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Mining the impact of evolution categories on object-oriented metrics

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Abstract Despite the relevance of the software evolution phase, there are few characterization studies on recurrent evolution growth patterns and on their impact on software properties, such as coupling and cohesion. In this paper, we report a study designed to investigate whether the software evolution categories proposed by Lanza can be used to explain not only the growth of a system in terms of lines of code (LOC), but also in terms of metrics from the Chidamber and Kemerer (CK) object-oriented metrics suite. Our results show that high levels of recall (ranging on average from 52 to 72 %) are achieved when using LOC to predict the evolution of coupling and size. For cohesion, we have achieved smaller recall rates (<27 % on average).

Keywords Software evolution categories · Patterns of evolution · Object-oriented metrics · CK metrics · Evolution matrix

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1 Introduction

As expressed by the Laws of Software Evolution (Lehman et al. 1997), evolution usually contributes to increased software size and complexity and therefore has negative impacts on both internal quality factors (like coupling, cohesion, readability, modularity, and separation of concerns) as well as in external quality factors (like correctness, robustness, and efficiency). However, despite the importance of the evolution phase, there are few studies in the literature aiming to evaluate the main patterns that describe the growth of software systems. This observation contrasts with the amount of work about the patterns of evolution in other research areas. For example, patterns are widely used to model the evolution of biological (Pagel 1999; Ledyard 1950) and financial systems (Lo et al. 2000).

One study of patterns in software evolution is the work of Lanza proposing a categorization of classes based on recurrent patterns detected when investigating techniques for the visualization of object-oriented systems (Lanza 2001). The categories proposed by Lanza rely on a vocabulary mostly taken from the astronomy domain to model the evolution of classes. For example, the proposed categorization covers the following phenomena: rapid growth in class size (supernova), rapid decrease in class size (white dwarf), rapid growth followed by rapid decrease in class size or vice versa (pulsar), class stability (stagnant), and limited class lifetime (dayfly).

Our central goal in this paper is to investigate the impact of the evolution categories proposed by Lanza on the behavior of classical metrics commonly used to evaluate properties of object-oriented systems, such as coupling, cohesion, and size. More specifically, our goal is to investigate whether the occurrence of a given evolution category (measured in terms of lines of code) implies an equivalent bevahior in metrics that are part of the well-known Chidamber and Kemerer (CK) metrics suite (Chidamber and Kemerer 1994). Stated otherwise, we investigate whether the proposed categories can be used to model not only the evolution of a system in terms of lines of code but also in terms of coupling, cohesion, and size. An eventual correlation between evolution categories measured in terms of size and evolution categories measured using the metrics considered in the paper emphasizes the importance of the former over the latter, showing that it is possible to predict the evolution of well-known software metrics by evaluating the evolution of a single size metric: lines of code (LOC).

To summarize, our contributions are threefold. The first contribution is a formal definition for the categories proposed by Lanza (Sect. 2). Our intention is to provide a rigorous specification for the criteria we describe in the paper when searching for evolution categories. The second contribution is a study—reported in Sects. 3 and 4—showing that at least four evolution categories are recurrent: stagnants, supernovas, white dwarfs, and dayflies. To reach this conclusion, we mined for the evolution categories in several versions of 10 open-source Java-based systems, comprising in most cases more than 3 years of evolution. Our third contribution is a study showing an important correlation between evolution categories measured in terms of LOC and evolution categories assessing size, coupling, and, to a less extent, cohesion (Sect. 5). Next, Sect. 6 discusses threats to validity, Sect. 7 presents related work, and Sect. 8 provides concluding remarks.

2 Formal definition

In this section, we provide a formal definition for the categories originally proposed by Lanza to describe the ways that a class can evolve over its lifetime (Lanza 2001). The

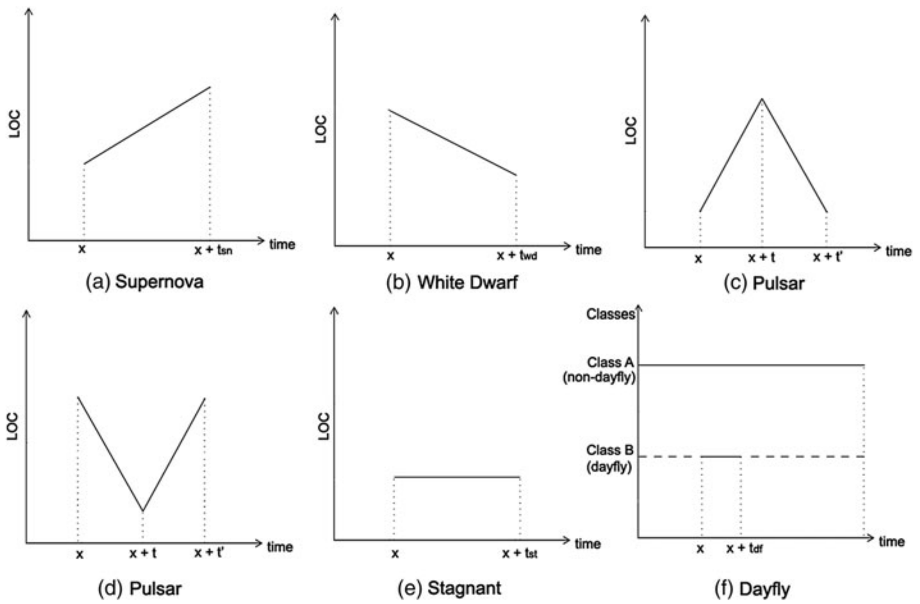


Fig. 1 Categories of class evolution

following notation is used: V_t denotes a version of a class C at a given time t and loc(V_t) is a function that returns the number of LOC of V_t.

2.1 Supernova

A class with supernova behavior suddenly explodes in size (Fig. 1a).[1] This explosion might be due to major refactorings, to the inclusion of new responsibilities in the class or the finalization of its implementation (i.e., the class could be working as a *stub* or a *sleeper class*). Formally, a class C is a supernova if there are at least two versions V_x and V_{x+t} such that

$$\mathrm{loc}(V_{x+t}) \geq k_{sn} \times \mathrm{loc}(V_x), \quad k_{sn} > 1, t \leq t_{sn}$$

that is, a supernova occurs whenever the size of the class increases by at least a factor k_{sn}, in a maximum time interval t_{sn}. From this definition, two observations are important: (a) to promote the reuse of the definition in different scenarios and systems, we deliberately do not fix the values of k_{sn} and t_{sn}, (b) a class can behave as a supernova more than once during its life cycle.

