# Closed source versus open source in a model of software bug dynamics

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#### Abstract

We introduce a microscopic model of software bug dynamics where users, programmers and maintainers interact through a given program. When the program is written from scratch, the first phase of development is characterized by a fast decline of the number of bugs, followed by a slow phase where most bugs have been fixed, hence, are hard to find. For a given set of parameters, debugging in open source projects is always faster than in closed source projects. Finally, we determine qualitative lowers bounds to quality of Linux programmers.

The importance of reliable software is obvious nowadays, as computers control an growing part of our life. At the same time the complexity of software is ever increasing. A particularly important problem is the management of software projects so as to minimize development cost or release software on time, while ensuring the quality of software. Appropriate methods of programming and team synchronization are designed to avoid errors in the first place [1,2]; on the other hand reliability growth models are used to estimate the expected time to detect or suffer from next failure [3] and to study the evolution of reliability as defects are detected and corrected. These models have to assume a reliability probability distribution and a mechanism of reliability increase when an error is corrected. Here we propose a microscopic model of software bug dynamics which does not rely on any of these assumptions, and which might open the path to microscopic foundations of reliability growth models. In contrast to previous work [4], our model shows that software projects can converge to a bug-free state even with imperfect programmers. In addition, as it has few parameters, it makes it possible to study the influence of each of them on the bug dynamics and convergence to bug-free state.

Our model can also address the issue of open-source [5] versus closed-source soft-ware, which has become quite relevant because of the rise of successful open source project like Linux [6] or Apache [7]. There are broadly speaking two types of open source projects, often called baazar and cathedral, as put by Raymond [8]. Baazar projects such as Linux release new versions as often as possible, while cathe-

dral projects release new versions at a much lower pace; in that respect cathedral projects are similar closed source projects, hence, cathedral open-source projects and closed-source projects have the same dynamics in our model, thus we shall refer to them as closed source, and to baazar projects as open source.

Our model studies the interaction between a program and its users and programmers. More precisely:

- (1) The program is split into L parts  $i=1,\cdots,L$ ; a part can be seen as a basic functionality such as file loading. Each part has M subparts. Subpart j of part i  $(j=1,\cdots,M)$  is either bug free, which is denoted by  $s_{i,j}=0$ , or buggy  $(s_{i,j}=1)$ . At time t, subpart i has  $b_i(t)=\sum_j s_{i,j}(t)$  bugs, and the total number of bugs is  $B(t)=\sum_i b_i(t)$ . Finally, the number of defective parts that have at least one bug is  $D(t)=\sum_i \Theta(b_i(t))$  where  $\Theta(x)=1$  if x>0 and 0 else, is the Heavyside function
- (2) There are  $N_u$  users. Each user is assumed to use one part of the program at each time step, and to report a buggy behaviour with probability equal to

$$P_u = \delta b_i / M, \tag{1}$$

that is, to the fraction of bugs in part i multiplied by a factor that takes into account the average number of subparts used at each time step by the user and her propensity to report bugs.  $P_u$  should be proportional to  $b_i$ : when one loads a file, one never clicks on all the buttons of the file dialogs, nor use all the features of the file dialog, nor all the file formats at the same time. Note that a feature request can be considered as a bug.

- (3) Each bug report only consists of the number of the buggy part, because if file loading fails, the user cannot describe in more details where the program is faulty. The bug list is hence a table indicating which parts are reportedly buggy. The number of reportedly buggy part is R(t).
- (4) There are  $N_p$  programmers. In addition to find bugs according to Eq. (1), each of them tries to correct one bug drawn at random from the list and reviews all the subparts of a given part. This process is assumed to fix a buggy subpart with probability  $\phi$  and break a working subpart with probability  $\beta$ . Mathematically,

$$P_p(s_{i,j} = 1 \to s'_{i,j} = 0) = \phi \tag{2}$$

$$P_p(s_{i,j} = 0 \to s'_{i,j} = 1) = \beta.$$
 (3)

Once a programmer has modified the code, she submits a patch to the maintainer.

(5) The role of the maintainer (who can be the programmer herself) is to determine whether a patch improves the code or not. Here we assume that the maintainer measures the number of bugs in the current code  $d(s_i)$  and in the proposed new version  $d(s_i')$ . The measure is made as follows: if subpart j of feature i is buggy, the maintainer detects it with probability  $\nu$  and is able to

correctly classify a working part with probability  $\omega$ . Then the maintainer accepts the patch if she thinks that it contains less bugs that the current version (d(s',i) < d(s,i)), and removes it from the bug list.

