Master Theorem:

```
Master theorem for "decreasing" functions

For the recurrence relation

T(N) = aT(\textbf{N-b}) + f(n)

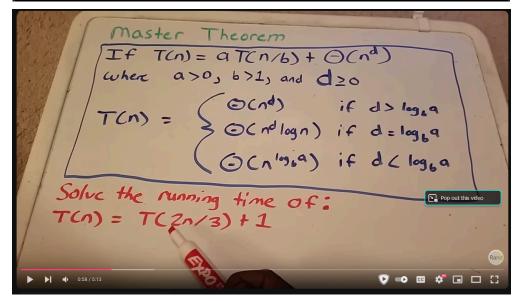
where

• a,b > 0, f(n) = O(N^k) and k > 0, and

1. If a < 1 then T(n) = O(n^k) or O(f(n))

2. If a = 1 then T(n) = O(n^{k+1}) or O(n * f(n))

3. if a > 1 then T(n) = O(n^k a^{n/b})
```



Functions to Recurrence Relation:

- T(n) = name of function such as someFunc(n)
- C1, c2, etc. = simple lines of code like print, comparison, etc.
- T(n-1), T(n/2), T(n/4) = recursive calls in code like someFunc(n-1), someFun(n/2), someFunc(n/4)
- (n+1) = for loops definition
- N = statements inside for loops since it's linear

Sorting Algorithms:

Average Time Complexities:

Insertion Sort - O(n^2)

- Merge Sort O(n log n)
- Quick Sort O(n log n)
- Heap Sort O(n log n)

Insertion Sort:

Pseudocode:

```
INSERTION-SORT (A, n)

1 for i = 1 to n

2 key = A[i]

3 // Insert A[i] into the sorted subarray A[1:i-1].

4 j = i - 1

5 while j \ge 0 and A[j] > key

6 A[j+1] = A[j]

7 j = j - 1

8 A[j+1] = key
```

Time/Space Complexity:

Time: O(n^2)
Space: O(1)

Mergesort:

```
Mergesort: The Algorithm

mergeSort (arr[], l, r)

If I < r:

mid = (I + r) / 2

mergeSort(arr, I, mid)

mergeSort(arr, mid + 1, r)

mergeSort (arr, I, mid, r)

Merge results
```

The Merge operation Now we can talk about pseudocode Merge (A, B, m, n) { i, j, k = 0 while (i <= m && j <= n) { if (A[i] < B[j]) { C[k++] = A[i++] } else {C[k++] = B[j++] } }... [continued]</pre>

Time/Space Complexity:

Time: **O(n log n)** for best, average, worst

Space: $\Theta(N)$ which is m+n elements (can be thought of as m=n=N)

Quicksort:

```
QuickSort: The Algorithm

quickSort (arr[], l, r)

if I < r:

pivot = partition(A, l, r)

quickSort(arr l, pivot_index - 1)

quickSort (arr, pivot_index + 1, r)

quickSort right half

[No need to Merge results]
```

The Partition operation

Time/Space Complexity:

Time: $\Theta(n \log n)$ - best, $\Theta(n \log n)$ - average, $\Theta(n^2)$ - worst Space: $\Theta(n)$ - worst

Things to know:

Quicksort is UNSTABLE

Heap sort:

Time/Space Complexity:

Time: $\Theta(n \log n) \rightarrow \Theta(n)$ for buildHeap, $\Theta(\log n)$ for delete Space: $\Theta(1) \rightarrow$ in-place algorithm

Things to know:

- It's an in-place algorithm (doesn't need extra space like mergesort)
- It's UNSTABLE (equivalent elements may be swapped)
- Slower than quicksort in practice

Counting Sort:

Time/Space Complexity:

Time: $\Theta(n + k)$ Space: $\Theta(n + k)$

Radix Sort:

Time/Space Complexity:

Time: **Θ**(**n*****d**) Space: **Θ**(**n** + **k**)