2.2 White dwarf

A class with white dwarf behavior goes through a sudden reduction in size (Fig. 1b). These classes may, for example, implement requirements that later become obsolete during the evolution of the system. Formally, a class C is a white dwarf if there are at least two versions V_x and V_{x+t} such that

[1] The representation of the evolution categories in this figure follows a linear model just for illustrative purposes. As can be checked, the definitions presented in the section do not assume a linear growth or contraction.

$$\text{loc}(V_{x+t}) \leq k_{wd} \times \text{loc}(V_x), \quad k_{wd} < 1, t \leq t_{wd}$$

that is, a white dwarf happens whenever the size of the class decreases by at least a factor k_{wd}, at a time t lower than a maximum time t_{wd}.

2.3 Pulsar

A class with pulsar behavior is a class whose size increases and then suddenly decreases or vice versa (Fig. 1c, d). The growth can occur either by adding or refactoring code. Decreases are more likely due to refactorings and restructuring of the class. Formally, a class C has a pulsar including a growth cycle between versions V_x and V_{x+t} and a shrinking cycle between versions V_{x+t} and $V_{x+t'}$, where $t < t' \leq t_{ps}$, if

$$\begin{aligned}&\text{loc}(V_{x+t}) \geq (1 + k_{ps}) \times \text{loc}(V_x) \wedge \\ &\text{loc}(V_{x+t'}) \leq (1 - k_{ps}) \times \text{loc}(V_{x+t}), \quad 0 < k_{ps} < 1\end{aligned}$$

Alternatively, a class with a pulsar behavior can include a decrease cycle between versions V_x and V_{x+t} and a cycle of growth between versions V_{x+t} and $V_{x+t'}$, where $t < t' \leq t_{ps}$, if

$$\begin{aligned}&\text{loc}(V_{x+t}) \leq (1 - k_{ps}) \times \text{loc}(V_x) \wedge \\ &\text{loc}(V_{x+t'}) \geq (1 + k_{ps}) \times \text{loc}(V_{x+t}), \quad 0 < k_{ps} < 1\end{aligned}$$

In these definitions, t_{ps} represents the maximum time frame for detecting a pulsar (i.e., the cycles of growth and decrease must occur in this time window) and k_{ps} denotes the minimum factor that characterizes both the growth $(1 + k_{ps})$ and the decrease $(1 - k_{ps})$ phases of a pulsar.

2.4 Stagnant

A class contains a stagnant when its size remains nearly constant over several versions (Fig. 1e). This stability might occur for many reasons. Examples include an obsolete class that is not removed from the system or a class with a stable design. Formally, a class C is a stagnant if

$$\frac{|\text{loc}(\mathrm{V_{x+t}}) - \text{loc}(\mathrm{V_x})|}{\text{loc}(V_x)} \leq k_{st}, \quad \forall t \leq t_{st}, \quad k_{st} \approx 0, \quad k_{st} \geq 0$$

that is, a class with a difference in size (in relative values) between any two versions V_x and V_{x+t}, separated by a maximum time t_{st}, lower than a small, but nonnegative factor k_{st}.

2.5 Dayfly

A dayfly is a class with a limited and short lifetime (Fig. 1f). Such classes are created, for example, to implement a requirement that is later discarded. Formally, a class C is a dayfly when its lifetime is less or equal than t_{df} time units:

$$\begin{aligned}&\text{loc}(V_{x-1}) = -1 \wedge \\ &\text{loc}(V_x) > 0 \wedge \text{loc}(V_{x+1}) > 0 \wedge \cdots \wedge \text{loc}(V_{x+t}) > 0 \wedge \\ &\text{loc}(V_{x+t+1}) = -1, t \leq t_{\text{df}}\end{aligned}$$

In this definition, $\text{loc}(V_i) = -1$ denotes that the class under analysis is not implemented in version V_i.

3 Dataset

Our dataset was originally conceived by D'Ambros et al. (2010) to evaluate bug prediction techniques. It includes temporal series for seventeen metrics of source code, including the number of LOC and the CK metrics suite. The metrics have been extracted in intervals of biweeks for four well-known Java-based systems: Eclipse JDT Core, Eclipse PDE UI, Equinox, and Lucene.[2] We extend the benchmark provided by D'Ambros in two ways: (a) by expanding the original time series of two systems: Eclipse JDT Core (from 91 to 183 biweeks) and Eclipse PDE UI (from 97 to 191 biweeks), and (b) by including historical information relative to another six open-source systems: Hibernate (a persistence framework), Spring (an application development framework), JabRef (a bibliography reference manager), PMD (a source code analyzer), TV-Browser (an electronic TV guide), and Pentaho Console (a console to administer business intelligence applications). It is also important to highlight that in the case of four systems—JabRef, PMD, TV-Browser, and Pentaho Console—our extension includes their complete evolution history (i.e., since the beginning of their development). Table 1 provides detailed information on our dataset.

To create this dataset, we extract the source code of each considered version from the associated revision control platforms in intervals of biweeks. We then use the Moose platform[3] to extract LOC and CK metrics values for each class of each considered version, excluding only test classes. Particularly, we have relied on VerveineJ—a Moose application—to parse the source code of each version and to generate MSE files. MSE is the default file format supported by Moose to persist source code models. Because Moose's current version does not calculate three CK metrics (CBO, LCOM, and RFC), we extend the platform with new routines for this purpose.

3.1 Growth models

In Fig. 2, we show the growth of the systems investigated in this study. We also evaluate the best growth trend model for each system, as presented in Table 2. For this purpose, we rely on Excel's trendline function, as described by Mens et al. (2008), to verify the fitness of the presented growth to the following models: quadratic, linear, exponential, and logarithmic models. In the case of quadratic models, we use the quadratic coefficient a to classify the growth as superlinear ($a > 0$) or sublinear ($a < 0$). Logarithmic growth is also classified as sublinear. Finally, to choose the model that best describes our data, we use the coefficient of determination (R^2) provided by each regression model. An $R^2 = 1.0$ indicates that the values predicted by the model perfectly fits the observed data. To avoid the extra complexity inherent to nonlinear models, we give a bonus of 5 % to the R^2 provided by the standard linear regression (i.e., in Table 2, we only indicated a nonlinear model as the "best model" when its coefficient of determination is more than 5 % greater than the linear model). As we can observe, five systems have a linear growth model, four systems have a sublinear growth model, and a single system has a superlinear growth.

