

$\log n = O(n^a) \sum_{i=1}^n (i+1) = \Theta(n^2) = \frac{(n+1)(n+2)}{2}$  **Divide + Conquer Strategy:** 1. Find simple base case. 2. Find way to reduce problem to that base case.

**Insertion Sort**

$O(n^2)$   $T(n) = T(n-1) + O(n)$

```
for j=2 to A.length
  key=A[j]
  i=j-1
  while i>0 and A[i]>key
    A[i+1]=A[i]
    i=i-1
  A[i+1]=key
```

Array is unsorted on the left and sorted on the right. Each item is shifted into correct position in sorted portion. Finishes when last item shifted.

**Merge Sort**  $\Theta(n \log n)$  Recursively

$T(n) = 2T(\frac{n}{2}) + O(n)$  breaks an array

```
Sort(A, p, r) in half until each
if (p<r) sub-array is one
  q=(p+r)/2 element. Then
  sort(A, p, q) merges the
  sort(A, q+1, r) resulting
  merge(A, p, q, r) sub-arrays
```

merge(A, p, q, r) by always adding the smaller item to a temporary array, while (i <= q and j <= r) then if (A[i] <= A[j]) copying over.

**Binary Search**

$O(\log n)$   $T(n) = T(\frac{n}{2}) + O(1)$

```
if n==null or val==n.key
  return n Begins at root
if val < n.key of tree and
  return func(n.left, v)
else traces a path down. If
  return func(n.right, v)
Key at current node equals
  value sought, return. Same
  if node is null. otherwise
```

make recursive call to L/R of leaving item out (taking square above) or taking item and using any remaining space (if 2 lb. left over, go up a row and use value at 2 lb.). Answer is in  $K[n][W]$  (last square in table).

**Knapsack**  $O(n \cdot W)$

```
int Knapsack(n, W, wt[], val[])
for i=0 to n
  for w=0 to W
    if i==0 or w==0, K[i][w]=0
    else if wt[i-1] <= w
      K[i][w] = max(
        val[i-1] + K[i-1][w-wt[i-1]],
        K[i-1][w])
    else, K[i][w] = K[i-1][w]
  return K[n][W]
```

Iterates over all items and weights. At each turn, items will fit, take max of leaving item out (taking square above) or taking item and using any remaining space (if 2 lb. left over, go up a row and use value at 2 lb.). Answer is in  $K[n][W]$  (last square in table).

**Longest Common Subsequence**  $\Theta(m \cdot n)$

$m = X.length$  all initialized to 0.  $n = Y.length$  values

```
new tables b[1..m, 1..n], c[0..m, 0..n]
for i=1 to m
  for j=1 to n
    with greater and
    if  $x_i = x_j$  greater values.
      c[i, j] = c[i-1, j-1] + 1
    else if  $c[i-1, j] > c[i, j-1]$ 
      c[i, j] = c[i-1, j]
    else if  $c[i, j-1] > c[i-1, j]$ 
      c[i, j] = c[i, j-1]
```

Prints LCS (b, X, x.length, Y.length) if (i==0 or j==0) return if (b[i, j] == "K") cell contains print LCS(b, x, i-1, j-1) print X; answer. Print LCS else if (b[i, j] == "K") uses "K" print LCS(b, x, i-1, j) to print else if (b[i, j] == "L") chars. print LCS(b, x, i, j-1)

**Longest Palindromic Sub.**

if input[i] == input[j]

```
T[i][j] = T[i+1][j-1] + 2
else Computes and saves
  T[i][j] = max(T[i+1][j],
  T[i][j-1]) longest
  From i to j and saves in
  T[i][j]. Final answer at
  T[0][input.length-1].
```

**Coin Changing**  $O(d \cdot A)$

Very similar to knapsack above, main difference is that for each cell we are calculating min like so:

```
T[r][c] = min(T[r-1][c], T[r][c-v_r]+1)
current column and value
answer in end row above (not taking coin) taking coin of the rth coin.
```

**Pipe Cutting**  $O(i \cdot T)$

Basically same as coin changing and knapsack. Each cell in table is calculated like so:

```
T[r][c] = max(T[r-1][c], T[r][c-l_r]+v_r)
length of pipe at row
value of pipe at row
```

**Recurrence Methods**

base case # of sub problems sub problem size work dividing and conquering recursion

```
T(n) = { O(1) if n=1
         2T(n/2) + O(n) if n>1
       }
Linear: O(n)
Quadratic: O(n^2)
Cubic: O(n^3)
Polynomial: O(n^k) k>0
Exponential: O(k^n) k>1
Factorial: O(n!)
```

**Hotel Stopping**  $\Theta(n^2)$  Two loops

$S[i] = \min$  total penalty for stop @ j

```
S[0]=0 both iterating over
for i=1 to n
  S[i]=∞ values, updating with
  for j=0 to i-1
    S[i]=min(S[i], S[j]+(200-(a_i-a_j))^2)
  return S[n]
```

