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Kyoto University
On greedy algorithms for
maximum weighted independent set problem

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1 Introduction

The optimization problem Maximum (Weighted) Independent Set (MIS(MWIS)) is one of the most
important problems in computer science [16, 14]. It is well known that the decision problem for MIS is
NP-complete. In the eighties, many natural graph classes for which MIS allows to have a polynomial
time algorithm were found, and many other natural classes for which MIS remains NP-complete were
also found [7]. In the nineties, approximateness have received much attention. With the advance of
study of relationship between nonapproximation and interactive proofs, the results on hardness of MIS
to approximate have been improved. It is shown that for MIS there is a polynomial time approxima-
tion algorithm with a ratio of $O\left(\frac{n}{(\log n)^2}\right)$ (which is of the form $n^{1-o(1)}$) [4]. Recently Håstad have
shown that MIS is hard to approximate within $n^{1-\epsilon}$ for any $\epsilon$ [13]. For graphs with degree bounded
by $\Delta$, MIS is known to be MAX SNP-complete [15] and can be approximable within $\frac{\Delta + 1}{\sqrt{3\epsilon}}$ for every
$\epsilon > 0$ [2]. For bounded degree weighted graphs, a polynomial time approximation algorithm with a
ratio of $\frac{\Delta + 2}{5 + \epsilon}$ is known. [11].

Greedy strategy is one of the most common heuristic method for optimization problems. For MIS,
two simple greedy algorithms were investigated. One is called MIN, which selects a vertex of minimum
degree, removes it and its neighbors from the graph, and iterates this process on the remaining graph
until no vertex remains. The other is called MAX, which deletes a vertex of maximum degree until no
edge remains. Halldórsson and Radhakrishnan showed that $MIN$ achieves approximation ratio $\frac{\Delta + 2}{3}$
and this bound is tight [12]. Griggs [10] and Chvátal and C. McDiarmid [5] proved independently that
$MAX$ outputs an independent set of size at least $\sum_{v \in V(G)} \frac{W(v)}{d(v)+1}$ for any graph $G$. This implies that the
approximation ratio is at most $\Delta + 1$. Halldórsson and Radhakrishnan showed that the ratio is at least
$\frac{\Delta+1}{2}$ [12].

In this paper, we consider three simple greedy algorithms and two parallel algorithms for MWIS.
In section 2, we review terminology and concepts used throughout the paper. In section 3, first we give
two simple algorithms $GWMIN$ and $GWMAX$ which are generalization of $MIN$ and $MAX$ respectively.
Then we show that both greedy algorithms output an independent set of weight $\geq \sum_{v \in V(G)} \frac{W(v)}{d(v)+1}$.
This can be considered as a natural extension of Turán's theorem. We also give another simple greedy
algorithm, which outputs an independent set of weight $\geq \sum_{v \in V(G)} \frac{W(v)^2}{\sum_{u \in \delta^+(v)} W(u)}$. This can be also
thought as an extension of Turán's theorem. In section 4, we present two parallel algorithms $PWMIN$
and $PWMAX$, which are parallelization of $MIN$ and $MAX$ respectively.

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2 Definitions

Let $G = (V, E, W)$ be a weighted undirected graph without loops and multiple edges, where $V$ is the set of vertices, $E$ is the set of edges, and $W$ is the vertex weighting function such that $W : 2^V \rightarrow N^+$ (i.e. each vertex has a positive integral weight), $W(u) \geq 0$ for all $u \in V$ and $W(S) = \sum_{u \in S} W(u)$ for $S \subseteq V$. We also use the notation $V(G)$ and $E(G)$ to denote the set of vertices and edges in $G$. For a subset $S \subseteq V$, $W(S)$ and $|S|$ are referred as the weight and size of $S$ respectively. $G$ is unweighted if $W(u) = 1$ for all $u \in V$. A subset $I \subseteq V$ is an independent set of $G$ if for any two vertices $u, v \in I$, $\{u, v\} \notin E$. An independent set $I$ of $G$ is maximum if there is no independent set $I'$ of $G$ such that $W(I) < W(I')$. We denote the weight of maximum independent set of $G$ by $\alpha(G)$ (i.e. $W(I) = \alpha(G)$ for a maximum independent set $I$ of $G$). Let $G[V']$ denote the subgraph of $G$ induced by $V'$, $d_G(u)$ the degree of vertex $u$, $\Delta_G$ the maximum degree of vertex in $G$, $d_G$ the average degree of $G$, $N_G(v)$ the neighborhoods of $v$, and $N^+_G(v) \{v\} \cup N_G(v)$. If $G$ is understood, then we often omit the inscription $G$ in $d_G(u)$, $\Delta_G$, $d_G$, $N_G(v)$, and $N^+_G(v)$. For an independent set algorithm $A$, $A(G)$ is the weight of the solution obtained by $A$ on graph $G$. The performance ratio $\rho_A$ of $A$ is defined by $\rho_A = \max_G \frac{\alpha(G)}{A(G)}$.

