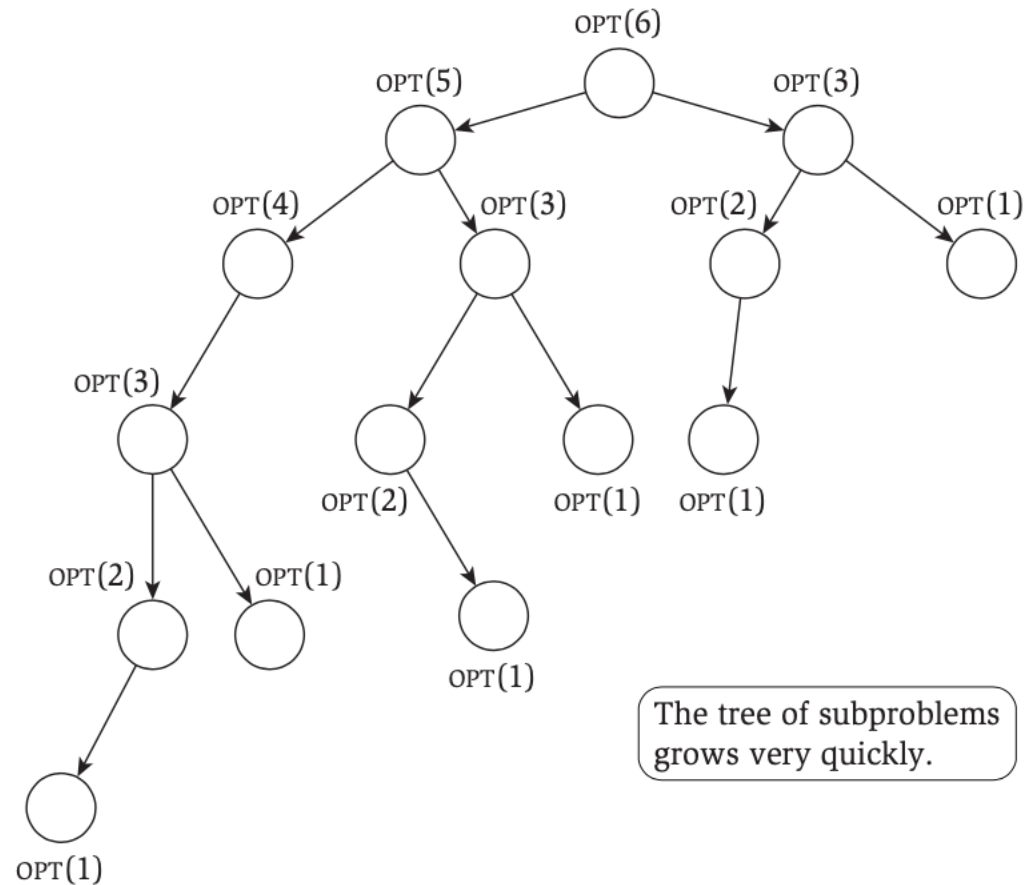
WEIGHTED INTERVAL SCHEDULING

$$OPT(j) = \begin{cases} 0 & \text{if } j = 0 \\ \max \{ v_j + OPT(p(j)), OPT(j-1) \} & \text{otherwise} \end{cases}$$

WEIGHTED INTERVAL SCHEDULING

1. Sort by finish time and rename to get $f_1 \leq \dots \leq f_n$: $O(n \log(n))$
 2. Compute $p(j)$ for each job j : $O(n^2)$
 3. For each job j run `compute- $OPT(j)$` :
 - If $j = 0$, return 0
 - Return $\max\{OPT(p(j)) + v_j, OPT(j - 1)\}$
-
- For `compute- $OPT(j)$` :
 - $T(n) = T(n - 1) + T(p(n)) + O(1)$
 - This is exponential!

WEIGHTED INTERVAL SCHEDULING



RECURSION? NO THANKS!

- Why recurse??
 - Just store the value of $OPT(j)$
- We've already seen this trick with Fibonacci!

3. For all j , $OPT[j] = 0$

4. For all j , run $\text{Compute-}OPT(j)$:

- If $j = 0$ return 0
- $OPT[j] = \max\{OPT[j - 1], OPT[p(j)] + v_j\}$

- Step 4 now takes linear time!

EDIT DISTANCE

- Motivation:
 - A spellchecker finds a misspelled word
 - Wants to look for close by words in the dictionary
 - What's an appropriate notion of distance?

S	—	N	O	W	Y
S	U	N	N	—	Y

Cost: 3

- Minimum number of edits (insertions, deletions and replacements) needed for the two string to be identical
 - “-” above means that you can place anything

EDIT DISTANCE

- Input:
 - Strings $x = x[1, \dots, m]$ and $y = y[1, \dots, n]$
- Output:
 - Minimum edit distance

EDIT DISTANCE

- How about solving it on the prefix?
- $E(i, j)$ = minimum edit distance between $x[1, \dots, i]$ and $y[1, \dots, j]$

Figure 6.3 The subproblem $E(7, 5)$.