**Master Method:**

Reg. condition:  $a \cdot f(\frac{n}{b}) \leq c \cdot f(n)$ ,  $c < 1$

```
• a < 1 → T(n) = O(n^d)
• " = 1 → T(n) = O(n^{d+1})
• " > 1 → T(n) = O(n^d \cdot a^{n/b})
```

**Asymptotic Properties:**

Reflexivity:  $f(n) = \Theta(f(n))$

Symmetry:  $f(n) = \Theta(g(n))$  iff  $g(n) = \Theta(f(n))$

Transpose Symmetry:  $f(n) = \Theta(g(n))$  iff  $g(n) = \Theta(f(n))$

Transitivity: IF  $f(n) = \Theta(g(n))$  and  $g(n) = \Theta(h(n)) \rightarrow f(n) = \Theta(h(n))$

**Longest Increasing Subsequence**

$O(n^2)$   $T(n) = T(n-1) + O(n)$

```
if arr[j] < arr[i]
  res[i] = max(res[i], res[j]+1)
for i=2 to n
  min ← R[1, i] stops.
  P[i] ← 1
```

Nested loops on array, always updating with max possible value.

**Car Rental**  $\Theta(n^2)$

$n = \#$  of trade posts

```
OPT[1]=0, P[1]=0 P[1] contains
for i=2 to n
  OPT[i]=min
  P[i]=k
```

Assumes that best for  $k=2$  to  $i-1$  option at each point if  $OPT[k]+R[k, i] < \min$  is to not stop. Then updates, checking and updating with nested for loop. return P[i]

**Dynamic Programming**

At each step, choice is made based on solutions of sub-problems.

- Sub-problems are solved first.
- Bottom-up approach.
- Slower and more complex.

**Greedy Algorithms**

At each step, choice is made based on what currently looks best. Locally optimal (greedy)

- Greedy choice made first.
- Top-down approach.
- Faster, simpler, may not give correct answer.

**Common Recurrences**

$2T(n-1)+1 = T(2^n)$

$T(n-1)+1 = T(n)$

$T(n-1)+n = \Theta(n^2)$

$T(\frac{n}{2})+c = \Theta(\log n)$

$T(\frac{n}{2})+n = \Theta(n)$

$2T(\frac{n}{2})+1 = \Theta(n)$

is to not stop. Then updates, checking and updating with nested for loop. return P[i]

amounts (each job takes 1 minute).

Greedy Clue: Uniform or unit-length

amounts (each job takes 1 minute).

**D.P. Properties**

Optimal sub-structure: The solution to the problem contains solutions to sub-problems.

Over-lapping: Revisits same problems repeatedly: Fibonacci, factorial, etc.

**Greedy Properties**

Optimal substructure: The same as for D.P.

Greedy choice: Making greedy choice at every step still results in optimal solution. Earlier choices never need to be reconsidered.

ready scheduling w/ priorities

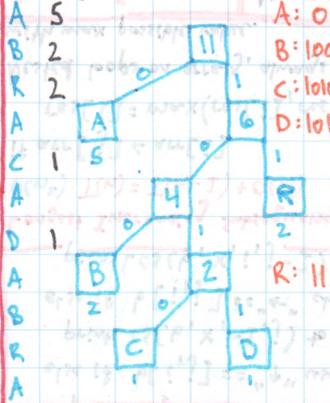
Sort by pen, increasing. Schedule as late as possible before deadline. NOT dominated by sorting

If no space available before deadline, schedule first available from end of array.

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### Huffman Coding $O(n \cdot \log n)$

- Rank letters by frequency.
- Form min heap from letters with internal nodes being sums of children.
- To encode, decode, traverse tree. Left is 0, right is 1. Stop at a letter.



### Kruskal's MST $O(E \cdot \log E)$

For each vertex  $v$  in  $G$  make empty set out of  $v$

Sort edges of  $G$  ascending for each edge  $u$  to  $v$  if  $u$  and  $v$  in different sets add  $(u, v)$  to  $T$  join  $u$  and  $v$  into set

return  $T$  Sort all edges in ascending order by weight Pick the smallest edge. If forms cycle with already chosen edges, discard. Else, include. Repeat until there are  $V-1$  edges in spanning tree

Set vertex with minimal temp distance as active. Mark its dist as permanent. Repeat until no permanent vertices have neighbors with temp distance.

### Dijkstra's Shortest Path $O(n^2)$

for each vertex  $v$  in  $G$  Start dist.  $dist[v] = \infty$  to all vert. at  $\infty$ .  $prev[v] = ?$  Dist. to start vert  $dist[src] = 0$  is permanent, others  $Q =$  all  $v$  in  $G$  are temporary. Set while  $Q$  !empty start vertex as  $u = v$  in  $Q$  w/ smallest  $dist[]$  remove  $u$  from  $Q$  active. Calc for each neighbor  $v$  of  $u$   $alt = dist[u] + dist\_btwn(u, v)$  if  $alt < dist[v]$  from active  $dist[v] = alt$  vert. to all  $prev[v] = u$  other accessible return  $prev[]$  verts. by summing  $dist$  with weight of edges. If calculated distance is smaller, update label  $v$  as visited

### BFS $O(V \cdot E)$

unmark all vertices choose start vertex  $x$ , mark list  $L = x$  Starts at vertex tree  $T = x$  and explores the while  $L$  !empty neighbor get vertex  $v$  from list front visit  $v$  nodes first, for each unmark neigh.  $w$  mark  $w$ , add to end list add edge  $vw$  to  $T$  then moves out to next level of neighbors, and so on till all visited.

