S.No.			
1	Algorithm	Program	
	Design time	Implementation time	
	Domain knowledge	Programmer	
	Any language even English and Maths	Programming language	
	Hardware and software independent	Hardware and operating system dependent	
	Analyze an algorithm	Testing of programs	
2	Priori Analysis	Posterior Testing	
	Algorithm	Program	
	Independent of language	Language dependent	
	Hardware independent	Hardware dependent	
	Time and space function	watch time and bytes	
3	Characteristics of algorithm		
	Zero or more inputs		
	Must generate atleast one output		
	Definiteness		
	Finiteness		
	Effectiveness		
4	How to analyze an algorithm		
	Time		
	Space		
	Network consumtion : Data transfer amount		
	Power consumption		
	CPU registers		
5	Frequency Count Method	Used for time snalysis of an algorithm	
	Assign 1 unit of time for each statement	, ,	
	For any repitition, calculate the frequency of repetition		

for(i = 0; i < n; i++)> condition is checked for n+1 times	2n + 2 units of time ~ n+1 as we see condition i < n only for now	
any statement within the loop will execute for n times		
Space complexity depends upon number and kind of variables used		
3 Algorithm : sum(A, n)		
Single for loop -		
Time complexity: O(N)		
Space complexity: O(N)		
Algorithm : Add(A, B, n)	Sum of two square matrices of dimesions nXn	
Two nested for loops -		
Time complexity: O(N^2)		
Outer for loop executes for N+1 times		
Inner for loop xecutes for N *(N+1) times		
Any statement within inner for loop executes for $(N + 1) * (N + 1)$ times		
Space complexity: O(N^2)		
Algorithm : Multiply(A, B, n)		
Time complexity: O(N^3)		
Space complexity: O(N^2)		
Different algorithm conditions		
-		
·	n+1 times	
·		
	any statement within the loop will execute for n times Space complexity depends upon number and kind of variables used Algorithm: sum(A, n) Single for loop - Time complexity: O(N) Space complexity: O(N) Algorithm: Add(A, B, n) Two nested for loops - Time complexity: O(N^2) Outer for loop executes for N+1 times Inner for loop xecutes for N *(N+1) times Any statement within inner for loop executes for (N + 1) * (N + 1) times Space complexity: O(N^2) Algorithm: Multiply(A, B, n) Three nested for loops - Time complexity: O(N^3)	any statement within the loop will execute for n times Space complexity depends upon number and kind of variables used Algorithm: sum(A, n) Single for loop - Time complexity: O(N) Space complexity: O(N) Two nested for loops - Time complexity: O(N^2) Outer for loop executes for N*(N+1) times Inner for loop executes for N*(N+1) times Any statement within inner for loop executes for (N + 1) * (N + 1) times Space complexity: O(N^2) Algorithm: Multiply(A, B, n) Three nested for loops - Time complexity: O(N^2) Space complexity: O(N^2) Different algorithm conditions For loops for (i = n; i > 0; i) Inter complexity: O(N-2) Inter complexity: O(N-2)

2 nested for loops where both i and j range from 0 to n	n^2 times	
2 nested for loops where j ranges from 0 to i	when i = 0; j loop repeats 0 times; when i = 1; j loop repeates 1 times; and so ontotal number of repetitions: $0 + 1 + 2 + 3 + 4 + n = O(n^2)$	
$p = 0$; for(i = 1; p<= n; i++){ p = p + i; }	p = $k(k+1)/2$ > assuming that the loop exits when p is greater than n> $k(k+1)/2$ > n	~ k^2 > n> O(root(n))
for(i = 1; i < n; i = i *2)	will execute for 2 ^k times	O(logn)
	Assume $i \ge n$; $i = 2^k \ge n$	
	k = logn with base 2	
for($i = n$; $i \ge 1$; $i = i/2$)	i	
	n	
	n/2	
	n/2^2	
	n/2^3	
	n/2^k	
	Assume i < 1 => n / 2^k < 1	~ O(logn) with base 2
for($i = 0$; $i * i < n$; $i++$)	i*i < n	
	i*i > -n	
	i^2 = n> i = root(n)	~O(root(n))
for(i = 0; i < n; i++) {}for(j = 0; j < n; j++){}	O(n)	
$p = 0$; for(i = 1; i < n; i*2){} for(j = 1; j < p; j*2){}	log n times for upper loop; lop p times for lower loop	~ O(log(logn))
for(i = 0; i < n; i++) {for(j = 0; j < n; j*2){}}	Outer loop repeats n times; inner loop repeats logn times	~O(nlogn)
for(i = 1; i < n; i = i*3)		~O(logn) with base 3
While loops		
while vs. do while	do while will execute for minimum one time	
for and while are almost similar	do while will execute as long as the condition is true; for loop will execute until the condition is false	

	a = 1;		
	while(a < b){ a = a *2;}	1, 2, 2^2, 2^32^k repetitions	~O(logb) with base 2
		assume a > b; 2 ^k > b ==> k = logb with base 2	
	i = n; while(i > 1) {i = i/2;}		~O(logn) with base 2
	$i = 1$; $k = 1$; while($k < n$){ $k = k + i$; $i++$;}		
		i k	
		1	1
		2 1 + 1	
		3 2 + 2	
		4 2 + 2 + 3	
		5 2 + 2 + 3 + 4	
	m	m(m + 1) /2	
	Assume, k >= n	m(m + 1)/ 2 >= n	~O(root(n))
	while(m != n) { if(m > n) m = m - n; else n = n - m;}		~O(n)
10	Types of time functions		
	O(1) constant		
	O(logn) logarithmic		
	O(n) linear		
	O(n^2) quadratic		
	O(n^3) cubic		
	O(2 ⁿ) exponential		
11	Order of complexity		
	1 < logn < root(n) < n < nlogn < n^2 < n^3 << 2^n < 3^n< n^n		

12	Asymptotic Notations		
	Representation of time omplexity in simple form which is understandable		
	Big O Notation - works as an upper bound	The function $f(n) = O(g(n))$ iff for all positive constants c and n_0, such that $f(n) <= c * g$ (n) for all n >= n_0; here, $f(n) = O(n)$	e.g. 2n + 3 <= 10n; All those functions in time order complexity above n become upper bound; below n become lower bound and n is the average bound
	Big Omega Notation - works as a lower bound	The function $f(n) = Omega(g(n))$ iff for all positive constants c and n_0, such that $f(n) >= c * g(n)$ for all $n >= n_0$; here, $f(n) = Omega(n)$	e.g. 2n + 3 >= 1n
	Theta Notation - works as an average bound	The function $f(n) = theta(g(n))$ iff for all positive constants c1, c2 and n0 such that c1 * $g(n) <= f(n) <= c2 * g(n)$	e.g. f(n) 2n + 3; 1n <= 2n + 3 <= 5n
	Most useful is theta notation, then why do we need the other two?	In case we are not able to get the average bound, then we point to its upper or lower bound	
13	Examples for asymptotic notations		
а	$f(n) = 2n^2 + 3n + 4$		
	2n^2 + 3n + 4 <= 2n^2 + 3n^2 + 4n^2 i.e. 9n^2	O(n^2)	
	2n^2 + 3n + 4 >= 1n^2	Omega(n^2)	
	1n^2 <= 2n^2 + 3n + 4 <= 9n^2	Theta(n^2)	
b	$f(n) = n^2 log n + n$		
	$n^2\log n \le n^2\log n + n \le 10n^2\log n$	O(n^2logn)	
		Omega(n^2logn)	
		Theta(n^2logn)	
С	f(n) = n!		
	1 <= 1*2*3*4*n-1*n <= n*n*n*n**n	O(n^n)	
		Omega(1)	
		Cannot find theta for n!	