E	X	P	O	N	E	N	T	I	A	L
P	O	L	Y	N	O	M	I	A	L	

- What's $E(i, j)$ in terms of subproblems we've already solved?
 - E.g. $E(i - 1, j)$, $E(i, j - 1)$, $E(i - 1, j - 1)$, and so on?

EDIT DISTANCE

- In the alignment of $x[i]$ and $y[j]$, one of three things can happen
 1. We have $x[i]$ and “ – ”
 2. We have “ – ” and $y[j]$
 3. $x[i]$ aligned with $y[j]$

EDIT DISTANCE

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 1. We have $x[i]$ and “ – ”
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- Case 1:
 - The remainder problem aligns $x[1, \dots, i - 1]$ and $y[1, \dots, j]$
 - That's just $E(i - 1, j)$

EDIT DISTANCE

- In the alignment of $x[i]$ and $y[j]$, one of three things can happen
 1. We have $x[i]$ and “ – ”
 2. We have “ – ” and $y[j]$
 3. $x[i]$ aligned with $y[j]$
- Case 2:
 - The remainder problem aligns $x[1, \dots, i]$ and $y[1, \dots, j - 1]$
 - That's just $E(i, j - 1)$

EDIT DISTANCE

- In the alignment of $x[i]$ and $y[j]$, one of three things can happen
 1. We have $x[i]$ and “ — ”
 2. We have “ — ” and $y[j]$
 3. $x[i]$ aligned with $y[j]$
- Case 3:
 - The remainder problem aligns $x[1, \dots, i - 1]$ and $y[1, \dots, j - 1]$
 - That's just $E(i - 1, j - 1)$
 - Almost!
 - $x[i] = y[j]$ and they're aligned
 - Or, $x[i] \neq y[j]$ and they're aligned
 - Define $\text{diff}(i, j) := 0$ if $x[i] = y[j]$ and 1 otherwise

EDIT DISTANCE

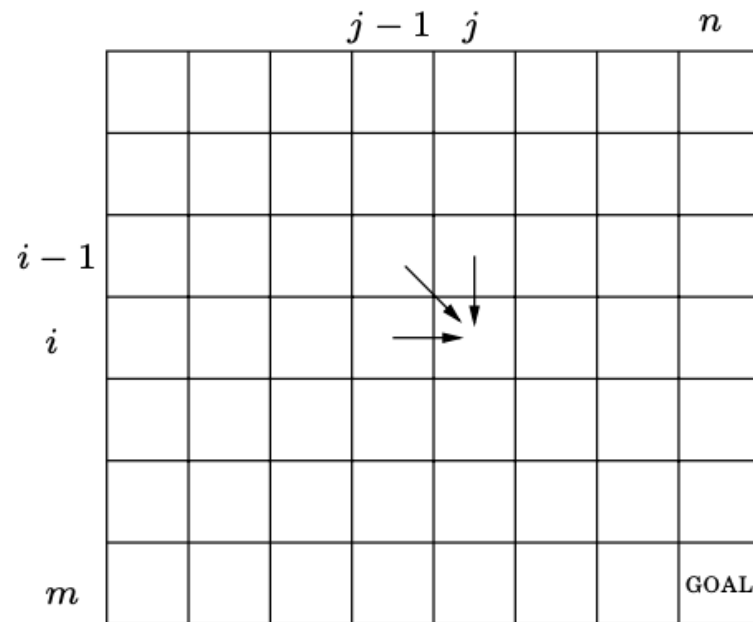
- In the alignment of $x[i]$ and $y[j]$, one of three things can happen
 1. We have $x[i]$ and “ — ”
 2. We have “ — ” and $y[j]$
 3. $x[i]$ aligned with $y[j]$
- Overall

$$E(i, j) = \min \begin{cases} diff(i, j) + E(i - 1, j - 1) \\ 1 + E(i - 1, j) \\ 1 + E(i, j - 1) \end{cases}$$

EDIT DISTANCE

- Example
 - EXPONENTIAL vs POLYNOMIAL
 - $E(4,3)$: EXPO vs POL
 - Either O and “ — ”
 - Either “ — ” and L
 - Or O aligned with L
 - $E(4,3) = \min\{1 + E(3,3), 1 + E(4,2), 1 + E(3,2)\}$