Bucket Sort:

Time/Space Complexity:

Time: $\Theta(n^2)$ Space: $\Theta(n + k)$

Hashmaps:

Hash Collisions:

- Linear probing
 - o Traverse linearly, put element in next empty space
 - Let's say C also hashes to index 2
 - It will put element into next empty space
- Quadratic Probing
 - Quadratic Probing is similar, but we increment faster if we keep running into collisions.
 - If the slot hash(x) is full, then we try hash(x) + 1*1
 - If hash(x) + 1*1 is also full, then we try hash(x) + 2*2
 - o If hash(x) + 2*2 is also full, then we try hash(x) + 3*3
 - o Rinse and repeat until you find an empty spot
- Separate Chaining
 - Uses additional data structures to allow for multiple values at the same index. E.g. linked lists
- Double Hashing
 - Uses a second hash function to reduce the chance of a collision happening

Time/Space Complexity:

Time: **O(1)** for inserting, deleting, and referencing

Space: $\Theta(N)$

Trees:

Binary Search Trees:

Time/Space Complexity:

Operation	Best	Average	Worst
Search	Θ(1)	Θ(log n)	Θ(n)
Insert	Θ(1)	Θ(log n)	Θ(n)
Delete	Θ(1)	Θ(log n)	Θ(n)

Worst case happen in skewed BSTs

Red-Black Trees:

Properties:

- Every node is either red or black
- Root is black
- NIL nodes are black
- Red node doesn't have red child
- Every path from given node to any of its descendant NIL nodes goes through same number of black nodes

Applications:

- Completely fair scheduler process scheduler for linux kernel
- Handling hash collisions in Java (separate chaining)
- Speeding up other algorithms

Time/Space Complexity:

Time: $\Theta(\log n)$ worst case for all operations

Graph Algorithms:

Graph Representation:

Adjacency Matrices:

- Use more memory Θ(n^2)
- Fast lookup and checks for presence of edges O(1)
- Slow to iterate over all edges
- Slow to add/delete a node O(n^2)
- Fast to add a new edge O(1)

Adjacency List:

- Memory usage depends more on number of edges, not nodes
- Helps when graph is sparse
- Slow lookup and checks for presence of edges O(k) (k = num of neighbor nodes)
- Faster to iterate all over edges
- Also fast to add/delete a node
- Fast to add new edge O(1)

When to use what:

- Use adjacency lists when expecting a sparse graph, or when you need fast lookup for neighbors of a vertex. Most real life situations will generate sparse graphs
- Use adjacency matrices when expecting a dense graph, or when you need fast lookup for edges
- Rule of thumb: If density (edges/nodes^2) goes over 1/64 (for 32-bit computers), use adjacency matrix

BFS/DFS:

Data structures:

- BFS uses queue
- DFS uses stack

Pseudocode (BFS):

- Create queue
- Mark vertex as visited and put into queue
- While queue is not empty
 - o Remove u (front) of queue
 - Mark and enqueue neighbors of u

Pseudocode (DFS):

- Create stack
- Push vertex v into stack
- Mark vertex v as visited
- While stack is not empty
 - Pop vertex v stack
 - o For all neighbors of v
 - If neighbor u is not visited
 - Mark u as visited
 - Push u into stack

Time/Space Complexity:

Time: O(V+E) for best, average, worst case for both

Space: O(V) for both

Topological Sort (Khan's Algorithm):

Pseudocode:

- Add all nodes with in-degree 0 to queue
- While queue is not empty:
 - Remove node from queue
 - For each outgoing edge from node, decrement in-degree of the destination node by 1
 - If the in-degree of a destination node becomes 0, add it to the queue

Other things to know:

- Only works on DAG
- Topological sort can be implemented using DFS and BFS
- Intuition for both:
 - Traverse graph to find two types of nodes:
 - Nodes with no outgoing edges go last

Nodes with no incoming edges go first

Time/Space Complexity:

