

Lecture 8

Lecturer: Mohsen Ghaffari

Scribe:

In this lecture, we discuss *sublinear-time centralized algorithms* for graph problems. As we shall see soon, the core part of these algorithms is a local procedure, quite similar to the LOCAL distributed algorithms that we have been discussing over the past few lectures.

Sublinear-time (centralized) algorithms are gaining importance with the constant increase in the size of the graph problems that need to be solved¹. In particular, for a range of problems of interest, the graphs have become so large that spending a linear-time to read the whole graph to solve the problem is well-beyond the time that we can afford. We instead want centralized algorithms that, on an n -node graph, spend $\Theta(1)$ time or at most $\text{poly}(\log n)$ time and provide some meaningful answer (e.g. approximation) about the problem at hand. As we will see, the prototypical way of achieving such results is via *local algorithms*. In a very rough sense, we will poke the graph at a few random places, and determine the solution at each of those places by performing a local procedure, which checks only a small neighborhood around there. At the end, we try to infer something about the overall solution by putting together the solutions at these few randomly sampled places.

Model We consider a graph $G = (V, E)$ with $n = |V|$ nodes and maximum degree Δ . Moreover, we will assume that the graph has no isolated vertex. For the graphs of interest, which are thought to be extremely large and complex, it is typical to assume that degrees are much smaller than the network size. Thus, we will think of Δ as a constant compared to n . The graph is represented by a query-access model, where each query is as follows:

- Query $Q(v, i)$ asks “*who is the i^{th} neighbor of node v ?*”.

We can also access a random node v , chosen uniformly at random from V . The main performance measure is the number of queries, which we will refer to as the algorithm’s *query complexity*. The goal would be to have a query complexity which depends only on Δ (aside from some precision and certainty parameters) and not on n . Moreover, we clearly prefer smaller dependencies on Δ , e.g., $\text{poly}(\Delta)$ is preferred to 2^Δ .

1 Approximating Maximum Matching

Consider the problem of computing an approximation of the size of maximum matching. Recall that a matching is a set of edges $M \subseteq E$ such that no two of the edges in M share an end-point. The size of a matching is simply the number of its edges. Computing a maximum matching, or approximating it, are classic optimization problems which have been studied for decades, at the very least since 1965 work of Edmonds [Edm65], which presented a polynomial-time algorithm for computing a maximum matching.

We next discuss an algorithm that computes a $(2 + \epsilon)$ -approximation of the size of maximum matching, for a desirably small constant $\epsilon > 0$ — say $\epsilon = 0.01$ — with query-complexity $2^{O(\Delta)}/\epsilon^2$, independent of how large the graph size n is.

The Algorithm’s Roadmap We will present a simple way of constructing a *maximal* matching M , namely a random greedy maximal matching procedure, which we will be able to simulate in a local manner. This allow us to pick a set S of randomly sampled nodes and infer whether

¹Does “*Big Data*” ring a bell?

each sampled node $s \in S$ is matched in the maximal matching or not, using a small number of queries around s . Then, the average fraction of sampled nodes that are matched give us an estimation of the size of the maximal matching M . Since any maximal matching is a 2-approximation of the maximum matching, we get an estimator for a 2-approximation of maximum matching. Using a large enough number $k = |S|$ of sampled nodes S , we can adjust the accuracy and certainty of this estimator. We next explain the details of this outline.

1.1 A Somewhat Local Procedure for Generating a Maximal Matching

Maximal Matching A *maximal matching* is a matching $M \subseteq E$ such that we cannot add any edge of $E \setminus M$ to M , without violating the property that we have a matching. Put more positively, in a maximal matching M , we have the property that for each edge $e \in E$, at least one endpoint $v \in e$ is incident on a matching edge $e' \in M$. Notice that a maximal matching is not necessarily a maximum matching. However, as we prove next, any maximal matching has a size close to that of a maximum matching.

Lemma 1. *In any graph, any maximal matching has size at least 1/2 of the maximum matching.*

Proof. Consider a maximum matching M^* and an arbitrary maximal matching M . We prove that $2|M| \geq |M^*|$. For that, we give one dollar to each M^* -edge and then ask this M^* -edge e to pass this dollar to one of its incident edges in M . Each edge has such an incident M -edge due to the maximality of M . This way, each M -edge receives at most two dollars, at most one through each of its endpoints (why?). Hence, we have redistributed $|M^*|$ dollars on the $|M|$ edges of M in a way that each receives at most two dollars. Hence, $2|M| \geq |M^*|$. \square

Next, we explain a simple algorithm for computing a maximal matching. We will not run this algorithm in its entirety, but rather, we will sample a few nodes and try to locally infer what would be the output of these nodes in the algorithm.

Random Greedy Maximal Matching Algorithm Suppose that for each edge $e \in E$, we pick a random number $r_e \in [0, 1]$. Then, we process the edges in non-decreasing order of their random numbers r_e , and we greedily add them to the matching M . More concretely, as we go through the (non-decreasing) sorted order of the edges, each time we add the edge e under process to the matching M if and only if no edge e' incident to e with a lower random number $r_{e'} < r_e$ has been added to the matching M before. This process always keeps M as a matching, and eventually, once we are done with the processing, M is a maximal matching.