	f(n) = logn!		
	1 <= log(1*2*3*n) <= log(n*n*n*n*n)	O(logn^n)	
		Omega(1)	
		Cannot find theta for logn!	
14	Properties of Asymptotic notations		
	General properties -		
	if f(n) is O(g(n)) then a*f(n) is O(g(n))		
	e.g. $f(n) = 2n^2 + 5$ is $O(n^2)$, then $7f(n)$ i.e. $14n^2 + 35$ is also $O(n^2)$	This would be true for both Omega and theta n as well	
	Reflexive property -		
	If f(n) is given then f(n) is O(f(n))		
	e.g. $f(n) = n^2$ then $O(n^2)$	A function is an upper bound of itself	
		Similarly, a function is a lower bound of itself	
	Transitive property -		
	If f(n) isO(g(n)) and g(n) is O(h(n)) then f(n) is O(h(n))		
	e.g. $f(n) = n$; $g(n) = n^2$ and $h(n) = n^3$	True for all notations	
	n is O(n^2) and n^2 is O(n^3) then n is O(n^3)		
	Symmetric property -		
	If f(n) is theta(g(n)) then g(n) is theta(f(n))	True for only theta(n)	
	e.g. $f(n) = n^2 g(n) = n^2$; $f(n) = theta(n^2)$ and $g(n) = theta(n^2)$		
	Transpose symmetric -	True for BigO and Omega notations	
	if $f(n) = O(g(n))$ then $g(n)$ is $Omega(f(n))$		
	e.g. $f(n) = n$ and $g(n)$ is n^2 then n is $O(n^2)$ and n^2 is $O(n^2)$		

	If $f(n) = O(g(n))$ and $f(n) = Omega(g(n))$ then $g(n) \le f(n) \le g$ (n) therefore $f(n) = theta(g(n))$	
	If $f(n) = O(g(n))$ and $d(n) = O(e(n))$ then $f(n) + d(n) = O(max(g(n), e(n)))$	
	e.g. $f(n) = n = O(n)$, $d(n) = n^2 = O(n^2)$ then $f(n) + d(n) = n + n^2 = O(n^2)$	
	If $f(n) = O(g(n))$ and $d(n) = O(e(n))$ then $f(n) * d(n) = O(g(n) * e(n))$	
15	Comparison of functions	
	First method is substituting values for n and comparing	
	Second method is applying log on both sides	
		Properties of log -
	Example -	logab = loga + logb
	$f(n) n^2logn; g(n) = n(logn)^10$	loga/b = loga - logb
	Apply log	loga^b = bloga
	log(n^2log(n)); log(n(logn)^10)	a^(log_cb) = b^(log_ca)
	log(n^2) + loglogn; logn + loglog^10	a^b = n then b = log_an
	2logn + loglogn ; logn + 10loglogn	
	here; 2logn is greater than logn and logn is a bigger term than loglogn	
	so, first term is greater than the second one	
	$f(n) = 3n^{(rootn)}$; $g(n) = 2^{(rootn log_2(n))}$	
	Applying log	
	3n(rootn); (n^rootn)log_2(2)	
	3n(rootn); nrootn	
	first term is greater than the second one value wise but asymptatically they are equal	

	$f(n) = n^{(\log n)}; g(n) = 2^{(rootn)}$		
	apply log,		
	log(n^logn); log(2^rootn)		
	logn*logn ; rootn (log_2(2))		
	log^2n; rootn		
	canot judge, so apply log again		
	2loglogn; 1/2logn		
	loglogn is smaller than logn		
	thus, second term is greater		
	and, coom is ground		
	$f(n) = 2^{(\log n)}; g(n) = n^{(rootn)}$		
	logn*log_2(2); rootn*logn		
	logn; rootn*logn		
	second term is greater		
	f(n) = 2n; g(n) is 3n		
	both are equal asymptotically		
	$f(n) = 2^n; g(n) = 2^(2n)$		
	applying log		
	log(2^n); log(2^2n)		
	n; 2n	after applying log, do not cut coefficients	
	second function is greater		
16	Best, worst and average case analysis		
	Example -		
а	Linear search		
	A = {8, 6, 12, 5, 9, 7, 4, 3, 16, 18} key = 7		
	In linear search, it will start checking for the given key from left hand side		

	total in 6 comparisons, we would get our key	
	Best case - key element is present at first index	
	Best case time - 1 i.e. B(n) = O(1); Omega(1); Theta(1)	
	Worst case - key element is present at the last index	
	Worst case time - n i.e. W(n) = O(n); Omega(n); Theta(n)	
	Average case = all possible case time / no. of cases	
	average case analysis is very difficult for most of the cases	
	Here, average case time = $1 + 2 + 3 + n/2 = n(n+1)/2n = n+1/2$	
	A(n) = n+1/2	
b	Binary search tree	
	height = logn	
	time taken for a particular key is logn	
	Best case - element present in the root	
	Best case time - k i.e. B(n) = O(1); Omega(!); Theta(1)	
	Worst case - searching for a leaf element - depends upon the height of the tree	
	Worst case time - logn i.e. O(logn)	
	min w(n) = logn; max w(n) = n	
17	Disjoint sets	
	No common numbers between two sets - intersection is zero	
	Operations - find, union	
	Find - search or check membership	
	Union - Add an edge	
	Krisgal algorithm: If you take an edge and both the vertices belong to the same set, then there is a cycle in the graph	
	Weighted union is used while adding edges and detectig cycle	

	Collapsing find - process of directly linking node to a direct parent of a set is called collapsing find - reduces the time to find	
18	Divide and conquer - Strategy 1	
10	Strategy - an apprach for solving a problem	
	If a problem cannot be solved, divide it into sub-problems and find a solution for each sub problem, combine the solutions. One point to note is that each sub problem should be similar to the original problem only.	
	Recursive in nature	
	Should have one method to combine the solutions of each sub problem	
19	Problems under Divide and Conquer	
	Binary search	
	Finding maximum and minimum	
	MergeSort	
	QuickSort	
	Strassen's matrix multiplication	
20	Recurrence relation 1: T(n) = T(n-1) + 1	
	void test(int n)	
	[
	if(n > 0){	
	printf("%d",n);	
	test(n-1)	
	}	
	}	
	test(3)	
	3. test(2)	

	2. test(1)		
	1 test(0)		
	each print statement takes constant time 1 and there are n+ 1 calls made to the function. we can ignore the last call when it is not printing		
	f(n) = n + 1 calls ; O(n)		
	T(n) = T(n-1) + 1; if we ignore if condition		
	Let us solve this relation;		
	if we know T(n-1), we can get T(n)		
	T(n-1) = T(n-2) + 1		
	T(n) = [T(n-2) + 1] + 1		
	T(n) = T(n-3) + 3		
	continue for k times		
	T(n) = T(n-k) + k		
	We would stop after k substitutions; now we need to find k		
	Assume n - k = 0; therefore n = k		
	T(n) = T(n-n) + n		
	T(n) = T(0) + n		
	T(n) = n + 1 i.e. theta(n)		
21	Recurrence relation 2: T(n) = T(n-1) + n (decreasing function)		
	void test(int n)	T(n)	
	{		
	if(n > 0)	1	
	{		
	for(i = 0; i <n; i++)<="" td=""><td>n+1</td><td></td></n;>	n+1	
	{		
	printf("%d", n);	n	
	}		
	test(n-1);	T(n-1)	