Therefore, our results reinforce the Lehman's law of "Continuing Growth" as a plausible model for the behavior of software systems, in terms of size (as visually shown in Fig. 2). However, it is difficult to make generalizations on the mathematical models

[2] The original dataset includes a fifth system (Mylyn). However, we have not considered this system because the dataset includes information for only 47 biweeks of its evolution.

[3] http://www.moosetechnology.org.

Table 1 Dataset

System	Period	No. of classes	No. of versions
Eclipse JDT	07/01/2001–06/14/2008	1,368	183
Eclipse PDE	06/01/2001–09/06/2008	3,082	191
Equinox	01/01/2005–06/14/2008	431	91
Lucene	01/01/2005–10/04/2008	946	99
Hibernate	06/13/2007–03/02/2011	1216	98
Spring	12/17/2003–11/25/2009	1,845	156
JabRef	10/14/2003–11/11/2011	823	212
PMD	06/22/2002–12/11/2011	1,425	248
TV-browser	04/23/2003–08/27/2011	1,229	221
Pentaho	04/01/2008–12/07/2010	317	72
Total	–	12,682	1,571

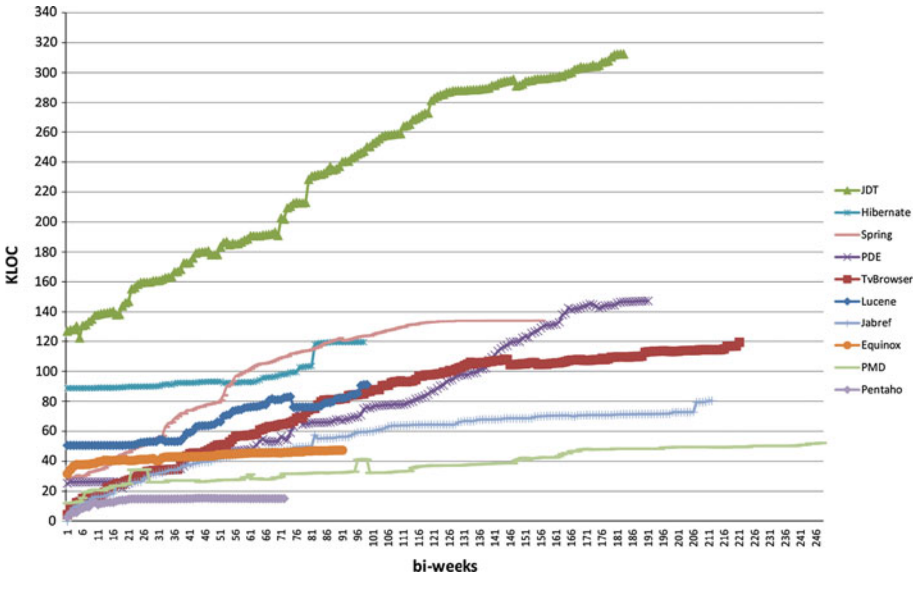


Fig. 2 Growth of the systems considered in the first study

governing such growth (as showed in Table 2 and reported in other studies (Godfrey and Tu 2000; Mens et al. 2008)).

We have also modeled the growth at the class level. For this purpose, we only consider classes whose size varies in the versions we have analyzed. In fact, 5,575 classes from our sample have a constant size over the entire study time frame (accounting for 43.9 % of the considered classes) and therefore were discarded. For the remaining classes, we investigate whether their growth fits a linear model. Figure 3 shows a histogram with the distribution of the coefficient of determination for the linear regressions calculated at the class level. We can observe that in most cases, the measured R^2 values are inferior to 0.75. In only 1,152 classes (16.2 %), the R^2 values are >0.75.

Table 2 Linear regression

System	Best growth model	Growth equation	R^2
Eclipse JDT	Linear	$y = 1{,}106.3x + 129{,}523$	0.97
Eclipse PDE	Linear	$y = 720.85x + 9{,}571.1$	0.97
Equinox	Linear	$y = 115.9x + 37{,}885$	0.90
Lucene	Linear	$y = 442.62x + 44{,}250$	0.91
Hibernate	Superlinear (quadratic)	$y = 6.6x^2 - 336.8x + 92{,}486$	0.91
Spring	Sublinear (quadratic)	$y = -6.1x^2 + 1, 698.5x + 16, 397$	0.99
JabRef	Sublinear (quadratic)	$y = -1.7x^2 + 655.8x + 11{,}066$	0.99
PMD	Linear	$y = 134.6x + 20{,}997$	0.92
TV-browser	Sublinear (quadratic)	$y = -2.6x^2 + 1{,}066.9x + 5169.6$	0.99
Pentaho	Sublinear (logarithm)	$y = 2, 785.9 \ln(x) + 4, 584.7$	0.87

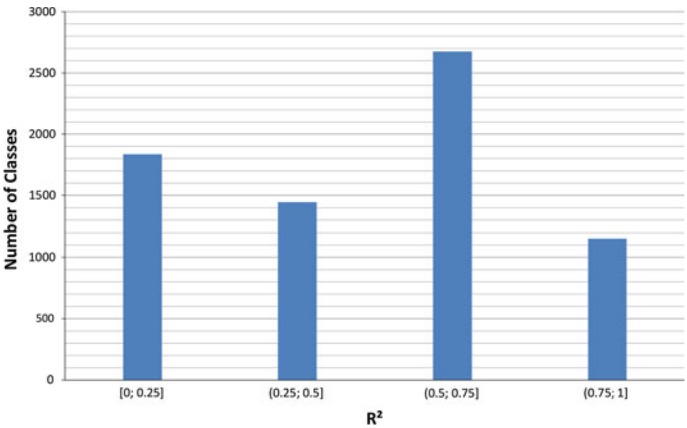


Fig. 3 R^2 coefficients for the linear regressions at the class level

To explain these results, we measured the number of white dwarfs per class in the following segments: $R^2 \leq 0.25$ and $R^2 > 0.75$, using $t_{wd} = 1$ and $k_{wd} = 0.9$. For the first segment, there are 0.45 white dwarfs per class; on the other hand, for the last segment, white dwarfs' density is around half this value (0.24 white dwarfs/class). Considering that white dwarfs are disruptive events for linear growth, such events are—as expected—much more common in the first segment.