Approximating the Size of Maximal Matching What we would do is as follows. We will pick a set S of k randomly chosen nodes (with replacement). The fraction of these nodes that are matched in M is an unbiased estimator of the fraction of vertices that are matched in M . More precisely,

$$\mathbb{E}\left[\sum_{s \in S} 1_{(\text{vertex } s \text{ matched in } M)} / |S|\right] = 2|M|/n.$$

Thus, we can output

$$\frac{n}{2|S|} \cdot \sum_{s \in S} 1_{(\text{vertex } s \text{ matched in } M)}$$

as an unbiased estimator of $|M|$, which by Lemma 1, we know is within a 2-factor of the size of the maximum matching.

The key thing that remains to be discussed is how do we deduct whether a given randomly sampled node s is matched in M or not, without running the entire maximal matching algorithm. Ideally, we should just check a few things around s and be able to infer whether s is matched in M or not. In particular, we will check each of the edges e incident on s separately, to see

whether $e \in M$. Once we discuss this part, we will afterward explain how to set the number of sampled vertices S to obtain a desired degree of certainty and accuracy for this estimator, using basic concentration of measure arguments (e.g. Chernoff bound).

1.2 Checking $e \in M$ for One Edge, and its Query Complexity

Imagine the following procedure. Instead of running the entire random greedy maximal matching procedure to figure out whether $e \in M$ or not, we do something simpler, which should get the same answer: We determine the random value r_e and also all the values $r_{e'}$ for edges e' incident on e . We then *recursively* check whether any of these edges e' for which $r_{e'} < r_e$ is in the matching M or not. If none of them is in the matching, then e is in the matching. Clearly, if we use the same random numbers r_e as in the procedure explained above, we can deduce whether $e \in M$ or not, when we run the entire algorithm.

Analysis

The only question is, what is the query complexity of this recursive procedure. A priori, we might end up opening another recursion branch on each neighboring edge and thus we may conceivably end up with a query complexity up to $O(m)$. However, that is not likely. We next prove that for a given edge e , the expected query complexity of the recursive procedure is upper bounded to $2^{O(\Delta)}$, which is independent of n .

Lemma 2. *The expected query complexity of the algorithm for an arbitrary given edge e , which is selected independent of the random values r'_e for $e' \in E$, is at most $2^{O(\Delta)}$.*

Proof. Let $Q(x)$ be the maximum expected number of queries for any edge e , conditioned on $r_e = x$. Notice that $x \leq y$ implies $Q(x) \leq Q(y)$. Let e_1, \dots, e_ℓ be the edges incident on e . Notice that $\ell \leq 2\Delta - 2$. We claim that

$$Q(x) \leq (2\Delta - 2) + \sum_{i=1}^{\ell} Pr[r_{e_i} < x] \cdot \mathbb{E}[Q(r_{e_i}) | r_{e_i} < x].$$

This is because, we first read all the up to $2\Delta - 2$ incident edges and then, for each neighboring edge e_i with $r_{e_i} < r_e$, we start a new recursion at e_i , which we know in expectation will take at most $Q(r_{e_i})$ queries. What remain is to solve this recursive relation $Q(x)$ and obtain an upper bound on it.

To simply the task of upper bounding this recursive inequality, we *discretize* it in some sense, that is, we upper bound it in only a bounded number of (well-spread) places. For any $j \in \{1, \dots, 4\Delta\}$, by setting $x = \frac{j}{4\Delta}$ in the above inequality, we have

$$\begin{aligned} Q\left(\frac{j}{4\Delta}\right) &< 2\Delta + \sum_{i=1}^{2\Delta} Pr[r_{e_i} < \frac{j}{4\Delta}] \cdot \mathbb{E}[Q(r_{e_i}) | r_{e_i} < \frac{j}{4\Delta}] \\ &\leq 2\Delta + \sum_{i=1}^{2\Delta} \sum_{k=1}^j \mathbb{E}[Q(r_{e_i}) | r_{e_i} \in [\frac{k-1}{4\Delta}, \frac{k}{4\Delta}]] \cdot Pr[r_{e_i} \in [\frac{k-1}{4\Delta}, \frac{k}{4\Delta}]] \\ &\leq 2\Delta + \sum_{i=1}^{2\Delta} \sum_{k=1}^j Q\left(\frac{k}{4\Delta}\right) \cdot \frac{1}{4\Delta} \leq 2\Delta + \frac{1}{2} \sum_{k=1}^j Q\left(\frac{k}{4\Delta}\right). \end{aligned}$$

By rearranging the terms around this inequality, we arrive at the following simpler recursion:

$$Q\left(\frac{j}{4\Delta}\right) \leq 4\Delta + \sum_{k=1}^{j-1} Q\left(\frac{k}{4\Delta}\right).$$

