

Approximation Algorithms for Finding Maximum Independent Sets in Unions of Perfect Graphs

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Agenda

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- Perfect Graphs and their Properties
- Summary of Results
- The Common Independent Set Problem
- LP Formulation for 2-MAXCIS
- The Rounding Algorithm and Analysis

The Maximum Independent Set Problem in Graphs

- Given a graph $G = (V, E)$, and a profit (weight) function $p : V \mapsto \mathbb{R}^+$, the goal is to find an independent set of maximum profit.
- If $p(v) = 1, \forall v \in V$, this is the cardinality version.
- [ZUCKERMAN]: It is NP-Hard to approximate MIS within a factor of $n^{1-\epsilon}$, for any $\epsilon > 0$.
- However, there are easy families of graphs for which MIS can be solved optimally in polynomial time.
- Examples are $\{interval, chordal, comparability\}$ graphs.
- All of them are *perfect graphs*.

What is a Perfect Graph?

- A perfect graph is one in which the chromatic number of every induced subgraph equals the size of the largest clique of that subgraph. For every $H \subseteq G$, $\chi(H) = \omega(H)$.
- THE PERFECT GRAPH THEOREM [LOVASZ]: A graph is perfect if and only if its complement graph is also perfect.
- THE STRONG PERFECT GRAPH THEOREM [CHUDNOVSKY, ROBERTSON, SEYMOUR, AND THOMAS]: A graph is perfect if and only if it has no induced subgraph that is an odd cycle of length at least five or its complement. These graphs are called *Berge graphs*.
- Perfect graphs can be recognized in polynomial time.
- For perfect graphs, graph coloring, maximum clique, and maximum independent set problems can all be solved in polynomial time using the ellipsoid method.

Common Independent Set

- A subset of vertices $X \subseteq V$ is called a common independent set (CIS) of graphs $G_i = (V, E_i), 1 \leq i \leq t$, if X is an independent set in each graph G_i .
- Alternatively, a CIS is an independent set in the union graph $G = (V, E)$, where $E = \bigcup_{i=1}^t E_i$.
- The goal is to find the maximum weight CIS (MAXCIS).
- For a fixed constant k , the k -MAXCIS problem is the special case where the number of input graphs is $t = k$.
- We consider restricted versions of the MaxCIS problem, where all the input graphs belong to a particular class of graphs \mathcal{C} .
- In this talk, \mathcal{C} will be the family of perfect graphs.

Summary of Results

- An $O(\sqrt{n})$ -approximation algorithm for the weighted 2-MAXCIS problem on perfect graphs.
- Can be easily generalized to an $O(n^{\frac{k-1}{k}})$ -approximation algorithm for the weighted k -MAXCIS problem on perfect graphs.
- The LP has an integrality gap of \sqrt{n} , even when both the graphs are comparability graphs and all the weights are unit.
- A stronger LP has an integrality gap of $n^{0.16}$, for unweighted comparability graphs.
- If $P \neq NP$, then the 2-MAXCIS problem on comparability graphs cannot be approximated within any constant factor.
- If $NP \not\subseteq \text{DTIME}[n^{O(\log n)}]$, then 2-MAXCIS on comparability graphs cannot be approximated within a factor of $2^{\sqrt{\log n}}$.

Weighted 2-MAXCIS Problem on Perfect Graphs

- Write an (exponential size) LP relaxation.
- Compute an optimal fractional solution for the LP.
- Partition the vertex set into sets of large and small vertices.
- Recover an $O(\sqrt{n})$ fraction of the LP solution for both large and small instances.
- This gives an $O(\sqrt{n})$ -approximation algorithm.

Linear Programming Formulation

We give a natural linear programming formulation for 2-MAXCIS. Here $x(v)$ denotes whether the vertex $v \in V$ is included in the independent set. \mathcal{C}_i is the set of all cliques in G_i .

$$\begin{aligned} \text{maximize} \quad & \sum_{v \in V} p(v)x(v) \\ \text{such that} \quad & \sum_{v \in C} x(v) \leq 1 \quad \forall C \in \mathcal{C}_1 \cup \mathcal{C}_2 \\ & 0 \leq x(v) \leq 1 \quad \forall v \in V \end{aligned}$$

This LP has exponentially many constraints in n . How to solve it?

Separation Oracle

- Assign $x(v)$ as the profit of v .
- Find the maximum profit clique in G_1 and G_2 .
- If both these cliques have profit at most 1, then x is a feasible solution.
- Otherwise, the constraint corresponding to the clique having profit greater than 1 is violated.

A Preparatory Lemma

Lemma

For any $X \subseteq V$, there exists a $I \subseteq X$ such that I is an independent set in $G = G_1 \cup G_2$ and $p(I) \geq \frac{p(X)}{\omega_1(X)\omega_2(X)}$.

- G_1 is perfect, so $G_1[X]$ can be colored with $\omega_1(X)$ colors.
- So, X can be partitioned into $\omega_1(X)$ color classes (independent sets), one of which must have profit at least $\frac{p(X)}{\omega_1(X)}$.
- Compute the maximum profit independent set I_1 in $G_1[X]$.
- Clearly, $p(I_1) \geq \frac{p(X)}{\omega_1(X)}$.

Proof of Lemma ...