	}		
	}	T() T(t) 10 10 11 11 11	
		T(n) = T(n-1) + 2n + 2 i.e. theta(n)	
	we can also write $T(n) = T(n-1) + n$ for $n > 0$		
	T(n) = 1 for n = 0		
	T(n)	n time	
	n T(n-1)	n-1 time	
	n-1. T(n-2)	n - 2 time	
	n-2 T(n-3)	n - 3 time	
	T(2)		
	2 T(1)	2 units of ti me	
	1 T(0)	1 unit of time	
	for T(0) it does nothing	0 unit of time	
	time taken -		
		0 + 1 + 2 ++ n-1 + n	
	theta(n^2)	T(n) = n(n+1)/2	
	T(n) = T(n-1) + n		
	T(n-1) = T(n-2) + n-1		
	thus, $T(n) = T(n-2) + (n-1) + n$	**remember, don't add the terms	
	T(n) = T(n-3) + (n-2) + (n-1) + n		
	T(n) = T(n-k) + (n-(k-1)) + (n-(k-2))+(n-1) + n	if we continue for k times	
	assume n - k = 0; n = k		
	Thus, $T(n) = T(n-n) + (n-n+1) + (n-n+2) + (n-1) + n$		
	T(n) = T(0) + n(n+1)/2		
	T(n) = 1 + n(n+1)/2	theta(n^2); this extra 1 is owing to the calls	
22	Recurrence relation 3: T(n) = T(n-1) + logn		
	void test(int n)	T(n)	

,		
{		
if(n>0)		
{		
for(i = 1; i <n; i="i*2)</td"><td></td><td></td></n;>		
{		
printf("%d", i);	log n times	
}		
test(n-1);	T(n-1)	
}		
}		
T(n) = T(n-1) + logn for n > 0		
T(n) = 1 for n = 0		
Solve using tree method,		
T(n)		
logn T(n-1)		
log(n-1) T(n-2)		
log(n-2) T(n-3)		
log2 T(!)		
log 1 T(0)		
logn + log(n-1) ++ log2 + log1		
log[n(n-1)(n-2)2.1] = log(n!)	there is no tight bound for this function but there is an upper bound for it	
O(nlogn)		
Solving using induction method.		
T(n) = T(n-1) + logn		
T(n) = T(n-2) + log(n-1) + log(n)		
T(n) = T(n-3) + log(n-2) + log(n-1) + logn		

	T(n) = T(n-k) + logn + log(n-1) +log1		
	Asume n-k = 0		
	T(n) = T(0) + logn!		
	T(n) = 1 + logn!		
	O(nlogn)		
23	How to get the direct answer for a recurrence relation?		
	T(n) = T(n-1) + 1	O(n)	
	T(n) = T(n-1) + n	O(n^2)	
	T(n) = T(n-1) + logn	O(nlogn)	
	$T(n) = T(n-1) + n^2$	O(n^3)	
	T(n) = T(n-2) + 1	O(n/2) ~ O(n)	
	T(n) = T(n-100) + n	O(n^2)	
	T(n) = 2T(n-1) + 1	???	
24	Recurrence relation 4: T(n) = 2T(n-1) + 1		
	Test(int n)	T(n)	
	{		
	if(n > 0)	1	
	{		
	printf("%d", n);	1	
	test(n-1);	T(n-1)	
	test(n-1);	T(n-1)	
	}		
	}		
		T(n) = 2T(n-1) + 1	
	T(n) = 2T(n-1) + 1 for $n > 0$		
	T(n) = 1 for n = 0		

	Solve using recursion tree method		
	1 T(n-1) T(n-1)		
	1 T(n-2) T(n-2)	1 T(n-2) T(n-2)	
	1 T(n-3) T(n-3) 1 T(n-3)	1 T(n-3) T(n-3) 1 T(n-3) T(n-3)	
	T(0). T(0)		2^k
	1 + 2 + 2 ² +2 ^k = 2 ^(k+1) - 1		
	as, $a + ar + ar^2ar^k = a(r^(k+1) - 1)/(r - 1)$		
	Assume n - k = 0		
	thus, 2^(n+1) - 1	O(2^n)	
	Back substitution method		
	T(n) = 2T(n-1) + 1		
	T(n) = 4T(n-2) + 2 + 1		
	T(n) = 8T(n-3) + 4 + 2 + 1		
	$T(n) = 2^kT(n - k) + 2^k(k-1) + 2^k(k)2^3 + 2^2 + 1$		
	Assume n - k = 0		
	n = k		
	$T(n) = 2^nT(0) + 1 + 2 + 2^n + 2^n - 1$		
	$T(n) = 2^n + 2^n - 1$ i.e. $2^n + 1 - 1$		
25	Master theorem for decreasing function		
	T(n) = T(n-1) + 1	O(n)	
	T(n) = T(n-1) + n	O(n^2)	
	T(n) = T(n-1) + logn	O(nlogn)	
	T(n) = 2T(n-1) + 1	O(2^n)	
	T(n) = 3T(n-1) + 1	O(3 ⁿ)	

	T(n) = 2T(n-1) + n	O(n2^n)	
	T(n) = 2T(n-2) + 1	O(2^n/2)	
	T(n) = aT(n-b) + f(n)		
	$a > 0$, $b > 0$ and $f(n) = O(n^k)$ where $k >= 0$		
	if $a = 1$, $O(n^k+1)$ or $O(n^*f(n))$		
	if a > 1, O(n^k * a^n/b)		
	$if(a < 1) O(n^k) or O(f(n))$		
26	Dividing functions		
	test(int n)	T(n)	
	{		
	if(n > 1)		
	{		
	printf("%d", n);	1	
	test(n/2)	T(n/2)	
	}		
	}		
	T(n) = T(n/2) + 1 for $n > 1$		
	T(n) = 1 for $n = 1$		
	T(n)		
	1 T(n/2)		
	1 T(n/2^2)		
	1 T(n/2^3)		
	continue for k times		
	1 T(n/2^k)		

	assume , n/2^k = 1	
	thus, we have taken k steps overall	
	since, $n/2^k = 1 \Rightarrow k = \log n$ with base 2	O(logn)
	Solving by substitution method	
	T(n) = T(n/2) + 1	
	$T(n) = T(n/2^2) + 2$	
	$T(n) = T(n/2^3) + 3$	
	$T(n) = T(n/2^k) + k$	
	assume n/2^k = 1	
	thus, k = logn with base 2	
	$T(n) = T(1) + \log n$	
	O(logn)	
27	Recurrence relation: $T(n) = T(n/2) + n$	
	T(n) = T(n/2) + n for n > 1	
	T(n) = 1 for n=1	
	T(n)	
	T(n/2) n	
	T(n/2^2) n/2	
	T(n/2^3) n/2^2	
	T(n/2^k). n/2^(k-1)	
	$T(n) = n + n/2 + n/2^2 + n/2^3 + n/2^k$	
	$T(n) = n[1 + 1/2 + 1/2^2 + 1/2^3 + \dots 1/2^k]$	
	T(n) = n*1 = n	
	O(n)	

	Using substitution method	
	T(n) = T(n/2) + n	
	$T(n) = T(n/2^2) + n/2 + n$	
	$T(n) = T(n/2^3) + n/2^2 + n/2 + n$	
	$T(n) = T(n/2^k) + n/2^k-1+n/2^2 + n/2 + n$	
	Assume n /2^k = 1	
	k = logn with base 2	
	$T(n) = T(1) + n[1/2^k-1+1/2^2+1]$	
	$T(n) = 1 + 2n \sim O(n)$	
20	Recurrence Relation: T(n) = 2T(n/2) + n	
20	void test(int n)	T(n)
	{ if(n > 1)	
	{	
	for(int i = 0; i <n ;="" i++)<="" td=""><td></td></n>	
	{	
	stmt	n
	}	
	test(n/2);	T(n/2)
	test(n/2);	T(n/2)
	T(n) = 2T(n/2) + n for n > 1	
	T(n) = 1 for $n = 1$	
	Salva vaina vaavvaian tvaa mathad	
	Solve using recursion tree method,	

