Maximum independent set (stable set) problem: Computational testing and a Satisfiability (3-SAT) model

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M.I.S. Definition

The decision version of the maximum independent set (M.I.S.) problem:

- Given: A constant P and a graph G = (V, E).
- Question: Is there a subset $S \subseteq V$ such that (i) no two members of S are adjacent to each other, and (ii) $|S| \ge P$?
- n = |V|, $1 \le P$ (integer) $\le n$.
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0-1 Integer Program for M.I.S.

$$\begin{array}{rcl} \text{Maximise } Z_1 &=& \sum_{j \in V} (F_j) \\ F_i + F_j &\leq& 1 \ \forall \ (i,j) \in E \\ F_j &\in& \{0,1\} \ \forall \ j \in V. \end{array} \tag{1}$$

 $F_j = 1$ if vertex $j \in ($ Independent set S), and zero otherwise. Ind. Set $S = \{ j \in V \mid F_j = 1 \}.$

Binary Search

Integer solution: For every vertex $i \in V$, F_i is either zero or one.

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Binary search approach: Do a binary search on the value of k for the following problem:

$$F_i + F_j \leq 1 \quad \forall \ (i,j) \in E$$

$$F_j \in \{0,1\} \quad \forall \ j \in V$$

$$\sum_{j \in V} (F_j) = k.$$
(2)

(Is there an independent set in G of size k?)

 $k = 1, 2, 4, 8, \cdots, n.$

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Linear relaxation:

$$F_{i} + F_{j} \leq 1 \quad \forall \ (i,j) \in E$$

$$\forall \ j \in V, \ 0 \leq F_{j} \leq 1$$

$$\sum_{j \in V} (F_{j}) = k.$$
(3)

How to find an integer solution to the Linear relaxation?

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Approach 1: Valid Inequalities

• Clique inequalities: For a clique of size k, add:

 $x_{c1}+x_{c2}+\cdots+x_{ck}\leq 1.$

• Cycle inequalities: For a cycle of size k, add:

 $x_{c1} + x_{c2} + \cdots + x_{ck} \leq \lfloor k/2 \rfloor.$

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• Adding Valid Inequalities improved the rate at which integer solutions were obtained.

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Linear relaxation:

$$\begin{split} x_i + x_j &\leq 1 \ \forall \ (i,j) \in E, \quad 0 \leq x_j \leq 1 \ (\forall \ j \in V), \quad \sum_{j \in V} (x_j) = k. \\ \text{Every vertex is a bin.} \quad \text{Amount in bin } j = x_j. \\ \text{Function value for bin } j &= g(x_j). \\ \text{Minimise } Z &= \sum_{j \in V} g(x_j). \\ X &= (x_1, x_2, \cdots, x_n). \end{split}$$

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(Needed) If for solution X, the function g achieves its minimum, then X should be an integer solution.

Helpful if g is a convex function; because a local min. is also a global min. for convex functions.

The sum of 2 convex functions is also a convex function.

Polynomial functions

$$g_1(x) = a_4 x^4 + a_3 x^3 + a_2 x^2 + a_1 x + C + \frac{b_1}{x} + \frac{b_2}{x^2} + \frac{b_3}{x^3} + \frac{b_4}{x^4}.$$

$$g_2(x) = a_4 x^4 + a_3 x^3 + a_2 x^2 + a_1 x + C + b_2 \sqrt{x} + b_3 \sqrt[3]{x} + b_4 \sqrt[4]{x}.$$

$$(0 \le x \le 1) \longrightarrow (0 < w \le x \le 1).$$

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Convexity:

Set the second derivative condition $g_1''(x) > 0$ as a constraint (or $g_2''(x) > 0$, whichever you use).

- for several values of x in the (0, 1) interval.

Outcome:

For g_1 , obtained convex functions for small values of n, but not for n = 150.

For g_2 , obtained convex functions with n = 256 (but depends on w).

Two stage process

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(b) Use the coefficients to solve a (continuous) minimisation problem:

$$\begin{array}{l} \text{Minimise } Z = \sum_{j \in V} g(x_j) \\ x_i + x_j \leq (1 + w) \ \forall \ (i, j) \in E \\ \forall \ j \in V, \ 0 < w \leq x_j \leq 1 \\ \sum_{j \in V} x_j = k + (n - k)w. \end{array}$$

$$\tag{4}$$

(binary search on k)

(1) Consider a bin (a vertex) *i* with a unit sized item $(x_i = 1)$ and another bin with $x_j = w$. (Total = 1 + w)

Rearranging (1 + w) into [(0.9) + (w + 0.1)] should be more expensive.