- (6) (a) Open source: all the users use the modified code at time t+1 and report bugs exclusively on the updated code. This assumes that all the users update their software at every release.
  - (b) Closed source: the modified program is made available to the users every T>1 time steps. Between two releases, the users continue to report bugs about the latest release, and the programmers work exclusively on the unreleased code.
- (7) points 2-6 are repeated until the code does not contain any more bugs.

Our model differs from earlier work in two major features: 1) the program is splitted into parts that each contain subparts, which is responsible to the slow decrease of the number of bugs R(t) when M is too large. 2) The feed-back from the fraction of bugs to the rate of bug discovery (Eq (1)) is one of the central assumptions of our model; it is responsible for the possibility of convergence to the bug-free state even with imperfect programmers and maintainer.

In closed source projets, the programmers are faced with a dilemma when a part is reported buggy by a user after it has been already fixed since the last release. Indeed, the users report bugs on the last release, whereas the programmers work on the next one, both diverging with time. The programmers can either ignore bug reports on an already modified part, or modify again the current code. In the latter case, the modification can be systematic, or after verification that the part in the current code is also buggy (according to Eq. 1). Without verification, D(t) is not a monotonically decreasing quantity, as a bug-free part can be partly broken by this process.

#### 1 Results

Figure 1 reports the typical dynamical behaviour of successful projects that start from scratch  $(s_{i,j}=0 \text{ for all } i \text{ and } j)$ : the number of defective parts  $D(t) \propto \exp(-\lambda t)$  for large t, as often assumed in reliability growth models. At a more microscopic level, one can distinguish two phases: in the early easy stage, the users find and report many bugs, keeping  $R(t) \gg N_p$ . The vast majority of bugs are fixed during this phase, where B(t) decreases linearly with time. When  $R(t) N_p$ , a slow regime appears, where  $B(t) \sim \exp(-t/\tau)$ ; in this regime, the average number of bugs per defective part B(t)/D(t) is small and fluctuates around a value that depends on the chosen parameters. This figure already shows that closed source projects are always slower to converge to a bug-free state than open source projects at constant parameters. In addition, ignoring bug reports on already modified code is the best option for closed source projects; this even outperforms open source at

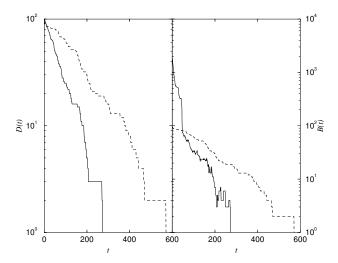


Fig. 1. Number of defective parts (left panel) and number of bugs (right panel) in an open source project (continuous lines), closed source projects with no bug report resubmission allowed between releases (dashed lines)  $L=100,\,M=20,\,N_u=100,\,N_p=10,\,\delta=1,\,\phi=0.9,\,\beta=0.1,\,\omega=0.9,\,\nu=0.9,\,T=1$  for open source and T=50 for closed source.

short time scales, because the programmers only work on fully buggy parts, hence the bug fixing rate is higher. Verification is generally a bad idea when bugs are becoming sparse, because the probability that both a user and a programmer agree that a part is buggy is small, hence verification slows down the process. The global temporal evolution can be characterized by the time to completion, i.e. the time needed to obtain a bug-free project, denoted by  $t_c$ . We shall investigate in particular its average  $\langle t_c \rangle$  over several runs.

In how many parts a program should be divided? Suppose that the project size S is known in advance and fixed to S=LM. What L and M are optimal? Fig. 2 plots  $\langle t_c \rangle$  as a function of M at fixed S=LM for open and closed source. It turns out that there is always an optimal value of M for any set of parameters or project type, whose position depends on all the parameters.

Having better programmers decreases  $\langle t_c \rangle$ , while the abilities of the maintainer has a much less dramatic influence. This is because the abilities of the programmers determine the typical fraction of bugs in a given part that they can fix in one pass, whereas the abilities of the maintainer act as a noise term damped by the bug detection feed-back of Eq. (1).

The average time to completion increases roughly linearly with T (Fig 4), hence, closed source projects are always slower to reach a perfect state. The reason why increasing T penalizes the performance of the project is simple: after each releases, the number of relevant bug reports comming from the users falls rapidly to zero, and the programmers are left on their own, hence the fast and the slow regimes alternate.

