Leetuve 9: Approximation Algorithms Motivation: If probis NP-hard Can't expect polytune algorithms
that exactly solve the problem. But. it may be possible to relax our goal and find approximate solutions efficiently.

Definization Problems

Minimize a cost measure cardidate

Solutions

Maximize a quality measure

eg. Max Flow

Input: directed G, capacities C(u,v), s, t

Cardidates: all valid flows f: E>IR;

Quality: total flow loaving S

eg. Minimum cat Input: G = GCV(E) Cardidates: all non-trivial cuts SEV St \$,V Cost: cut(s) = { { uov} | { | u,v} n s | = 1} Both these problems admit an efficient algo that we studied in previous lectures. Let's take a key example we will study today. Minimum Vertex Cover Definition: A set of vertices SEV is a vertex cover en a graph GCVIE) if for every edge {u,v}EE, at least one of u or v is en S.

Informally, 5 "covers" or "touches" every edge.

Problem (Min VC)

Input: G(VIE)

Goal: compute a vertex cover S of

G with minimum possible size.

Condidates: all possible vertex covers of Costo Size (= number of vertices)

Fact: MinVCIS NP-hard.

Theorem 0: There is an O(m+n) time algo to compute a SSV such that 1) Sisa vertex cover. 2) +S1 \le 2.15*1 where S* is ony min VC in G ISI < 2. OPT Let's develop some basic vocabulary l understand this statement Defution: OPT(G):= minumum cost (for minimization problem)

(for minimization problem)

OPT(G) = maximizedish

(for maximizedish

problem)

APPROXIMATION RATIO

Let & be an algorithm to compute Vertex cover.

For any graph G, let's write A (6) for the Cost of the VC computed by A'

Then: approx-ratio of A

= Max A(G)
all possible OPT(G)
graphs G

Worst-case multiplicative slack in the cost over and above the optimum Cost. [hoovem) (Same thm, new language) There is an algorithm of for VC that 1) runs en time O(m+n), and, 2) has approx vario <2. Kemarks we've chosen to measure the loss of quality or extra cost paid over and above the optimum in a multiplicative way. We could have asked for additive evror": Sol of Cost OPT+ EXTRX-COST & then taken the worst-case extra-cost paid as our measure to focus on. But this would become

less maaringfal if OPT is ting Still, additive approx. can be sensible un some seltings. We will not see them in this course. Kenark 2: Here's a basic conundrum of approx. algo design: he want to reason about the quality of solution found by the algorithm & compare it to OPT. But, we don't know OPT! Indeed, we've looking for approx-aloos because! I we don't know how to compute OPT efficiently !

Key Idea "Certificates" of lower or upper bounds on OPT. We will develop this suportant Conceptual idea by focusing on VC -> our current example | goal. Bounding OPT Let's ask the following question that Seens to not be directly related to the goal of computing a min VC at first. Try to find structures in G that

emply lower bounds on any VC. Let's play with some examples. = Red vertices area VC Blue vertex is also a VC Blue vertex is also a min VC. How do you prove this? Easy: take any edge. Any VC must contain one of its end points bethus has size 7/1. 2. What about this? Can you fend a min VC here?

how do you convince yourself that no better vc con exist?

Definition (Matching) A matching M SE in a graph G(VIE) is a collection of edges s.t. no vertex participates en more than one (can be Zero) edge in M. Blue edges form a matching Courtion: Matching may not touch all vertices of G. Matchings yield a lower bound on Verlex Lemma1: Let MSE be any matching.
Then every vertex cover of G has size at least [M].

Proot: Let 5 be a vertex cover of G. Then 5 must contain at least one vertex from every edje in 19. Since the edges in M donat share vertices, 1517 MI. What's the best lower bound we can hope to obtain on the VC in G His Way? Corollary: VCC6) 7 Max-Matching CG) how good is such a certificate? Can we use matchings to compute VCs?

eig. G=KG Clearly, all vertex Call possible edges on 6 covers of K6 must use 5 vertices. vertices) But maximim matching is of size 3. So if ne gist took a max matching & kept one vertex from each edge, we will definitely not get a vertex cover. Key Observation: If we take both vertices of every edge in Mg then we must get a vertex cover. Infact this is true even if M is just maximal as opposed to maximum

