

# Fast maximal cliques enumeration by locally optimal vertex ordering

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# 1 Algorithm

## 1.1 Preliminaries

1. A simple undirected graph is denoted as  $G(V, E)$ .
2. For a vertex  $v \in V$ ,  $\Gamma(v)$  denotes all vertices adjacent to  $v$  in  $G$ . Note that  $v \notin \Gamma(v)$ .

## 1.2 Algorithm design

The algorithm described here is used for fast maximal cliques enumeration (MCE) of undirected graphs. Most optimizations are attributed to “locally optimal vertex ordering”, so we named the new algorithm as “LOVO”.

LOVO, inspired by Bron-Kerbosch's algorithm, operated three disjoint sets of vertices during the search for maximal cliques:

$X$ :  $x \in X$  are searched vertices. Maximal cliques that contain  $\forall x \in X$  have been enumerated.

$R$ :  $\forall r \in R$  links to each other.

$P$ :  $\forall p \in P$  links to all vertices in  $R$ , but  $p \in P$  not necessarily links to each other. When vertex  $p_1$  deleted in  $P$ , the set  $\{p \in P | p \neq p_1\}$  is denoted as  $\{P \setminus p_1\}$ .

Status  $s$  is defined as a combination of  $X$ ,  $R$ , and  $P$ .

$$s : \{x \in X\}, \{r \in R\}, \{p \in P\}$$

### 1.2.1 Raw Bron-Kerbosch's algorithm

Raw Bron-Kerbosch's algorithm could be expressed as:

- Step1: randomly select a vertex  $p_1$  in  $P$ , then generate a new status  $s_{new}$ :

$$s_{new} : \{x \in X\}, \{r \in R, p_1\}, \{\Gamma(p_1) \cap P\} \quad \mathbf{1}$$

- Step2: iterate Step1 until  $P = \emptyset$ :

$$s_{stop} : \{x \in X\}, \{r \in R, p_1, \dots, p_n\}, \{\}$$

Check if  $R$ , a clique, is a subset of any  $\Gamma(x | x \in X)$ . If not, then  $R$  is a new maximal clique.

- Step3: backtrack to a updated status  $s$ :

$$s_{updated} : \{x \in X, p_1\}, \{r \in R\}, \{P \setminus p_1\} \quad \mathbf{2}$$

It means for status  $s$ ,  $p_1$  has been completely searched. Then, repeat Step1 and Step2 until all vertices in  $P$  are searched, in another words,  $P = \emptyset$ , so we get all maximal cliques from status  $s$ .

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The initial status of  $G(V, E)$  could be set as:

$$s_{init} : \{\}, \{\}, \{v \in V\}$$

### 1.2.2 LOVO

LOVO is designed based on the fact that:  $\forall p \in P$  are searched in status  $s$ , and cliques in  $s_{stop}$  is checked by  $\Gamma(x)$ , so for a given  $x_n \in X$  if  $P$  containing only  $P \cap \Gamma(x_n)$  can be skipped when  $R \subset \Gamma(x_n)$ .  $R \subset \Gamma(x_n)$  can be met with high possibility, because  $X$  is kept growing in Step3. Moreover, in a dense graph  $\Gamma(x_n)$  covers most vertices that make the restriction above to be met more easily.

The skippable status is described as:

$$s_{skip} : \{x \in X\}, \{r \in (R | R \subset \Gamma(x_n))\}, \{P \cap \Gamma(x_n) | x_n \in X\}$$

In LOVO,  $x_n$  is chosen to maximize  $|N(x_n)|$ , which is equal to the number of skipped iterations:

$$N(x_n) = (R \cup P) \cap \Gamma(x_n)$$

The LOVO is described as:

- step1: select  $x_n$  to maximize  $|N(x_n)|$ ,

Case1:  $R \not\subset \Gamma(x_n)$ , randomly select  $p_1$  from  $P$ .

Case2:  $R \subset \Gamma(x_n)$  and  $P \setminus N(x_n) \neq \emptyset$ , randomly select  $p_1$  from  $P \setminus N(x_n)$ . In this way,  $p \in P \setminus N(x_n)$  are always searched in last rank.

Case3:  $R \subset \Gamma(x_n)$  and  $P \setminus N(x_n) = \emptyset$ , skip current status, then backtrack to the second latest status.

The status  $s_{new}$  has the same format as **1**. The status  $s$  is updated as **2**.