EDIT DISTANCE



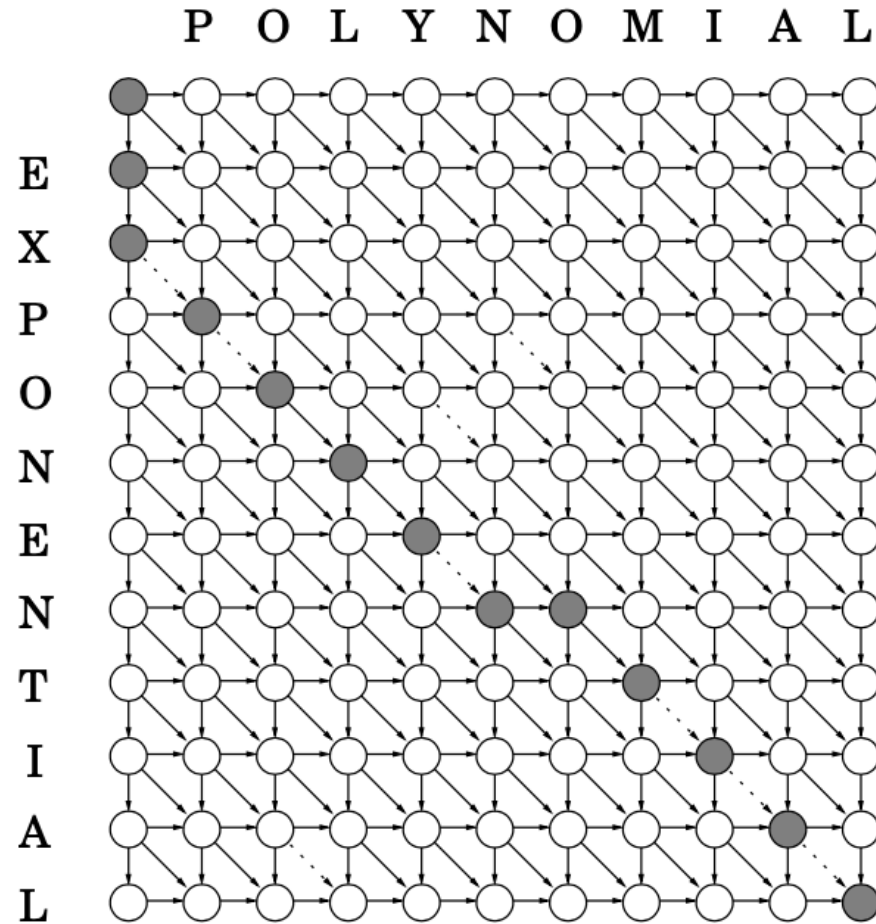
EDIT DISTANCE

- Where do we start?
- For $i = 0, \dots, m$: $E(i, 0) = i$
- For $j = 0, \dots, n$: $E(0, j) = j$
- For $i = 1, \dots, m$
 - For $j = 1, \dots, n$:
 - $E(i, j) = \min\{\dots\}$
- Return $E(m, n)$
- Running time: $O(mn)$

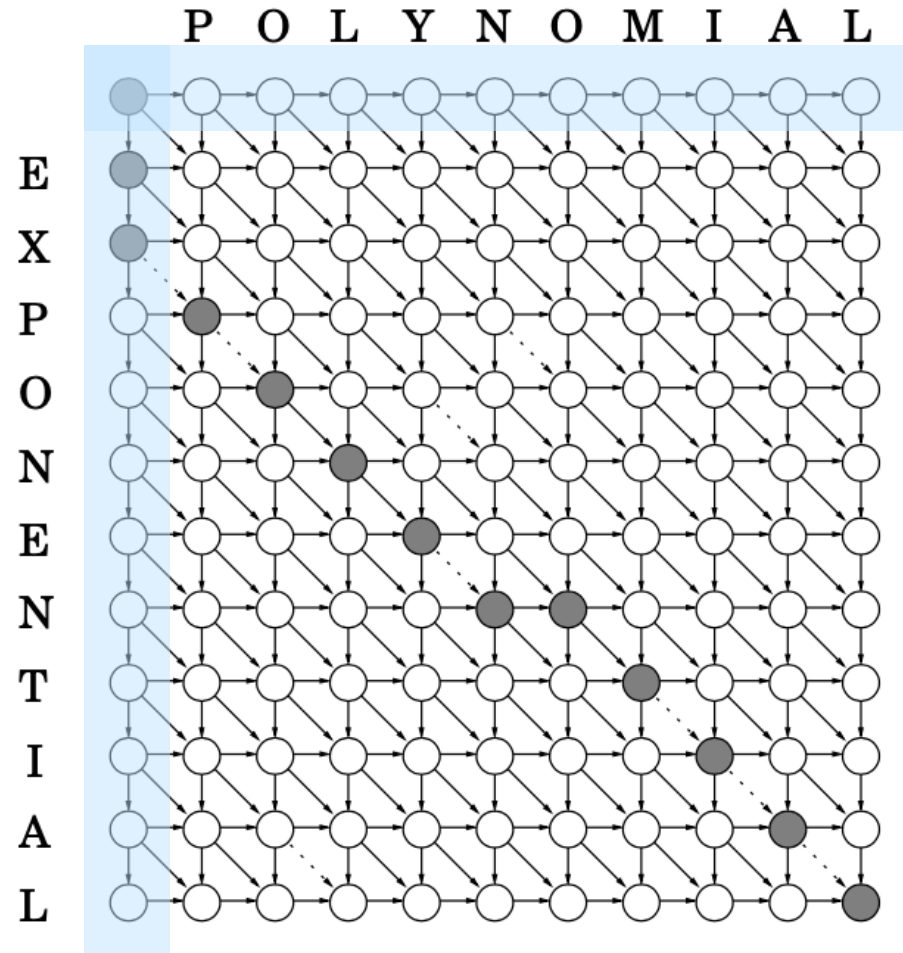
Make sure we have actually solved all subproblems we need!



