

# Dominating Sets in Web Graphs\*

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## Abstract

In this paper we study the size of generalised dominating sets in two graph processes which are widely used to model aspects of the world-wide web. On the one hand, we show that graphs generated this way have fairly large dominating sets (i.e. linear in the size of the graph). On the other hand, we present efficient strategies to construct small dominating sets.

The algorithmic results represent an application of a particular analysis technique which can be used to characterise the asymptotic behaviour of a number of dynamic processes related to the web.

## 1 Introduction

In recent years the world wide web has grown dramatically. Its current size is measured in billions of pages [20], and pages are added to it every day. As this graph (nodes correspond to web pages

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and edges to links between pages) continues to grow it becomes increasingly important to study mathematical models which capture its structural properties [6, 19]. Such models can be used to design efficient algorithms for web applications and may even uncover unforeseen properties of this huge evolving structure. Several mathematical models for analysing the web have been proposed (for instance [5, 9, 19]). The (evolution of the) web graph is usually modelled by a (random) process in which new vertices appear from time to time. Such vertices may be linked randomly to the existing structure through some form of *preferential attachment*: existing vertices with many neighbours are somewhat more likely to be linked to the newcomers.

The main focus of research so far has been on capturing empirically observed [3, 6] features of the web. No attempt has been made to characterise graph-theoretic sub-structures of such graphs. We initiate such investigation by looking at sets of vertices that, in a sense, cover all other vertices. More formally, a vertex in a graph *dominates* all vertices that are adjacent to it (parallel edges give multiple domination). In the spirit of Harary and Haynes [14], an *h-dominating set* for a graph  $G = (V, E)$  is a set  $\mathcal{S} \subseteq V$  such that each vertex in  $V \setminus \mathcal{S}$  is dominated at least  $h$  times by vertices in  $\mathcal{S}$ . Let  $\gamma_h = \gamma_h(G)$  denote the size of the smallest  $h$ -dominating sets in  $G$ . The *minimum h-dominating set* problem (MhDS) asks for an  $h$ -dominating set of size  $\gamma_h$ .

Dominating sets play an important role in many practical applications, e.g. in the context of distributed computing or mobile ad-hoc networks [2, 10, 22]. The reader is referred to [15, 16] for an in-depth view of the subject. The typical fundamental task in such applications is to select a subset of nodes in the network that will 'provide' a certain service to all other vertices. For this to be time-efficient, all other vertices must be directly connected to the selected nodes, and in order for it to be cost-effective, the number of selected nodes must be minimal. In relation to web graphs, a dominating set may be used to devise efficient web searches. For  $h > 1$  an  $h$ -dominating set can be considered as a more fault-tolerant structure. If up to  $h - 1$  vertices or edges fail, the domination property is still maintained (i.e. it is still possible to provide the service).

The MhDS problem is NP-hard [13, 18] and, moreover, it is not likely that it may be approximated effectively [12, 18]. Polynomial time algorithms exist on special classes of graphs (e.g. [21]). The M1DS problem has been studied also in random graphs. In the *binomial model*  $G(n, p)$  [24] the value of  $\gamma_1$  can be pin-pointed quite precisely, provided  $p$  is not too small compared to  $n$ . In random regular graphs of degree  $r$  (see for example results in the *configuration model* [26] and references therein) upper and lower bounds are known on  $\gamma_1$ .

In this paper we look at simple and efficient algorithms for building small  $h$ -dominating sets in graphs. The performance guarantees of these algorithms are analysed under the assumption that the input is a random web graph. We also analyse the tightness of the performances of such algorithms, by proving combinatorial lower bounds on  $\gamma_h$ , for any fixed  $h \geq 1$ . Such bounds, often disappointingly weak, offer nevertheless a proof that, most of the times, the sets returned by the various algorithms are only a constant factor away from an optimal answer. Finally, we compare the quality of the solutions returned by (some of) our algorithms with empirical average values of  $\gamma_1$ .

The main outcome of this paper can be stated informally by saying that web graphs have fairly large dominating sets. Hence a crawler who wants to use a dominating set to explore the web will need to store a large proportion of the whole graph. Interestingly, the results in this paper

also uncover a(nother) difference between models of the web based on preferential attachment and more traditional random graph models. The tendency to choose neighbours of high degree affects the size of the smallest dominating sets.

Most of our algorithms are *on-line* in the sense that the decision to add a particular vertex to the dominating set is taken without total information about the web graph under consideration, and *greedy* in the sense that decisions, once taken, are never changed. The algorithms are also quite efficient: only a constant amount of time is used per update of the dominating set. Such algorithms are of particular interest in the context of web graphs. As the web graph is evolving, one wants to decide whether a new vertex is to be added to the already existing dominating set without recomputing the existing dominating set and with minimal computational effort. On-line strategies for the dominating set problem have been considered in the past [11, 17] for general graphs. However the authors are not aware of any result on on-line algorithms for this problem in random graphs.

Our results hold *asymptotically almost surely* (a.a.s.), i.e. with probability approaching one as the size of the web graph grows to infinity. The algorithmic results are based on the analysis of a number of (Markovian) random processes. In each case the properties of the process under consideration lead to the definition of a (deterministic) continuous function that is very close (in probability) to the values of the process, as the size of the graph grows. It should be pointed out at this stage that the proposed analysis methodology is quite general. We apply it to analyse heuristics for the  $MhDS$  problem only, but it would allow to prove results about other graphs parameters such as the independence or the chromatic number. The method is closely related to the so called *differential equation method* [25]. In fact a version of the main analytical tool proposed by Wormald can be adapted to work for the processes considered in this paper. However the machinery employed in [25] is not needed to analyse the processes considered in this paper. Our results are obtained by proving concentration of the various processes of interest around their mean and by devising a method for getting close estimates on the relevant expectations. In Section 2 we review the definitions of the models of web graphs that we will use. We also state our main result in the context of these models, and present more detailed comments on our general analysis method. In the following section we consider a very simple algorithm and apply the proposed method to obtain non-trivial upper bounds on  $\gamma_1$ . Refined algorithms are introduced and analysed in Section 4 and 5. In Section 6 we discuss generalisations to  $h > 1$ . Then we turn to lower bounds. In Section 7 and 8 we present our argument for the lower bounds stated in Section 2. Finally we briefly comment on some empirical work carried out on a sub-class of the graphs considered in this paper.