3 Greedy algorithms and extension of Turán's theorem

3.1 Known results

The following theorem is known as Turán's theorem [3].

**Theorem 3.1** For any unweighted graph $G$,

$$\alpha(G) \geq \frac{n}{d_G + 1}.$$ 

Erdős showed that for unweighted graphs MIN attains the above bound [6]. The following extension of Theorem 3.1 was proved first by Wei and later by Alon and Spencer in a different way from Wei.

**Theorem 3.2** For any unweighted graph $G$,

$$\alpha(G) \geq \sum_{v \in V} \frac{1}{d(v) + 1}.$$ 

Wei demonstrated that MIN outputs an independent set of at least $\sum_{v \in V} \frac{1}{d(v) + 1}$ vertices [18]. Alon and Spencer gave an elegant probabilistic proof of Theorem 3.2 [1], and Selkow improved the probabilistic proof [17]. The probabilistic proof is nonconstructive, however. We can apply the probabilistic proof to the case where graphs are weighted. Thus we have the next theorem.

**Theorem 3.3** For any weighted graph $G$,

$$\alpha(G) \geq \sum_{v \in V(G)} \frac{W(v)}{d_G(v) + 1}.$$ 

3.2 An extension of MIN

Let us consider the following framework of MIN type algorithm.
Algorithm WMIN

INPUT : A weighted graph $G$
OUTPUT : A maximal independent set in $G$.

begin
$I := \emptyset; i := 0; G_{i} := G$;
while $V(G_{i}) \neq \emptyset$ do
    Choose a vertex, say $v_{i}$, in $G_{i}$;
    $I := I \cup \{v_{i}\}$;
    $G_{i+1} := G_{i}[V(G_{i}) - N_{G_{i}}^{+}(v_{i})]$;
    $i := i + 1$;
end
Output $I$;

end.

Theorem 3.4 In WMIN, if each $v_{i}$ (0 $\leq i \leq |I|$) satisfies $\sum_{u \in N_{G_{i}}^{+}(v_{i})} \frac{W(u)}{d_{G_{i}}(u)+1} \leq W(v_{i})$ (there exists such a node for any graph), then WMIN outputs an independent set of weight at least $\sum_{v \in V} \frac{W(v)}{d_{G}(v)+1}$.

We refer to a simple greedy algorithm (based on WMIN) in which a vertex $v$ maximizing $\frac{W(v)}{d_{G}(v)+1}$ over all $u \in V(G_{i})$ is selected in each iteration as GWMIN.

Corollary 3.5 GWMIN outputs an independent set of weight at least $\sum_{v \in V} \frac{W(v)}{d_{G}(v)+1}$.

Theorem 3.6 $\Delta - 1 \leq \rho_{GWMIN} \leq \Delta + 1$.

It seems to be worth noting that we cannot guarantee the performance if we pick up a vertex maximizing $\frac{W(v)}{d_{G}(v)}$. The graph depicted in Fig.1 is a counterexample. In the graph, $\sum_{v \in V} \frac{W(v)}{d(v)+1} = 14$. If we choose the vertex $v_{2}$ (which maximizes $\frac{W(v_{2})}{d(v_{2})+1}$), we get the independent set $\{v_{2}\}$, and the total weight is 30. On the other hand, if we choose the vertex $v_{1}$ (which maximizes $\frac{W(v_{1})}{d(v_{1})}$), we get the independent set $\{v_{1}, v_{3}, v_{4}\}$, and the total weight is 13.

3.3 An extension of MAX

Let us consider the following framework of MAX type algorithm.
The next theorem is a generalization of the result of Griggs and Chvátal and C. McDiarmid. The essence of the proof is the same as Griggs’s proof.

**Theorem 3.7** In $WMAX$, if each $v_i (0 \leq i \leq |V(G) - I|)$ satisfies $\sum_{u \in G} N(:v) \frac{W(u)}{d_G(u)(d_G(u)+1)} \geq \frac{W(v)}{d_G(v)+1}$ and $d_G(v_i) \neq 0$ (there exists such a node for any graph $G$ such that $E(G) \neq \emptyset$), then $WMAX$ outputs an independent set of weight at least $\sum_{v \in V(G)} \frac{W(v)}{d_G(v)+1}$.

We refer to a simple greedy algorithm (based on $WMAX$) in which a vertex $v$ minimizing $\frac{W(u)}{d_G(u)(d_G(u)+1)}$ for all $u \in V(G_i)$ is selected in each iteration as $GWMAX$.

**Corollary 3.8** $GWMAX$ outputs an independent set of weight at least $\sum_{v \in V(G)} \frac{W(v)}{d_G(v)+1}$.

**Corollary 3.9** A simple greedy algorithm (based on $WMAX$) in which outputs an independent set of weight at least $\sum_{v \in V(G)} \frac{W(v)}{d_G(v)+1}$.