	T(n)		
	T(n/2). T(n/2) n	n	
	T(n/2^2) T(n/2^2) T(n/2^2) T(n/2^2) n/2	n	
	T(n/2^3). T(n/2^3). T(n/2^3). T(n/2^3). T(n/2^3). T(n/2^3). T(n/2^3).	n	
		n	
	T(n/2^k)		
		n	
	assume n / 2 ^k = 1		
	k = logn with base 2		
	$T(n) = nk \sim O(n\log n)$		
	Using backsubstitution method;		
	T(n) = 2T(n/2) + n		
	$T(n/2) = 2T(n/2^2) + n/2$		
	$T(n) = 2[2T(n/2^2) + n/2] + n$		
	$T(n) = 2^2T(n/2^2) + n + n$		
	$T(n) = 2^3T(n/2^3) + 3n$		
	continue for k times		
	$T(n) = 2^k T(n/2^k) + kn$		
	Asume $T(n/2^k) = T(1)$		
	k = logn with base 2		
	Thus, $T(n) = n + n \log n \sim O(n \log n)$		
29	Masters Theorem for dividing functions		
	T(n) = aT(n/b) + f(n)	loga with b	
	$a = 1$; $b > 1$; $f(n) = theta(n^k \log^p n)$	k	
	case 1: if loga with base b > k then theta(n^(loga with base b))		
	case 2: if loga with base b = k then		

if $p > -1$ theta($n^{klog^{(p+1)n}}$)	
if p = -1 theta(n^kloglogn))	
if p < -1 then theta(n^k)	
case 3: if loga with base b < k	
then, if $p \ge 0$, theta($n^k \log^p p$)	
if $p < 0$, theta(n^k)	
T(n) = 2T(n/2) + 1	
a = 2	
b = 2	
$f(n) = theta(n^{(0)} * log n^{0})$	
k = 0; p = 0	
here, loga with base b > k	
theta(n^1) where loga with base b is 1	
T(n) = 4T(n/2) + n	
log a with base b = 2	
k = 1	
p = 0	
this is an example of case 1	
theta(n^2)	
T(n) = 8T(n/2) + n	
log8 with base 2 = 3 > k = 1	
theta(n^3)	
T(n) = 9T(n/3) + 1	
loga with base b = 2 > k	
theta(n^2)	

$T(n) = 9T(n/3) + n^2$		
loga with base b = 2 = k	case 2	
theta(n^2)		
T(n) = 8T(n/2) + n		
theta(n^3)		
T(n) = 2T(n/2) + n		
loga with base $b = k = 1$; $p = 0$		
case 2		
theta(nlogn)		
$T(n) = 4T(n/2) + n^2$		
theta(n^2logn)		
$T(n) = 4T(n/2) + n^2 log n$		
theta(n^2logn^2)		
$T(n) = 8T(n/2) + n^3$		
theta(n^3logn)		
T(n) = 2T(n/2) + n/logn		
log a with base b = k = 1		
p = -1		
theta(nloglogn)		
$T(n) = 2T(n/2) + n/logn^2$		
p = -2		
theta(n)		

	$T(n) = 2T(n/2) + n^2$	
	loga with base b < k	
	theta(n^2)	
	$T(n) = 2T(n/2) + n^2$	
	theta(n^2logn)	
	$T(n) = 2T(n/2) + n^3$	
	loga with base b < k	
	theta(n^3)	
30	T(n) = 2T(n/2) + 1	
	loga with base b = 1	
	k = 0	
	loga with base b > k	
	theta(n^1)	
	T(n) = 4T(n/2) + 1	
	loga with base b = 2	
	k = 0	
	theta(n^2)	
	T(n) = 4T(n/2) + n	
	loga with base b = 2	
	k = 1	
	theta(n^2)	
	$T(n) = 8T(n/2) + n^2$	
	loga with base b = 3	
	k = 2	

theta(n^3)	
$T(n) = 16T(n/2) + n^2$	
loga with base b = 4	
k = 2	
theta(n^4)	
T(n) = T(n/2) + n	
log a with base b = 0	
k = 1	
theta(n)	
$T(n) = 2T(n/2) + n^2$	
loga with base b = 1	
k = 2	
theta(n^2)	
$T(n) = 2T(n/2) + n^2 log n$	
loga with base b = 1	
k = 2	
theta(n^2logn)	
$T(n) = 4T(n/2) + n^3\log^2 2n$	
loga with base b = 2	
k = 3	
theta(n^3log^2n)	
$T(n) = 2T(n/2) + n^2 / logn$	
log a with base b = 1	
k = 2	

theta(n^2)	
T(n) = T(n/2) + 1	
log a with base b = 0	
k = 0	
theta(logn)	
T(n) = 2T(n/2) + n	
log a with base b = 1	
k = 1	
p = 0	
theta(nlogn)	
T(n) = 2T(n/2) + nlogn	
log a with base b = 1	
k = 1	
p = 1	
theta(nlog^2n)	
$T(n) = 4T(n/2) + n^2$	
log a with base b = 2	
k = 2; $p = 0$	
theta(n^2logn)	
$T(n) = 4T(n/2) + (nlogn)^2$	
log a with base b = 2	
k = 2, p = 2	
theta(n^2 log^3n)	
T(n) = 2T(n/2) + n/logn	

	log a with base b = 1	
	k = 1; p = -1	
	theta(nloglogn)	
	$T(n) = 2T(n/2) + n/log^2n$	
	log a with base b = 1	
	k = 1; p = -2	
	theta(n)	
31	Root function Recurrence relation	
	T(n) = T(root(n) + 1) for n>2	
	T(n) = 1 for $n = 2$	
	T(n) = T(root(n)) + 1	
	$T(n) = T(n^{(1/2)}) + 1$ equation 1	
	using substitution	
	$T(n) = T(n^{(1/2^2)}) + 2equation 2$	
	$T(n) = T(n^{(1/2^3)}) +3$ equation 3	
	$T(n) = T(n^{(1/2^k)}) + kequation 4$	
	assume, n = 2 ⁿ m	
	$T(2^m) = T(2^m/2^k) + k$	
	assume T(2^(m/2^k)) = T(2)	
	thus, m/2^k = 1	
	m = 2^k	
	k = log m with base 2	
	substituting value of n	
	m = logn with base 2	
	therefore, k = loglogn with base 2	
	theta(loglogn with base 2)	

32	Binary Search Iterative Method		
	To perform binary search, the prerequisite is that the list must be in sorted order	A = {3, 6, 8, 12, 14, 17, 25, 29, 31, 36, 42, 47, 53, 55, 62}	
	we need two index pointers, one is low at the starting point and the other is high at the end point	I = 1, h = 15 (lowest and highest index); mid = 8	
	mid = low + high / 2 and we take the floor value	key value = 42; A[mid] = 29> key > A [mid]	
	the key value is on the right hand side as key value is greater than A[mid]		
	we will change low to mid + 1	I = 9, h = 15; mid = 9 + 15 / 2 = 12	
		A[mid] = 47 > key	
	we will change high to mid - 1 as key < A[mid]		
		h = 11, I = 9, mid = 10; A[mid] = 36	
		A[mid] < key	
	we will change low to mid + 1	I = 11; h = 11; mid = 11; A[mid] = 42	
	we can return the index as we have found the key value	A[mid] = key	
	therefore, binary search looks faster than linear search. It just took 4 comparisons		
	int BinSearch(A, n, key)		
	{		
	I = 1, h = n		
	mid = I + h / 2 - take floor value		
	while(I <= h){		
	if(key == A[mid])		
	{ return index i.e.element is found}		
	else if(key < A[mid])		
	{h= mid-1;}		
	else {		
	I = mid + 1;}		
	}		