Time: O(V+E)

Space: O(V) for queue/stack

MST Algorithms:

Prim's Algorithm:

How to run:

- Add starting vertex v to visited list
- Examine all neighbors of v
- Pick cheapest cost that connects to an unvisited node
- Add that node to visited list
- From visited node(s), repeat step 3-5

Pseudocode:

- Pick starting vertex
- Create queue
- Create visited boolean array
- While queue is not empty
 - Explore neighboring vertices
 - Pick cheapest cost and mark as visited
 - Repeat as long as it doesn't create a cycle

Time/Space Complexity:

Time: O(V^2) for adj. matrix, O(V log V + E log V) for adj. list

Kruskal's Algorithm:

How to run:

- Pick smallest edge
- Repeatedly look for smallest edge that doesn't create a cycle

- Create empty set to store mst
- Create priority queue and add starting vertex with key 0
- While PQ is not empty:
 - Extract vertex u with minimum key from PQ.
 - o Add u to set.
 - For each neighbor v of u:
 - If v is not in S and weight(u, v) < key(v):
 - Update key(v) with weight(u, v).
 - Update parent(v) with u.
- Return set.

Time/Space Complexity:

Time: O(E log E)

Other notes:

Data Structures:

- Prim's uses lists and heaps
- Kruskal's uses disjoint sets
 - A list of disjoint sets
 - Uses union-find

Applications:

- Constructing trees for broadcasting in computer networks
 - o On ethernet networks: spanning tree protocol
- Curvilinear feature extraction in computer vision
- Cluster analysis:
 - Clustering points in the plane (K means)
 - Graph-theoretic clustering (social networks)
 - o Clustering gene expression data

Shortest Path Algorithms:

Intuition:

- 3 algorithms to find shortest path and what they work on
 - BFS designed for unweighted graphs, can be modified (use heap instead of queue)
 - DFS may take longer to complete in case of cycles
 - o Topological Sort only works on DAGs

Dijkstra's Algorithm:

Pseudocode:

- For each vertex in graph
 - Set distance to infinity
 - Set previous to undefined
- Set distance of starting vertex to 0
- While queue is not empty
 - o Remove vertex u with smallest distance
 - o For each neighbor v of u
 - Relax edges

Time/Space Complexity:

Time: $\Theta(V^2)$ for array implementation (Improves to $\Theta(E + V \log V)$ if we use fibonacci heap which is fastest sssp algorithm known today)

Space: **O(V)** in both cases

Other things to know:

- Doing updates is unnecessary work. We can make more intelligent choices by comparing edges in terms of (edge weight + shortest distance to get to that edge) instead of just edge weight.
- Dijkstra's will fail if there is a negative weight! Fix for this is actually a simple modification!

Bellman-Ford:

Pseudocode:

```
BELLMAN-FORD(G, w, s)

1 INITIALIZE-SINGLE-SOURCE(G, s)

2 for i = 1 to |G, V| - 1
```

3 **for** each edge $(u, v) \in G.E$

4 Relax(u, v, w)

5 for each edge $(u, v) \in G.E$

6 **if** v.d > u.d + w(u,v)

7 return FALSE

8 return TRUE

- Initialize graph like dijkstra
- For i = 1 to v-1
 - Relax edges
- Check for negative cycles

Time/Space Complexity:

Time: **O(E)** - Best, **O(V*E)** - average, worst Space: **O(V)**

What it is:

- Essentially Dijkstra's algorithm but is fixed for negative weights
- Basic idea is that the longest path in a graph is V-1 length
- If you are looking at a path length of V or more, during iteration, some cycle is present in your graph
- All we need to do is systematically look through our graph V-q times and update the shortest path that many times.