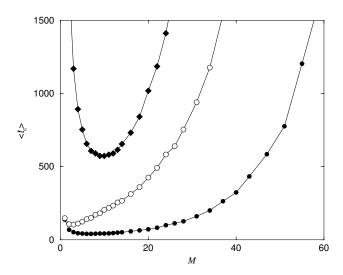


Fig. 2. Average time to completion  $\langle t_c \rangle$  as a function of the number of subpart per part M at constant size LM=1000 for open source projects (full circles), closed source without bug report resubmission between two releases (empty squares), and closed source with bug report resubmisson (full diamonds).  $N_u=1000, N_p=10, \delta=1, \phi=0.9, \beta=0.1, \omega=0.9, \nu=0.9$ , closed source T=150, average over 100 runs. Continous line are for eye-guidance only.

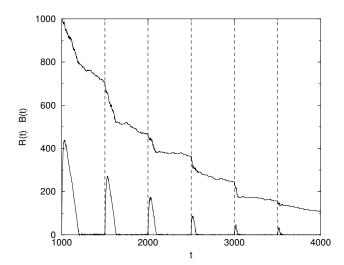


Fig. 3. Dynamics of the number of bugs and bug reports in closed source projects (T=500).  $L=1000,~M=40,~N_u=1000,~N_p=10,~\delta=1,~\phi=0.9,~\beta=0.1,~\omega=0.9,~\nu=0.9$ 

Fig. 5 shows how  $\langle t_c \rangle$  depends on  $N_u$  and  $N_p$ :  $t_c$  is reasonable well fitted by  $c_1 + c_2 N_u^{-\alpha}$  with  $\alpha \sim 1$ : the rate of improvement is slow as  $N_u$  increases; even worse, it reaches a plateau  $c_1$  whose value depends on the number of programmers  $N_p$  and their abilities; the exponent  $\alpha$  also depends on the programmers abilities, but not on their number. Similarly, adding more programmers decreases  $t_c$ . The exponent  $\alpha$  depends on the number of users, but not on the programmers abilities. In other words, hiring more programmers or having more users is an inefficient way of

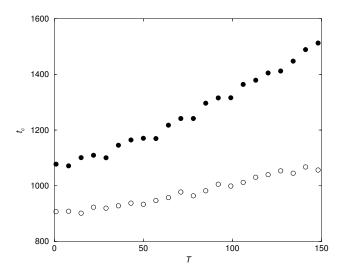


Fig. 4. Average time to completion  $t_c$  as a function of the time between releases T. Full symbols:  $L=1000,\ M=10$ , empty symbols  $L=2000,\ M=5;\ N_u=100,\ N_p=10,$   $\delta=1,\ \phi=0.9,\ \beta=0.1,\ \omega=0.9,\ \nu=0.9$  average over 100 realisations.

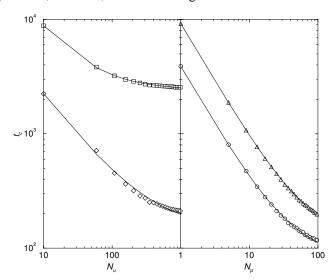


Fig. 5. Average time to completion  $t_c$  versus the number of users (left panel) and the number of programmers (right panel).  $L=1000, M=10, \delta=1, \omega=0.9, \nu=0.9; N_p=10$  (left panel),  $N_u=1000$  (right panel).  $\phi=0.9, \beta=0.1$  (diamonds and circles),  $\phi=0.7, \beta=0.3$  (squares), and  $\phi=0.6, \beta=0.1$  (triangles); average over 100 realisations.

improving the speed of debugging when  $N_u$  or  $N_p$  is large enough.

From our model we conclude that open source projects converge always faster to a bug-free state for the same set of parameters, which is precisely the argument of Ref. [8]. This finding clearly indicates that closed-source projects must have enough programmers, good enough ones, and have enough users in order to achieve the same software quality in the same amount of time. On the other hand, the quality of open source project programmers does not need to be as high as those of close source projects in order to achieve the same rate of convergence to bug-free

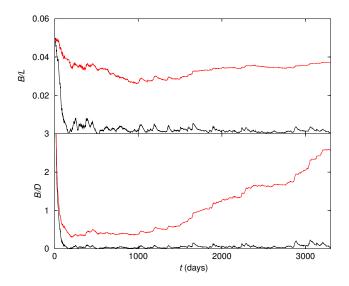


Fig. 6. Average number of bugs per part (upper panel) and per defective part (lower panel) versus time in a reconstructed Linux history.  $M=20,\,N_u=100000,\,\delta=1,\,\phi=0.8,\,\beta=0.1$  (black lines)  $\beta=0.2$  (red lines),  $\omega=0.5,\,\nu=0.5$ 