	return 0;		
	}		
	Time taken for binary search = logn		
	min time: O(1)		
	max time: O(logn)		
	avg time = add time for each element and divide by number of elements		
33	Binarysearch Recursive method		
	Alogirthm RBinarySearch(I,h,key)	T(n)	
	{		
	if(l==h)	1	
	{		
	if(A[low]== key)		
	{		
	return I;		
	}		
	else		
	{		
	return 0;		
	}		
	else		
	{		
	mid = I + h / 2 //taking floor value	1	
	if(key == A[mid])	1	
	{return mid;}		
	if(key < A[mid])	1	
	{		
	return RBinarySearch(I, mid - 1, key)	T(n/2)	
	}		

	else		
	{		
	return RBinarySearch(mid+1, h, key)	T(n/2)	
	}		
	}		
		T(n) = 1; n =1	
		T(n) = T(n/2) + 1 for $n > 1$	
		theta(logn)	
34	Heaps		
а	Representation of a binary tree using an array		
	T {A, B, C, D, E, F, G}		
	if a node is at index i;		
	its left child is at node 2*i		
	its right child is at node 2*i + 1		
	its parent is at node i/2		
	if there are missing nodes, we leave a blank in its place in the array		
b	Full binary tree		
	In its hieght, it has maximum number of nodes and if we wish to add a node, height would increase		
	Max no. of nodes = 2 ^h - 1		
С	Complete binary tree		
	there is no missing element from first element to the last element in array representation of the binary tree		
	Every full binary tree is also a complete binary tree		
	A complete binary tree is a full binary tree until height h - 1		
	Height of a complete binary tree would be minimum i.e. logn		
d	Неар		

	Heap is a complete binary tree	
	Max Heap: every node has value greater than all its descendants {50, 30, 20, 15, 10, 8, 16}	
	Min Heap: every node has value smaller or equal to than all its descendants {10, 30, 20, 35, 40, 32, 25}	
35	Insert operation in a max heap	
	Insert 60 in the above given max heap	
	this value should be inserted in the last free space in the array	
	i.e. left child of the left most leaf node	
	Then, adjust the elements to make it as a heap	
	So, compare and move 60 up the levels and in the array check at i/2 indices where initially i would be the last empty index where 60 was inserted	
	Time taken would be equal to the number of swaps	
	this depends upon the height of the tree i.e. logn, hence O (logn)	
	minimum time is of no swaps O(1); max would be O(logn)	
36	Delete operation in a max heap	
	From the heap, we need to remove the root / top most element only	
	The last element in the complete binary tree would come in its place	
	Adjust the elements to maintain heap order	
	From the root towards the leaf, adjust	
	Compare the children (2i and 2i +1) and whichever child is greater than compare with the parent	
	Time taken depends upon the height; max could be O(logn)	
	Whenever you delete from max heap, you get the next max element and in case of min heap, it would be the next min element	

37	HeapSort		
	For a given set of numbers, create a heap		
	Delete all the elements from the heap		
	Total N elements we have inserted; each element we assume is moved up to the root; so time taken O(NlogN)		
	Then we delete the elements		
	Store deleted elements in the array in free space in the end		
	Deletion also takes O(NlogN) time		
	Thus, heapsort takes O(NlogN)		
38	Heapify		
	The process of creating heap but direction is opposite than creating a heap		
	O(N)		
39	Priority Queue		
	elements will have priority and they would be inserted and deleted as per the priority order		
	For min heap, smaller the no. higher the priority		
	For max heap, greater the no. higher the priority		
	O(logN) for insertion and/or deletion		
40	TwoWay MergeSort - Iterative method	Algorithm Merge(A, B, m, n)	
	merging two sorted lists to get a sorted result	{i = 1, j = 1, k = 1;	
	A = {2, 8, 15, 18} i	while(i <= m && j<=n){	
	B = { 5, 9, 12, 17} j	if(A[i] < B[j])	
	Compare A(i) with B(j) to get C(k) and move to next location	{	
	m + n elements are obtained , thus theta(m + n)	C[k++] = A[i++];	
		}	
		else {	
		C[k++] = B[j++];	

		}
		for(; i <=m; i++){
		C[k++]=A[i];
		}
		for(;j<= n;j++){
		C[k++] = B[j];
		}
		}
41	Merging more than two lists	
	M-way merging	
	A = {4, 6, 12}	
	B = {3, 5, 9}	
	C = {8, 10, 16}	
	D = {2, 4, 18}	
	One way is that we merge A and B; C and D and then finally merge the two resulting lists> so we perform merge three times here	
	Another way is that we first merge A and B; then we merge resulting list with C; and the resulting list with D	
	Two-way mergesort is an iterative process whereas mergeSort is a recursive process	
	A = {9, 3, 7, 5, 6, 4, 8, 2} - given an array and we have to sort them using 2-way mergesort	
Ist pass	We would consider each element as a sorted list and merge	merged n elements in this pass
	First select two lists 3 and 9; then merge them - 3, 9	
	Similarly, we select two lists 7 and 5 , merge them - 5 and 7	
	Another lists we get are {4, 6} and {2, 8}	
	Now, we have 4 lists with two elements each	
2nd pass	When we merged we kept the resulting 4 lists in another array B; B = {{3, 9}, {5, 7}, {4, 6}, {2, 8}}	merged n elements in this pass

	We merge two lists each		
3rd pass	$C = \{\{3, 5, 7, 9\}, \{2, 4, 6, 8\}\}$	merged n elements in this pass	
	we merge the above two lists to get a single sorted list		
	D = {2, 3, 4, 5, 6, 7, 8, 9}		
	log(no of elements) = no. of passes		
	Time complexity: O(n(logn))		
42	MergeSort		
	A = {9, 3, 7, 5, 6, 4, 8, 2}	Algorithm MergeSort(I, h){	T(n)
	If there is a single element, we can consider it as a base or small problem {Divide and conquer}		
		if(l < h){	
		mid = (I + h) / 2;	
		MergeSort(I, mid);	T(n/2)
		MergeSort(mid + 1, h);	T(n/2)
		Merge(I, mid, h);	n
		}	T(n) = 2T(n/2) + n for n > 1
		}	T(n) = 1 for $n = 1$
	time complexity: theta(nlogn)		using master's theorem, a = 2, b = 2, k = 1
	merging is done in post order traversal		loga with base b = 1 = k
			thus, it is case 2
			theta(nlogn)
43	Pros of MergeSort	Cons of MergeSort	
	works great for Large size lists	Extra space (not inplace sort)	
	suitable for Linked List	no small problem	
	supports external sorting	recursive and uses a stack (need n + logn space) i.e. space complexity: O(n + logn) where n is the extra space and logn is the stack space	
	stable: the order of duplicates is maintained		
		insertion sort (O(n^2))	

		mergesort O(nlogn)	
		for small problems, n <= 15; insertionsort works better> use insertion sort	
43	QuickSort		
	students arranging themselves in increasing order of heights		
	10 80 90 60 30 20		
	5 6 3 4 2 1 9		
	4 6 7 10 16 12 13 14		
	A = {10, 16, 8, 12, 15, 6, 3, 9, 5, INFINITY}	partition(I, h){	
	select first element as a pivot	pivot = A[I];	
	pivot = 10	i = l; j = h;	
	we need to find the sorted position for 10	while(i <j){do< td=""><td></td></j){do<>	
	i starting form pivot and j starting from infinity	{	
	i would check for elements greater than 10; j would heck for elements smaller than pivot	i++;	
	we are using the partitioning procedure	} while(A[i]<= pivot);	
	increment i until next vlue is greater than 10 and decrement j until next value is smaller than pivot; stop and swap	do	
	{10, 5, 8, 9, 3, 6, 15, 12, 16}	{	
	send pivot element at j position	j;	
	now, we can sort the two lists around the partitioning position by performing quicksort recursively	<pre>}while(A[j] > pivot);</pre>	
		if(i <j){< td=""><td></td></j){<>	
	QuickSort(I, h)	swap(A[i], A[j]);	
	{	}	
	if(I < h)	swap(A[I], A[j]);	
	{	return j;	
	j = partition(l, h);	}	
	QuickSort(I, j);		
	QuickSort(j+ 1, h);		