## 2 Models and Results

The models used in this paper are based on the work of Albert and Barabasi [3]. A *web graph* (see also [9]) can be defined as an ever growing structure in which, at each step, new vertices, new edges or a combination of these can be added. Decisions on what to add to the existing graph are made at random based on the values of a number of defining parameters. The existence of these parameters makes the model very general. For the purposes of this paper, to avoid cluttering the

Table 1: Numerical bounds for the minimum dominating set problem.

$m$	$\alpha_{\text{lo}}^R$	$\alpha_{\text{up}}^R$	$\alpha_{\text{lo}}^C$	$\alpha_{\text{up}}^C$
1	0.3678	0.5	0.2939	0.3333
2	0.1868	0.3714	0.0286	0.2342
3	0.1488	0.3054	0.0148	0.1777
4	0.1259	0.2634	0.0097	0.1422
5	0.1102	0.2335	0.0066	0.1178
6	0.0987	0.2110	0.0049	0.1000
7	0.0898	0.1932	0.0038	0.0865

description of our results, we prefer to make a drastic simplification. We will consider graphs generated according to two rather extreme procedures derived from the general model. In each case the generation process is governed by a single integer parameter  $m$ . The second of these mimics the preferential attachment phenomenon. The first one, related to more traditional random graph models, is considered mainly for comparison.

**uar graph process.** The initial graph  $G_0^{R,m}$  is a single vertex  $v_0$  with  $m$  loops attached to it. For  $t \geq 1$ , let  $G_{t-1}^{R,m}$  be the graph generated in the first  $t - 1$  steps of this process, to define  $G_t^{R,m}$  a new vertex  $v_t$  is generated, and it is connected to  $G_{t-1}^{R,m}$  through  $m$  (undirected) edges. The neighbours of  $v_t$  are chosen uniformly at random (uar) with replacement from  $\{v_0, \dots, v_{t-1}\}$ .

**Pure copy graph process.** The initial graph  $G_0^{C,m}$  is a single vertex  $v_0$  with  $m$  loops attached to it. For  $t \geq 1$ , graph  $G_t^{C,m}$  is defined from  $G_{t-1}^{C,m}$  by generating a new vertex  $v_t$ , and connecting it to  $G_{t-1}^{C,m}$  through  $m$  (undirected) edges. A vertex  $u \in \{v_0, \dots, v_{t-1}\}$  is connected to  $v_t$  with probability  $\frac{|\Gamma(u)|}{2mt}$  (where  $\Gamma(u) = \{w : \{u, w\} \in E(G_{t-1}^{C,m})\}$ ).

We will often refer to the uar graph process as a random graph process. The edges have an intrinsic direction which we ignore.

Both models are dynamic, with new vertices and edges continuously increasing the size of the graph. However they represent two extreme cases. In the uar graph process the terminal vertex of an edge is chosen randomly from the set of available vertices, whereas in the copy model the terminal vertex of an edge is chosen proportional to the current degree of the various vertices.

Let  $M \in \{R, C\}$ , and  $m$  be a positive integer. The results in this paper can be summarised by saying that for each  $h \geq 1$  there exist positive real constants  $\alpha_{\text{lo}}^M$  and  $\alpha_{\text{up}}^M$  (dependent on  $M$ ,  $m$  and  $h$  but independent of  $t$ ) with  $\alpha_{\text{lo}}^M < \alpha_{\text{up}}^M < 1$  such that  $\alpha_{\text{lo}}^M \cdot t \leq \gamma_h(G_t^{M,m}) \leq \alpha_{\text{up}}^M \cdot t$  a.a.s. For  $h = 1$ , the values of the aforementioned constants are reported in Table 1. Bounds for  $h > 1$  are reported (and briefly commented) in Section 6. In particular the upper bounds are proved by analysing the size of the dominating set returned by a number of simple polynomial time algorithms, whereas the lower bounds come from combinatorial arguments.

The proof of the algorithmic results are based on the fact that natural edge-exposure martingales can be defined on the graph processes under consideration [9]. More precisely, if  $f(G)$  is any graph theoretic function (e.g. the size of the dominating set returned by a particular algorithm), the random process defined by setting  $Z_0 = \mathbf{E}(f(G_t^{M,m}))$ , and  $Z_i$  (for  $i \in \{1, \dots, mt\}$ ) to be the expectation of  $f(G_t^{M,m})$  conditioned on the “exposure” of the first  $i$  edges in the graph process is a martingale. Notice that the space of all graphs which can be generated according to the given model  $G_t^{M,m}$  is partitioned into classes (or  $i$ -blocks) containing all those graphs which coincide w.r.t. the first  $i$  edge exposures.

In the forthcoming sections we will repeatedly use the following concentration result (for a proof see, for instance, [1]).

**Theorem 2.1** *Let  $c = Z_0, \dots, Z_n$  be a martingale with  $|Z_{i+1} - Z_i| \leq 1$  for all  $i \in \{0, \dots, n-1\}$ . Then  $\Pr[|Z_n - c| > \lambda\sqrt{n}] \leq 2e^{-\lambda^2/2}$ .*

In all our applications  $c = \mathbf{E}(f(G_t^{M,m}))$ ,  $n = mt$  and  $\lambda = O(\log t)$ . In order to apply Theorem 2.1 one needs to prove that  $|Z_{i+1} - Z_i| \leq 1$ . Such inequality follows from the smoothness of  $f$  (i.e.  $|f(G) - f(H)| \leq 1$  if  $G$  and  $H$  differ w.r.t. the presence of a single edge) and the ability to demonstrate the existence of a measure preserving bijection between  $i+1$ -blocks in a same  $i$ -block. This is obvious in the random graph process as edges are inserted independently. In the case of the copy model it is convenient to identify each graph with the projection of a particular type of *configuration*, i.e. an ordered collection of  $mt$  labelled pairs of points (see [4]). Let  $C_1$  and  $C_2$  be two such configurations that are identical up to the  $i$ th pair. Suppose the  $i+1$ -st pair is  $\{a, b\}$  in  $C_1$  and  $\{a, c\}$  in  $C_2$ . If  $C_1$  never uses point  $b$  again then the image of  $C_1$  under the measure preserving bijection will be a configuration  $C'$  identical to  $C_1$  except that pair  $\{a, b\}$  is replaced by pair  $\{a, c\}$ . If  $b$  is used in a following pair (say  $\{d, b\}$ ) of  $C_1$  then  $C'$  will have  $\{a, c\}$  instead of  $\{a, b\}$  and  $\{d, c\}$  instead of  $\{d, b\}$ , and so on. Similar construction is presented in [9]. Finally we will need the following