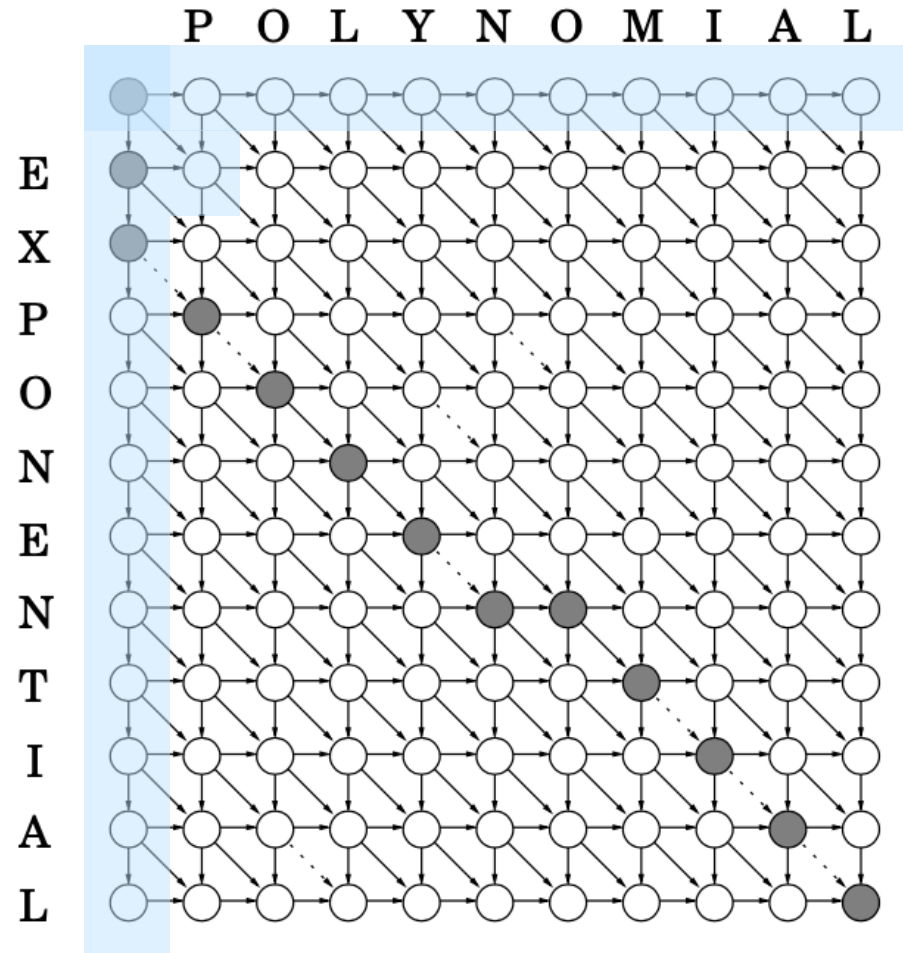
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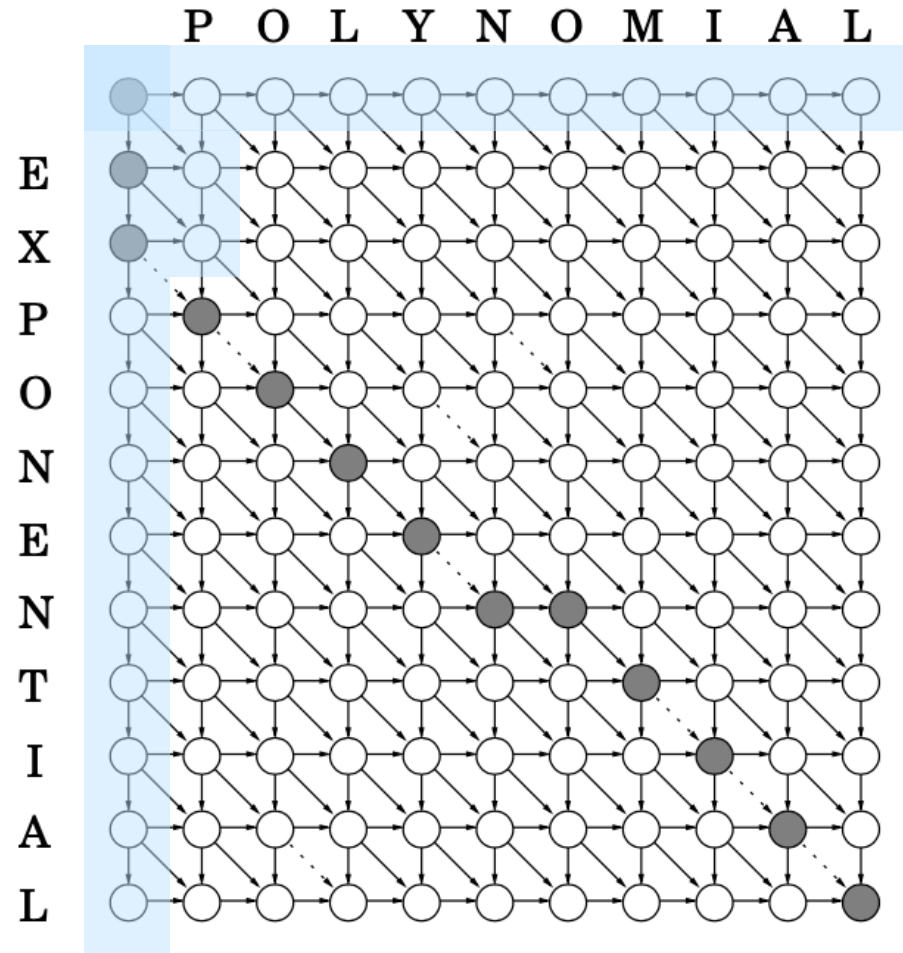
