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1 Introduction

1.1 Exploring a Graph Using BFS

There are at least three methods to explore a graph:

1. DFS (earlier lectures)
2. BFS (today)
3. Random Walks

1.2 Applications of Low Diameter Decomposition

1. Spanners: Distance preserving sparse graphs.
2. Hop Set: Added set of extra edges to a graph to decrease number of edges used in shortest paths.
3. Low Stretch Spanning Tree (LSST): Preserve distances on average. Applications of LSSTs include fast algorithms for:
 - (a) Linear solvers
 - (b) Max flow
 - (c) Image processing

2 Definitions

1. Undirected and unweighted graph $G = (V, E)$.
2. $n \equiv |V|$
3. $m \equiv |E|$
4. $d(v) \equiv$ degree of $v \in V$

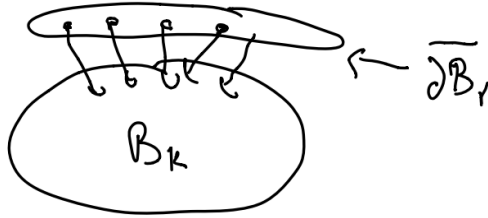
Definition 2.1. $Vol(W) = \sum_{v \in W} d(v)$, where $W \subseteq V$

Note: $Vol(V) = 2m$, since each edge in the graph is counted twice.

Definition 2.2. $Boundary(W) \equiv \partial W = \{(x, y) \mid x \in W, \text{ and } y \notin W, (x, y) \in E\}$, where $W \subseteq V$.

¹Originally 15-750 notes by Andrew Chung

Figure 1: An illustration of $\overline{\partial B_r}$.



Intuitively, ∂W is the set of outgoing edges from the cluster that connect to vertices in W .

Definition 2.3. The Isoperimetric Number of $W \equiv \Phi(W) = \frac{|\partial W|}{Vol(W)}$

The Isoperimetric Number of W is the fraction of outgoing edges to the double-counted edges remaining within the cluster W .

Definition 2.4. The distance $dist(v, w)$ is the minimal distance between two vertices $v, w \in G$.

3 Low Diameter Decomposition

3.1 Problem Statement

Given $G = (V, E)$, $x \in V$, and $0 < \beta < 1$, **want to find:**

$$x \in W \subseteq V \text{ of nearby points such that } \Phi(W) \leq \beta$$

3.2 Ball Growing

Definition 3.1. $B(x, r) = \{y \in V \mid dist(x, y) \leq r\}$

We can think of $B(x, r)$ as a “ball” of radius r , centered at x . The cluster (or ball) consists of vertices that are no further than a distance of r from x .

Algorithm 1 Ball Growing

```

1: function GROWBALL( $G = (V, E), x, \beta$ )
2:    $r \leftarrow 1$ 
3:   while  $\Phi(B(x, r)) > \beta$  do
4:      $r \leftarrow r + 1$ 
5:   end while
6:   return  $B_r = B(x, r), R = r$ 
7: end function

```

Claim 3.2. $R = O(\frac{\log(m)}{\beta})$, where R is the largest radius returned from *GrowBall*.

Note: If $r < R$, then $|\partial B_r| \geq \beta \cdot Vol(B_r)$

Definition 3.3. $\overline{\partial B_r} = \{y \in V \mid (x, y) \in E, x \in B_r, y \notin B_r\}$

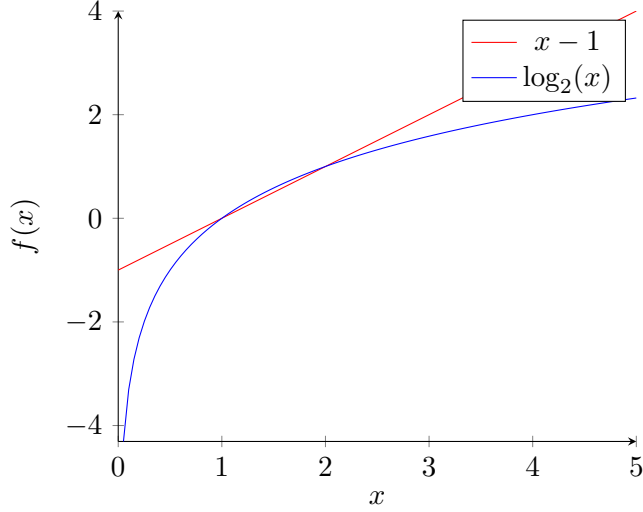


Figure 2: $\log_2(1 + \beta) \geq \beta$ for $0 \leq \beta \leq 1$

Intuitively, $\overline{\partial B_r}$ is the set of vertices that are “neighbors” of the cluster B_r . They are the vertices that are in consideration to be added in at the next increment of r . For an illustration, please refer to Figure 1.