- $G_2[I_1]$ can be colored with $\omega_2(I_1) \leq \omega_2(X)$ colors.
- Hence, $G_2[I_1]$ has an independent set of profit at least $\frac{p(I_1)}{\omega_2(X)}$.
- Compute the maximum profit independent set I in $G_2[I_1]$.
- Note that, $p(I) \geq \frac{p(I_1)}{\omega_2(X)} \geq \frac{p(X)}{\omega_1(X)\omega_2(X)}$.
- Moreover, I is an independent set in both G_1 and G_2 . So, it is an independent set in G .

The Rounding Algorithm

- Let x be the optimal fractional solution to the LP.
- Let $LP^*(X) = \sum_{v \in X} p(v)x(v)$, $X \subseteq V$.
- Partition the vertex set V in two parts, SML and LRG , the set of small and large vertices respectively.
- $SML = \left\{ v : 0 \leq x(v) \leq \frac{1}{\sqrt{n}} \right\}$.
- $LRG = \left\{ v : \frac{1}{\sqrt{n}} < x(v) \leq 1 \right\}$.
- $LP^* = LP^*(V) = LP^*(SML) + LP^*(LRG)$ is the profit of the optimal LP solution.
- Let $P_{\max} = \max_{v \in V} p(v)$ be the maximum profit and let v_{\max} be the corresponding vertex.

Handling Large Vertices

- Define, $U_i = \left\{ v : \frac{2^i}{\sqrt{n}} < x(v) \leq \frac{2^{i+1}}{\sqrt{n}} \right\}$, for $0 \leq i \leq \ell - 1$, where $\ell = \frac{1}{2} \log n$.
- $U_0, \dots, U_{\ell-1}$ forms a partition of LRG .
- Using the Lemma on U_j , find an independent set I_j of G such that $p(I_j) \geq \frac{p(U_j)}{\omega_1(U_j)\omega_2(U_j)}$, for $0 \leq j \leq \ell - 1$.
- Among these ℓ independent sets, let I^* be the one having the maximum profit.
- If $p(I^*) > P_{\max}$, output I^* ; else output $\{v_{\max}\}$.
- Let I be the independent set output by the algorithm.

Analysis for Large Vertices

Lemma

$$LP^*(U_j) \leq \left(\frac{2\sqrt{n}}{2^j} \right) \cdot p(I_j), 0 \leq j \leq \ell - 1.$$

- Define $\beta = \frac{2^j}{\sqrt{n}}$. We have to show that $LP^*(U_j) \leq \frac{2p(I_j)}{\beta}$.
- We know that, $\beta \leq x(v) \leq 2\beta$.
- Hence, $LP^*(U_j) \leq 2\beta \cdot p(U_j)$.
- Let $\omega_{\min} = \min\{\omega_1(U_j), \omega_2(U_j)\}$ and $\omega_{\max} = \max\{\omega_1(U_j), \omega_2(U_j)\}$.

- There exists a subset $C \subseteq U_j$, which is a clique in $G_1[X]$ or $G_2[X]$ such that $|C| = \omega_{\max}$.
- The LP contains a constraint corresponding to this clique C .
- Hence, $\sum_{v \in C} x(v) \leq 1$.
- Since $x(v) \geq \beta$, we have $\beta \omega_{\max} \leq 1$, i.e., $\beta \leq \frac{1}{\omega_{\max}}$.
- Thus, $LP^*(U_j) \leq \frac{2p(U_j)}{\omega_{\max}}$.
- Since, $p(I_j) \geq \frac{p(U_j)}{\omega_{\min} \omega_{\max}}$, it follows that $LP^*(U_j) \leq 2\omega_{\min} p(I_j)$.
- But, $\omega_{\min} \leq \omega_{\max} \leq \frac{1}{\beta}$. So, $LP^*(U_j) \leq \frac{2p(I_j)}{\beta}$.

Lemma

$$LP^*(LRG) \leq 4\sqrt{n} \cdot p(I^*).$$

Proof.

$$\begin{aligned} LP^*(LRG) &= \sum_{j=0}^{\ell-1} LP^*(U_j) \\ &\leq \sum_{j=0}^{\ell-1} \left(\frac{2\sqrt{n}}{2^j} \right) \cdot p(I_j) \\ &\leq 2\sqrt{n} \cdot p(I^*) \sum_{j=0}^{\ell-1} \left(\frac{1}{2^j} \right) \\ &\leq 4\sqrt{n} \cdot p(I^*). \end{aligned}$$



The Final Analysis

Lemma

$$LP^* \leq 5\sqrt{n} \cdot p(I).$$

- Since $p(I) \geq P_{\max}$, $LP^*(SML) \leq \sqrt{n} \cdot P_{\max} \leq \sqrt{n} \cdot p(I)$.
- Moreover, $LP^*(LRG) \leq 4\sqrt{n} \cdot p(I^*) \leq 4\sqrt{n} \cdot p(I)$.
- Hence, $LP^* = LP^*(SML) + LP^*(LRG) \leq 5\sqrt{n} \cdot p(I)$.
- Therefore, this is an $O(\sqrt{n})$ -approximation algorithm.

An Interesting Observation

- In perfect graphs, MIS can be computed in polynomial time.
- In union of k perfect graphs, MIS can be approximated within a factor of $O(n^{\frac{k-1}{k}})$.
- As $k \rightarrow \infty$, the approximation factor approaches $O(n)$, which is no better than general graphs.
- This indicates that as we add more perfect graphs in the union, the *perfection* of the resulting graph reduces.