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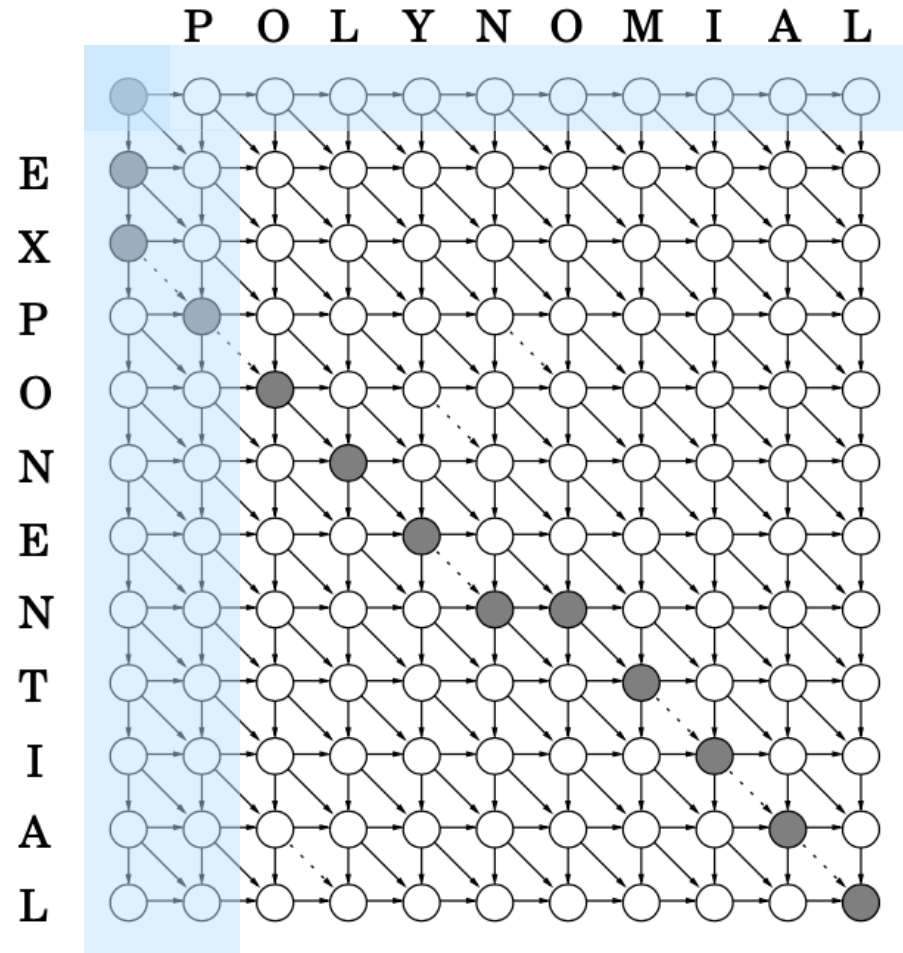
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