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Work Fragmentation in Developer Interaction Data

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1. INTRODUCTION

Work fragmentation is a phenomenon that has been extensively investigated in the literature. Several observational studies in company settings have shown that work fragmentation is very common in the workplace. These studies have also shown that work fragmentation is detrimental to the actual work taking place: after such a context switch, time is necessary for information workers to regain their bearings. A particularly harmful kind of work fragmentation is interruptions, where an external signal (email, chat, phone call, or direct conversation) forces an information worker to switch activity at an unplanned moment and for an unknown duration.

If the literature contains extensive studies of interaction workers, it lacks in two aspects: (1) most studies target information workers (fewer target the specific population of software developers), and (2) the studies are usually field studies, which are limited in the amount of data they contain.

Work fragmentation is indeed an important phenomenon within the context of modern software development, and the impact there may be even worse since developers build and maintain complex mental models of the software they are working on—these models may be more sensible to interruptions, and costly to rebuild.

In this paper, we present a study addressing these issues by (1) being focused on software developers, and (2) using MSR techniques to base its conclusions on a much larger amount of data (specifically, thousands of development sessions recorded by Mylyn and the Eclipse Usage Data Collector). The downside is that the data exploited, being operational data [1], is of lower quality than data extracted from a full-fledged observational study. Trading quality for quantity allows us to explore different aspects of the problem, and to generate hypotheses for subsequent studies of work fragmentation and interruptions in software development. We address the following three questions:

- **RQ1:** What is the relationship between the observed interruptions and the observed developer productivity?
- **RQ2:** Is the observed relationship more pronounced in the presence of prolonged interruptions?
- **RQ3:** What is the observed relationship in the vicinity of interruptions?

Additionally, the Eclipse Usage Data Collector (UDC) interaction data allows us to dig further into more specific aspects, resulting in the following two complementary research questions:

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- **RQ4:** How is the developer's performance during the recovery time after an interruption?
- **RQ5:** What events are more common during recovery time?

A note on terminology: in this paper we (ab)use the word *interruption* to refer to a *gap of activity* observed in IDE activity. We do not presume that all of these activity gaps are actual interruptions (our results lead us to believe otherwise); rather, we assume they are indicators of work fragmentation in general (that is, a programmer switching contexts to perform other activities while developing, such as answering email, looking for the solution of a problem on the Internet, etc). There also actions taking place outside of the computer, such as taking phone calls, interacting with people or leaving one's desk. Of note, work by Zou and Godfrey [2] found that interruptions were a common cause for a lack of observed activity, and classified all periods of inactivity as interruptions.

Structure of the paper. We start with a literature review of studies of work fragmentation in Section 2. This section also contains a review of studies performed with the Mylyn and UDC datasets that we use. In Section 3, we describe the Mylyn dataset in further detail, highlighting potential issues in the operational data that we use in the analysis. Section 4, describes the measurements used in this study, and details the processing of the data that is applied to alleviate the issues described in Section 3. The same section shows how we convert interaction traces to multivariate time series representing development sessions, and present the metrics in the analysis. In Section 5, we answer our first research question: we find an inverse relationship between number of interruptions and our three productivity indicators. In Section 6, we answer our second research question, finding that this relationship is more pronounced for development sessions with at least one longer interruption. In Section 7 we answer our third research question and find that our productivity indicators are indeed lower in the vicinity of interruptions; we further find three patterns of interruptions with different characteristics. Starting in section 8, we focus on the UDC dataset; this section describes the dataset and gives details on the selection and transformation procedures. In Section 9, we replicate our first three research questions with the UDC data; we find that all of the previous conclusions agree with this new data, although the size of the observed effects differ. In Section 10, we answer the fourth research question, finding a gradual increase of productivity during the recovery time after an interruption and a relation with the nature of the interruption, whether is positive or negative. Finally Section 11 answers our fifth research question; based on the type of events executed, we find differences in the activities performed after a positive or negative interruption. In Section 12 we discus about the differences between both datasets. We close the paper by discussing the threats to validity of this study in Section 13, before concluding in Section 14.

2. RELATED WORK

2.1. Empirical Studies of Work Fragmentation

Studies of information workers In the modern workplace, people routinely multitask and shift their attention to multiple areas, projects and activities. An observational study by Gonzalez and Mark found that information workers experience high level of multitasking, averaging 3 minutes on a task before switching to another task [3]. This often results in work fragmentation and interruptions which some studies found has detrimental effects to knowledge workers, such as stress and frustration [4]. Work fragmentation as result of interruptions usually demands extra effort to recover and resume pending activities: a study of 24 information workers found that a worker needs on average 25 minutes to get back on an interrupted task [5]. Similarly, Iqbal and Horvitz [6] found that people experience disorientation and loss of context when multitasking. Czerwinsky et al. found that after experiencing work fragmentation people found it more difficult to perform interrupted tasks and took longer to complete them [7].

While these studies already show the effect of work fragmentation is hurtful, they are mostly observational studies over a limited time, and do not address specifically the sub-population of programmers.

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Studies specific to programmers Zou and Godfrey performed an analysis of interaction histories of 3 industrial programmers for a month [2]. One of their findings was the omnipresence of inactivity in the interaction data, that they interpreted as interruptions. They corroborated this with the programmers which agreed that many such periods of inactivity were indeed interruptions.

Similar to other information workers, software developers experience work fragmentation due to the nature of the activity. Ko et al. [8] performed an observational study of 17 Microsoft developers, where the average time before a switch was five minutes. Some switches were due to necessary changes between tasks, but others were due to interruptions.

Parning and Rugaber evidenced the presence of an edit lag in the majority of a large sample of development session spanning several datasets, hence showing that developers need time to resume work after an interruption [9]. Parnin and DeLine evaluated several cues to help programmers resume work after interruptions forcing them to multitask [10].

Maalej et al. [11] performed a study on the program comprehension strategies of software developers. They found that developers often preferred direct interaction to consulting documentation. As such, experts on a piece of code were often interrupted in their work to answer questions from others.

Fritz et al. studied the perception developers have of their productivity. They found that developers perceived they were more productive on days where they accomplished significant tasks, and when they were not significantly interrupted [12].