Given this recursion, by a simple induction on j , we can prove that $Q(\frac{j}{4\Delta}) \leq 4\Delta(2^j - 1)$ (why?). Hence, $Q(r_\epsilon) \leq Q(1) = Q(\frac{4\Delta}{4\Delta}) \leq 4\Delta(2^{4\Delta} - 1) = 2^{O(\Delta)}$. \square

Observation 3. *The overall expected query complexity for checking a set S of nodes, to see whether they are matched in M or not, is at most $|S| \cdot \Delta 2^{O(\Delta)} = |S| \cdot 2^{O(\Delta)}$.*

This essentially determines the query complexity of our algorithm. Even for a small sample set S , this is an unbiased estimator. However, we usually would like to say that the estimator has a good probability to be a good approximation of its target value. Next, we discuss how by picking a large enough sample set size $k = |S|$, we can satisfy these desires.

1.3 Adjusting the Sample Set For the Desired Accuracy and Certainty

Lemma 4. *For any certainty parameter $\delta \in [0, 0.25]$ and any precision parameter $\epsilon > 0$, suppose that we choose a set S of $k = \frac{20\Delta \log 1/\delta}{\epsilon^2}$ nodes at random, with replacement, and check whether each $s \in S$ is matched in the maximal matching M or not. Then, the function*

$$\frac{n}{2|S|} \cdot \sum_{s \in S} 1_{(\text{vertex } s \text{ matched in } M)}$$

provides a $(1 + \epsilon)$ approximation of the size of maximal matching, with probability at least $1 - \delta$. Hence, this is a $2(1 + \epsilon)$ approximation of the size of maximum matching.

Notice that by the above observation, the expected query complexity of our algorithm becomes $k 2^{O(\Delta)} = 2^{O(\Delta)} \cdot \frac{\log 1/\delta}{\epsilon^2}$. The proof of this lemma follows by applying the Chernoff bound, which is a basic concentration of measure tool that allows us to show that a summation of certain independent random variables is distributed with concentration around its expected value, i.e., it is not likely to deviate from its expectation. The proof of this theorem can be found in most textbooks on randomized algorithms and probabilistic processes. See, e.g., [MR10].

Theorem 5. *(Chernoff Bound) Suppose X_1, X_2, \dots, X_n are independent random variables taking values in $[0, 1]$. Let $X = \sum_{i=1}^n X_i$ denote their sum and let $\mu = \mathbb{E}[X]$ denote the sum's expected value. For any $\delta > 0$, we have*

$$\Pr[X \notin [\mu(1 - \epsilon), \mu(1 + \epsilon)]] \leq 2e^{-\epsilon^2 \mu/3}.$$

Proof of Lemma 4. Define X_i to be the random variable that is equal to 1 if the i^{th} node in our sample set S is matched in M , and is equal to 0 otherwise. Notice that $\Pr[X_i = 1] = \frac{2|M|}{n}$. Hence, $\mu = \mathbb{E}[\sum_{i=1}^k X_i] = \sum_{i=1}^k \mathbb{E}[X_i] = \sum_{i=1}^k \Pr[X_i = 1] \cdot 1 = k \frac{2|M|}{n}$. Therefore, by Chernoff bound, the probability that $X = \sum_{i=1}^k X_i$ deviates by more than a $(1 + \epsilon)$ factor from its expectation μ is at most

$$2e^{-\epsilon^2 \mu/3} = 2e^{-\epsilon^2 k \cdot 2|M|/(3n)} = 2e^{-\epsilon^2 \frac{20\Delta \log 1/\delta}{\epsilon^2} 2|M|/(3n)} = 2e^{-10 \frac{\Delta|M|}{3n} \cdot \log 1/\delta} \leq \delta.$$

The last inequality uses $|M| \geq \frac{n}{4\Delta}$. This fact holds because we have assumed that the graph has no isolated edge, and thus it has at least $n/2$ edges, and moreover, each edge in the maximal matching M can hit at most 2Δ edges (including itself) and all edges must be hit. \square

Remark The algorithm presented here is (a streamlined variant of) a result of Nguyen and Onak [NO08]. See their paper for how this technique can be used for a range of other approximation problems. In the exercises of this lecture, we will see an alternative method for computing an approximation of maximum matching, which has a better query complexity as a function of Δ , but with a slightly worse dependency on the precision parameter ϵ .

References

- [Edm65] Jack Edmonds. Maximum matching and a polyhedron with 0, 1-vertices. *Journal of Research of the National Bureau of Standards B*, 69(125-130):55–56, 1965.
- [MR10] Rajeev Motwani and Prabhakar Raghavan. *Randomized algorithms*. Chapman & Hall/CRC, 2010.
- [NO08] Huy N Nguyen and Krzysztof Onak. Constant-time approximation algorithms via local improvements. In *Foundations of Computer Science. FOCS'08. IEEE 49th Annual IEEE Symposium on*, pages 327–336. IEEE, 2008.