	1	
	}	
	}	
44	QuickSort Analysis	
	suppose it is partitioning in the middle of 1 and 15th index	
	then, two partitions: [1, 7]; [9, 15]	
	further partitions: [1, 3]; [5, 7]; [9, 11]; [13, 15]	
	at each level , n elements are being handled	
	and there are logn levels	
	thus time complexity for best case: O(nlogn)	
	median : middle element of a sorted list	
	best case of quicksort is that the partitioning occurs exactly at the middle	
	worstcase: if we have an already sorted list	
	time complexity for worstcase: O(n^2)	
	to handle this, try taking middle element as a pivot	
	2. select random element as a pivot	
45	Strassen's matrix multiplication	
	A = [a11 a12	
	a21. a22]	
	B = [b11 b12	
	b21 b22]	
	Cij = Summing up Aik*Bkj	
	for(i = 0; i < n; i++){	
	for($j = 0$; $i < n$; $j++$){	
	C[i,j]= 0;	
	for(k=0;k <n;k++){< td=""><td></td></n;k++){<>	
	C[i,j] += A[i, k]*B[k, i];	

}		
}		
}		
C11 = a11*b11 + a12*b21		
C21 = a11*b12 + a12*b22	A = [a11]	
C21 = a21*b11 + a22*b21	B = [b11]	
c22 = a21*b12 + a22*b22	C = [a11*b11]	
for [2*2] matrix, we would use above formula	for [1*1] matrix, use above formula	
we assume that the matrix has dimensions of power of 2	Algorithm MM(A, B, n)	
	{	
	if(n <= 2	
8 times the function is calling itself	{	
$T(n) = 8T(n/2) + n^2 $ for $n > 1$	C = 4 formula stated above;	
a = 8, $b = 2$, $log a with base b = 3$	}	
k = 2	else	
it is case 1 of master's theorem	{	
theta(n^3)	mid = n/2	
	MM(A11, B11, n/2) + MM(A12, B21, n/2);	
	MM(A11, B12, n/2) + MM(A12, B22, n/2);	
	MM(A21, B11, n/2) + MM(A22, B21, n/2);	
	MM(A22, B22, n/2) + MM(A21, B12, n/2);	
	}	
	}	
Strassen's approach -		
has given 4 different formulas with 7 multiplications	P = (A11 + A22)(B11 + B22)	
C11 = A11*B11 + A12*B21	Q = (A21 + A22) B11	
C21 = A11*B12 + A12*B22	R = A11(B12 - B22)	
C21 = A21*B11 + A22*B21	S = A22(B21 - B11)	

	C22 = A21*B12 + A22*B22	T = (A11 + A12)B22	
		U = (A21 - A11)(B11 + B12)	
		V = (A12 - A22)(B21 + B22)	
		C11 = P + S - T + V	
		C12 = R + T	
		C13 = Q + S	
		C22 = P + R- Q + U	
		$T(n) = 7T(n/2) + n^2 $ for $n > 2$	
		$T(n) = 1 \text{ for } n \le 2$	
		using master's theorm,	
		$O(n^{(\log 7 \text{ with base 2})}) = O(n^{2.81})$	
	Strategies used for solving optimization problems - Greed and bound	ly Method, Dymanic programming, branch	
46	Greedy method		
	Design wich we can adopt to solve similar problems		Greedy method says that each problem should be solved in stages - each stage we give an input, check if the solution is feasible then we pick it up and move to next stage
	Solving optimization problems		Algorithm Greedy(a, n) $a = \{a1, a2, a3, a4, a5\}$; $n = 5$
	Optimization problem : Problems which require either minimum or maximum result		{
	Suppose we have a problem P where we need to travel from source A to destination B, we can have several solutions such as walking on foot, travel by an airplane, ride on a bike, travel by a bus, drive on a car, go by a train and so on Now, we notice that we also have some constraints. The solutions that satisfy the conditions given in a problem are called feasible solutions	Minimum cost journey - "Minimization problem"; then feasible solutions giving minimum cost are called optimal solutions. There can be many feasible solutions but only one optimal solution	for i = 1 to n do {x = select(a):
	canca leasible solutions		

	Method 1: Looking at all the models available in the city	Method 2: Conduct an assessment center to filter people at each stage and get the best person	{
	Method 2: Checking for the features of the cars and filtering and selecting based on your preferences - greedy method	So, the person may not be the best but the approach is greedy here as we are using our criteria and constraints to choose the best person	solution = solution + x;
47	Knapsack problem		1
4/	n = 7; m = 15	Bag capacity is 15 kgs and we have been given 7 objects. we have to fill this bag with these objects. Profit is the gain we get by transferring this object. Problem is a container loading problem. Problem is filling the container with the objects as the capacity of container is limited	}
Objects	{0 1 2 3 4 5 6 7}	Optimization and maximization problem	}
Profits	{P 10 5. 15 7 6 18 3 }	Constraints : Bag weight limit	
Weights	{W 2 3 5 7 1 4 1}		
Profit by weight	{P/W 5 1.3 3 1 6 4.5 3}		
0<=x<= 1	Objects are divisible i.e. we can take just half kg of object 1 and may be 2 kgs of object 2 and so on		
x	()		
	x1 x2 x3 x4 x5 x6 x7		
Method 1	Take the thing that have maximum profit		
Method 2	Take things with smaller weight so that you can put in more things		
Method 3	Take things that have highest profit by weight		
	Let's use method 3		

	First, I include object 5 that has maximum profit by weight. Then I check remaining weight I can put in. We can still put in 14 kgs. Then we select all the quantity of object 1. Remaining weight limit 12 kgs. Add all of object 6. Remaining weight limit 8 kgs. Add all of object 3. Remaining weight limit 3 kgs. Add all of object 7. Remaining weight limit is 2 kgs. Add 2/3 of object 2 as we have only 2 kgs limit remaining.	
x	(1 2/3 1 0 1 1 1)	
	Calculate total profit and verify weight	
	Total weight = 1*2 + 2/3*3 + 1*5 + 0*7 + 1*1 + 1*4 + 1*1 = 15	//Multiplying x elements by Weight w for each object
	Total profits = 1*10 + 2/3*5 +1*15 + 1*6 + 1*18 + 1*3 = 54.6	//Multiplying x elements by Profit P for each object
40	0/4 Knamaaali washlam	
48	0/1 Knapsack problem	
	Objects are indivisble and fractions are not allowed i.e. either you include the whole thing or you do not include it at all	
	, ,	
49	Job sequencing with deadlines	n = 5 (tasks)
Jobs	J1 J2 J3 J4 J5	
Profits	20 15 10 5 1	
Deadlines	2 2 1 3 3	
	Assume that there is a machine, on which each job has to be processed and each job takes 1 unit of time (hour) for completion	
	Set of the jobs which can be completed within their deadlines such that profit is maximized	Constraints: deadlines must be met
deadlines	03	maximum 3 slots / jobs
time slots	9am10am11am12am	
Jobs chosen	J2 J1 J4	
Profits	15 + 20 + 5 = 40	
Sequence	J1> J2> J4 J2> J1> J4	