### programs.

The parameters of our model do not have to be fixed, hence, one can investigate the dynamics of real projects where the size, the number of programmers etc change with time. Linux is an ideal candidate, as it is possible to measure  $N_n(t)$ ,  $N_n(t)$  and S(t). The number of programmer can be obtained from the CREDITS file from kernel 1.0, and seems to obey a linear fit 80 + 0.1d where d is the number of days since Linux 1.0. The number of users is hard to estimate because of the free nature of Linux. The four estimates of Ref [9] can maybe be fitted with with a power law  $N_u(y) \propto [S(y) - 1991]^{3.6}$  where y denotes the year and 1991 is Linux' date of birth. Since  $N_u \gg L$ , one can fix  $N_u$  at 100'000. The size S(t) can be measured in number of lines divided by the typical number of lines in a subpart; it has been fitted with a quadratic function [10]. This super-linear growth is not seen for instance in Mozilla whose size grows linearly, nor in fetchmail which evolves according to  $s_0 + s_1 t^{0.43}$ , and contradict Lehman's laws of software growth [13] (although the latter are about the number of modules and not the software size itself). This leaves the question of how Linux could grow at such a pace without compromising its quality. We can use our model in order to answer this question. The parameters that cannot be determined directly from Linux are obviously the qualities of the programmers and the maintainers  $(\delta, \beta, \phi, \omega)$ , and M. In an attempt to be pessimistic, we considered a random maintainer, that is,  $\phi = \omega = 1/2$  and assumed that a subpart contains 10 lines of code and M=20. The parts of Linux that are added are assumed to be all first completely buggy. Figure 6 shows a transition between two very different behaviours depending on the choice of  $\phi$  and  $\beta$ ): if the programmers abilities are good enough, Linux converges fast to the slow regime, which is stable with respect to sudden increases of the system size, and where the number of bug per part decreases in time (e.g.  $\phi = 0.8$  and  $\beta = 0.1$ ); if the programmers are

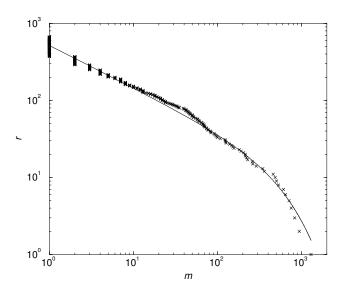


Fig. 7. Number of modifications m per programmer and its rank r for Linux 2.5.5 to 2.5.69. The continuous line is a non-linear fit  $r(m) \sim r^{-0.55} \exp(-C_m x)$ 

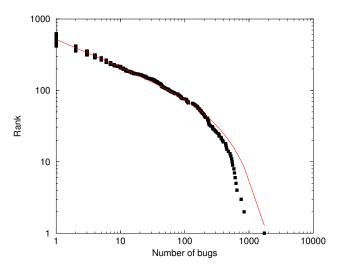


Fig. 8. Number of assigned bugs per programmer b in the Mozilla project and its rank r. The continuous line is a non-linear fit  $r \sim b^{-0.38} \exp(-C_b b)$ 

bad enough, Linux falls into the region where the number of bugs diverges (e.g.  $\phi=0.8,\,\beta=0.2$ ); this happens when Linux 2.3 is introduced. Therefore, rapid software growth can indeed lead to high quality software, even in adverse conditions, provided that the programmers' quality is high enough.

Our model is designed for simplicity and rests on many assumptions. The most important one is that the parts are assumed to be independent, whereas they are linked through a scale-free network [14,15] that is highly asymmetric [15], hence, bugs can propagate on this graph and affect other parts [15]. The next step is therefore to study this model on scale-free networks; it may be possible that the decay of the number of bugs will not be exponential anymore, but a power-laws, as assumed in

some reliability growth models [3]. Power-laws also found in the frequency of use a given a part, as shown by program profiling. The number of modifications per programmer is a truncated power-law (see Fig 7), as is the number of bugs assigned and corrected per programmer (Fig. 8). All these non-uniform distributions may change the dynamics obtained here. Finally, assigning a higher bug fixing priority to the parts that have more bug reports may counteract the emergence of power-laws in the decrease of the number of bugs.

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