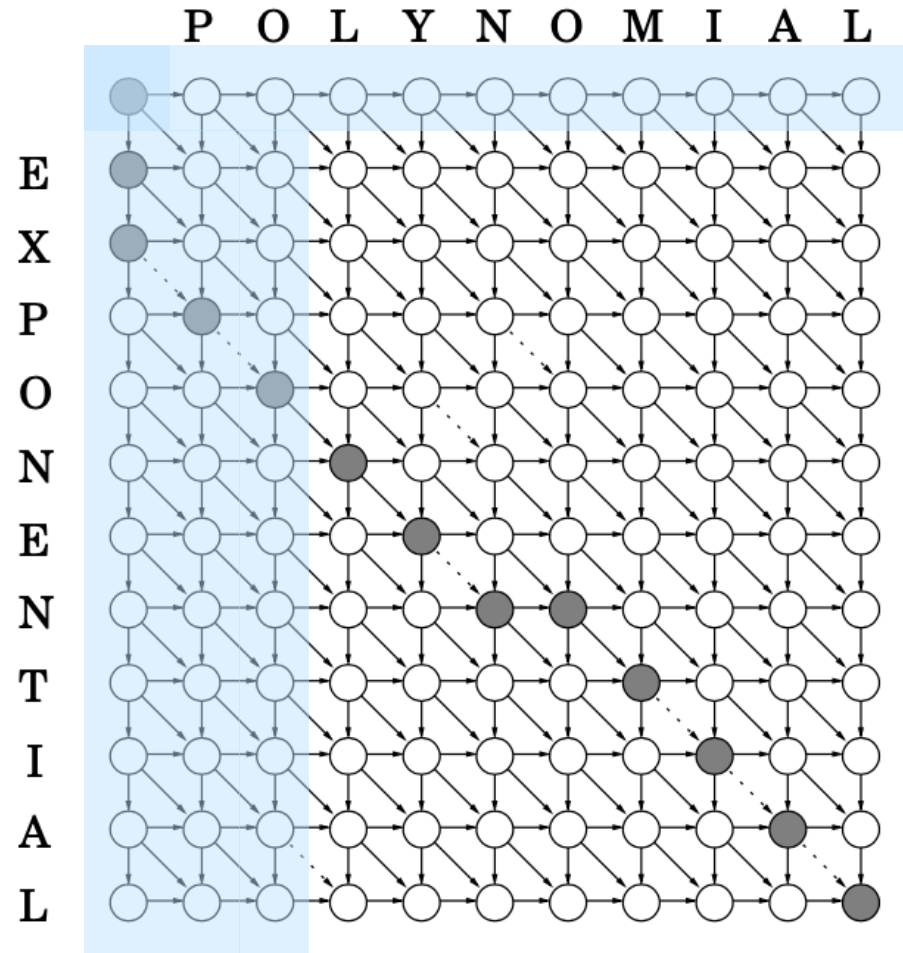
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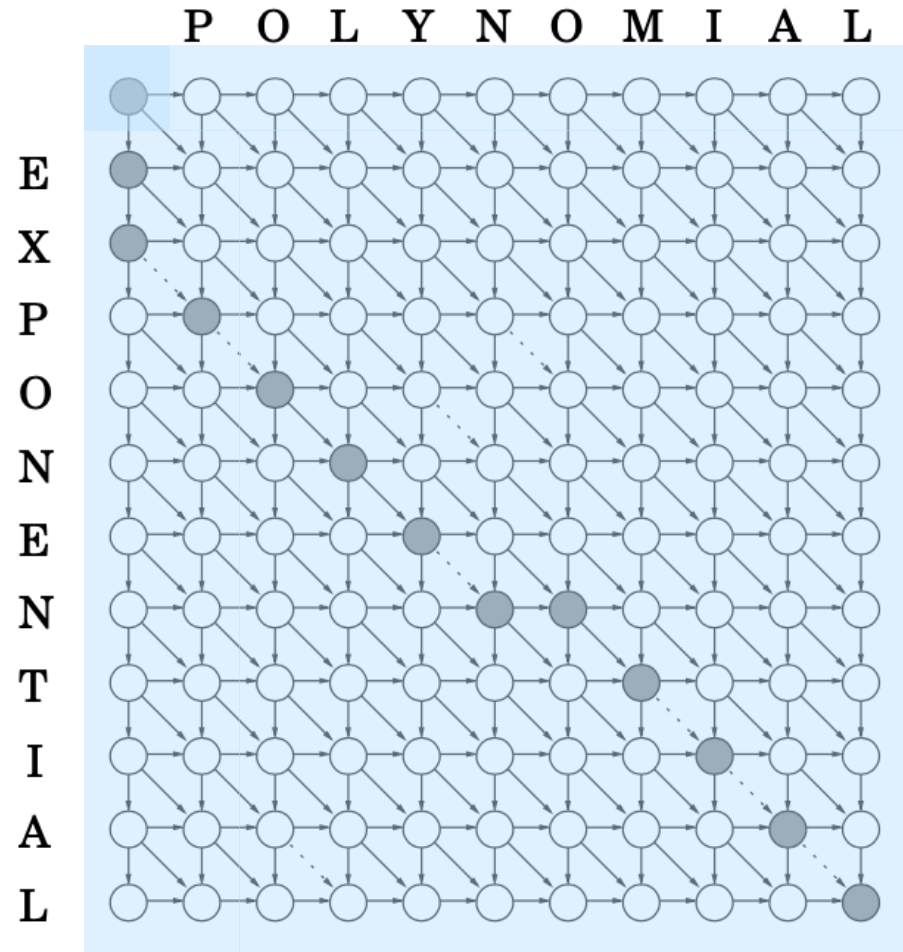
EDIT DISTANCE