**Lemma 1** *If  $Z_n$  is a martingale and there exist constants  $c_1, c_2 > 0$  such that  $\mu_n = \mathbf{E}(Z_n) \in [c_1 n, c_2 n]$ , then for each fixed integer  $j > 0$ , there exists positive constant  $K$  and  $\epsilon$  such that  $|(Z_n)^j - (\mu_n)^j| \leq Kn^{j-\epsilon}$  a.a.s..*

**Proof.** If  $Z_n$  is a martingale, then by Theorem 2.1,  $\mu_n - \lambda\sqrt{n} \leq Z_n \leq \mu_n + \lambda\sqrt{n}$  where w.l.o.g. we assume  $\lambda = o(\sqrt{n})$ . From this we also have, for each fixed integer  $j > 0$ ,

$$(\mu_n)^j \left(1 - \frac{\lambda\sqrt{n}}{\mu_n}\right)^j \leq (Z_n)^j \leq (\mu_n)^j \left(1 + \frac{\lambda\sqrt{n}}{\mu_n}\right)^j.$$

The result now follows (provided  $K$  is chosen big enough) since, the assumptions on  $\lambda$  and  $\mu_n$  entail that  $\left(1 + \frac{\lambda\sqrt{n}}{\mu_n}\right)^j$  is at most  $1 + \frac{j^2\lambda\sqrt{n}}{\mu_n}$ , whereas  $\left(1 - \frac{\lambda\sqrt{n}}{\mu_n}\right)^j$  is at least  $1 - \frac{2j\lambda\sqrt{n}}{\mu_n}$   $\square$

### 3 Simplest algorithm

The algorithm presented in this section is a very simple “first attempt” solution for the problem at hand. Although in many cases it does not lead to a very small dominating set, it represents a natural benchmark for any more refined heuristic.

**Algorithm 1.** Before the first step of the algorithm the graph consists of a single vertex  $v_0$  and  $\mathcal{S} = \{v_0\}$ . At step  $t$  if the newly generated vertex  $v_t$  does not have any neighbours in  $\mathcal{S}$  (i.e.  $\Gamma(v_t) \cap \mathcal{S} = \emptyset$ ) then  $v_t$  is added to  $\mathcal{S}$ .

In the forthcoming discussion  $m$  is a fixed positive integer. Let  $X_t$  denote the size of the dominating set  $\mathcal{S}$  computed by Algorithm 1 before  $v_t$  is added to the current graph and let  $\mu_t = \mathbf{E}(X_t)$ . For graphs generated according to the  $G_t^{R,m}$  model, the probability that  $v_t$  misses the dominating set is  $(1 - \frac{X_t}{t})^m$ . Hence we can write

$$\mu_{t+1} = \mu_t + \mathbf{E} \left[ \left(1 - \frac{X_t}{t}\right)^m \right].$$

Let  $x = x(m)$  be the unique solution of the equation  $x = (1 - x)^m$  in  $(0, 1)$ . Table 2 gives the values of  $x$  for the first few values of  $m$ .

**Lemma 2** For any  $\frac{1}{2} < \rho < 1$  constant, there exists an absolute positive constant  $C$  such that for all  $t > 0$ ,  $|\mu_t - xt| \leq Ct^\rho$  a.a.s.

**Proof.** We claim that the difference  $|\mu_t - xt|$  satisfies a recurrence of the form

$$|\mu_{t+1} - x(t+1)| \leq |\mu_t - xt| + O\left(\sqrt{\frac{\log t}{t}}\right).$$

This can be proved by induction on  $t$ . By definition  $X_1 = 1$ , hence  $|\mu_1 - x| = 1 - x$ . We also have  $|\mu_{t+1} - x(t+1)| = |\mu_t - xt + \mathbf{E}[(1 - \frac{X_t}{t})^m] - (1 - x)^m|$ . The difference  $\mathbf{E}[(1 - \frac{X_t}{t})^m] - (1 - x)^m$  can be rewritten as  $-\frac{m}{t}(\mu_t - xt) + \{\mathbf{E}[(1 - \frac{X_t}{t})^m] - 1 + m\frac{\mu_t}{t} - (1 - x)^m + 1 - mx\}$ . Hence  $|\mu_{t+1} - x(t+1)| = |(1 - \frac{m}{t})(\mu_t - xt) + \{\mathbf{E}[(1 - \frac{X_t}{t})^m] - 1 + m\frac{\mu_t}{t} - (1 - x)^m + 1 - mx\}|$ .

To complete the proof notice that, by Lemma 1,

$$\mathbf{E}[(1 - \frac{X_t}{t})^m] - 1 + m\frac{\mu_t}{t} = (1 - \frac{\mu_t}{t})^m - 1 + m\frac{\mu_t}{t} + O(\sqrt{\frac{\log t}{t}}).$$

and the function  $f(z) = (1 - z)^m - 1 + mz$  satisfies  $|f(z_1) - f(z_2)| \leq m|z_1 - z_2|$ , for  $z_1, z_2 \in [0, 1]$ .  $\square$

The following Theorem is a direct consequence of Lemma 2 and the concentration result mentioned in the previous section.

**Theorem 3.1**  $X_t \sim xt$  a.a.s.

Table 2: Numerical values defined in Lemma 2.

$m$	$x$
1	0.5
2	0.382
3	0.3177
4	0.2755
5	0.2451
6	0.2219
7	0.2035

## 4 Improved approximations in the random graph process

Although Algorithm 1 is quite simple, it seems difficult to beat, as a glance at  $\alpha_{\text{up}}^R$  in Table 1 and 2 shows. This is especially true for  $m = 1$  where no improvement could be obtained. For larger values of  $m$ , a better way of finding small dominating sets is obtained by occasionally allowing vertices to be dropped from  $\mathcal{S}$ . It is convenient to classify the vertices in the dominating set as *permanent* (set  $\mathcal{P}$ ) and *replaceable* (set  $\mathcal{R}$ ). Thus  $\mathcal{S} = \mathcal{P} \cup \mathcal{R}$ . Let  $P_t$  and  $R_t$  denote the sizes of such sets at time  $t$  (set  $P_1 = 0$  and  $R_1 = 1$ ).