- step2: Use the same vertex selection and ordering method for  $s_{new}$ . Note that  $x'_n$  in  $s_{new}$  may be different from the  $x_n$  in  $s$ . It means  $x_n$  is always chosen according to the current status  $s$  and make the  $|N(x_n)|$  local optimal. Repeat step1 until  $P = \emptyset$ , then check whether current  $R$  is a maximal clique.
- step3: backtrack to the second latest status, and repeat step2 until no status left.

A search tree of status  $s$  looks like:

```
{s}
{s_u, s_n} ## update s to s_u, generate s_n from s.
{s_u, s_u1, s_n1} ## update s_n to s_u1, generate s_n1 from s_n.
{s_u, s_u1, s_u2, s_n2}
{s_u, s_u1, s_u2, s_u3, s_n3} ## P in s_n3 is empty, check whether R in s_n is maximal clique.
{s_u, s_u1, s_u2, s_u3', s_n3'} ## update s_u3 to s_n3', generate s_n3' from s_u3.
{s_u, s_u1, s_u2, s_n3'} ## s_n3' is skipped because case3 above occurs.
...
{} ## Stop when no status left.
```

## 1.3 Optimization

### 1.3.1 Check before search

Different from Bron-Kerbosch's algorithm, `LOV0` "ordered" vertices in  $P$  that roughly split  $P$  into two groups  $N(x_n)$  and  $P \setminus N(x_n)$ . Vertex  $p$  for next search was randomly selected from  $P \setminus N(x_n)$ .

`LOV0` always checked the union of  $R$  and  $P$  is part of searched maximal cliques, so invalid iterations could be avoid. *Case3* in `step1` above described the condition,  $R \subset \Gamma(x_n)$  and  $P \setminus N(x_n) = \emptyset$  that equals to  $(R \cup P) \subset \Gamma(x_n | x_n \in X)$ . Besides, maximized  $|N(x_n)|$  guaranteed that largest possible searched maximal cliques or parts were checked in high priority.

It is possible that a chosen vertex  $p_x$  from  $P \setminus N(x_n)$  actually formed a searched maximal cliques.  $p_x$  is omitted just because its corresponding  $N(x_m)$  is not maximal. Any  $p_x$  like below should not be searched:

$$\{\Gamma(p_x) \cap P \cup R, p_x\} \subset \Gamma(x_m | x_m \in X)$$

`LOV0` only did one more search for  $p_x$ . Because when  $p_x$  was selected, new status would be:

$$s_{new} : \{x \in X\}, \{r \in R, p_x\}, \{\Gamma(p_x) \cap P\}$$

Clearly,  $s_{new}$  would be skipped before next search.

### 1.3.2 Quick skip when $P = \emptyset$

When  $P = \emptyset$  in status  $s$ , a clique  $R$  appeared. A continuously changed  $P$  and  $R$  may occur in continuous status. The multiple status could be skipped at once. For example:

```
{s_u, s_u1, s_u2, s_u3, s_n3}
s_n3: R is {R, p1, p2, p3}, P is empty
s_u3: R is {R, p1, p2}, P is {p3}
s_u2: R is {R, p1}, P is {p2, p3}
s_u1: R is {R}, P is {p1, p2, p3}
```

Status  $\{s_x | x \in \{last - 1, last - 2, last - 3, \dots\}\}$  were immediately skipped in `LOV0`, when:

$$|R_x| + |P_x| < |R_{last}|$$

$$P_{last} = \emptyset$$

### 1.3.3 `bitset` transformation of linked vertices

Compared to Bron-Kerbosch's algorithm, `LOV0` added the step  $N(x_n)$  that handled huge amount of `set intersection` and `set union` operation. Instead of holding a integer vector for vertex indices, `LOV0` implemented a `bitset` for edge representation. A similar strategy called `bitscan` is used.

For example, using integer vector a triangle graph is represented as:

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```
0: 1, 2
1: 0, 2
2: 0, 1
```

In LOV0, the graph is transformed as:

```
110
101
011
```

LOV0, even the operation  $\Gamma(p_1) \cap P$  in Bron-Kerbosch's algorithm, benefited greatly from bit and or with hardware optimization in different languages. Moreover, `bitset` used much less memory compared to integer vector. For the example above, integer vector needed at least  $N \times 6$  bits where  $N$  is usually 16 or 32, while `bitset` used 9 bits.

## 2 Unsolved problems

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### 2.1 Vertices ordering in $P$

**Strategy 1:** choose  $v \in P$  that maximizes  $\Gamma(v) \cap P$ , then  $v$  will be move to  $X$  in the next status  $s$ . The search number will be reduced.

### 2.2 Maximize $|(R \cup P) \cap \Gamma(x_n)|$ or $|P \cap \Gamma(x_n)|$ ?

## 3 References

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