EDIT DISTANCE



EDIT DISTANCE



EDIT DISTANCE

- Can you do better?
- Probably not...
 - Backurs and Indyk [2015]
 - If the edit-distance can be computed in time $O(n^{2-\delta})$ for some constant $\delta > 0$, then SAT can be solved in time $2^{n(1-\epsilon)}$ for some constant $\epsilon > 0$. Also known as SETH (Strong Exponential Time Hypothesis)
 - Not as widely believed as $P \neq NP$, but pretty reasonable
 - If you don't believe it, you don't have to worry about finding algorithms for SAT, just beat $O(n^2)$ for edit distance!

KNAPSACK

- During a robbery, a burglar finds much more loot than he had expected and has to decide what to take
- His bag can take total weight of W
- There are n items to pick from
 - Item i has weight w_i and value v_i
- What's the most valuable collection of items that can fit in the bag??

KNAPSACK

- $W = 10$
- Unlimited amount of each item:
 - Item 1 and two of item 4: \$48
- One of each item:
 - Item 1 and item 3: \$46

Item	Weight	Value
1	6	\$30
2	3	\$14
3	4	\$16
4	2	\$9

KNAPSACK

- Greedy?
- Clearly picking highest value would be a bad idea (not for this instance, but generally)
- What about sort by v_i/w_i (bang-per-buck)
- Also suboptimal:
 - Will put in items 1 and 2

Item	Weight	Value
1	6	\$30
2	3	\$14
3	4	\$16
4	2	\$9

KNAPSACK: WITH REPETITION

- THE question in dynamic programming:
 - What are the subproblems?
- Smaller knapsack (i.e. W)? Fewer items?
- $K(w)$ = maximum value with weight w
- What's the value of $K(w)$?
- If i is included, then it's $v_i + K(w - w_i)$
 - Which i ??
 - Try all!
- $$K(w) = \max_{i:w_i \leq w} \{K(w - w_i) + v_i\}$$

KNAPSACK: WITH REPETITION

Item	Weight	Value
1	6	\$30
2	3	\$14
3	4	\$16
4	2	\$9

- $K(0) = K(1) = 0$
- $K(2) = 9$ (only item 4 fits)
- $K(3) = \max\{ K(0) + v_2, K(1) + v_4 \} = 14$
- $K(4) = \max\{ K(1) + v_2, K(0) + v_3, K(2) + v_4 \} = \max\{14, 16, 9 + 9\} = 18$
- ...
- $K(W)$ is the solution

KNAPSACK: WITHOUT REPETITION

- Previous subproblem is useless
- It's not enough to know $K(w)$
 - We need to know the items used, so that we don't repeat them!
- $K(w, j)$ = maximum value with knapsack of size w with items $1, \dots, j$

KNAPSACK: WITHOUT REPETITION

- Case 1: *OPT* doesn't select i
 - $K(w, i) = K(w, i - 1)$
- Case 2: *OPT* selects i
 - $K(w, i) = K(w - w_i, i - 1) + v_i$
- Pick the best of the two!

$$K(w, i) = \max\{ K(w, i - 1), K(w - w_i, i - 1) + v_i \}$$

KNAPSACK

- Running time?
- In both versions, we have at least as many subproblems as W
 - Linear?
 - No!!!
- We only need $\log W$ bits to represent W
- Exponential running time!!!!
- Can we do better?
- Probably not...

SHORTEST PATHS

- Input:
 - Directed graph $G = (V, E)$ with weighted (and maybe negative) edges
- Output:
 - The shortest path between all pairs of vertices

SHORTEST PATHS

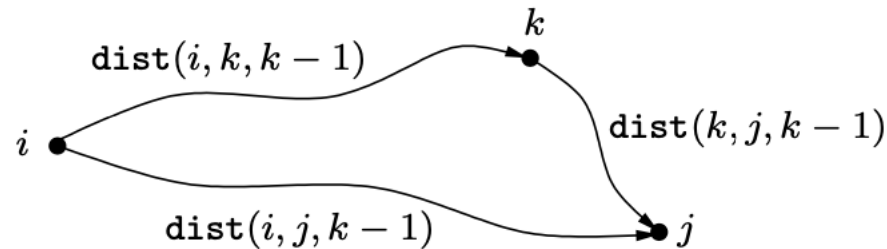
- Bellman-Ford from each vertex s
 - $O(|V|^2|E|)$
- We'll do $O(|V|^3)$
 - The Floyd-Warshall algorithm
- THE question:
 - What's a good subproblem?