As above, most of these studies operate on small datasets. The study of Parnin and Rugaber is the closest to ours in terms of amount of data considered. However, the analysis performed on large datasets in their study focused principally on the edit lag metric, while we investigate metrics which are indicators of productivity along the entire session.

2.2. *Empirical Studies on Mylyn Data*

Several studies mining interaction data have been presented. Kersten and Murphy evaluated the effectiveness of their degree of interest (DOI) model by showing that in a field study of developers, users of their tools had a significantly higher edit to selection ratio [13]. Fritz et al. evaluated how well DOI values reflected the developers knowledge of the code, and encountered mixed results [14]. The lessons they learned allowed them to develop a Degree of Knowledge (DOK) model, an extension of the DOI containing authorship information, and that was found useful in a variety of situations [15]. The DOI has been implemented in Mylyn, and the data it generated has been used in several studies. Based on the data generated by an early version of Mylyn (which recorded additional data, namely usage of commands), Murphy et al. described how 41 Java developers used Eclipse, reporting on the most commonly used views and commands [16]

The Mylyn data available in the Eclipse issue tracking system was used in several studies. Ying and Robillard characterized the edit strategies of developers in the Mylyn dataset, finding three: edit-first, edit-last, and edit-throughout [17]. Lee et al. developed Micro Interaction Metrics in order to enhance defect prediction models [18]. We investigated whether the duration of a task could be used to evaluate the accuracy of expertise metrics, with promising early results [19]. Soh et al. studied the exploration patterns in the developer sessions of the Mylyn datasets, and classified their exploration strategies as referenced or unreferenced exploration; they find that unreferenced exploration were less time consuming [20]. Soh et al. conducted another study of this dataset, finding that the effort spent by a developer in a patch is not correlated with the implementation complexity of the patch [21]. Bantelay et al. improved the accuracy of evolutionary couplings metrics for change prediction (usually computed with commit data); by adding interaction data, recall increased by 13%, with a 2% drop in precision [22]. Zanjani et al. integrated this approach with information retrieval techniques to support impact analysis based on textual descriptions of change requests [23].

2.3. *Empirical Studies with Usage Data Collector*

The Usage Data Collector dataset is a large collection of information about interaction data of Eclipse's users. It is publicly available and has been used in several studies mining interaction data.

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On refactoring activities, Murphy-Hill et al. used this data to understand how programmers are using refactoring tools analyzing patterns on refactoring practices, finding that most programmers don't make deep use of these tools, leaving untouched most of the configuration parameters and performing manually most of the refactoring [24]. Liu et al. identified refactoring tactics (floss refactoring and root canal refactoring, following Murphy-Hill's terminology), finding that the majority of them are floss refactoring and detecting differences on activities performed depending on the type of the refactoring [25]. Sahin et al. analyzed the energy usage changes after refactoring and used the UDC data to identify the most common refactoring events and selected those that fulfill the requirements of being common and cause structural changes [26].

On coding tools and strategies, Murphy-Hill et al. investigated command recommendations for software developers depending on their past history of command usage and tested a set of algorithms using UDC data to obtain CVS and editing commands, getting positive feedback on a live evaluation with users [27]. Yoon et al. use UDC data to compare the results obtained from a proposed plug-in for the capture of low-level events, finding a very similar report on command distribution from both tools [28].

And on a different note, Khodabandelou used the UDC data to prove a proposed model for mining user's intentions and strategies from recorder user's traces, resulting on a model for UDC developers activities and the construction of a map followed by them [29].

3. MYLYN DATA DESCRIPTION

3.1. *Mylyn Data*

For our analysis, we used the Mylyn dataset of development data. Mylyn [13] is an Eclipe plugin that monitors the program elements a programmer interacts with in order to build a task context. A subset of Eclipse developers (principally from the Mylyn and PDE Eclipse projects) use the Mylyn Monitor tool to capture fine-grained usage data of their IDE that they attach to the bug fixes as a task context they submit to Eclipse. This allows reviewers of the bug fixes to use the same task context when they review the changes. The task context contains the entire interaction history since a developer activated the task he or she was working on, and as such is a rather reliable account of IDE usage over time (barring a few issues explained below).

To collect the data, we crawled the bugzilla data of the Eclipse project (`http://bugs.eclipse.org`), and downloaded all the bugs that had as an attachment a Mylyn task context. In total, there were 6182 bug reports which contained 8102 Mylyn task contexts.

3.2. *Interaction History Format*

The interaction history is a sequence of ordered events in time [17]. An event is associated to a direct action of the programmer in program elements, for instance: edit and selection events. Other interaction events are indirect [13]: they are issued by Mylyn itself while it is maintaining its DOI model of a programmer's task context. However these events are not edit or selection events. Each event captures several pieces of information: the timestamp, the kind of event and the signature of the code element that was interacted with (package, class, attribute, or method signature—including name and parameters).

In Table I we show the different kinds of events and their description; in Table II we show an example of an interaction history. However, certain characteristics in the data present challenges around the data mining we plan to perform [30]. These cases must be detected and resolved in order to get a representative time series model of programmer activity. We describe these issues and our solutions below.

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Table I. Kinds of interaction events [13].

kind	mode	description
selection	direct	Editor and view selections via mouse
edit	direct	Textual and graphical edits
command	direct	Operations such as saving, building, preference setting
manipulation	direct	Direct manipulation of interest
propagation	indirect	Interaction propagates to structurally related elements
prediction	indirect	Capture of potential future interaction events

Table II. Example of interaction history.

	StartTime	EndTime	EventKind	Method
1	10:30:00	-	selection	m1
2	10:30:40	-	manipulation	-
3	10:30:40	-	edit	m1
4	10:31:03.700	-	selection	m1
5	10:31:03.800	-	selection	m2
6	10:31:03.850	-	selection	m3
7	10:32:05	10:33:07	edit (5)	m2
8	10:33:10	-	prediction	-

3.3. Special Characteristics of Mylyn Data

Below, we describe the characteristics of Mylyn data one has to consider before processing them. This is especially relevant in our case since our study needs a representation of the activity as close to reality as possible. In Section 4.2 we describe the criteria used to process these characteristics.