Note: $Vol(\overline{\partial B_r}) \geq \beta \cdot Vol(B_r)$.

We trivially get this from $|\partial B_r| \geq \beta \cdot Vol(B_r)$

Thus: $Vol(B_{r+1}) \geq (1 + \beta) \cdot Vol(B_r)$

Going back to proving Claim 3.2:

Proof.

$$(1 + \beta)^r \leq Vol(B_r) \leq 2m$$

$$\text{Taking logs} \implies r \cdot \log_2(1 + \beta) \leq \log_2(2m)$$

$$\text{Provided that } \log_2(1 + \beta) \geq \beta \text{ for } 0 \leq \beta \leq 1 \implies r \cdot \beta \leq \log_2(m) + 1$$

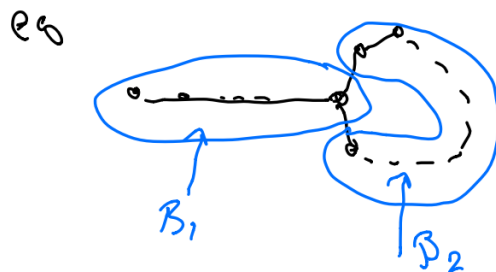
$$\implies r \leq \frac{\log_2(m) + 1}{\beta}$$

□

3.3 Low Diameter Decomposition Through Ball Decomposition

We now introduce a simple sequential algorithm *BallDecomp* that uses *GrowBall* to get a partition of V .

Figure 3: An illustration of distance between balls in a graph.



Algorithm 2 Ball Decomposition

```

1: function BALLDECOMP( $G = (V, E), \beta$ )
2:    $balls \leftarrow \emptyset$ 
3:   while  $V \neq \emptyset$  do
4:     Pick  $x \in V$                                 ▷ Pick an arbitrary vertex as the center for creating a new ball
5:      $B_r \leftarrow GrowBall(G, x, \beta)$            ▷ Creates a ball with  $x$  as the center
6:      $balls \leftarrow \cup\{B_r\}$                  ▷ Add the new ball to the set of balls
7:     Remove  $B_r$  and  $\partial B_r$  from  $G$            ▷ Remove components of the ball from the graph
8:   end while
9:   return  $balls$ 
10: end function

```

Note: $dist_G(V, W) \ll dist_B(V, W)$ for $V, W \in B \equiv \text{Ball}$. Essentially, the distance between two vertices within a ball may be much greater than their distance in the whole graph. For an illustration, please refer to Figure 3.

3.4 Ball Growing Using Exponential Decay

In this section, we will introduce a ball-growing technique using the properties of exponential distributions.

3.4.1 Algorithm definition

Algorithm 3 Ball Growing Using Exponential Delay

```

1: function EXPONENTIALDELAY( $G = (V, E), \beta$ )
2:   for each  $v \in V$  draw  $X_v \sim \text{Exp}(\beta)$ 
3:    $X_{max} \leftarrow \max_{v \in V} X_v$ 
4:   for each  $v \in V$  compute  $S_v \leftarrow X_{max} - X_v$ 
5:    $t \leftarrow 0$ 
6:   while True do
7:     for each  $v \in V$  where  $S_v = t$  do
8:       if  $v$  is not owned at time  $S_v$  then
9:          $v$  owns  $v$ , start BFS from  $v$ 
10:      else
11:         $v$  is owned by first arrival vertex, do nothing
12:      end if
13:    end for
14:    if All  $v \in V$  are owned then
15:      break
16:    end if
17:     $t \leftarrow t + 1$ 
18:  end while
19: end function

```

Note: At each time step each of the active BFSs move outward a distance of 1.

Definition 3.4. $u \in \text{cluster}(v)$ if

1. $v = \arg \min_v \{ \text{dist}(u, v) + S_v \}$ **or**
2. $v = \arg \max_v \{ X_v - \text{dist}(u, v) \}$,

where $u, v \in V$ and S_v and X_v are defined as in Algorithm 3.