**Theorem 3.10** $\Delta \leq \rho_{GWMAX} \leq \Delta + 1$.

### 3.4 New greedy algorithm

**Theorem 3.11** A simple greedy algorithm (based on $WMIN$) in which a vertex $v$ maximizing $\frac{W(u)}{\sum_{w \in N_G^+(v)} W(u)}$ over all $u \in V(G_i)$, is selected in each iteration, outputs an independent set of weight at least $\sum_{v \in V(G)} \frac{W(v)^2}{\sum_{w \in N_G^+(v)} W(u)}$.

If $W(v) = 1$ for all $v \in V(G)$ (i.e. unweighted case), then $\sum_{v \in V(G)} \frac{W(v)^2}{\sum_{w \in N_G^+(v)} W(u)}$ is equal to $\sum_{v \in V(G)} \frac{1}{d(v)+1}$ which is the bound of Turán’s theorem.

### 4 Parallel algorithms

Goldberg and Spencer gave a parallel algorithm for MIS which finds an independent set of size at least $\frac{n}{d_G+1}$ [9]. In [12], Halldórsson and Radhakrishnan parallelized $MIN$. In this section, we show that $WMIN$ and $WMAX$ can be parallelized using the same technique in [12]. Due to limitations of...
space, we give only WMIN type parallel algorithm. It is easy to see that we can construct WMAX type parallel algorithm in the same way. We assume the PRAM model.

Let $D_G(v) = W(v) - \sum_{u \in N_{G}^{+}(v)} d_{G}(u)+1$ and $\overline{D}_{G}(v) = \sum_{u \in N_{G}(v)} d_{G}(u)+1 - W(v)$. In order to estimate roughly the number of vertices satisfying $D_G(v) \geq 0$ in Lemma 4.3 ($\overline{D}_{G}(v) \geq 0$ in Lemma 4.4), we need the following two propositions.

**Proposition 4.1** $E[D_G(v)] = 0$.

The next proposition can be shown in the same way as proposition 4.1.

**Proposition 4.2** $E[\overline{D}_G(v)] = 0$.

**Lemma 4.3** There are at least \( \frac{|V(G)|}{1+(\Delta+1)!W_{\max}} \) vertices \( v \) which satisfies \( D_G(v) \geq 0 \), where \( \Delta = \max_{v \in V(G)} d_G(v) \), \( W_{\max} = \max_{v \in V(G)} W(v) \).

Then the next lemma can be shown in the same way as lemma 4.3.

**Lemma 4.4** There are at least \( \frac{2|V(G)|}{2+\Delta(\Delta+1)!W_{\max}} \) vertices \( v \) which satisfies \( \overline{D}_G(v) \geq 0 \), where \( \Delta = \max_{v \in V(G)} d_G(v) \), \( W_{\max} = \max_{v \in V(G)} W(v) \).

If there are vertices \( u \) and \( v \) such that \( D_G(v) \geq 0 \), \( D_G(u) \geq 0 \), and the distance between \( u \) and \( v \) in \( G \) is greater than three, then we can select \( u \) and \( v \) in parallel. Because the selection of \( u \) does not affect the selection of \( v \). This suggests the following natural WMIN type parallel algorithm, where \( G^3 \) denote the graph obtained by taking the adjacency matrix of \( G \) to the third power.

**Algorithm WMIN**

INPUT : A weighted graph \( G \)

OUTPUT : A maximal independent set in \( G \).

begin
  \( I := \emptyset \);
  while \( (V(G) \neq \emptyset) \) do
    \( SAT := \{ v \in V(G) : D_G(v) \geq 0 \} \);
    \( H := G[\overline{SAT}] \);
    \( NEW := \) a maximal independent set of \( H \);
    \( I := I \cup NEW \);
    \( G := G[V(G) - \bigcup_{v \in NEW} N_G^{+}(v)] \);
  od
end.

From Lemma 4.3, \( |SAT| \geq \frac{|V(G)|}{1+(\Delta+1)!W_{\max}} \) in each iteration. Since the maximum degree of \( H \) is at most \( \Delta + \Delta(\Delta - 1) + \Delta(\Delta - 1)^2 \leq \Delta^3 \), and \( H \) is a maximal independent set, the size of \( NEW \) is at least \( \frac{|V(G)|}{1+\Delta(\Delta+1)!W_{\max}} \). Thus, the number of iterations is \( O((1 + (\Delta + 1)! W_{\max})(\Delta^3 + 1) \log n) \).

It is known that there is an algorithm which finds a maximal independent set of a graph \( G \) in time \( O((\log D_G)((\Delta_G)^3 + \log^* n)) \) using a linear number of processors [8]. As \( \Delta \) and \( W_{\max} \) do not depend on \( n \), we have the next theorem.

**Theorem 4.5** Let \( \Delta \) and \( W_{\max} \) be fixed integers. For a graph for which the maximum degree is at most \( \Delta \) and each vertex has a positive integral weight bounded by \( W_{\max} \), WMIN outputs an independent set of weight at least \( \sum_{v \in V} \frac{W(v)}{d_G(v)+1} \) in time \( O((\Delta^6 + \log^* n)(\log \Delta)(1 + (\Delta + 1)! W_{\max})(\Delta^3 + 1) \log n) \) using linear number of processors in the EREW model.
References