Aggregate events. This type of event includes several actions on the same program element. These actions usually occur within an interval of short duration time. Whenever an aggregation occurs, the event is expanded to include two timestamps defining a range of time, instead of a single timestamp, and a number of events. Accordingly, these aggregate events lose their specific time besides the range of time. The reason of this is that for scalability—in terms of storage—Mylyn does not register all the user events.

For example, Table II shows an aggregate edit event in row 7. We indicate in parenthesis the number of actions associated and the field *EndTime* registers the timestamp of the last occurrence. Clearly, too much aggregation in a given trace severely compromises the detection of work fragmentation as this relies on accurate timestamps.

Massive events. Such an event occurs when the same action is executed on more than one program element in a very short time. This massive action generates consecutive events of the same kind and with a tiny gap between them.

For example, massive events are produced when we select an entire group of classes from the navigation tree panel in Eclipse. In Table II we show a massive selection on the methods m1, m2 and m3 in rows 4, 5 and 6. This massive selection produces three consecutive events with a time gap of not more than 0.1 seconds. These events overstate the activity of developers as each of these does not correspond to an individual developer action; rather, the entire sequence is.

Very long events. These events have a duration time ($|EndTime - StartTime|$) much larger than the mean. This mainly occurs in aggregate events. We believe that this issue is due to factors related to Mylyn, since it can register the end time of an event when the task is resumed after a long downtime. Another cause of these events is when one selects a code fragment and maintains this action for a long time.

After exploring a sample of traces, we noticed that a long interruption of activity implicitly splits a trace into two sub-traces. Moreover, we have realized that many long events happen around this border. That is, they began before the interruption and finished immediately after the interruption, which confirms the observation above (resumption of a task after a long downtime). However this has the side effect of hiding the gaps of activity in the sequence of events if care is not taken. Consequently, the duration of these events is overstated; however, finding their actual duration is not trivial.

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4. PREVIEW PHASES FOR KNOWLEDGE DISCOVERY

We used the phases of the process *Knowledge Discovery in Databases (KDD [31])* to discover useful knowledge from our collection of data: we first select data, then preprocess it, before transforming it to time series. We close this section by presenting the metrics we use in this study.

4.1. Selection

Our purpose is the analysis of work fragmentation and interruptions in software development. Therefore, we focused only in the interaction data of the user with the program elements. The variables of interest for our study are [19]:

1. Duration: the time that a programmer took to perform a programming task.
2. Edition: the amount of code changes that were necessary to perform said task.
3. Navigation: how many program elements were consulted in a task; represented by selection events.
4. Edit ratio: as in previous studies [13], the ratio of edits over edits and selections is an indicator of more efficient work since program exploration is reduced.

First, we have kept only the edit and selection events that are associated to a program element. These type of events are distributed in 8058 traces. On the other hand, edit-type events also occur when the programmer double clicks on a file. In these events the starting time and ending time are the same [18]. We consider that the double-clicking actions form part of the user navigation, therefore these events are transformed into selection events.

Second, we have kept all traces without aggregate information. Unfortunately, we cannot know the distribution in time of the actions that have been aggregated in a single event: without additional information, an aggregation of 15 events over one hour is as likely every 4 minutes than to have 10 events in the first 5 minutes and 5 more in the last 10 minutes. Therefore, designing a correct disaggregation task to this traces is very difficult, if not impossible.

In order to keep as many traces as possible, we have also kept a little group of traces with aggregate information where the aggregate events have a maximum duration time of five minutes (to minimize uncertainty) or have only two aggregate actions (since the actual event timestamps are known in this case). Thus, we were left with 6260 traces.

It could be possible that these traces we discarded were biased in one way or another. In Figure 1, we note that in our data the traces with aggregation information appear from the year 2008 on, and slowly increase in frequency from then. We would expect such a pattern from a change to the version of Mylyn, rather than a change to the type of tasks being performed. This is corroborated with our tests of a recent version of Mylyn, which seems to be even more aggressive in discarding information (it only keeps information at the class level, discarding method level information). As such, our assumption is that it is unlikely that this change is due to anything else than the version of Mylyn that was in use (and hence is not due to different tasks, people, etc). This leads us to believe that it is unlikely that filtering these traces would introduce other sources of bias.

Finally, we found that 26% of traces had at least an interruption over 8 hours, which is hence large enough to represent the difference between two working days. In these cases, we treated these long activity gaps as splitting points in order to decompose a long trace in several development sessions [32].

After this, we considered a minimum duration time of 30 minutes in order to ensure a minimum of activity during a session. In this way, we obtained a final total of 4284 useful sessions to be processed in the next phase.

4.2. Preprocessing

After filtering out traces, we describe the final processing steps that yield the final development *sessions* that we study:

Sorting. We sort chronologically all the events by their starting time. Before that, we normalize the timezone of each trace. We found 156 traces (3%) with more than one timezone.

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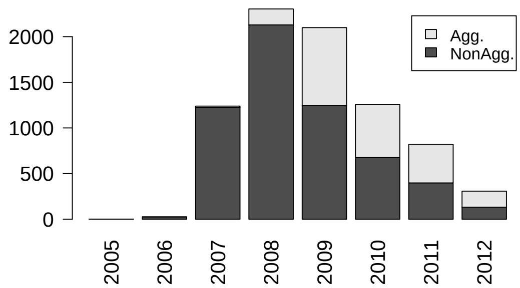

Figure 1. Grouping by date all the traces, with aggregate information (light gray) and without aggregate information (dark gray).

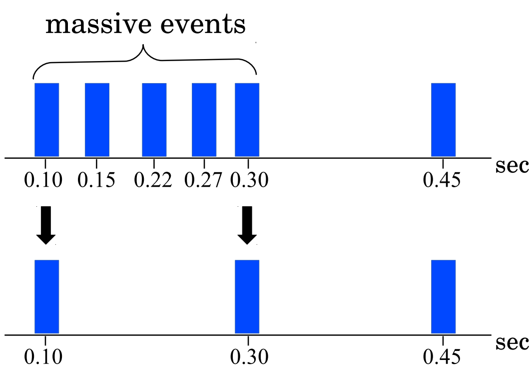

Figure 2. Replacing five massive events with only two events.