We can think of S_v as an additional distance that v has to travel to u , and u will belong to the cluster centered at v whose total distance (including S_v) from v to u is the smallest.

3.4.2 What is the maximum cluster radius?

Lemma 3.5. At time X_{max} , all of the nodes will be owned.

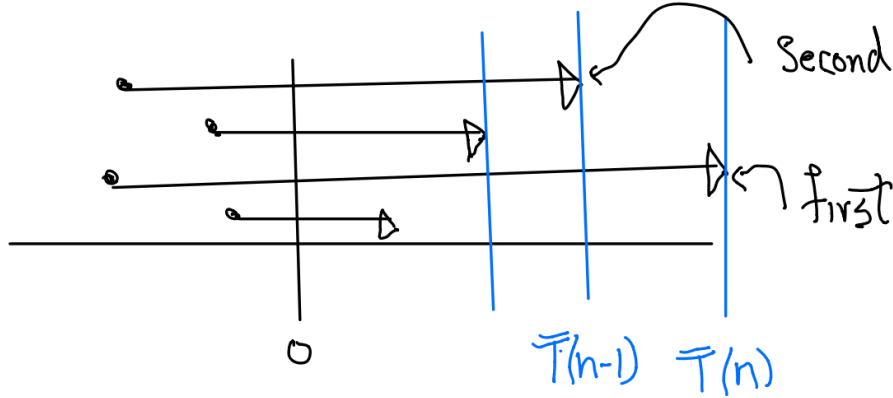
Proof. Intuitively, at time X_{max} each node must have either been owned by another vertex or has started its own BFS. \square

Corollary 3.6. Max cluster radius $\leq X_{max} \leq \frac{2 \ln n}{\beta}$ with probability $\geq 1 - \frac{1}{n}$, where $n = |V|$.

This follows from Lemma 3.5 and $X_{max} \sim \text{Exp}(\beta)$.

Note: Remember that the max of $n \text{Exp}(\beta)$'s is at most $\frac{2 \log n}{\beta}$ with high probability.

Figure 4: An illustration of the horse race and photo finish framing of the intercluster edges problem.



3.4.3 What is the probability that an edge is intercluster?

In other words, what is the probability that an edge is cut?

To answer this question, let e be some edge and c be the midpoint of edge e . We think of each vertex doing a BFS of G starting at time $S_{v_i} = S_i$.

Definition 3.7. The arrival time at c will be a random variable

$$T_i = X_{max} - X_i + \text{dist}(v_i, c) = S_i + \text{dist}(v_i, c)$$

$$\text{Early arrival: } \bar{T}_i = X_{max} - T_i = X_i - \text{dist}(v_i, c)$$

The probability that an edge is intercluster is bounded above by the probability that the difference between two arrival times is less than a unit of time.

A way to frame this problem is to think of it as a horse race and photo finish, where $\text{dist}(v_i, c)$ can be thought of as the handicap and X_i can be thought of as the speed. Figure 4 serves as an illustration.

Definition 3.8. $\text{Gap}_1 = \bar{T}(n) - \bar{T}(n-1)$

By the memoryless property of exponential distributions, $\text{Gap}_1 \sim \text{Exp}(\beta)$, and thus $\Pr(\text{Gap}_1 < 1) = 1 - e^{-\beta}$.

Claim 3.9. $1 - e^{-\beta} < \beta$

Proof.

$$\begin{aligned} e^{-\beta} &= 1 - \beta + \frac{\beta^2}{2!} - \frac{\beta^3}{3!} + \dots \\ \implies 1 - e^{-\beta} &= \beta - \frac{\beta^2}{2!} + \frac{\beta^3}{3!} - \dots \\ \implies 1 - e^{-\beta} &< \beta, \text{ by Taylor's Theorem} \end{aligned}$$

□

Hence, we show that the probability that an edge is intercluster is $< \beta$.

4 Exponential Delay

Theorem 4.1. *Exponential delay generates a clustering such that*

1. *Max radius in expectation is $\frac{\ln(n)}{\beta}$*
2. *Max radius is $\frac{2\ln(n)}{\beta}$ with probability $1 - \frac{1}{n}$*
3. *The expected number of intercluster edges is $m \cdot \beta$*
4. *Run time is $O(m + n)$*
5. **Strong Diameter Property:** *If $w \in \text{Cluster}_v$, then shortest path from v to w is in cluster v , where v is the center of the cluster and $v, w \in V$*