Amortized Analysis -> most op cheap -> rare op expensive Linear Programming poly (n,m) ;f optimal sola exist \* NO probability ⇒ unbounded ⇒ infeasible [ no possible sol?] -> not necessarily integral soly Variables: x, , ... , xn 1. Aggregate Analysis Maximise: E C; X; (Simplex always at vertex) -> average cost of worst sequence of operations |x|=y -> x < y and x :- y and 320 → simple to understand but tedious in practice Constraints : x, , ... , xn 30 [non - negative] a<sub>11</sub>x<sub>1</sub> + ... + a<sub>11</sub>x<sub>1</sub> £b, }m <u>linear</u> constraints 2. Accounting (Banker's) Method true after any i [no 1g, power, xy etc] → set c(:) for each op st & t(:) ≤ & c(i) min⇒max : multiply by -1 2.2 = ⇒ ≤ not non-neg : replace x w/ (x'-x") -> invariant : always enough credit to pay off any next op Assigning bits to objects or choose subsets set c(:) as low as possible -> SAT or Partition t(i) -> overpay c(i) -) cheap 1. tighter bound -> expensive t (:) -> lower c (i) if Bis easy. A is easy Reductions 1) but small fixed set 2. analysis easier (credit nearer to 0) 3. Potential Method I. A ≤ B [transitive] → klolor, 3lolor > A reduces to B in p(m) - time Arrange in order → cheap op → d\$(i) >0 3. A can be solved in polynomial time using black box for B Dir/Undir Hamiltonian OR TSP → expensive op → △\$(:) < 0 -> prove like typical → \$ (i) is "cred;t amount" after i-th op Small subset satisfying constraints 4. Can transform instance of  $A \rightarrow$  instance of B \* state & check -> Min Verlex Cover 1. \$ (o) = 0 Large subset satisfying constraints a show it's in p(m) -> show YES-instance of A -> YES instance of B 2. \$ (i) \$ 0 V ; to be valid \$ function Max Ind Set or Max Clique or Max SAT Factor .  $t(i) + \phi(i) - \phi(i-i)$ Knapsack DP posendo-poly: poly in numeric value & exponential in length Partition -> Partition **(**;) . amortized cost = actual cost +  $(\phi(n) - \phi(o))$ number "3" appears -> 3SAT or 3Color NP P (NP n co - NP) Fador e (NP n co - NP) \* is an upper bound P (deterministic polynomial): can solve in poly time of instance SubsetSum -> Partition : add sum(s), 2T Dynamic Programming ( -> polynomial subproblems; huge overlap of subproblems NP (non-deterministic polynomial) : verify ves in poly time of instance co-NP: verify NO in poly time of instance - I YES/NO certs Vinstances - V(instance, certificate) -> iterative bottom-up fashion w/ DP table [Basier to prove run-time] Recursive Formulation : base cases + inductive cases A : S NP-hard : P V BENP: B=PA [NP=P NP-hard] <u>NP-complete</u> = NP and NP-hard [equivalent to 3-SAT, show NP + reduce known NP-complete to this] Optimal Substructure : an optimal sole to a problem contains optimal sole to subproblems 3-SAT: (x, v x, v x, ) ^ (x, v x, v x, \*... -> prove w/ int & paste CNF : \$ = C, A C2 A ... A C. 1. Suppose exists a sole that is NOT using "optimal" is optimal Pick arbitrary \_\_\_\_ Approximation -> CANNOT reduce in general 2. add x [:] -> even "better"; swap to use "optimal" instead let A be set \_\_\_\_ chasen 3. solution is improved / still optimal, contradiction / OK to swap ... so |A| ≤ C\* C\* : cost of optimal C : cost found by approx. algo. [worst / expected case] since C= k |A| . C = k C\* Overlapping subproblems minimisation: <u>C</u> > 1 ⇒ k - approximation ideally small & constant Greedy -> one subproblem at each step -> "locally optimal is also globally optimal " maximisation : C > 1 Polynomial - Time Approximation Scheme (PTAS): run in poly(n)f(E) and approx ratio (1+E), E>0 Optimal substructure -> prove w/ int & paste Fully Polynomial-Time Approximation Scheme (FPTAS): run in poly(n, 1/e) and approx ratio (1+E), E>O Greedy-choice property : exists an optimal soly that makes the greedy choice for ( d = 1 to n - 1 ) for ( i = 1 to n - 1 - 0) j = ; t & -> prove w/ out & paste Approx Proof: 1) correct sol? Diagonal DP (2) approx ratio (1) capacity: ∀ (u,v) € E: O ≤ f(u,v) ≤ c (u,v) Greedy interval : start last or ends first Max Flow (2) flow conservation : for u & V - fs, t} : Sf(v, u) = Sf(v, v) Ford - Fulkerson | DFS : O(IE| . Imax flow | ); Edmond Karp's : O(IVIIE1<sup>3</sup>); Dinic's : O(IVI<sup>a</sup>IEI) LCS DP  $if (u,v) \in E : c_p(u,v) = c(u,v) - f(u,v) \quad [can increase by cf]$  $LCS(i, o) = \phi$   $LCS(o, i) = \phi$  $if(v,u) \in E : c_f(u,v) = f(v,u)$  $if a_n = b_m, L(S(n,m) = L(S(n-1, m-1)) + a_n$ [can reduce by cp ] if an \$ bm, LLS(n,m) = bigger of LLS(n-1,m) or LLS(n,m-1) : *Cf* (u, v) = 0 if neither Minimum Cut 1. All \$/ ... . = 0 2. (hoose a path from s -> t Max Flow LP S = fvertices reachable from s} vars: f(u,v) for (u,v) e E 1. m=min Cp(u,v) on path T = V - S maximise & f(s,v) veneigh(s) max flow = & c(u,v) for ufs, vet 2. if m=0, skip path → ∀ (n,v) € E : f (n,v) 30 3. for each (u,v) in path: → ¥ (u,v) E E : f(u,v) ≤ c(u,v) 1. if (u, u) E E, increment f(u, u) by m → ∀ u ∈ V \ fs,t} : E f(u,v) = E f(v,v) 2. if (v, m) & E, decrement f(v, w) by m

<sup>⇒</sup> always integral if inputs are integral