Massive events. We use a short spacing interval to join consecutive massive events in only two, the first and the last event (Figure 2). We have considered a spacing size of 0.1 seconds (100 milliseconds). All the massive events we found were of type “selection”, which concurs which our observation above (multiple selection of several entities at the same time). The total number of selection events was reduced by 45%.

Disaggregation. We disaggregate all the actions associated with each remaining aggregate event with equidistant separation, as was done by Ying and Robillard [17]. Due to the filtering above, this was only applied on traces that had aggregate events of short duration ($\leq$ 5 minutes).

Event splitting. Finally, we split all the long duration events. A normal event does not generally have duration (EndTime is null). However, 12% of normal events had a duration > 0 seconds and 3% ≥ 1 hour, these events are outliers. Therefore, we split each long event in two events: one at the start and the other at the end of the interval. This is the same criteria applied for massive and aggregate events.

Table III shows the ratio of variation of the number of events after preprocessing.

Table III. Number of events after preprocessing.

type event	before	after	% variation
edit	452236	475554	+5%
selection	658768	527652	-20%
total	1111004	1003206	-10%

4.3. *Transformation*

Our goal is to build compact and representative models from each session. In this sense, we used aggregation of events to generate a multivariate time series (MTS). An MTS is a sequence of multivariate observations taken at continuous time intervals coming from a same phenomenon. We build the MTS with edit and navigation variables; the time unit is the minute, and the amplitude is the sum of all the events that occurred in this minute. We selected the minute as unit time because it seemed to be an appropriate and minimal representation of the user interaction in a programming task—obviously a subjective decision.

Mylyn data has another characteristic which is unusual for time series: the time of occurrence of the events is not periodic (see column *StartTime* in Table II). That is to say, events occur with non-equidistant separation gaps between them. However, in a time series, the values must be evenly spaced and chronologically sorted. For this reason, we compressed the size of the multivariate time series, pulling apart all the interruptions as a new time series variable. Then, each time series value represents the interruption duration in this minute (Figure 3).

Consequently, the temporal component represents the *real working time* of a programming task, excluding inactivity. This allows us to compute our activity indicators (number of edits, selections, edit ratio) independently of the amount of inactivity in a session.

We define empirically an interruption as a pause of programming of duration ≥ 3 minutes. This is based on previous work where we observed that short interruptions lasted usually this long [3]. Based on additional observations from this work, we defined a prolonged interruption as one lasting for more than 12 minutes. These thresholds are also supported by the Activity Theory models of Kaptelinin and Nardi [33]. This study presented work fragmentation at two different levels: actions and activities. Interruptions originated after a period of around three minutes of sustained attention to the previous action were considered when people were switching at the level of interactions with artifacts of people. Interruptions originated after a period of twelve minutes of sustained attention to a previous activity where considered when people were switching at the level of interactions with projects or topics.

We identified that 98% of sessions had at least one gap of activity. Moreover, we observe that the short interruptions predominate over the prolonged interruptions (Table IV). This first result tells us that work fragmentation is extremely prevalent in our dataset.

Table IV. Prevalence of interruptions according to their duration time.

duration	ratio	examples
$[3 - 12min\rangle$	69%	short pause, answer a question, thinking, looking for interruption
$[12 - 30min\rangle$	18%	coffee break, short meeting, extended interruption
$[30min - 2hr\rangle$	9%	lunch break, a meeting
$[2hr - 8hr\rangle$	4%	extended meeting

4.4. *Metrics Used in This Study*

We use the following six metrics to measure interruptions and productivity, while controlling for the unproductive time in a session, the length of time of the session itself, and the efficiency of the development that took place during the session:

Metrics characterizing interruptions:

- *Number of interruptions*: counts all the interruptions that occur in a development session.
- *Duration of interruption*: it is the time duration in minutes of the each interruption.

Metrics characterizing productivity and activity:

- *Productive work time:* the duration of a development session, substracting the duration of all the interruptions present in the session, to control for inactivity.
- *Number of edits per minute:* the total number of edits events, divided by the productive work time to control for length of the session. This is an indicator of user activity during the session.
- *Number of selections per minute:* is the total number of selection events, divided by the productive work time. Also an indicator of activity.

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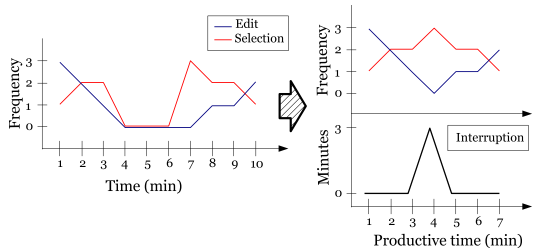

Figure 3. Example of how to compress a time series.

- *Edit ratio:* the number of edits divided by the sum of edits and selections, as used by Kersten and Murphy [13]; an efficient developer spends less time exploring code and more time editing it.

5. RQ1: RELATIONSHIP BETWEEN INTERRUPTIONS AND PRODUCTIVITY

5.1. Relation between Interruptions, and Edits and Selections

As mentioned above, we use the metrics of edit, selection, and edit ratio as indicators of productivity. We first examine the number of edits and selections, and how their distribution varies in function of the number and type of interruptions.

We split the data in five groups: The first group contain all the sessions without interruptions (*none*). For the others groups, we have considered four ranges of number of interruptions delimited by their quartiles (Table V). Then, for each group, we display the distribution of events per minute and edit ratio via boxplots (Figure 4). We observe a large difference between the sessions without interruptions and the ones who do. Further, we observe that the rate of events per minute decreases slightly when the session has more interruptions. Therefore, we can intuit that the relationship between number of interruptions and the productivity indicators that are edits and selections, tends to be inversely proportional.