SHORTEST PATHS

- Hint: Intermediate nodes
 - What if none are allowed?
 - Easy: shortest path is just an edge, if it exists
 - What if v_1 is the only allowed intermediate node?
 - Shortest (u, v) path is the smaller of (1) the edge $w_{u,v}$ if the edge exists, (2) the edge from u to v_1 plus the edge from v_1 to v
 - Keep growing this

SHORTEST PATHS

- $dist(i, j, k)$: the length of the shortest path from i to j in which the only intermediate nodes allowed are $\{1, \dots, k\}$
 - $dist(i, j, 0) = w_{i,j}$, or ∞ if no edge exists
- Adding a vertex k
 - Need to re-examine all pairs i, j
 - Easy: either you use k or you don't



SHORTEST PATHS

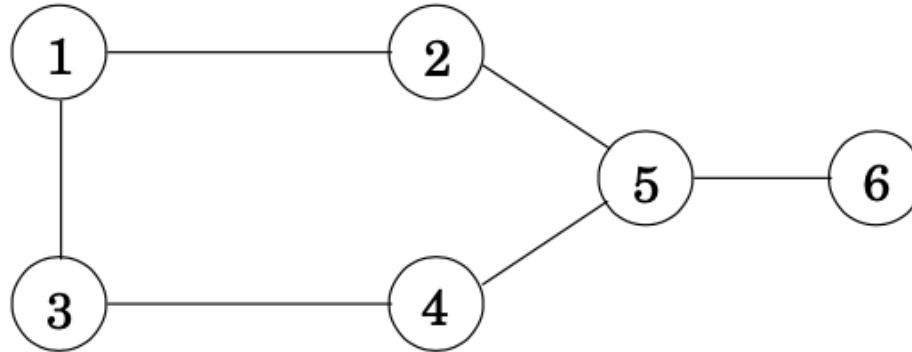
- Note: we are assuming no negative cycles
 - Where??
 - We implicitly assumed that the shortest path from i to j goes through k at most once!
 - We can detect these cycles by running Bellman-Ford
- Under the assumption:

$$\text{dist}(i, j, k) = \min \begin{cases} \text{dist}(i, j, k - 1) \\ \text{dist}(i, k, k - 1) + \text{dist}(k, j, k - 1) \end{cases}$$

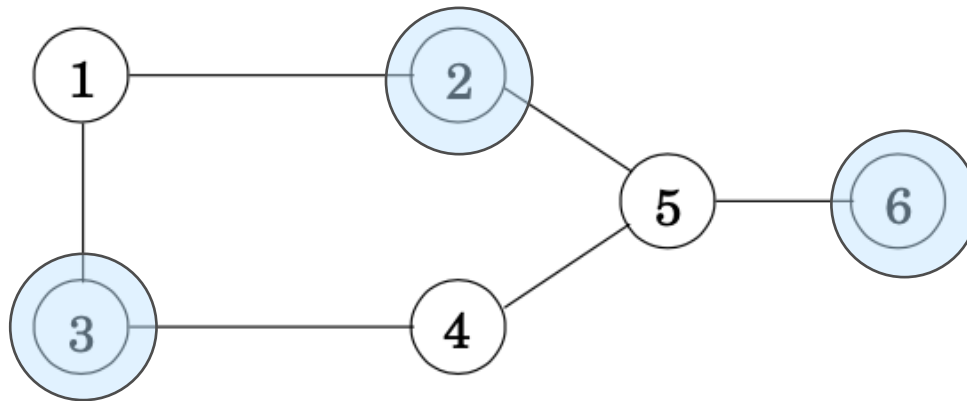
INDEPENDENT SETS IN TREES

- Definition: A subset of vertices S is an *independent set* in an undirected graph G if there is no edge (v, u) where both v and u are in S
- Problem:
 - Input: a tree $G = (V, E)$
 - Output: the (size of the) largest independent set

INDEPENDENT SETS IN TREES



INDEPENDENT SETS IN TREES



INDEPENDENT SETS IN TREES

- Independent set in general graphs is difficult
 - Very very very difficult
- Trees are a rare subcase where the problem is tractable
 - Neat dynamic program

INDEPENDENT SETS IN TREES

- THE question:
 - What's the subproblem?
- Root the tree from some node r
- OPT either has r or it doesn't
 - If it does, then it can't contain any of its children
 - If it doesn't then we can recurse in the subtrees
 - Since there are no edges between them we are in good shape: the optimal solutions are independent

INDEPENDENT SETS IN TREES

- $I(r)$ = weight of maximum independent set of subtree hanging from r
- $$I(r) = \max \begin{cases} 1 + \sum_{\text{grandchildren } u \text{ of } r} I(u) \\ \sum_{\text{children } u \text{ of } r} I(u) \end{cases}$$
- Start from leaves and go up the tree
- Done!