**Algorithm 2.** Before the first step of the algorithm the graph consists of a single vertex  $v_0$  and  $\mathcal{R} = \{v_0\}$ . After  $v_t$  is created and connected to  $m$  neighbours, if  $\Gamma(v_t) \cap \mathcal{P} \neq \emptyset$  then  $v_t$  is moved to  $V \setminus \mathcal{S}$ . Otherwise  $v_t$  is added to  $\mathcal{R}$  if  $\Gamma(v_t) \cap \mathcal{R} = \emptyset$ , otherwise  $v_t$  is added to  $\mathcal{P}$  and all vertices in  $\Gamma(v_t) \cap \mathcal{R}$  are moved to  $V \setminus \mathcal{S}$ .

The expectations  $\pi_t = \mathbf{E}(P_t)$  and  $\rho_t = \mathbf{E}(R_t)$  satisfy:

$$\begin{aligned}\pi_{t+1} &= \pi_t + \mathbf{E} \left[ \left(1 - \frac{P_t}{t}\right)^m \right] - \mathbf{E} \left[ \left(1 - \frac{P_t}{t} - \frac{R_t}{t}\right)^m \right], \\ \rho_{t+1} &= \rho_t + \mathbf{E} \left[ \left(1 - \frac{R_t}{t} - \frac{P_t}{t}\right)^m \right] - m \mathbf{E} \left[ \frac{R_t}{t} \left(1 - \frac{P_t}{t}\right)^{m-1} \right].\end{aligned}$$

Define  $\alpha_{\text{up}}^R$  as  $p + r$ , where  $p = p(m)$  and  $r = r(m)$  satisfy

$$\begin{aligned}r &= \frac{(1-p)^{m-p}}{1+m(1-p)^{m-1}}, \\ p &= (1-p)^m - (1-p-r)^m.\end{aligned}$$

**Lemma 3** For any  $\frac{1}{2} < \rho < 1$  constant, there exist absolute positive constants  $C_1$  and  $C_2$  such that for all  $t > 0$ ,  $|\pi_t - pt| \leq C_1 t^\rho$  and  $|\rho_t - rt| \leq C_2 t^\rho$  a.a.s.

**Proof.** The proof is, essentially, a generalisation of that of Lemma 2. We present the argument in some details for  $\pi_t$ . At the inductive step:

$$|\pi_{t+1} - p(t+1)| = |\pi_t - pt + \mathbf{E} \left[ \left(1 - \frac{P_t}{t}\right)^m \right] - (1-p)^m - \{ \mathbf{E} \left[ \left(1 - \frac{P_t}{t} + \frac{R_t}{t}\right)^m \right] - (1-p-r)^m \}|.$$

The proof is completed by decomposing the differences  $\mathbf{E} \left[ \left(1 - \frac{P_t}{t}\right)^m \right] - (1-p)^m$  and  $\mathbf{E} \left[ \left(1 - \frac{P_t}{t} - \frac{R_t}{t}\right)^m \right] - (1-p-r)^m$  in parts that are proportional to either  $P_t - \pi_t$  or  $\pi_t - pt$ .

The result about  $\rho_t$  is proved similarly after noticing that  $r$  satisfies:

$$r = (1-p-r)^m - mr(1-p)^{m-1}.$$

□

Let  $X_t^2$  denote the size of the dominating set returned by Algorithm 2 when run on a random graph process until time  $t$ .

**Theorem 4.1**  $X_t^2 \sim (p+r)t$ , a.a.s.

**Proof.** Theorem 2.1 implies that the sum  $p+r$  is a.a.s. very close to  $\frac{|S|}{t} = \frac{P_t}{t} + \frac{R_t}{t}$ . The result follows. □

The values of  $p+r$  for  $m \leq 7$  are reported in the column labelled  $\alpha_{\text{up}}^R$  of Table 1.

## 5 Improved approximations in the pure copy process

Algorithm 1, described in Section 3, can be analysed in the copy model as well. The expected change in the variable  $X_t$  can be computed by keeping track of the total degree of the dominating set,  $D_t$ . In particular the following relationships hold

$$\mathbf{E}(X_{t+1}) = \mathbf{E}(X_t) + \mathbf{E}\left[\left(1 - \frac{D_t}{2mt}\right)^m\right],$$

$$\mathbf{E}(D_{t+1}) = \left(1 + \frac{1}{2t}\right)\mathbf{E}(D_t) + m\mathbf{E}\left[\left(1 - \frac{D_t}{2mt}\right)^m\right].$$

Not surprisingly an analysis similar to the one described in the previous sections implies that such algorithm returns dominating sets of size  $xt$  in  $G_t^{C,m}$ . However, in the copy model we can improve on this by pushing high degree vertices in the dominating set. The natural way to accomplish this would be, for any newly generated uncovered vertex, to select a neighbour of maximum degree and add it to  $\mathcal{S}$ . Unfortunately such algorithm is not easy to analyse because in the graph processes that we consider there may be few vertices of rather large degree (this is a consequence of the power law distribution of vertex degrees [3, 8]). However a draconian version of this heuristic can be analysed. The following algorithm takes as input an additional integer parameter  $k > 0$ .

**Algorithm 3.** Before the first step of the algorithm the graph consists of a single isolated vertex  $v_0$  and  $\mathcal{S} = \{v_0\}$ . After  $v_t$  is created and connected to  $m$  neighbours, let  $Z$  be the set of all neighbours of  $v_t$  in  $V \setminus \mathcal{S}$  of degree  $km + 1$ . If  $Z \neq \emptyset$  then all vertices in  $Z$  are added to  $\mathcal{S}$ . Otherwise if  $v_t$  is not dominated by some element of  $\mathcal{S}$  then a vertex of maximum degree in  $\Gamma(v_t)$  is added to the dominating set.

Notice that after each  $v_t$  is generated and connected to  $G_{t-1}^{C,m}$ , all vertices whose degree has become larger than  $km$  are moved inside  $\mathcal{S}$ . The analysis of the evolution of  $|\mathcal{S}|$  is based again on the definition of a random process that describes the algorithm dynamics and on the proof that such process behaves in a predictable way for large  $t$ .