Table V. Thresholds used to group sessions based on their number of interruptions

	25%	50%	75%
quartile	3	5	10

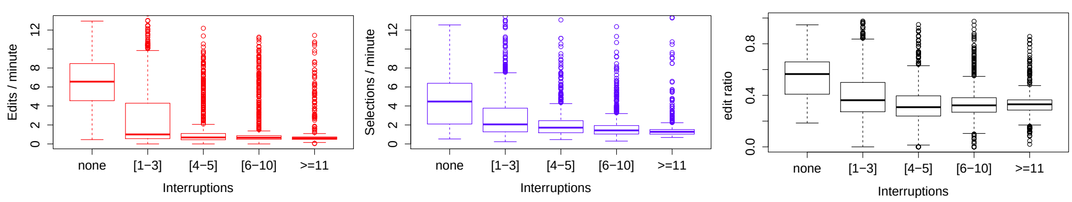

Figure 4. Boxplots showing the relation between the number of edits and selection events per minute, the edit ratio, and the number of interruptions.

Beyond visual inspection, we also quantify the statistical and the practical significance of these observations. First, all the differences observed are statistically significant with very low p-values (see Table VI) according to the Mann-Whitney U-test. This is not surprising, given the shape of the boxplots and the size of the samples.

More importantly, we used *Cohen's d* to measure the practical significance of these results in term of effect size [34]. *Cohen's thresholds* are defined as follows: trivial (< 0.2), small ($\langle 0.2 - 0.5]$),

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moderate ($\langle 0.5 - 0.8]$) and large effect (> 0.8). As shown in Table VI, we note that the effect size of the interruptions over the number of edits by minute is (very) large. In selections, the effect is moderate for sessions having up three interruptions, and large to very large for sessions with over four interruptions. This reinforces our impressions that interruptions and user activity follow inverse relationships, and that they are quite pronounced.

Table VI. Effect size and significance of the relationship between number of edit per minute, selection per minute, edit ratio, and number of interruptions

	none	≤ 3	$[4-5]$	$[6-10]$	≥ 11
Edits					
mean	6.29	2.59	1.55	1.29	0.91
U-test	$\hookrightarrow$	$<$ 2.2e-16			
Cohen's d	$\hookrightarrow$	**1.23**	**2.02**	**2.37**	**3.31**
Selections					
mean	4.73	2.93	2.26	1.79	1.54
U-test	$\hookrightarrow$	8.1e-13	$<$ 2.2e-16		
Cohen's d	$\hookrightarrow$	**0.66**	**1.17**	**1.93**	**1.78**
Edit ratio					
mean	0.55	0.39	0.33	0.34	0.33
U-test	$\hookrightarrow$	4.2e-14	$<$ 2.2e-16		
Cohen's d	$\hookrightarrow$	**0.84**	*1.33*	*1.48*	*2.12*

5.2. *Effect on the Edit Ratio*

Finally, we want to know the effect the interruptions over the ratio of edits in each session, as this is the often seen as a better indicator of productivity than raw activity, since the programmer spends less time navigating the source code in search of information, and more time actively editing it [13].

We first analyze the relationship between edit ratio and number of interruptions (Figure 4, bottom). We observe that the edit ratio decreases when the session has more interruptions: the effect is pronounced between session that do not have interruptions and ones that do, and is more subtle as the number of interruption grows. A look at the practical and statistical significance of these results (Table VI, bottom) show that the results are (unsurprisingly) statistically significant, and that the observed effect sizes are large to very large.

Adding this to our previous result, we observe that both the user activity (in terms of raw quantity of edits and selections per minute) and the user productivity (in terms of edit ratio), both follow an inverse relationship with the number of interruptions. This finding agrees with the previous literature on the harmfulness of multitasking, work fragmentation, and interruptions. Furthermore, the effect sizes are very large.

6. RQ2: RELATIONSHIP BETWEEN DURATION OF INTERRUPTIONS AND PRODUCTIVITY

In this section we analyze whether or not the interruption duration is a factor in the relationship between interruptions and developer productivity. To substantiate this claim, we have built two groups of sessions with interruptions:

- *short*: the first group consists of sessions that only have short interruptions (< 12 minutes of duration). These sessions constitute 18% of the total.
- *prolonged*: the second group consists of the remaining sessions, which have at least one prolonged interruption (≥ 12 minutes of duration). These session constitute 80% of the total.

We then displayed the distribution of events by minutes and edit ratio of these two groups and compared them with the sessions without interruptions (Figure 5). We observe that the number of events per minute is lower in sessions with at least one prolonged interruption.

As in the previous case, the differences are significant, and we used *Cohen's d* to measure the practical significance of the means (Table VII). We note that the effect size of the interruption duration over the number of edits per minute is very large. In selections, the effect is moderate for short interruptions, and large for prolonged interruptions. We conclude that the relationship between user activity and interruptions could be adversely affected by interruptions of longer duration.

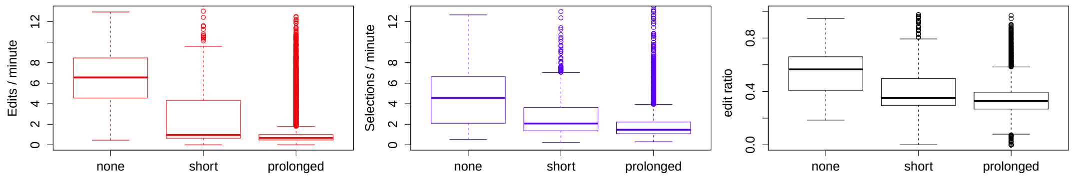

Figure 5. Boxplots showing the relation between the number of edits and selections per minute, the edit ratio and interruption duration

Table VII. Effect size and statistical significance of the relationships between edits and selection per minute, edit ratio, and duration of interruptions

	none	short	prolonged
		Edits	
mean	6.96	2.98	1.76
U-test	$\hookrightarrow$	$< 2.2e\text{-}16$	
Cohen's d	$\hookrightarrow$	**1.23**	**2.11**
		Selections	
mean	5.20	3.33	2.47
U-test	$\hookrightarrow$	6.197e-13	$< 2.2e\text{-}16$
Cohen's d	$\hookrightarrow$	**0.63**	**1.24**
		Edit ratio	
mean	0.55	0.40	0.34
U-test	$\hookrightarrow$	3.72e-14	$< 2.2e\text{-}16$
Cohen's d	$\hookrightarrow$	*0.86*	*1.32*

Similar results occurs when we look at the edit ratio (Figure 5, bottom): the edit ratio is smaller in sessions that have prolonged interruptions, compared to the ones that only have short interruptions. At the bottom of Table VII, we show the statistical and practical significance of these results. As before, we observe large effect sizes when comparing sessions who do not have interruptions with ones that do have, and larger effect sizes for sessions with at least one longer interruption.