### DFS $O(V \cdot E)$

DFS( $G, v$ ) for all edges from  $v \rightarrow w$  in  $G$ . adjacent Edges ( $v$ ) do: if vertex  $w$  is not visited call DFS( $G, w$ ) Starts at a root  $v$  and explores as far as possible before backtracking

### Fractional Knapsack $O(n \cdot \log n)$

Sort by density, descending current item  $i$  to total items while  $i \leq n$  and weight  $\leq W$  capacity if  $weight + W[i] \leq W$   $x[i] = 1$  percent to take else  $x[i] = (W - weight) / W[i]$  weight  $\rightarrow weight + x[i] \cdot W[i]$   $i++$  current weight of individual item Take as much of highest value item as possible, then as much of next highest, and so on. Array  $x[i]$  contains fraction to take of each item  $i$

### NP-Completeness

If  $A$  reduces to  $B$ , then  $A$  is no harder to solve than  $B$ . ( $A \leq_p B$ ). Prereqs: 1. Input for  $A$  can be converted to input for  $B$  in polynomial time. 2. A given input must have same output for both  $A$  and  $B$ .

Proving NP-Complete: 1. Prove that problem is reducible to known NP-Complete problem. 2. Prove that a given solution can be verified in polynomial time.

### Example: Prove 4-SAT is NP-Complete

1. Show that 4-SAT can be verified in polynomial time (which means that it's NP). Set 4-SAT instance and proposed truth assignments. Can be verified in polynomial time. 2. Show that a known NP-Complete problem can be reduced to 4-SAT in poly time. ( $3-SAT \leq_p 4-SAT$ )

### Linear Programming:

- Define decision variables.
- Write objective function equation (min, max)
- Write each constraint equation
- Graph and determine vertices of feasibility.

Microsoft Example:  
 $X_t$  = full time employees starting @ shift  $t$   
 $Y_t$  = part-time employees  
 Objective:  $\min_{shifts} cost_{shifts}^{full-time} (X_1 + \dots + X_6) + part-time (Y_1 + \dots + Y_2)$   
 Constraints:  $X_1 + X_6 + \frac{1}{6} Y_1 \geq 15$   
 etc. enough people on shift  
 $X_1 + X_6 \geq \frac{2}{3} (X_1 + X_6 + Y_1)$   
 etc.  $\frac{2}{3}$  must be full-time  
 $X_t \geq 0, Y_t \geq 0$  non-negativity

### Greedy Coin Change $O(n \cdot \log n)$

sort from highest value lowest for  $i=0$  to denom.length while  $V \geq denom[i]$   $V = V - denom[i]$  ans. push(denom[i])

### Greedy Scheduling $O(n \log n)$

sort  $F[]$  by earliest finish time and permute  $S[]$ , start times, to match sorts the count = 1,  $T[count] = 1$  input for  $i=2$  to  $n$  so that the if  $S[i] > F[T[count]]$  event count++ with earliest  $T[count] = i$  finish return  $T[1..count]$  time is first. Adds this event, then looks for the next event that starts after the previously-added event finishes.

### Product Sum Optimization Formula:

$OPT[j] = \begin{cases} 0 & \text{if } j=0 \\ V & \text{if } j=1, \text{ else: adding multiplying } \\ \max(OPT[j-1] + v_j, OPT[j-2] + v_j \cdot v_{j-1}) \end{cases}$

BREATHE

**Greedy Scheduling Proof:** Let  $f$  be the class that finishes first.  $X$  is a maximal, conflict-free schedule that excludes  $f$ . Let  $g$  be first to finish in  $X$ . Since  $f$  finishes before  $g$ , it cannot conflict with any event in  $X$ . We can replace  $g$  with  $f$  and still be maximal and conflict-free. The best schedule that includes  $f$  must contain optimal schedule that doesn't conflict with  $f$ . Greedy algorithm chooses  $f$ , then by inductive hypothesis, computes optimal schedule of classes from  $L$ . There can be more than one optimal!

3-SAT  $\rightarrow$  4-SAT  $\rightarrow$  Clique  $\rightarrow$  Independent Set  $\rightarrow$  Vertex Cover  $\rightarrow$  Long-Path  $\rightarrow$  Knapsack  $\rightarrow$  TSP  $\rightarrow$  Color  $\rightarrow$  Ham-cycle  $\rightarrow$  Ham-Path  $\rightarrow$  Course Time  $\rightarrow$  Decision