Let  $n = (k-1)m + 1$ . For each  $i \in \{0, \dots, n-1\}$  and  $t > 0$ , define  $Y_t^i = |V_{m+i} \setminus \mathcal{S}|$  in  $G_{t-1}^{C,m}$  ( $V_i$  is the set of vertices of degree  $i$ ) before  $v_t$  is added to the graph. Let  $Y_t^n$  denote the total degree inside  $\mathcal{S}$  (i.e.  $Y_t^n = \sum_{v \in \mathcal{S}} |\Gamma(v)|$ ) and  $X_t$  the size of the dominating set before  $v_t$  is added to the graph. The state of the system, at each step  $t$ , is modelled by the (random) vector  $(Y_t^0, \dots, Y_t^n, X_t)$ . Notice that, for each  $t > 0$ , the variation in each of the variables is at most  $m$ . Also,  $Y_t^n + \sum_{i=0}^{(k-1)m} (m+i)Y_t^i = 2mt$ , and, at each step  $t \geq 1$ , when  $v_t$  is created the probability that it hits a vertex of degree  $m+i$ , for  $i \in \{0, \dots, (k-1)m\}$  (resp. the dominating set) in any one of the  $m$  trials available to it is approximately (omitting  $o(1)$  factors, for  $t$  large) equal to  $P_i = \frac{((m+i-1)(1-\delta_{i,n})+1)Y_t^i}{2mt}$  (where  $\delta_{i,n} = 1$  if  $i = n$  and zero otherwise).

For  $d \in \{0, \dots, n-1\}$  (resp.  $d = n$ ), let  $E_d$  denote the event “ $v_t$  missed  $\mathcal{S}$  and the maximum degree in  $\Gamma(v_t)$  is  $m+d$ ” (resp. “ $v_t$  did not miss  $\mathcal{S}$ ”). The expected change to  $Y_t^i$ , conditioned to the process history up to time  $t$  can be computed by further conditioning on the family of events  $(E_d)_{d \in \{0, \dots, n\}}$ . We can write such quantity as

$$\sum_{d=0}^n \mathbf{E}(Y_{t+1}^i - Y_t^i \mid E_d) \mathbf{Pr}[E_d].$$



For  $t$  large, the probability in the expression above is approximately  $\chi_d = (S_0^d)^m - (S_0^{d-1})^m$  (notation  $S_a^b$  stands for  $P_a + \dots + P_b$ , with  $S_a^b \equiv 0$  if  $a > b$ ). Furthermore, we can approximate  $\mathbf{E}(Y_{t+1}^i - Y_t^i | E_d)$  by the expression:

$$\sum C(h_0, \dots, h_d, 0, \dots, 0) \frac{m!}{h_0! h_1! \dots h_d!} \prod_{i=0}^d P_i^{h_i} \frac{1}{\chi_d}$$

where  $C$  has  $n+1$  arguments, the righthmost  $n-d$  of which are zero, the sum is over all possible ordered tuples of values  $h_0, \dots, h_d$  such that  $\sum_{i=0}^d h_i = m$  and  $h_d > 0$ , and  $C(h_0, \dots, h_d, 0, \dots, 0)$  contains:

- a term for the addition of  $v_t$  to  $G_{t-1}^{C,m}$ ;
- a term  $\phi_{i,d}$  for the change to  $Y_t^i$  due to the handling of the chosen vertex of maximum degree  $m+d$  in  $\Gamma(v_t)$  (for  $d=n$  this is just one of the vertices hitting  $\mathcal{S}$ ), and
- a term  $\psi_{i,s}$  for the change to  $Y_t^i$  due to the handling of a vertex accounted for by  $Y_t^s$  in  $\Gamma(v_t)$ , for  $s \leq d$ .

The first of these is simply  $\delta_{i,0}$ . We also have

$$\phi_{i,d} = \delta_{d,n} \times \delta_{i,d} + (1 - \delta_{d,n}) \times \{(m+d+1)\delta_{i,n} - \delta_{i,d}\}$$

(if  $d=n$  (i.e. if  $v_t$  hits the dominating set) then one is added to  $Y_t^n$ , otherwise  $Y_t^d$  is decreased and  $m+d+1$  units are added to  $Y_t^n$ ), and

$$\psi_{i,s} = \delta_{s,n} \times \delta_{i,s} + (1 - \delta_{s,n}) \times \{((m+s)\delta_{i,s-1} + 1)\delta_{i,s+1} - \delta_{i,s}\}$$

(if  $s=n$  then  $Y_t^n$  is increased by one, if  $s=n-1$  the newly created vertex of degree  $n$  must be added to  $\mathcal{S}$ , and finally, in any other case the vertex that has been hit is moved from  $V_{m+s}$  to  $V_{m+s+1}$ ). Therefore

$$C(h_0, \dots, h_d, 0, \dots, 0) = \delta_{i,0} + \phi_{i,d} + (h_d - 1)\psi_{i,d} + \sum_{s=0}^{d-1} h_s \psi_{i,s}.$$

Doing all the sums, for each  $i \in \{0, \dots, n\}$ , the expected change to  $Y_t^i$  is approximately equal to

$$\delta_{i,0} + \sum_{d=0}^n \left\{ \chi_d \phi_{i,d} + \psi_{i,d} \left[ m P_d(S_0^d)^{m-1} - \chi_d \right] + \frac{m[\chi_d - P_d(S_0^d)^{m-1}]}{S_0^{d-1}} \sum_{s=0}^{d-1} \psi_{i,s} P_s \right\}.$$

Also  $\mathbf{E}(X_{t+1} - X_t)$  is approximately equal to

$$\frac{km \mathbf{E}(Y_t^{n-1})}{2t} + \mathbf{E} \left[ \left( 1 - \frac{Y_t^n}{2mt} - \frac{kY_t^{n-1}}{2t} \right)^m \right].$$

For each positive integer  $m$ , let  $x$  be the value  $km y^{n-1} + (1 - \frac{y^n}{2m} - \frac{ky^{n-1}}{2})^m$  where  $y^i$ , for  $i \in \{0, \dots, n\}$  satisfy  $y^i = \left[ \mathbf{E}(Y_{t+1}^i) - \mathbf{E}(Y_t^i) \right] |_{Y^i=y^i, i \in \{0, \dots, n\}}$  and the parameter  $k$  can be chosen arbitrarily (larger values of  $k$  give slightly smaller values of  $x$ ). The main result about Algorithm 3 is the following theorem whose proof is a consequence of the argument above and Theorem 2.1.