These findings seem to indicate that the inverse relationship between productivity and time of duration is more pronounced in session with at least one longer interruption. This agrees with the literature for information workers.

7. RQ3: LOCAL RELATIONSHIPS BETWEEN INTERRUPTIONS AND PRODUCTIVITY

7.1. Generic Sessions

In order to better understand the relationship between work fragmentation and productivity, we need to delve deeper and perform local analyses of the development sessions. In the first step, we wanted to summarize how the activity of users is distributed over time in sessions which have no interruptions, short interruptions, and prolonged interruptions.

To summarize the development sessions, we have resized each time series to a single $size$, using local means. We have used $size = 10$, that is, dividing each session in 10 chunks of equal time, since because it yielded better global visualization (better uniformity) of the user interaction along a session. For each chunk, we choose the median value of edits and selections for each group, and compose one summary time series for each group; these are the time series displayed in Figure 6.

We observe that the median activity in sessions with interruptions is less than in sessions without interruptions, mainly in the edit frequency. Moreover, the edit frequency exceeds the selection frequency in sessions without interruptions. The opposite occurs in sessions with at least one interruption—and is more pronounced when there is at least one prolonged interruption—, where

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the code navigation tends to exceed the frequency of edits. These results agree with our earlier results.

We also notice that the time series without interruptions have much more edits in the middle of the session than the others. This observation matches the hypothesis that developers need time to build their mental model for their task, and are less productive early in a session. This is similar to the edit lag in Parnin's study [9]: in sessions without interruptions, the edit lag is clearly visible at the start of the session. This behavior is not visible in sessions with interruptions; indeed, each session may have several edit lags (after each interruptions), and those would be equally distributed over the entire duration of the session, resulting in the "flat lines" that we see for these sessions.

These results support our previous observations at a finer level, an corroborate the literature saying that time is needed to start or get back on task.

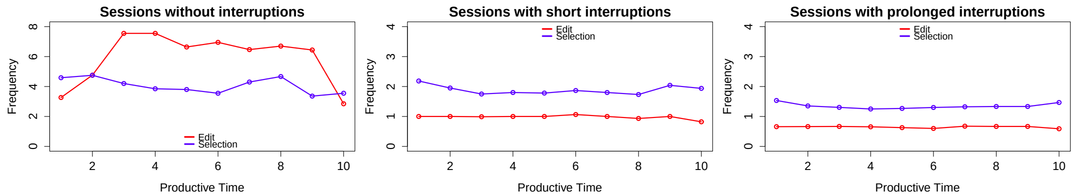

Figure 6. Global representation of a session with: no interruptions (top); only short interruptions (middle); and at least one prolonged interruption (bottom).

7.2. *Local Analysis*

Having presented the global effect of the interruptions over the user productivity, we now focus on the local activity before and after interruptions. We take a maximum real time interval of 30 minutes around each detected interruption, obtaining a set of 26988 time series subsequences. Then, we compute the median of all these subsequences as a generic local representation (Figure 7). We also plot with dashed lines the median values of edits and selections per minute in the sessions with interruptions in order to give more context to the observed values. Below we describe some observations:

- *In the center,* we find the interruption point. There is clearly a negative effect on the time series, as the area before and after the interruption is the area with the lowest activity. The activity is well below the median activity of time series with interruptions, showing that the effect is indeed more pronounced near interruptions.
- *On the right,* the trend of the time series increases steadily. We hypothesize that the programmer is immersing again into the programming task, increasing progressively the activity as represented by the number of edits and selections. We see that in the average case, it reaches the median activity 12 to 18 minutes after the interruption. It then rises further than the session median, which is not surprising, as we expect higher than median activity further away from interruptions.
- *On the left,* we observe that the number of events near the interruption also goes down well below the median value. This is might be because of two reasons: the programmer could have found a problem while coding, who at first will try to solve it by reading the code, switching out from the IDE, navigating the call stack and debugging, before going to ask another teammate, according to LaToza et al. [35]; this set of actions end up with an interruption and reduce the observed activity within the IDE. Also, when the interruption is imminent or expected, the programmer make use of different suspension strategies like writing physical notes, making a mental note or leaving a reminder cue on the code or window, as mentioned by Parnin and DeLine [10]. These activities reduce the activity before the gap and they are seen in the interaction data mostly as selection events. The latest can be better visualized in Figure 13 with the UDC data as a significant decrease of edit events, being below the selection events approximately 10 minutes before the interruption.

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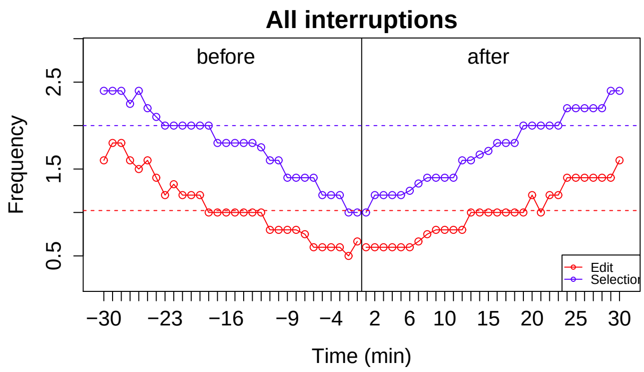


Figure 7. Local effect of an interruption in the user activity.

We investigated whether the drop in activity local to interruptions was also accompanied by a drop in the edit ratio. We computed the edit ratio over slices of 5 minutes before and after each interruption (smaller intervals would be too sensitive to noise). The boxplots in Figure 8 show that the edit ratio drops slightly the closer we are to an interruption. The effect is small, but significant (see Table VIII). As a reference, the mean edit ratio for sessions with short interruptions is 0.4, so the edit ratio close to the interruptions are clearly lower in the 5 to 10 minutes around an interruption. This matches the observations Parnin made with the edit lag [9].