3.2 Conclusions

Linear and sublinear models—including quadratic and logarithmic models—best explain the overall growth of nine out of the 10 systems that we evaluated. On the other hand, linear models cannot explain the growth behavior of fine-grained components, such as classes, which confirms results from previous work (Godfrey and Tu 2000). Therefore, our findings reinforce the importance of studying the growth behavior of individual classes, which is the central purpose of the evolution categories considered in this paper.

4 Mining for categories of class evolution

In this section, we describe a study to check whether the categories of evolution—as formalized in Sect. 2—are actually found in real software evolution settings.

4.1 Tool support

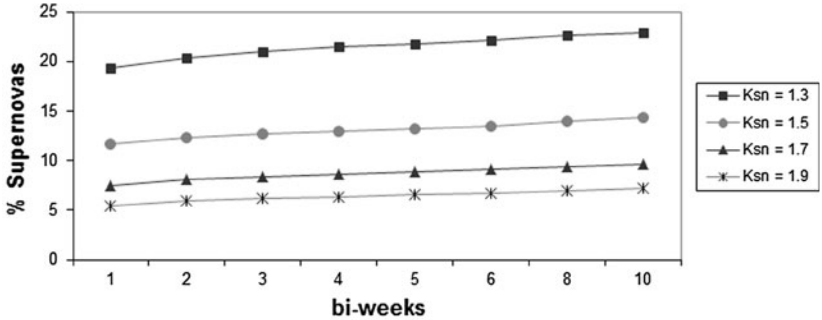
To mine for the five categories of evolution, we implemented a small Java system that searches for the categories using the definition proposed in Sect. 2. The input of this program is a table whose rows are the classes that existed in at least one version of the target system and the columns represent the biweeks considered in the study. A cell (r, c) in this table contains the size (in LOC) of the class in row r at the biweek represented by column c. The output of the program is a list of the classes that match each of the categories of evolution considered in the paper. For each matching category, the program also outputs some information (for example, for a supernova, it outputs the initial and final biweeks of the supernova, with the size of the class in both versions and the growth rate).

4.2 Parameters calibration and estimation

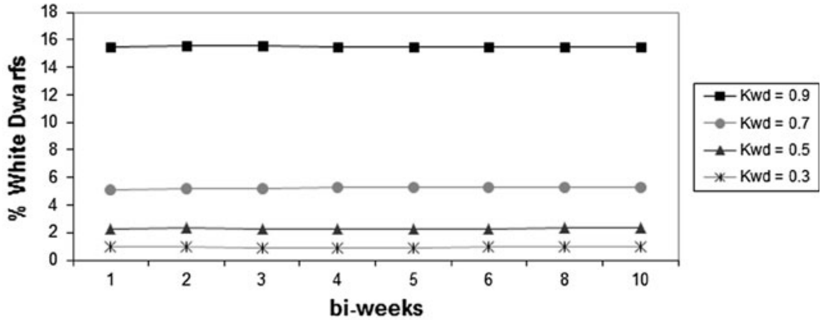
A critical decision when mining for the evolution categories is setting the parameters used in the formal definitions presented in Sect. 2. To help in this decision, we tested several possible values using the systems in our dataset as input,[4] aiming to check how our results are affected by different parameter values. Figures 4 and 5 show the percentage of classes presenting each of the evolution categories, which is summarized as follows:

- Figure 4a shows how the number of supernovas is affected by changing the time interval followed in the observation (x axis) and the growth factor k_{sn}. As expected, the number of supernovas increases as we increase the time interval or decrease the growth factor.
- Figure 4b shows the analysis for white dwarfs. We can see that the results are greatly affected by changing the shrinking factor k_{wd}, but not by variations in the observation time. In other words, significant reductions in the size of a class tend to occur quickly, in the interval of a single biweek.
- Figure 4c shows the analysis for pulsars. The number of pulsars is mostly affected by changes in the growth/shrinking parameter k_{ps}. However, in the best scenario—observations lasting 12 biweeks and $k_{ps} = 0.3$—the percentage of classes with a pulsar behavior is slightly >1 %.
- Figure 4d shows how changes in the time frame followed in the observation and in the parameter k_{st} affect the number of stagnants. The figure shows that the detection of stagnants is not affected by changes in k_{st}, that is, stagnants tend to have a near constant number of LOC. On the other hand, the number of stagnants is heavily impacted by the observation threshold. For example, for observations lasting 12 biweeks, the number of stagnants is four times the number of classes, whereas in the case of observations lasting 60 biweeks, this value is reduced to around 50 % of the classes.

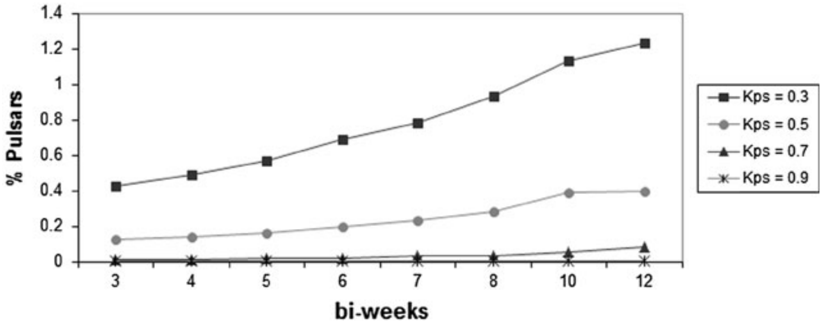
[4] For Eclipse JDT and Eclipse PDE, we only considered the original time frame of the series available in the D'Ambros dataset.