**Theorem 5.1**  $X_t \sim xt$ , *a.a.s.*

For each  $m \leq 7$  values of  $k \leq 20$  give the values of  $x$  reported in Table 1 in the column labelled  $\alpha_{\text{up}}^C$ .

Table 3: Upper bounds on  $\gamma_h/t$ , for  $h > 1$ .

$m$	$h = 2$	$h = 3$	$h = 4$	$h = 5$	$m$	$h = 2$	$h = 3$	$h = 4$	$h = 5$
2	0.4484				2	0.5			
3	0.368	0.3836			3	0.4075	0.6		
4	0.3162	0.3307	0.332		4	0.3359	0.4852	0.6663	
5	0.2795	0.2929	0.2944	0.2931	5	0.282	0.4073	0.5423	0.7036
6	0.2517	0.2641	0.2658	0.2647	6	0.2428	0.3523	0.4613	0.5862
7	0.2298	0.2413	0.2431	0.2422	7	0.2132	0.3066	0.4035	0.5056

Algorithm 4.

Algorithm 5.

## 6 Generalisations

The algorithms presented in the previous sections generalise naturally to larger values of  $h$ . We present here the generalisation of Algorithm 2 for finding an  $h$ -dominating set in the random graph process and of Algorithm 3 for the pure copy process. We then briefly sketch the analysis of the first heuristic, and comment on the numerical results presented in Table 3.

**Algorithm 4.** A vertex in the  $h$ -dominating set can be either *permanent* (set  $\mathcal{P}$ ) as it will never be removed from the set or  *$i$ -removable* (set  $\mathcal{R}_i$ ) meaning that it is dominated  $i \in \{0, \dots, h-1\}$  times by other permanent vertices.

Before the first step of the algorithm the graph consists of a single vertex  $v_0$  and  $\mathcal{R}_0 = \{v_0\}$ . After  $v_t$  is created and connected to  $m$  neighbours,  $v_t$  is added to  $\mathcal{R}_0$  if  $\Gamma(v_t) \cap (\mathcal{P} \cup \cup_i \mathcal{R}_i) = \emptyset$ , otherwise if  $\Gamma(v_t) \cap \mathcal{P} = \emptyset$ ,  $v_t$  is added to  $\mathcal{P}$ , any vertex in  $\Gamma(v_t) \cap \mathcal{R}_i$ , for  $i < h-1$  is moved to  $\mathcal{R}_{i+1}$  and any vertex in  $\Gamma(v_t) \cap \mathcal{R}_{h-1}$  is moved to  $V \setminus \mathcal{S}$ .

The process in Algorithm 4 can be modelled by  $h$  sequences of random variables:  $R_t^i$  for  $i \in \{0, \dots, h-1\}$  with  $R_t^i = |\mathcal{R}_i|$  in the graph  $G_{t-1}^{R_t, m}$  just before  $v_t$  is added to it, and  $P_t = |\mathcal{P}|$ . The expected changes in these variables satisfy

$$\mathbf{E}(P_{t+1}) = \mathbf{E}(P_t) + \mathbf{E}[(1 - \frac{P_t}{t})^m] - \mathbf{E}[(1 - \frac{P_t}{t} - \sum_i \frac{R_t^i}{t})^m]$$

$$\mathbf{E}(R_{t+1}^i) = \mathbf{E}(R_t^i) + \mathbf{E}[(1 - \frac{P_t}{t} - \sum_i \frac{R_t^i}{t})^m] \delta_{i,0} + m \mathbf{E}[(\frac{R_t^{i-1}}{t}(1 - \delta_{i,0}) - \frac{R_t^i}{t})(1 - \frac{P_t}{t})^{m-1}]$$

therefore, we have  $P_t \sim pt$  where  $p$  satisfies:

$$p = (1-p)^m - \{1 - [(1-p)^m - p][1 - (\frac{m(1-p)^{m-1}}{1+m(1-p)^{m-1}})h] - p\}^m$$

and  $R_t^i \sim r^i t$  where  $r^0 = \frac{(1-p)^m - p}{1+m(1-p)^{m-1}}$ , and  $r^i = \frac{m(1-p)^{m-1}}{1+m(1-p)^{m-1}} r^{i-1}$ . The values reported in Table 3 below are given by  $p + \sum_{i=0}^{h-1} r^i$ .

**Algorithm 5.** Before the first step of the algorithm the graph consists of a single vertex  $v_0$  and  $\mathcal{S} = \{v_0\}$ . After  $v_t$  is created and connected to  $m$  neighbours, the set  $Z$  of all newly generated

Table 4: Lower bounds on  $\gamma_h/t$ , for  $h > 1$ .

$m$	$h = 2$	$h = 3$	$h = 4$	$h = 5$	$m$	$h = 2$	$h = 3$	$h = 4$	$h = 5$
2	0.1317				2	0.0545			
3	0.1001	0.178			3	0.0316	0.0351		
4	0.0687	0.1342	0.1678		4	0.023	0.0333	0.0246	
5	0.0649	0.0935	0.1346	0.1938	5	0.0183	0.0284	0.0302	0.0183
6	0.0535	0.0849	0.1155	0.1573	6	0.0141	0.0233	0.0299	0.0269
7	0.0406	0.0692	0.1033	0.1349	7	0.0113	0.0203	0.0271	0.0283

Random graph.

Pure copy.

vertices of degree more than  $km$  are added to  $\mathcal{S}$ . If  $v_t$  is dominated  $h - x$  times by elements of  $\mathcal{S}$  then the  $x$  vertices of highest degree in  $\Gamma(v_t) \setminus Z$  are added to the dominating set.

## 7 Tightness of the algorithmic results

An interesting and simple argument can be used to complement the algorithmic results presented in the previous sections. The argument is based on the following result.