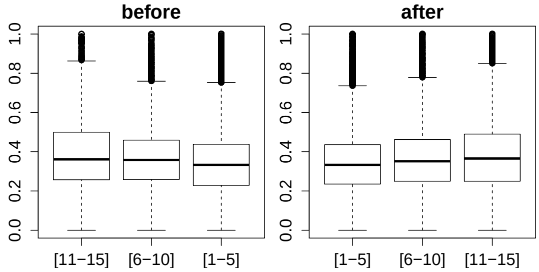


Figure 8. Ratio of edits around the interruption.

Table VIII. Effect size of the ratio of edits around the interruption.

	[1-5]	[5-10]	[11-15]
		before	
mean	0.34	0.37	0.39
U-test	↪	< 2.2e-16	
Cohen's d	↪	**0.16**	**0.24**
		after	
mean	0.34	0.37	0.39
U-test	↪	5.67E-16	< 2.2e-16
Cohen's d	↪	**0.14**	**0.22**

7.3. *Patterns of Interruptions*

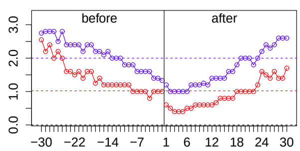
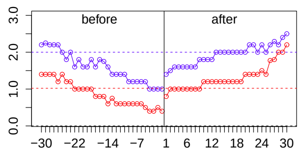
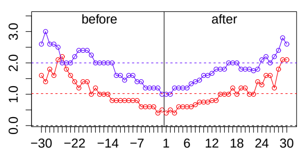
Given the overall activity pattern we noticed in the local analysis, we hypothesize that there are several kinds of interruptions, matching the scenarios observed in the literature: actual interruptions distracting the programmer from the task at hand, and switching tasks in case of being stuck in the current task.

We hence looked for patterns in the interruptions. After applying clustering techniques over all the subsequences, we always found the formation of three recurrent patterns that show different effects of the interruption: neutral, positive and negative. The clustering was performed with the K-Mediods [36] technique, the Silhouette metric [37] to interpret and evaluate the results, the Dynamic Time Warping [38] as distance measure, and feature extraction techniques to reduce the dimensionality. For this reason, we classified empirically each interruption by its local effect.

We did so by computing Cohen's d on the quantity of edits before and after the interruption. To obtain a significant effect, we need the presence of activity both before and after. Not all the interruptions meet this criteria however: some are located close to the start or the end of a session, or too close to another interruption. In total, 53% of the interruptions had enough data before and after the interruption and were selected for the analysis. Table IX shows the applied thresholds and the results, accompanied with a typical example of an interruption in each category. This local analysis shows that there are indeed three well-defined groups of interruptions, with the two largest of them having clear effects on the activity in the session.

Finally, we briefly report on the edit ratios for positive and negative interruptions (see Figure 9). We see distinct patterns as well: positive interruptions have a higher edit ratio after the interruption (in accordance with the hypothesis of a more efficient activity after having looked for missing information), while negative interruptions have a lower edit ratio after the interruption (in accordance with the hypothesis that the programmer may be rebuilding his context after an unwanted task switch).

Table IX. Local Effect of Interruption.

effect	pattern
negative (45%): when the frequency of edit events decreases after the interruption (Cohen's $d < -0.2$)	
positive (44%): when the frequency of edit events increases after the interruption (Cohen's $d > 0.2$)	
neutral (11%): when there is no well defined effect before or after the interruption ($abs(d) <= 0.2$)	

8. ECLIPSE USAGE DATA COLLECTOR DATA DESCRIPTION

8.1. The Eclipse UDC

The Usage Data Collector (UDC) dataset is a large compendium of information about interaction data from users of Eclipse, collected from December 2008 to August 2010, with the intention to keep track of how programmers are using the IDE. The framework listens to the events triggered by the user or the system, such as: edition and navigation commands; the startup of a plug in; or the closing of the platform. More specifically, UDC collects information about loaded bundles, commands accessed via keyboard shortcuts, actions invoked via menu or tool-bars, perspective changes, view usage and editor usage. The UDC is a large dataset that contains information of

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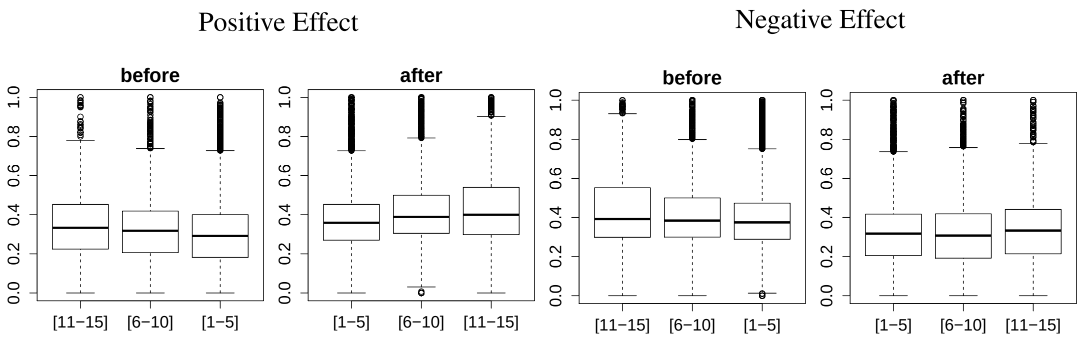

Figure 9. Ratio of edits for positive and negative local effect.

around 1,800,000 users, and has a total of 2,323,233,101 unique rows with 5 attributes each. Table X show a description of the attributes.