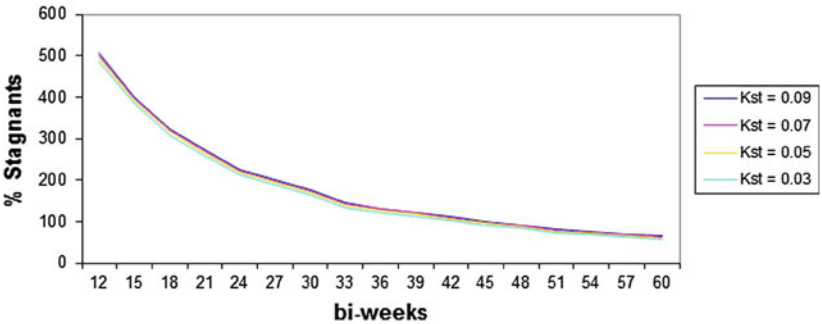
(a) Supernovas



(b) White Dwarfs



(c) Pulsars



(d) Stagnants

Fig. 4 Effect of the input parameters in four evolution categories

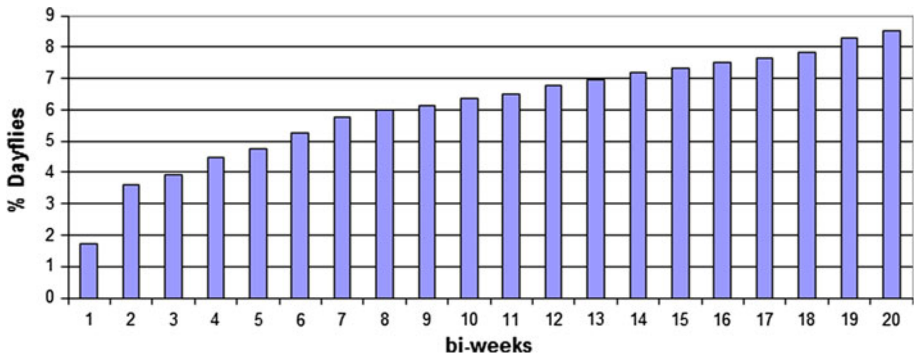


Fig. 5 Effect of the input parameters in the number of dayflies

- Figure 5 shows the analysis for dayflies. We can observe that lifetimes >12 biweeks have a minor impact in the number of dayflies. For example, assuming a maximal lifetime of 12 bi-weeks, we have counted around 7 % of dayflies. Increasing the interval to 20 biweeks, the percentage of dayflies increases to around 8.5 %.

Based on this analysis, we decided to set the input parameters in the following way:

- Supernova: $k_{sn} = 1.5$ and $t_{sn} = 5$ bi-weeks.
- White dwarf: $k_{wd} = 0.7$ and $t_{wd} = 1$ bi-week.
- Pulsar: $k_{ps} = 0.5$, and $t_{ps} = 7$ bi-weeks.
- Stagnant: $k_{st} = 0.03$ and $t_{st} = 36$ bi-weeks.
- Dayfly: $t_{\mathrm{df}} = 7$ bi-weeks.

We follow two criteria to make this selection. When the detection of an evolution category is heavily impacted by a given parameter, we select the average between the best and the worst values, among the tested values. For example, we set $t_{st} = 36$ biweeks, which is the average between our inferior and superior limits for stagnants. When the detection is not affected by a given parameter, we select the lowest value tested. For instance, we set $k_{st} = 0.03$ for stagnants.

4.3 Results

Table 3 shows the number of evolution categories detected in the systems considered in this first study. Each cell of this table contains the number of occurrences of each category. In addition, each value is accompanied by its percentage (shown in parenthesis) relative to the total of number of classes in each system. It is worth noting that the mined categories are not mutually exclusive. For instance, a class may behave as a pulsar for a period of time and then become a white dwarf. As another observation, a class may also behave as stagnant more than once along its lifecycle. This fact explains why some of the values showed in Table 1 are >100 %.

Next, we comment the results of our mining study for each evolution category:

- Stagnants are a fairly common phenomenon, as indicated by the study of the class-level growth in Sect. 3. In fact, the number of stagnants usually exceeds the total number of classes in the systems. JabRef is the system with the highest percentage of stagnants

Table 3 Absolute and relative occurrences of the evolution categories

System	Stagnant	Supernova	White dwarf	Dayfly	Pulsar
Eclipse JDT	1,560 (1,14.0)	285 (20.8)	89 (6.5)	67 (4.8)	4 (0.2)
Eclipse PDE	1,439 (46.6)	380 (12.3)	188 (6.0)	655 (21.2)	13 (0.4)
Equinox	233 (54.0)	40 (9.2)	28 (6.4)	13 (3.0)	1 (0.2)
Lucene	589 (62.2)	91 (9.6)	25 (2.6)	16 (1.6)	2 (0.2)
Hibernate	1,449 (119.1)	89 (7.3)	13 (1.0)	5 (0.4)	2 (0.1)
Spring	2,137 (115.8)	575 (31.1)	170 (9.2)	168 (9.1)	6 (0.3)
JabRef	1,865 (226.6)	136 (16.5)	33 (4.0)	32 (3.8)	0 (0.0)
PMD	1,545 (108.4)	173 (12.1)	87 (6.1)	78 (5.4)	11 (0.7)
TV-browser	1,685 (137.1)	244 (19.8)	77 (6.2)	91 (7.4)	3 (0.2)
Pentaho	106 (33.4)	40 (12.6)	13 (4.1)	86 (27.1)	0 (0.0)

(226.6 %), whereas Pentaho presents the lowest percentage (33.4 %). Figure 2 validates Lehman's sixth law of software evolution that states that software systems are predestinated to grow continuously. However, the high number of stagnants we have detected suggests that such growth—at least when measured at the class level—happens in well-defined and delimited snapshots (i.e., at the class level, growth is not a strictly increasing function).

- Supernovas are also common. For example, they are observed in more than 9 % of the classes in all systems, with the exception of Hibernate. Spring is the system with the highest relative number of supernovas (31.1 %). Combined with the results for stagnants, the values related to supernovas suggest that most class growth happens in the form of a burst.
- White dwarfs are less frequent than supernovas, responding for at most 6.5 % of occurrences in nine out of 10 systems. Spring has been the system with more white dwarfs (9.2 %). In general, these values suggest that it is more common to observe bursts of growth than bursts of contraction when monitoring size at the class level.
- Dayflies are less common than white dwarfs, with the exception of three systems (Eclipse PDE, TV-Browser, and Pentaho). Moreover, Hibernate is the systems with the lowest number of dayflies (only five classes) and 27.1 % of the Pentaho Console classes appear and disappear soon after.
- Finally, pulsars are rare events, occurring in fewer than 1 % of the classes of the 10 systems.