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(actually we did it slightly differently)

 $w_1 = 1 + w$.

Convex combination of $w_1 = p(1) + q(w)$, p + q = 1 and $p, q \ge 0$.

 $g(0.9w_1) + g(0.1w_1) - g(1) - g(w) \ge eps.$

(actually we did it slightly differently)

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Desired solution:

The unit-sized items occupy k bins. Total volume = (1)(k) = k.

The *w*-sized items occupy the remaining (n - k) bins. Total volume = (w)(n - k) = nw - kw.

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Break every unit-sized item into p (=5) equal pieces of size 1/p (=0.2) each.

So now these 0.2 sized items occupy more bins (5k, not k).

The remaining volume of nw - kw should be squeezed into fewer bins, that is, (n - 5k) bins, NOT (n - k) any more.

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Fewer bins – so size in each bin will increase from w to $z_5 = \frac{nw - kw}{n - 5k}$. $5k * g(0.2) + (n - 5k) * g(z_5) - k * g(1) - (n - k) * g(w) \ge eps$. Similarly, for various values of p, as long as $w \le x_i \le 1$.

LP to determine coefficients

Combining all conditions, we get an LP with the coefficients a_1 , a_2 , a_3 , a_4 , C, b_1 , b_2 , b_3 and b_4 as the unknowns.

For a given (n, k) combination, we experiment with different values of w and eps – pick the (w, eps) for which we get a feasible solution to the LP.

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Does this process — finding coefficients for a given (n, k) — need to run in polynomial time?

Perhaps not; once we have the coefficients for a given (n, k), in principle, we can re-use them for numerous instances (in step 2) for which n and k are the same.

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Software used:

Step 1 (Linear Program): GLPK first, Gurobi later.

Step 2 (Non-linear Minimisation): MINOS.

Step 2: Minimise a non-linear function to get an integer solution

Desired solution value = (k)g(1) + (n-k)g(w). (known)

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MINOS optimisation is sensitive to the initial solution.

We used $x_i = 1$ (for every *i*) as the initial solution.

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• Not necessary to obtain a (w, 1) solution.

For an edge (3, 7), $x_3 + x_7 \le (1 + w)$.

If $x_3 > 0.5(1 + w)$, which means that $x_7 < 0.5(1 + w)$ \rightarrow include vertex 3 in the independent set, but **not** 7.

True for every neighbour of vertex 3 in the graph.

• <u>A 25-vertex instance</u>: Convex function in Step 1, and integer optimal solutions in Step 2.

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- A 150-vertex instance with opt 29: No convex function in Step 1;

For k = 20, w = 0.008, obtained integer solution. (using function g_1)

For k = 29, obtained non-integer solution which can be easily converted to an integer solution. (using function g_2 and an initial solution for 5/150 vertices).

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• A 53-vertex instance with opt 26:

For $10 \le k \le 26$, we obtained integer solution with the parameters from the 150-vertex instance (but with slightly different w = 0.19).

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• A 256-vertex instance with opt 30:

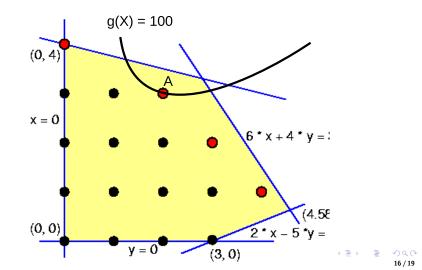
For $(k \le 22)$: Able to re-use the parameters (AND the corresponding function g_1) from the 150-vertex instance.

(k = 30): Testing continues.

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LP polytope: Generate functions to get integer solution?

Point A is the integer solution that we desire. If A is in the interior, then NO matter what function g you use, there are an infinite number of feasible solutions with g(X) = 100! (A is NOT unique)

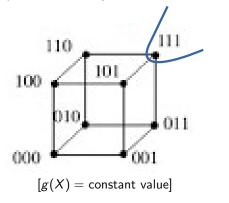


Generating functions for integer solutions - 2

But luckily, $x_i^* = 1$ for at least one $i \in V$. $(x_i \leq 1.)$

Every feasible integer solution X is a vertex of the LP polytope. $X = (x_1, \dots, x_n) = ($ zeroes and ones).

So there is hope that we can design a function whose intersection with the LP polytope is just a "small" region around X^* .



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Recently, we started modelling the M.I.S. as a Satisfiability problem (3-SAT, in particular).

You can follow the results on Researchgate:

https://www.researchgate.net/publication/380034972
(the 3-SAT approach)

https://www.researchgate.net/publication/361555319 (the continuous non-linear optimisation approach)

Thank you for listening!