Job consider	Slot assign	Solution	Profit
J1	[1,2]	J1	20
J2	[0,1][1,2]	J1J2	20 + 15
J3	[0,1][1,2]	J1J2	20 + 15
J4	[0,1][1,2][2,3]	J1J2J4	20 + 15 + 5
J5	[0,1][1,2][2,3]	J1J2J4	20 + 15 + 5
50	Job sequencing with deadlines another example	n = 7 (jobs)	
Jobs	J1 J2 J3 J4 J5 J6 J7		
Profits	35 30 25 20 15 12 5		
Deadlines	3 4 4 2 3 1 2		
deadlines	04	4 SLOTS AVAILABLE	
Jobs chosen	J4 J3 J1 J2		
Profits	20 25 35 30	110	
51	Optimal Merge Patern		
	A = {3, 8, 12, 20}		
	B = {5, 9, 11, 16}		
	C = {3, 5, 8, 9, 11, 12, 16 20}	How merging works for two sorted lists ; time = theta(m + n)	
	what happens if we have 4 lists?		
List	A B C D		
Sizes	6 5 2 3		
Choice 1	We can merge at a time two lists - first A and B; the merge it with C and finally with D. total cost= 11 + 13 + 16 = 40		

Choice 2	Merge A anb; C and D that gives cost 11 and 5 respectively. Merge resulting two lists which will cost 16. Total cost would be 11 + 5 + 16 = 32		
Choice 3	Merge Cand D, resulting list is merged with B and then finally with A; total cost = 5 + 10 + 16 = 31		
optimal method	Always merge two small sized lists , then combined time would be reduced		
Example:			
List	x1 x2 x3 x4 x5		
Sizes	20 30 10 5 30		
Increasing order of sizes	5 10 20 30 30		
Lists	x4 x3 x1 x2 x5		
	First x4 and x3 are merged, cost = 15; then result is merged with x1; cost = 35; x2 and x5 are merged with cost = 60; the two resulting lists are merged with cost = 95		
Total cost	15 + 35 + 60 + 95 = 205		
	3*5 + 3*10 + 2*20 + 2*30 + 2*30 = 205	//multiplying distance of each node and size of each node	
52	Huffman Coding		
	Compression technique used to reduce the size of data or message		
Message	BCCABBDDAECCBBAEDDCC		
oooayo	Length = 20		_
	it has to be sent using ASCII codes (8- bit)		
	A 65 01000001	Size = 8*20 = 160 bits	
			\neg
	B 66 01000001	SIZE - 0 ZU - 100 DIIS	

	C 67	
	D 68	
	E 69	
	Can we use our own codes instead of ASCII codes?	
	Fixed size method	
Character	A B C D E	
Count	3 5 6 4 2	Total count = 20
Code	000 001 010 011 100	
message	BCCABBDDAECCBBAEDDCC	
bit code	001010	size = 20*3 = 60 bits
		5*8 = 40 bits for ASCII code translations
		5*3 = 15 bits> our assigned codes
		40 + 15 = 55 bits
		message: 60 bits
		chart: 55 bits
		total message size: 115 bits
		so, the message size reduced from 160 bits to 115 bits
		thus, 40% reduction in size with fixed sized code
		element that appears more / often should
	Huffman coding - variable sized code	have a smaller sized code
character	A B C D E	
count	3 5 6 4 2	
code		
	first, arrange the letters with increasing count / frequency	
character	E A D B C	
count	2 3 4 5 6	

code	000 001 01 10 11	Merge two smaller ones, we get 5, then combine with D, we get 9. Combine B and C, we get 11. Finally, combine two resulting lists, we get 20.
bit count	6 9 8 10 12	On left side paths, mark as 0 and on right side mark as 1
total bits for message	45 bits	Bit count for message can also be obtained from the tree, by counting number of edges for a letter and multiplying by the number of occurences for that letter in the message i.e. summation of distance and frequency of a letter
ASCII codes for chart	5*8 = 40 bits	
assigned codes	12 bits	
total bits for tree/table	52 bits	
Size of total msg	52 + 45 = 97 bits	
Message transferred	00111110110111100101100011111010001010000	A tree or a table would be needed along with it
Decoding	BCCD	
53	Minimum Cost Spanning Tree	
	G = (V, E)	
	V = {1, 2, 3, 4, 5, 6}	V = n = 6
	E= {(1,2), (2,3), (3,4), (4,5), (5, 6), (6,1)}	V - 1 = 5 edges
	the tree should not have a cycle	
	S is a subset of G, WHERE IN S = (V', E')	V' = V; E' = V - 1
	Number of edges in graph = 6 out of which I have to select 5 edges for spanning tree - thus i can select in 6C5 ways	Suppose we have 7 edges, out of which the seventh edge (3,5) divides the graph into two cycles of less tha 6 vertices, then we can select 5 edges for spanning tree in 7C5 - 2 ways

General formula	E C(V -1) - no. of cycles		
Torritaia			
	Now, if we have a weighted graph, I wish to know the number of possible spanning tree		
	Vertices = 4		
	Edges = 3		
	cost = 14		
	similarly , depending upon the edges we select, cost may vary each time		
	Can I found the minimum cost spanning tree?		
Method 1	Try all possible spanning trees and get the minimum cost spanning tree		
Method 2	Prim's algorithm (Greedy method)		
Method 3	Kriskal's algorithm (Greedy method)		
Method 2:	Prim's algorithm		
	Select the minimum cost edge from the graph first	(6,1); w = 10	
	Then, following this select minimum cost edge but make sure it is connected to previously chosen vertices	(5, 6); w = 25	
		(5, 4); w = 22	
		(4, 3); w = 12	
		(3, 2); w = 16	
		(2, 7); w = 14	
	Now, if we add costs of all the chosen edges, total cost = 99		
	For non connected graphs we cannot find the minimum cost spanning tree or spanning tree		
Method 3	Kruskal's method		
	Always select smallest cost edge		
	(1,6); w = 10		

	(3, 4); w = 12		
	(2, 7); w = 14		
	(2, 3); w = 16		
	(4, 5); w = 22		
	(5, 6); w = 25		
	total cost = 99		
	vertices count : V	To get a minimum cost edge each time, min heap can be used	
	edges count: V - 1	theta(nlogn)	
	theta(V E)		
	theta(n.e) = theta(n^2)		
	for non-connected graphs, spanning tree cannot be found		
	Kruskal algo may give spanning tree for those non connected componr=ents but bot for the graph as a whole		
	if in a certain graph, certain edges' weights are missing, then use the given weights of remaining edges to guess the weight		
54	Dijkstra algorithm		
	Single source shortest path to all the vertices		
	find the sortest path to a vertex annd update it to other vertices. this updation is called relaxation		
	Relaxation		
	$if(d[u] + c(u,v) < d[v]){d[v] = d[u] + c(u,v)}$		
	no of vertices = V		
	at most no. of vertices relaxing = V		
	worst case time of Dijkstra algorithm: theta(n*n)		

	Example - starting vertex is 1
	Example - Starting Vertex is 1
selected vertex	2 3 4 5 6
4	50 45 10 infinity infinity
5	50 45 10 25 infinity
2	45 45 10 25 infinity
3	45 45 10 25 infinity
6	45 45 10 25 infinity
	Another example - starting vertex is 1
selected	ro
vertex	$\{2, 3, 4\}$
	{3, infinity, 5}
	{3, infinity, 5}
3	{3, 7, 5}
	{3, 7, 5}
	Another example - starting vertex is 1
selected vertex	{2, 3, 4}
2	{3, infinity, 5}
4	{3, infinity, 5}
3	$\{3, 7, 5\}$
	{-3, 7, 5}
	Dijkstra algorithm might work or might not work in case of en edge having negative weightage
55	Dynamic programming
	Dynamic programming vs greedy method