**Lemma 4** *Let  $\mathcal{S}$  be an  $h$ -dominating set in a graph  $G = (V, E)$ . If the total degree of the vertices in  $\mathcal{S}$  is at least  $d$ , then  $|\mathcal{S}| \geq \sum_{i>i_0} |V_i|$ , where  $i_0$  is the largest index  $i$  for which  $\sum_{j>i} j|V_j| \geq d$ .*

**Proof.** Let  $i_0$  be defined as in the statement of the result. If  $\Delta = \max_{v \in V} |\Gamma(v)|$ , then the set  $V_{i_0} \cup \dots \cup V_\Delta$  is the smallest set of vertices in  $G$  with total degree at least  $d$  (any other vertex in  $G$  would have smaller degree and therefore it would contribute less to the total degree).  $\square$

The total degree of an  $h$ -dominating set in  $G_t^{M,m}$  must be at least  $h(t - |\mathcal{S}|) \geq ht(1 - \alpha_{\text{up}}^M)$ . Hence a lower bound on the size of any dominating set in a web-graph is obtained by using information on the proportional degree sequence.

In the pure copy web graphs Bollobas *et al.* [5] (see also Cooper [8]) proved that  $|V_i| = tn_i + O(\sqrt{t \log t})$  a.a.s. for any  $i \geq m$ , where

$$n_i = \frac{2m(m+1)}{i(i+1)(i+2)}.$$

In the same paper (p. 288) it is possible to find a result about  $G_t^{R,m}$ . In the random graph process, for any  $i \geq m$ ,

$$n_i = \frac{1}{m+1} \left( \frac{m}{m+1} \right)^{i-m}.$$

Again it is possible to prove that  $|V_i|$  is concentrated around  $n_i t$ .

For  $m \geq 2$ , the lower bounds given for  $G_t^{C,m}$  in Table 1 are obtained using Lemma 4 and the approximations above for  $|V_i|$  in each case. Bounds for  $h > 1$  are in Table 4.

For the uar graph process  $G_t^{R,m}$  we can produce better a.a.s. lower bounds using the Markov inequality. The method is explained in Section 7.1 below. For  $m \geq 2$  these are the lower bounds given for  $G_t^{R,m}$  in Table 1.

## 7.1 Existential lower bounds for the uar process

For simplicity we present the argument for  $h = 1$  (i.e. dominating sets) only.

**Lemma 5** *There exists a function  $f(x, y) : \mathbb{R} \rightarrow \mathbb{R}$ , such that, for each positive integer  $m$ , there exists a positive real number  $d = d(m)$ , defined by  $f(m, d) = 1$ , such that a.a.s. there is no dominating set in  $G_t^{R,m}$  of size at most  $dt$ .*

*The values of  $d$  for the first few values of  $m$  are given in the following table:*

$m$	1	2	3	4	5	6	7
$d(m)$	0.26894	0.18683	0.14881	0.12591	0.11027	0.09876	0.08986

**Proof.** In the proof we assume that the  $t$  vertices in  $G_t^{R,m}$  are labelled  $1, 2, \dots, t$ . The argument is as follows:

(i) Let  $\mathcal{S}^* = [s] = \{1, \dots, s\}$ , let  $|\mathcal{S}| = s$ , then

$$\Pr(\mathcal{S} \text{ dom. } \bar{\mathcal{S}}) \leq \Pr(\mathcal{S}^* \text{ dom. } \bar{\mathcal{S}}^*).$$

(ii) For  $s \leq dt$  the expected number of dominating sets of size  $s$  is at most

$$\binom{t}{s} \Pr(\mathcal{S}^* \text{ dom. } \bar{\mathcal{S}}^*) \rightarrow 0.$$

Thus Marvov inequality implies that a.a.s. there is no dominating set  $\mathcal{S}$  of size at most  $dt$ .

**Proof of (i).** We regard the  $m$  out-edges  $(e_1, \dots, e_m)$  of any vertex as labelled and ordered so that all  $t$  vertex graphs  $G$  have the same probability in the uar graph process ie.  $\Pr(G) = 1/((t-1)!)^m$ . (Vertex  $v_0$  has  $m$  loops).

Given a partition  $(\mathcal{S}, \bar{\mathcal{S}})$  of  $[t]$  with  $|\mathcal{S}| = s$ , let  $u$  be the smallest element  $u = v_i \in \bar{\mathcal{S}}$  such that the next vertex  $v = v_{i+1} \in \mathcal{S}$  in the natural ordering  $1, 2, \dots, t$ . If  $u$  does not exist then  $\mathcal{S} = \mathcal{S}^*$ .

We swap  $u, v$  to give the partition  $(\mathcal{S}', \bar{\mathcal{S}}')$  where  $\mathcal{S}' = \mathcal{S} - v + u, \bar{\mathcal{S}}' = \bar{\mathcal{S}} - u + v$ . We prove that

$$\Pr(\mathcal{S} \text{ dom. } \bar{\mathcal{S}}) \leq \Pr(\mathcal{S}' \text{ dom. } \bar{\mathcal{S}}').$$

We do this by showing that for every graph  $G \in \{\mathcal{S} \text{ dom. } \bar{\mathcal{S}}\}$  for which the swap destroys the dominance property, ie.  $G \notin \{\mathcal{S}' \text{ dom. } \bar{\mathcal{S}}'\}$  ( $G$  is good but goes bad on swapping) there is a unique bad graph  $H = H(G)$  ( $H \notin \{\mathcal{S} \text{ dom. } \bar{\mathcal{S}}\}$ ) which becomes good on swapping ( $H \in \{\mathcal{S}' \text{ dom. } \bar{\mathcal{S}}'\}$ ). Thus the set of good graphs is of non-decreasing size (and hence probability) on swapping.