To complement the previous analysis, we also measure how much of the lifetime of the evaluated classes is modeled by the considered evolution categories. Specifically, there are segments in a class lifetime that do not fit any of the studied evolution categories, which we refer as *undefined* time frames. The *undefined ratio* is the percentage of a lifetime that a class remains in an undefined state. Figure 6 shows the cumulative distribution function for the undefined ratios for the classes of the considered systems (i.e., for each system, the function maps a given undefined ratio p to the probability of a class having an undefined ratio less or equal to p). The distribution functions reveal that undefined ratios of <20 % ranges from 14.3 % of the classes in the Hibernate system to 74.5 % of the classes in the PMD system. However, by our definition, the segments of stability with fewer than 36 biweeks are computed as undefined (and not as stagnants). After adding such segments to the small segments that not match any of the evolution categories, we find that the overall

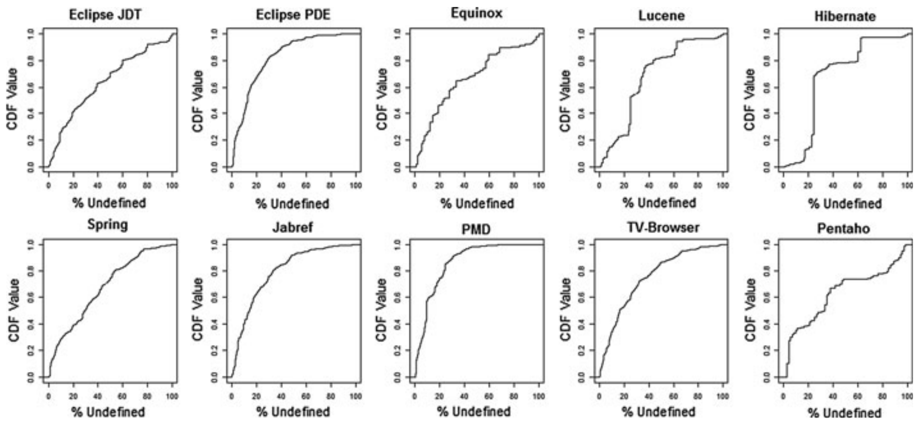


Fig. 6 Cumulative distribution function for the percentage of undefined time frames

percentage of undefined states cannot be neglected. On the other hand, even using these criteria, the undefined segments do not outweight the categories considered in this paper.

4.4 Conclusions

Our findings for the first study show that four out of the five evolution categories (stagnants, supernovas, dayflies, and white dwarfs) are probable events, whereas pulsars are atypical events.

5 Impact on CK metrics

To answer our central question in this paper, this section describes a study that investigates the impact of the evolution categories proposed by Lanza on the values of common object-oriented metrics. Our goal is to evaluate possible correlations between the evolution categories and the evolution of class-level metrics assessing cohesion, coupling, and size. We start by describing the dataset employed in this second study and the adopted methodology. Finally, we present and discuss the results.

5.1 Dataset

In this second study, we will reuse the same systems from the first study. However, we restrict our analysis to the most common categories detected in the first study (i.e., stagnants, supernovas, white dwarfs, and dayflies). In our experiments, we use the CK metrics presented in Table 4, which is probably the most used metric suite to measure properties of object-oriented systems. The table also presents the software properties measured by the CK metrics, using the classification framework proposed by Briand et al. (1996). Although LCOM does not have a precise classification according to this framework, we classify it as a cohesion measure.

Table 4 CK metrics

Metric	Description	Properties
WMC	Weighted method count	Size
DIT	Depth of inheritance tree	Length
RFC	Response for class	Size, coupling
NOC	Number of children	Size
CBO	Coupling between objects	Coupling
LCOM	Lack of cohesion in methods	Cohesion

5.2 Methodology

This second study assumes the following predicates are available:

$$\text{Supernova}\,(M, C, t_1, t_2)$$
$$\text{Whitedwarf}\,(M, C, t_1, t_2)$$
$$\text{Stagnant}\,(M, C, t_1, t_2)$$
$$\text{Dayfly}\,(M, C, t_1, t_2)$$

where M denotes the metric used to detect the behavior prescribed by the evolution category; C denotes the class with the behavior prescribed by the evolution category; and t_1 and t_2 denote the time frame in which the evolution category occurs. For example, supernova(LOC, C, 34, 38) asserts that class C behaves as a supernova—measured in terms of LOC, as defined in Sect. 2—in the time frame defined by biweeks 34 and 38.

The proposed predicates can also be applied to other metrics, besides LOC. For example, supernova(WMC, C, 34, 38) asserts that class C behaves as a supernova—measured in terms of WMC values—between biweeks 34 and 38. In other words, this predicate checks whether an explosion in the values given by WMC for this class happens between the mentioned biweeks. In general, we reuse the definitions from Sect. 2 to detect the following behaviors associated with the values of CK metrics: rapid growth (supernova), rapid decrease (white dwarf), stability (stagnant), and limited observation (dayfly).

To evaluate the impact of the evolution categories measured in terms of LOC on the values of CK metrics, we rely on the notions of precision and recall. Figure 7 shows our definition for precision and recall of the impact of a given evolution category evol measured in terms of LOC in the values of a given metric M. The presented definition relies on two sets:

$$precision(evol, M) = \frac{|\ P(evol, M)\ |}{|\ T(evol, LOC)\ |}$$

$$recall(evol, M) = \frac{|\ P(evol, M)\ |}{|\ T(evol, M)\ |}$$

where T and P are sets defined as:

- $T(evol, M) =$ all the occurrences of $evol(M, C, t_1, t_2)$
- $P(evol, M) = \{\ evol(LOC, C, t_1, t_2) \in T(evol, LOC) \mid evol(LOC, C, t_1, t_2) \rightarrow evol(M, C, t_1, t_2)\ \}$

Fig. 7 Precision and recall

- T(evol, M): set containing all the occurrences of a given evolution category evol measured in terms of the metric M;
- P(evol, M): set containing the occurrences of the evolution categories in T(evol, LOC) that have caused an equivalent behavior in the values of the metric M. Therefore, $P(\text{evol}, M) \subseteq T(\text{evol}, \text{LOC})$.

