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# Algorithms for Big Data (VII)

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# REVIEW

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Compute graph properties in  $o(n^2)$  time.

This can be done for connectivity and bipartiteness.

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# SHORTEST PATH

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Our algorithm computes a subgraph  $H = (V, E_H)$  of  $G$  such that

$$\forall u, v \in V, \quad d_G(u, v) \leq d_H(u, v) \leq \alpha \cdot d_G(u, v)$$

for some constant  $\alpha \geq 1$ .

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**Algorithm** Shortest Path

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**Init:**

$E_H \leftarrow \emptyset;$

**On Input**  $(u, v)$ :

**if**  $d_H(u, v) \geq \alpha + 1$  **then**

$H \leftarrow H \cup \{(u, v)\}$

**end if**

**Output:** On query  $(u, v)$

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In all, we have

$$d_H(u, v) \leq \alpha \cdot d_G(u, v).$$



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It is clear that  $g(H) \geq \alpha + 2$ .

### Theorem

Let  $G = (V, E)$  be a sufficiently large graph with  $g(G) \geq k$ . Let  $n = |V|$  and  $m = |E|$ .  
Then

$$m \leq n + n^{1 + \frac{1}{\lfloor \frac{k-1}{2} \rfloor}}.$$

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The number of the vertices satisfies

$$n \geq \left( \frac{d}{2} - 1 \right)^{\lfloor \frac{k-1}{2} \rfloor} = \left( \frac{m}{n} - 1 \right)^{\lfloor \frac{k-1}{2} \rfloor}.$$

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This bound is in fact tight, can you prove it?

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The problem of **finding maximum matching** is a famous polynomial-time solvable problem.

Now we try to **approximate** it in the streaming setting.

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**Algorithm** Maximum Matching

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**Init:**

$M \leftarrow \emptyset;$

**On Input**  $(u, v)$ :

**if**  $M \cup \{(u, v)\}$  is a matching **then**

$M \leftarrow M \cup \{(u, v)\}$

**end if**

**Output:**

Output  $|M|$ .

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Let  $\widehat{M}$  denote our estimate and  $M^*$  denote the maximum matching.



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$M^*$  is a **maximal** matching. Each  $e \in M$  intersects at most two edges in  $M^*$ .

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Each edge  $e \in E$  is associated with a non-negative weight  $w(e) \geq 0$ .

Compute a matching  $M$  to maximize  $\sum_{e \in M} w(e)$ .

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### Algorithm Maximum Weighted Matching

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**Init:**  $M \leftarrow \emptyset$ ;

**On Input**  $(u, v)$ :

**if**  $M \cup \{(u, v)\}$  is a matching **then**  $M \leftarrow M \cup \{(u, v)\}$

**else**

$C \leftarrow \{e \in M : u \in e \vee v \in e\}$ ;

**if**  $w(u, v) > 2w(C)$  **then**  $M \leftarrow (M \setminus C) \cup \{(u, v)\}$ ;

**end if**

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**Output:** Output  $|M|$ .

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# ANALYSIS

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We call an edge  $e$ :

- ▶ **born** if we added it to  $M$ ;
- ▶ **die** if it was removed from  $M$ ;
- ▶ **murdered by  $e'$**  if it dies because we add  $e'$ .



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For every  $e \in M$ , we define the family of victims:

$$C_0(e) = \{e\}, C_1(e) = \text{edges murdered by } e, \dots, C_i(e) = \bigcup_{f \in C_{i-1}(e)} \text{edges murdered by } f, \dots$$

## Lemma

For every  $e$ ,

$$w \left( \bigcup_{i \geq 1} C_i(e) \right) \geq w(e).$$

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## Proof.

By the definition of **murdering**,  $w(C_{i+1}) \leq w(C_i)/2$ . Therefore

$$2 \sum_{i \geq 1} w(C_i(e)) \leq \sum_{i \geq 0} w(C_i) = w(e) + \sum_{i \geq 1} w(C_i).$$



## Lemma

$$w(M^*) \leq \sum_{e \in M} \left( 4w(e) + 2w \left( \bigcup_{i \geq 1} C_i(e) \right) \right).$$

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We consider  $e_1^*, e_2^*, \dots$  of  $M^*$  in the order of the stream.

- ▶ if  $e_i^*$  is born, charge  $w(e_i^*)$  to  $e_i^*$ ;
- ▶ if  $e_i^*$  is not born, charge  $w(e_i^*)$  to its conflicting edges ( $w^*(e)$  is divided proportional to the weight of the conflicting edges);
- ▶ if some  $e' = (u, v)$  murdered some  $e = (u', v)$  and  $e$  has been charged by some  $e^* = (u'', v)$ , then move the charge from  $e$  to  $e'$ .

At last, we have

- ▶ for every  $e \in M$ , its charge is at most  $4w(e)$ ;
- ▶ for every  $e \in \bigcup_{i \geq 1} C(e')$  for some  $e'$ , its charge is at most  $2w(e)$ .

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The analysis is not pushed to the limit yet, can you improve the approximation ratio 6?  
(Exercise)



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Consider an vector  $\mathbf{f} = (f_T)_{T \in \binom{[n]}{3}}$ , where for every  $T = x, y, z$ ,  
 $f_T = |\{\{x, y\}, \{x, z\}, \{y, z\}\} \cap E|$ .

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So if for some  $T = \{x, y, z\}$ ,  $f_T = 3$ , then  $x, y, z$  is a triangle in  $G$ .

The algorithm simply outputs  $F_0 - 1.5F_1 + 0.5F_2$ , where  $F_i = \|\mathbf{f}\|_i^i$ .

We can expand  $F_0 - 1.5F_1 + 0.5F_2$  as

$$\sum_{T \in \binom{[n]}{3}} 0.5f_T^2 - 1.5f_T + \mathbf{1}[f_T \neq 0].$$

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The “polynomial”  $f(x) = 0.5x^2 - 1.5x + \mathbf{1}[x \neq 0]$  satisfies

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The **multiplicative error** of the algorithm is unbounded!