More formally, let  $\mathcal{G}(t) = G_t^{R,m}$  denote the space of uar graph processes after the  $t$ -th vertex has been added. Let  $\mathcal{S}$  be the distinguished set. Let  $gg$  denote the subset of  $\mathcal{G}$  which is good for both  $\mathcal{S}$  and  $\mathcal{S}'$  (ie.  $gg = \{G : \mathcal{S} \text{ dom. } \bar{\mathcal{S}}\} \cap \{G : \mathcal{S}' \text{ dom. } \bar{\mathcal{S}}'\}$ ) and similarly  $gb, bg, bb$ , so that  $gb$  is the set of graphs which are good for  $\mathcal{S}$  but not  $\mathcal{S}'$  etc. Thus  $gg, gb, bg, bb$  is a partition of  $\mathcal{G}$ . We define (below) a one-one map  $\phi : \mathcal{G} \rightarrow \mathcal{G}$  such that  $\phi(gb) \subseteq bg$ . It follows that

$$|\{G : \mathcal{S} \text{ dom. } \overline{\mathcal{S}}\}| = |gg| + |gb| = |gg| + |\phi(gb)| \leq |gg| + |bg| = |\{G : \mathcal{S}' \text{ dom. } \overline{\mathcal{S}}'\}|.$$

With some abuse of notation, we associate  $\text{out}(x)$  the sequence of out-edges of vertex  $x$  with the multi-set of terminal vertices, and similarly for  $\text{in}(x)$  (the sequence of in-edges of  $x$  ordered naturally) with their initial vertices.

*Construction of  $\phi$ .* Let  $[t] = (1, 2, \dots, u-1, u, v, v+1, \dots, t)$  where  $u, v$  are the swap pair. Consider the graph  $G$ .

Let  $i(x) = \text{in}(x) \cap [v+1, \dots, n]$  and  $o(x) = \text{out}(x) = \text{out}(x) \cap [1, \dots, v]$ .

Let  $i'(u) = i(v)$ ,  $i'(v) = i(u)$ .

*Case that there is no edge  $(v, u)$ .* Let  $o'(u) = o(v)$ ,  $o'(v) = o(u)$ .

Construct  $\phi(G) = H(G)$  from  $G$  by replacing  $i(x), o(x)$  by  $i'(x), o'(x)$ ,  $x = u, v$ . The graph  $H$  is uniquely associated with  $G$ , as we can reconstruct  $G$  from  $H$ .

*Case that there are edges  $(v, u)$ .* Let the  $(v, u)$  edges be  $\{e_k, k \in K\}$  where  $K$  indexes their occurrences in  $(e_1, \dots, e_m)$ . Let  $\{f_k\}$  be the out-edges of  $u$  with the same index set.

Let  $o'(u) = o(v) - \{e_k\} + \{f_k\}$ , let  $o'(v) = o(u) + \{e_k\} - \{f_k\}$ .

Thus  $v$  keeps its out edges to  $u$ , and  $u$  keeps its out edges with the same labels.

If there is no  $(v, u)$  edge and  $G \in gb$  then  $H$  was bad but becomes good (ie.  $H \in bg$ ). For, in  $H$ ,  $u$  (now in the dom. set) has the  $v$  edges from  $G$ , and  $v$  (no longer in the dom. set) got the  $u$  edges from  $G$ .

If there is a  $(v, u)$  edge and  $G \in gb$ , then  $u$  dominates  $v$  after the swap, just as  $v$  dominated  $u$  before. The in edges have been swapped over to preserve any dominance which  $v$  made with them (now made by  $u$ ). The edge set  $\{f_k\}$  was not necessary for  $G$  to be good, as  $v$  dominated  $u$  and  $u$  did not dominate anybody. If  $v$  dominated anybody else with  $o(v) - \{e_k\}$  then  $u$  still does it with  $o'(u) = o(v) - \{e_k\} + \{f_k\}$ . Thus  $H$  is good.

**Proof of (ii).** Let  $s = dt$  then

$$\binom{t}{s} \leq \left( \frac{1}{d^d(1-d)^{(1-d)}} \right)^t.$$

and

$$\begin{aligned} \Pr(\mathcal{S}^* \text{ dom. } \overline{\mathcal{S}}^*) &= \prod_{v=s}^{t-1} \left( 1 - \left( 1 - \frac{s}{v} \right)^m \right) \\ &= \exp \sum_s^{t-1} \log \left( 1 - \left( 1 - \frac{s}{v} \right)^m \right) \\ &= \exp(1 + o(1)) \int_{s+1}^t \log \left( 1 - \left( 1 - \frac{s}{v} \right)^m \right) dv \\ &= \exp(1 + o(1)) dt \int_d^1 x^{-2} \log(1 - (1-x)^m) dx. \end{aligned}$$

We compute the largest  $d$  such that

$$\left( \frac{1}{d^d(1-d)^{(1-d)}} \right) \exp d \int_d^1 x^{-2} \log(1 - (1-x)^m) dx < 1,$$

and obtain  $(m, d)$  as given. □

Table 5: Average values obtained over 1000 experiments for each value of  $t$ .

$t$	$\gamma_1(G_{1,t}^R)/t$	$\gamma_1(G_{1,t}^C)/t$
10000	3745.053	2943.157
20000	7489.3	5887.301
30000	11233.68	8829.288
40000	14980.384	11772.175
50000	18725.448	14714.073
...		
100000	37451.20312	29424.216

## 8 Trees

For  $m = 1$  the graph processes under consideration generate a connected graph without cycles. Such structural property can be exploited to obtain improved lower bounds on  $\gamma_1$ . Without loss of generality, any vertex in such graphs that has at least one neighbour  $u \in V_1$  must be part of a minimum size dominating set. The number of such vertices is precisely  $t - |V_1| - |I|$  where  $|I|$  is the number of vertices that have no neighbour in  $V_1$ . The cardinality of  $I$  can be estimated in both models via either a martingale argument similar to those used in previous sections or through the technique exploited in [8] to estimate  $|V_i|$ . The lower bounds in Table 1 for  $m = 1$  come from this argument.

We end this Section reporting on some simple empirical results which help put the mathematical analysis performed so far into context. It is well known [7] that minimum size dominating sets can be found efficiently in trees. We implemented Cockayne et al's algorithm and tested its performance. For different values of  $t$ , we repeatedly ran the two graph processes up to time  $t$ , and then applied the optimal algorithm mentioned above. Table 5 reports the average values we obtained. The least square approximation lines over the full set of data we collected are (coefficients rounded to the sixth decimal place)  $y = 0.374509x - 0.214185$  for the random graph case, and  $y = 0.294294x + 0.32284$  for the pure copy case. These results indicate that our algorithms are able to get better results for graphs generated according to the pure copy process ( $\alpha_{\text{up}}^C = 0.3333$ ) than for graphs generated by the other process ( $\alpha_{\text{up}}^R = 0.5$ ). We leave the finding of improved algorithms especially in the random graph process or indeed better lower bounds in either models as an interesting open problem of this work.

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