To illustrate this definition, suppose that in a given system, we have detected 100 supernovas in terms of LOC (i.e., $|T(\text{supernova, LOC})| = 100$) and 120 supernovas in terms of the CBO metric (i.e., $|T(\text{supernova, CBO})| = 120$); suppose also that 80 of the supernovas detected in terms of LOC have also been detected in terms of the CBO metric, for the same class and at the same time interval (i.e., $|P(\text{supernova, CBO})| = 80$). Therefore, precision(supernova, CBO) = 80/100 and recall(supernova, CBO) = 80/120.

To simplify analysis and provide a single model showing the correlation between LOC and CK metrics, we also rely on the F measure (or F_1 score) that combines precision and recall in a single weighted average:

$$F_1\text{score} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$

In the best case, precision = recall = 1.0 and therefore F_1 score = 1.0. The worst case happens when precision = 0.0 or recall = 0.0, and therefore F_1 score = 0.0.

5.3 Results

Tables 5, 6, and 7 show the mean and the standard deviation (mean ± standard deviation) for precision, recall, and F_1 score calculated for each system. Suppose, for example, the supernova evolution category (evol's column) and the CBO metric (M's row). In this case, Table 5 shows that 38 ± 7 % of the supernovas measured in terms of LOC have shown the same behavior when measured in terms of CBO. Furthermore, Table 6 shows that such supernovas both in terms of LOC and CBO represent 53 ± 1 % of the supernovas measured only in terms of CBO. As presented in Table 7, when combined, these ratios result in a F_1 score of 44 ± 7 %.

More specifically, we can make the following observations about the results in Tables 5, 6, and 7.

Table 5 Precision results (mean ± SD)

M	Evol			
	Dayfly	Stagnants	Supernova	White dwarf
CBO	1.00 ± 0.00	0.89 ± 0.04	0.38 ± 0.07	0.41 ± 0.16
LCOM	1.00 ± 0.00	0.98 ± 0.01	0.28 ± 0.05	0.20 ± 0.09
WMC	1.00 ± 0.00	0.98 ± 0.01	0.70 ± 0.10	0.71 ± 0.07
RFC	1.00 ± 0.00	0.93 ± 0.04	0.54 ± 0.10	0.62 ± 0.14
DIT	1.00 ± 0.00	0.98 ± 0.02	0.02 ± 0.01	0.04 ± 0.01
NOC	1.00 ± 0.00	0.98 ± 0.01	0.01 ± 0.01	0.00 ± 0.00

Table 6 Recall results (mean ± SD)

M	Evol			
	Dayfly	Stagnants	Supernova	White dwarf
CBO	1.00 ± 0.00	0.84 ± 0.06	0.53 ± 0.01	0.52 ± 0.13
LCOM	1.00 ± 0.00	0.75 ± 0.08	0.26 ± 0.08	0.21 ± 0.11
WMC	1.00 ± 0.00	0.89 ± 0.04	0.70 ± 0.07	0.72 ± 0.07
RFC	1.00 ± 0.00	0.90 ± 0.05	0.68 ± 0.09	0.65 ± 0.01
DIT	1.00 ± 0.00	0.63 ± 0.11	0.08 ± 0.08	0.13 ± 0.31
NOC	1.00 ± 0.00	0.62 ± 0.12	0.10 ± 0.12	0.14 ± 0.31

Table 7 F_1 score results (mean ± SD)

M	Evol			
	Dayfly	Stagnants	Supernova	White dwarf
CBO	1.00 ± 0.00	0.86 ± 0.04	0.44 ± 0.07	0.46 ± 0.11
LCOM	1.00 ± 0.00	0.85 ± 0.05	0.27 ± 0.05	0.20 ± 0.10
WMC	1.00 ± 0.00	0.93 ± 0.03	0.70 ± 0.07	0.72 ± 0.06
RFC	1.00 ± 0.00	0.91 ± 0.03	0.60 ± 0.08	0.64 ± 0.08
DIT	1.00 ± 0.00	0.77 ± 0.08	0.03 ± 0.02	0.06 ± 0.06
NOC	1.00 ± 0.00	0.76 ± 0.09	0.02 ± 0.03	0.01 ± 0.01

5.3.1 Dayflies

As expected, in the case of dayflies, the precision and recall rates have always been 1.00 ± 0.00. In other words, we can check the lifetime of a class by looking the values of its size or the values of any of the considered CK metrics. In fact, when the class did not exist in any of the considered biweeks, we denoted this fact by using the value −1 for any of the mentioned metrics.

5.3.2 Stagnants

The F_1 scores for stagnants are >0.85 ± 0.05 for CBO, LCOM, WMC, and RFC. Therefore, changes in a class that have no impact in its size usually do not impact the mentioned metrics. Finally, stagnants in terms of LOC usually imply that they are stagnant in terms of DIT and NOC (precision above 0.98 ± 0.02), but the reverse implication is less frequent (recall < 0.63 ± 0.11).

5.3.3 Supernovas and white dwarfs

First, we have observed some level of correspondence between supernovas and white dwarfs in terms of CBO, WMC, and RFC and the same events in terms of LOC (recall ranging from 0.52 ± 0.13 to 0.72 ± 0.07). In other words, on average, more than 52 % of the sudden explosions or contractions in the values of such metrics occur due to similar events in terms of LOC. On the other hand, the reverse implication is less common, since the precision results have been less than or equal to the recall ratios. Second, there is less correspondence between LOC-based supernovas and white dwarfs and the same events in terms of LCOM (F_1 score = 0.27 ± 0.05). Finally, the results show a lack of correspondence between supernovas and white dwarfs in terms of LOC and in terms of metrics designed to measure inheritance relations, such as DIT and NOC (F_1 score inferior or equal to 0.06 ± 0.06). For example, due to a supernova, the size of the class `core.index.DiskIndex` from Eclipse JDT has increased from 842 to 1271 LOC in the interval of a single biweek. However, the values of DIT and NOC remained constant.