Definition (Maximal Matching) A matching MSE in G(VE) is maximal if for every edge eEEM, MUZez is not a matching. equivalently, every edge e in EM touches some vertex already used in M. Informally, you cannot grow M by adding any edge from the unused pile eg. blue edges form a maximal matching of size 3 red edges also forma maximal matching but of size 4. Caution: 1) maximal matching can be smaller er size than a maximum matching - (e.g. above) 2) A maximum matcheng is maximal. (but not vice-versa, ci general). One cool observation is that it is very easy to compute a Maximal Matching Lemma 2: There is a O(m+n) tene algorithm to compute a maximal matching in G (VIE) (assuming Eisguenas adj list) Let Eu = ? ?u,v} {u,v} EE}

Input: G(V)E)

Inihalize M:= \$.

Ecari=E Ecari = Ecarrl If size>0 pick any e= {u,v} = Ecurr M < MU gez Ecurr = E/ EUUE,

Size < size-1Eul-1Eul+1 else, return M. Informally: repeatedly add an edge {uiv} from Ecuri E to Mkvenove all edges vicident on u or v in E. Stop when E is empty. Claiml: runtime of the also is O(m+n) Proof: Computing size & initializing Ecurr takes O(m) time. Picking an edge takes O(1) time. Removing Eu & Ev takes Oa) time. Updating size takes O(|Eul+ |Ev1) time.

In total, since for each vertex 40 En con be removed at most once, $fotal Cost = O(m + \sum_{u} (E_{u}I)$ = O(m)Correctness: Let M be the output of the algo. Claim 2 ° M is a matching. We argue by induction on # iterations of while loop.

Clearly of is a matching - this completes the base case. Inductively assume Mis a matching after first i iterations.

In the next it evation, any edge c is added must be incident on Vertices not already touched by an ege in M since me vemove all edges from Ecurr that are encident on such vertices -So MUJe? must be a matching. If no such edge exists, nothing to prove Claim 3: Mis maximal. Suppose not for a Contradiction. Then, there must be an edge

e=quiv} that is in E but no edge incident on 4 orvis part of M. But then Ecurr = E U Eu + p. Contradicting the termination condution
of the algorithm

D This completes the analysis of the algorithm

Vertex Covers from Maximal atchings Kay: If you take both vertices of every edge en a maximal matching, then its a vertex cover. Lennaz: let MSE be a maximal matching. Then, S= {u | Jv: {u,v} EM} is a vertex cover of G(V,E). Proof: Suppose S is not a V.C. of G. Then there must exist

anadge quovice E such that $S \cap \{u,v\} = \emptyset$ But then MN EuU Ev = \$ since s contains all vertices touched by any edge in M. In that case MUZEu,v7} is a matching & thus Mis NOT maximal. This is a Contradiction.

We have thus arrived at a natural algorithm to compute a VC in G by relating VCs to matchings. Algo: Input: GCV(E) Operation: 1) Use algo above to find a maximal matching M 2 Output S = { U| fv: {u|v} EM} Lenma 4: Soutputby the algo

Proof's Immediate from Lemma 3. Lemma 5: |S| < 209T(G). Proof: Let M be the matching computed in Stepl. Then by [lemmal, OPT(G) 7/ [M]. OtoH, clearly, ISI = 2.1M1 So: $|S| \le 2.1M1 \le 2.0PT(G)$.

We have thus established the theorem O. Take-aways: One can think of this as a greedy algorithm (since M is computed greedily) for approx V.C. Key Insight : 1) matchings can be used to give a lower bound on all V.C.s. 2) maximal matchings con le

used to construct a vertex Cover. 3) maximal matchings are easily computable. Did we analyze the abovithm
optimally? Could our algorithm do better than 2-approx. ? -> Sometimes eg. if the graph itself is a matching our

also has approximation of 1. Here's another example ishere the also does quite well. Exercise: Let Kan be the Complete graphon 2n vertices en,

of Kan has size Then, 2n-1, and 2) every maximal matching Of Kan has size n.

But in the worst-case our algo is tight. Exercise: Let Knin be the complete bipartile graph with Left d'right vertex sets each of size n' Then 1) Min-VCCKnin) = n. 2) Every maximal matching of Knin has size n.

So our algo gets an approx.

Tation of $\frac{2n}{2n-1} = 1 + \frac{1}{2n-1} \rightarrow 1$ as $n \rightarrow \infty$

Thus our algo for Knin will output a VC of size 2n even though there's a VC of size n evi the graph.