A*:

What it is:

- The general case of Dijkstra's algorithm
- Basic idea is instead of just looking at edge weights, we add a heuristic function value to each edge weight
- Algorithm is essentially:
 - Calculate/approximate the heuristic

Do Dijkstra's with heuristics applied to weights

Heuristic:

- Heuristic is like hash functions, it could be anything
- Examples:
 - Euclidean distance
 - Manhattan distance
 - Arbitrary coin flip
 - Traffic on a road
- They are expensive to compute/store for large graphs, so we approximate for A*
- Quality of heuristic defines how quickly you descend on the right results

Applications:

- Dijkstra and A* is what Google Maps uses
- They are used in:
 - All of graph-based ML
 - Quant trading
 - Social network analysis
 - o Pathfinding in video games
 - City planning
 - And many more!

Floyd-Warshall Algorithm:

```
Floyd-Warshall Algorithm Pseudocode

dist is a |V| × |V| array of minimum distances initialized to ∞ or nil

1. for each edge (u, v) do
2. dist[u][v] ← w(u, v) // The weight of the edge (u, v)
3. for each vertex v do
4. dist[v][v] ← 0
5. for k from 1 to |V|
6. for i from 1 to |V|
7. for j from 1 to |V|
8. if dist[i][j] > dist[i][k] + dist[k][j]
9. dist[i][j] ← dist[i][k] + dist[k][j]
```

- N = num of vertices
- A = matrix
- For k = 1 to n
 - \circ For i = 1 to n
 - For j = 1 to n
 - Distance[i][j] = min(distance[i][j], distance[i][k] + distance[k][j]

Time/Space Complexity:

Time: **Θ(n^3)** Space: **Ο(V^2)**

Other notes:

- Algorithm is best suited for dense graphs
- Exhaustive search

Johnson's Algorithm:

What it is:

- Makes use of Dijkstra's and Bellman-Ford
 - Run Bellman-Ford on graph and do a transformation to remove negative edges
 - Run Dijkstra's for every vertex on the resultant graph
- Faster than Floyd-Warshall for sparse graphs

Dynamic Programming:

Intuition:

- Fibonacci normally implemented using recursion time complexity is
 O(2ⁿ) and space complexity is O(1)
- We can improve time complexity by using space to store previously known results which is a tradeoff (but is worth it)
- Now it would be O(n) time and O(n) space complexity
- Not an algorithm, but a paradigm (way of thinking)
- Basic idea is that the problem can be divided into subproblems but unlike divide and conquer, the problems overlap
- Overlapping subproblems is the first property that hints that we can use dynamic programming to solve a particular problem.
- When in doubt, always think about whether we are repeating unnecessary work, to determine whether we can use DP for a problem.

Memoization:

- Memoization makes subsequent runs of the function/algorithm much, much faster.
 - If we know fibo(4), then fibo(4) or fibo(3) becomes an O(1) lookup since we already computed it in a previous run
- Another cool thing about memoization is that it's guaranteed to use just enough memory to get to the required result
 - We didn't calculate fibo(6) because we didn't need to, for fibo(4)

Tabulation:

- More work to do since we may end up doing more work than needed to arrive at the optimal solution
- But the hope is that if we solve each subproblem optimally, we arrive at an optimal solution
- Optimal substructure is actually the 2nd property we need to do problems in DP (also helps with greedy algorithms)
- Ideally, we should always use memoization but sometimes tabulation can't be avoided.

P and NP:

Every problem (sorting, searching, tree traversal, topological sort, MST, etc.) we've looked at so far has been solvable algorithmically, in polynomial time. This is formally called **P** or **P-class** problems/algorithms

Sudoku 3x3 is easy to bruteforce/solve, 9x9 takes longer, and so on. Verifying the correctness of these is always fast. These problems are called NP (nondeterministic-polynomial)

If P = NP, then every problem can pretty much be solved

If P!= NP, then we will know for sure that some problems are hard to solve

"Algorithmica" - P = NP, every problem has a nice algorithm

"Heuristica" - P != NP, but most hard problems are tractable

"Cryptomania" - P != NP, most problems are too hard