We summarize our findings in this second study in the following way:

- The evolution categories have an important impact in the values of the following CK metrics: CBO (a coupling measure), WMC (a size measure, according to Briand et al. (1996)), and RFC (both a coupling and size measure). In other words, it is possible to make reliable predictions on changes in the levels of these metrics by monitoring the occurrence of the evolution categories (recall ranging from 0.52 ± 0.13 to 0.72 ± 0.07).
- There is an impact of the evolution categories on cohesion, as measures by LCOM, but it is more limited (F_1 score inferior to 0.27 ± 0.05). Specifically, the results show that the following changes in classes are common: (a) changes with an important effect in LCOM values, but not in the class size (e.g., minor changes that make the methods in the class access new fields), (b) changes that have an important effect in LOC values, but not in LCOM values (e.g., major changes that do not affect the set of the fields accessed by the changed methods).
- There is no impact of the categories considered in the study on metrics designed to capture properties associated to inheritance. Stated otherwise, it is not possible to infer changes in inheritance by observing only the evolution categories.

6 Threats to validity

As common to empirical studies in software engineering, we cannot assure that our results generalize beyond the specific systems we have evaluated. To minimize this threat concerning the external validity of the study, we rely on a dataset carefully designed by a researcher not directly related to our study. Moreover, we extend this dataset with six well-known open-source systems. In total, the dataset of our study includes 10 systems, although two of them—Eclipse JDT and Eclipse PDE—are part of the same high-level project. We also highlight that any generalization attempt must be confined to systems written in statically typed, object-oriented languages. Finally, our evaluation relies on large systems, with hundreds of classes and tens of thousands of LOC. Hence, it is possible that our findings do not apply to small systems.

7 Related work

The evolution categories proposed by Lanza were first described in his study on using evolution matrices to visualize the evolution of object-oriented software systems (Lanza 2001). Rows in evolution matrices represent classes, whereas columns denote versions of the target system. Each cell encodes two metrics at a time: its height scales to the number of instance variables (NIV) of the class denoted by the containing row, and its width is proportional to the number of methods (NOM) in the same class. Lanza evaluates evolution matrices using two Smalltalk systems, in which supernovas, white dwarfs, pulsars, stagnants, and dayfly classes are visually identified in terms of NIV and NOM. The evaluated systems, however, are not representative of industrial-strength object-oriented systems.

Lanza and Ducasse (2003) propose the use of *polymetric views*, which contrary to Lanza's evolution matrices, can encode up to five metrics measurements. A polymetric view is a graph representing a given relationship between source code entities (e.g., classes), where nodes encode metric measurements by means of colors, position, and size. Colors are in gray scale, with white standing as the least value and black the maximum metric measurement. Positions are (x and y) coordinates, and node size encodes two measurements by its size and width. Polymetric views are designed to assist developers in understanding the structure and the design quality of software systems, along with information on how these two properties evolve over time. The authors argue that such an approach help detecting evolution patterns in terms of class, method, and attribute metrics, but excluded CK metrics from their analysis.

Godfrey and Tu (2000) study the Linux Kernel and its evolution over 96 versions, showing that it follows a super-linear rate, contradicting Lehman and Turki's hypothesis of an inverse square growth rate (Lehman et al. 1998). Israeli and Feitelson perform a larger study, with the analysis of 810 Linux kernel releases over 14 years (Israeli and Feitelson 2010). Their analysis suggests that the kernel agrees with Lehman's Law of Software Evolution. In particular, the authors report strong evidence toward continuing growth and change laws, but anecdotal evidence of the self-regulation and feedback system laws. Gonzalez-Barahona et al. (2009) study the evolution of the Debian Linux distribution, opposed to studies focusing on the kernel alone, and point out that the package mean size in Debian is often constant across stable releases. However, the number of packages and the LOC size of the distribution (the sum of all LOC in each source file) doubles at each release. They also find that 7 % of packages from version 2.0 are still present in version 4.0, and that around 18 % of such packages remained unchanged (something we would characterize as a stagnant behavior).

Herraiz and Hassan (2010) investigate the correlation between LOC and other software metrics. In particular, the authors analyze how LOC/SLOC measurement of C files in Arch Linux packages correlates with McCabe's control flow complexity and Halstead's metrics. Overall, they find a high correlation ($\geq$84 %) between size and Halstead's metrics, but an average correlation (60 %) between SLOC and McCabe's cyclomatic complexity for non-header files. Finally, a low correlation between McCabe's complexity and SLOC/LOC is present. As discussed by the authors, this is expected, as header files do not contain control flow information. Similar results are reported in Herraiz et al. (2007), but with FreeBSD as a subject of analysis. Altogether, these works measure correlations between metric values taken from a single version of the target systems, which are restricted to the domain of operating systems. Opposed to that, we use different versions of the systems in our experiments, thus taking into account the temporal variations over the metric values. Furthermore, our target systems comprise a rich set of applications from different domains.

El Emam et al. (2001) points out the potential confounding effect of class size on CK metrics when predicting fault-proneness (El Emam et al. 2001). Subramanyan and Krishnan further investigates such effect (Subramanyam and Krishnan 2003), but opposed to Eman, show a strong association of defects to a subset of CK metrics, even after controlling for size. Their results, however, are dependent on the programing language. In future work, we also intend to investigate correlations between evolution categories and bugs, similar to the ones we investigate regarding CK metrics.

8 Conclusions

Our findings from the studies reported in this paper can be summarized as follows:

- The first study (Sect. 4) shows that stagnants, supernovas, white dwarfs, and dayflies are probable events in the lifetime of classes.
- The second study (Sect. 5) shows that by monitoring only the occurrence of the evolution categories, we can make reliable predictions of the values of metrics designed to measure coupling (CBO), both coupling and size (RFC), size (WMC), and to a less extent cohesion (LCOM). On the other hand, there is no connection between the evolution categories considered in the paper and properties derived from inheritance relations (as measured by NOC and DIT metrics).

As further work, we have the following plans: (a) to consider external software quality metrics, such as number of warnings raised by static analysis tools (Araujo et al. 2011) and number of bugs (Hora et al. 2012), (b) to consider the use of evolution categories as an independent variable in bug prediction models (Couto et al. 2012), (c) to investigate how software evolution categories in general (and their particular relations to software metrics as investigated in this paper) can be incorporated in software quality monitoring tools and models.

The dataset with the software metrics time series used in this paper is available at: http://java.llp.dcc.ufmg.br/sqj2013.

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