In Greedy method, we try to follow a predefined procedure that gives us the best / optimal result. The procedure is already known for optimization. But, in dynamic programming, we try to get all the solutions and then decide the best solution. Mostly dynamic programming questions are solved using recursive procedures. They follow a prnciple of optimality. In greedy method, decision is taken just once and followed through whereas in dynamic programming, decision is taken at each step		
Example:		
Fibonacci series		
fib(n) = 0 if $n = 0$	$T(n) = 2T(n-1) + 1{Approximating T(n-2) \sim T (n-1) here}$	
fib(n) = 1 if n = 1	Time taken would be O(2^n) by using Master's theorem	
fib(n) = fib(n-2) + fib(n-1) if $n > 1$	Why can't we reduce the function calls to reduce the time taken?	
	For this, we would take a global array and initially fill it with -1	
int fib(n) {	F = {-1,-1,-1,-1}	
if(n<= 1){	Then, as the function calls f(1), mark it as 1	
return n;}	Then f(0) is marked as 1	
return fib(n-2) + fib(n-1);	Then use the stored result to get the rest.	
}	Finally, F would get updated as we solve: F = {0, 1, 1, 2, 3, 5}	
	Total 6 calls are made then i.e. n+1 calls i.e. O(n)	
	This is called result of memorization	
From the above example, we can see reduction in number of calls from O(2^n) to O(n) using memorization. It follows top down approach. The same problem can be solved using tabular method (iterative process) as shown below:		
int fib(int n) {		
if(n <= 1) {		
return n;}		
F[0] = 0; F[1] = 1;		

	for(int i = 2; i <= n; i++){	
	F[i] = F[i-2] + F[i-1];	
	}	
	return F[n];	
	}	
	F= {0, 1, 1, 2, 3, 5}	
	This is a bottom - up approach i.e. starting from F[0] and moving to F[n]	
56	Multistage Graph	
	A multistage graph is a directed weighted graph. The vertices are divided into stages such that the edges are connecting vertices from one stage to next stage only. First stage and last stage will have only one vertex to represent start and end point. This is usually used to represent resource allocation.	
	The objective of the problem is that I have to select a path which gives me minimum cost.	//it is a minimization or optimization problem
	Dymanic programming works on principle of optimality. Principle of optimality says that a problem can be solved in a squence of decisions.	
	From first stage I have to select one optimal vertex that leads to minimum cost and I have to take this decision at each stage. Thus, I can apply dynamic programming here.	
V	1 2 3 4 5 6 7 8 9 10 11 12	
Cost		cost(5, 12) = 0; here 5 is the stage and 12 is the vertex
d	2/3 7 6 8 8 10 10 10 12 12 12 12	cost(4, 9) = 4
		cost(4, 10) = 2
	Formula for multistage graph:	cost(4, 11) = 5
		$cost(3, 6) = min\{ C(6, 9) + cost(4, 9), C(6, 10) + cost(4, 10) \} = min\{6 + 4, 5 + 2\} = 7$
		Similarly, $cost(3, 7) = min\{8, 5\} = 5$
	Now, we will solve it by going in forward direction and taking decisions based on above data;	$cost(3, 8) = min\{7, 11\} = 7$

	d(1,1) = 2 $d(2,2) = 7$ $d(3,7) = 10$									Similarly, $cost(2, 2) = min\{C(2, 6) + cost(3, 6), C(2, 7) + cost(3, 7), C(2, 8) + cost(3, 8)\}$ = $min\{11, 7, 8\} = 7$	
										$cost(2, 3) = min\{9, 12\} = 9$	
										$cost(2, 4) = min\{18\} = 18$	
	C	d(4, 10) = 12								cost(2, 5) = min{16, 15} = 15	
	F	Path: 2	> 7>	> 10	-> 12					cost(1,1) = min{16, 16, 21, 17} = 16	
	C	l(1, 1) = 3	3								
	C	I(2, 3) = 0	6								
	C	l(3, 6) =	10								
	C	l(4, 10) =	: 12								
	F	Path: 3	-> 6>	10	-> 12						
	5	So, we ha	ave two	paths	with s	same o	ost.				
57	7 N	Multistage Graph (Program)									
	(Cost adja	acency	Matri	ix					main(){	
	0	1	2	3	4	5	6	7	8	int stages = 4, min;	
	0 0	0	0	0	0	0	0	0	0	int n = 8;	
•	1 C	0	2	1	3	0	0	0	0	int cost[9], d[9], path[9];	
	2 0	0	0	0	0	2	3	0	0	int $c[9][9] = \{\{0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0$	
	3 C	0	0	0	0	6	7	0	0	cost[n] = 0;	
	4 C	0	0	0	0	6	8	9	0	for(int i = n-1; i >=1; i){	
	5 0	0	0	0	0	0	0	0	6	min = 32767;	
	6 0	0	0	0	0	0	0	0	4	for(int $k = i + 1$; $k \le n$; $k++$){	
•	7 C	0	0	0	0	0	0	0	5	$if(C[i][k] != 0 && C[i][k] +C[k] < min){$	
	8 0	0	0	0	0	0	0	0	0	min = C[i][k] + C[k];	
										d[i] = k;	
	0	1	2	3	4	5	6	7	8		
cost	-	- 9	7	11	12	6	4	5	0	}	
d	-	- 2	6	6	5	8	8	8		}	

path	1 2 6 8	cost[i] = min;
		}
	Path is calculated using the following formula: p[i] d[p[i-1]] ; p [2] = d[p[2-1]] = d[1] = 2	p[1] = 1; p[stages] = n;
	time complexity: O(n^2)	for(i = 2; i < stages; i++){
		p[i] = p[d[i-1]];
58	All Pairs Shortest Path	
	If I use Dijkstra algorithm on each vertex to find the shortest path of all, the time complexity would be O(n^3).	
A0 =	1 2 3 4	
1	0 3 INF 7	
2	8 0 2 INF	
3	5 INF 0 1	
4	2 INF INF 0	
	Considering vertex 1 as intermediate vertex	A0[2,3] A0[2,1] + A0[1,3]
A1 =	1 2 3 4	2 < 8 + INF
	0 3 INF 7	
2		A0[2,4] A0[2,1] + A0[1,4]
3		INF > 8 + 7 = 15
4	2 8 INF 0	
		A0[3,2] A0[3,1] + A0[1,2]
	Considering vertex 2 as intermediate vertex	INF > 5 + 3 = 8
A2 =	1 2 3 4	
	0 3 5 7	A[1,3] A[1,2] + A[2,3]
2		INF < 3 + 2 = 5
3		
4	2 5 7 0	for(k = 1; k <= n; k++){
		for(i = 1; i <= n; i++){
	Considering vertex 3 as intermediate matrix	for(j= 1; j <= n; j++){

A3 =	1	2	3	4	A[i,j] = min(A[i,j], A[i,k] + A[k,j])	
1	0	3	5	6	}	
2	7	0	2	3	}	
3	5	8	0	1	}	
4	2	5	7	0		
	Considering vertex 4 as intermediate matrix					
A4 =	1	2	3	4		
1	0	3	5	6		
2	5	0	2	3		
3	3	6	0	1		
4	2	5	7	0		
	Formula used to make the above matrices:			to make the above matrices:		
	$A[i,j] = min\{A[i,j], A[i,k] + A[k, j]\}$], A[i,k] + A[k, j]}		
	time complexity = O(n^3)			ty = O(n^3)		
59	59 Matrix chain multiplication					