Table X. Attributes in UDC data.

attribute	description
userId	Unique number that identifies a user
what	The action of the event (deactivated, activated, opened, executed, etc.)
kind	What kind of event was executed (workbench, view, command, etc.)
bundleId	Description of the event's package
bundleVersion	Version of the bundle's event
description	Description of the event
datetime	Date and time in UNIX format

8.2. *Selection and transformation*

We used the data pre-processed by Murphy-Hill, that is published on Google BigQuery [39]. This is an alternative version of the original UDC dataset, that is cleaned and preprocessed, so that the transformation phase is simple and focused on our needs. Due to the magnitude of the dataset we only worked on a fragment of it. We took a random sample of 1,000 users, which is large enough to be representative; in fact, this is larger than the dataset we were able to obtain for the Mylyn study.

The first step was to query the dataset to get the data from 1,000 random users. We delimited the query to obtain only those events dispatched by the user, ignoring system events. We also ignored the bundle version and formatted the UNIX date into a more legible datetime format. From this query we extracted 4,321,349 unique events, which is around 0.18% of the whole dataset.

After obtaining the data, the next step was to add the attributes required by every event in order to match as closely as possible the format of the Mylyn data; this allowed us to reuse a part of our analysis. We hence added fields corresponding to the type of the event (edition or selection), its duration (time elapsing between this event and the next event, used to determine where interruptions take place and sessions end) and an ID to identify the different sessions present on the data. For the latter, we sorted the data by *userId* and by *datetime* afterwards. This was required because by default the user's data is mixed and we needed it not only chronologically correct but also sorted by users to tag the sessions of every user without interferences.

Once the events were classified and sorted, we split the dataset into sessions, defining a session as a period of registered work between interruptions of 8 hours or larger, as we did with Mylyn. We did this splitting the data by users to avoid a conflict between the last event of a user and the first one of the next. After this, we obtained a total of 28,989 different sessions; after a filter to keep only those with at least 30 minutes of productive time (as we did with the Mylyn dataset), we ended up with 15,825 useful sessions, in contrast with the 4,284 we had from Mylyn.

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8.3. Classification of events

Mylyn events belonged to two principal categories: edition and selection. The UDC data doesn't have this, so we inferred a classification manually. Note that we reuse the same term of selection in the following text, as it was used in Mylyn data. Strictly speaking, the word "navigation" would be better suited to the variety of events present in the UDC data, but we keep the old term for consistency.

We took into consideration the attributes *what*, *kind* and *description* to choose the best classification for every event. Starting by the kind attribute, some events are labeled as *view* which are precisely those that open, activate or close a view such as the console, the package explorer or the variables view. Therefore, the events of the kind *view* were classified as selection-type events.

The classification for the rest of the events is more complex: we needed to check directly the command description and the bundle name it belongs to in order to precisely infer its meaning (e.g., . We could label as edition all those commands with the attributes *command* and *executed*. The majority of them are in fact of that type, but some commands executed also can open a view, navigate through the text or go to another class. For this reason we took a closer look into the bundle name and what the description can tell us about the events.

Thus, by default, all events of the attributes *command* and *executed* were classified as edition and afterwards we did a thorough analysis to identify those that are actually selection events. This way we categorized as selection all the events where we could tell based on the description if they have the purpose to, for instance, navigate to another window, open a perspective, find and replace words, search code, debug code, or perform window management. The description contains the whole path from the top package to the class that implements the event, so we look for key words to apply the classification. The proportion of events after the classification is shown in the table XI. We used an iterative process involving two of the authors of the paper to arrive to this result; the process was iterative, until we reached consensus. A sample of the classification can be seen in the Table XII.

Table XI. Proportion of events.

event	percentage
edition	34.6%
selection	31.1%
system	31.5%
control	0.8%

Table XII. Sample of classified events.

description	type
org.eclipse.ui.edit.delete	edition
org.eclipse.ui.file.save	edition
org.eclipse.ui.edit.undo	edition
org.eclipse.jdt.ui.CompilationUnitEditor	selection
org.eclipse.ui.console.ConsoleView	selection
org.eclipse.debug.ui.commands.StepOver	selection
org.eclipse.ui.workbench	system
org.eclipse.team.sync.views.SynchronizeView	control

The edition and selection types are the ones we are interested in for the study. The system classification is composed of the events that activate and deactivate the workspace of Eclipse; it is difficult to determine when and why this events are executed (they can be executed either via user or system action, and the order of execution in relation with associated events is not clear) so we decided to establish this particular classification for them. Finally, the events of the type control are those related to the version control system.

After processing the data, we were able to reuse the same data analysis pipeline we used for Mylyn, in order to verify whether the results hold with this other dataset.

9. RESULTS OF RQ1, RQ2, AND RQ3 ON UDC

9.1. RQ1: Relationship between interruptions and productivity

We used the same metrics to investigate whether we could observe a similar behavior with the new dataset. To analyze the effects of interruptions on productivity we divided the sessions according to the quantiles of the distribution of the number of interruptions they hold. We obtained slightly different results to Mylyn, and consequently we changed the thresholds used to classify the sessions by the number of interruptions. Although the change is small, the distribution of the number of interruptions differs and indicates that on UDC the sessions contains less interruptions. It is important to reflect this change on the results and compare them against the results with Mylyn on fair ground, as the same procedure was done with that dataset. The new thresholds are shown in the Table XIII and were used to classify every session according to the number of interruptions that it has.

Table XIII. Thresholds used to group sessions based on their number of interruptions for the UDC data

	25%	50%	75%
quartile	2	4	7

For every session, we calculated the number of editions and selections per minute, and the edit ratio. The boxplots on the Figure 10 show a similar pattern in comparison with the results with Mylyn. When facing zero interruptions the editions and selections per minute are greater than with one or more interruptions, and as more interruptions occur this metrics gradually decrease.

Table XIV. Effect size and significance of the relationship between number of editions per minute, selections per minute, edit ratio, and the number of interruptions on UDC data

	none	≤ 2	$[3-4]$	$[5-7]$	≥ 7
			Edits		
mean	3.97	2.18	1.82	1.70	1.59
U-test	$\hookrightarrow$		< 2.2e-16		
Cohen's d	$\hookrightarrow$	**0.58**	**0.88**	**1.05**	**1.35**
			Selections		
mean	3.10	2.93	1.80	1.77	1.63
U-test	$\hookrightarrow$		< 2.2e-16		
Cohen's d	$\hookrightarrow$	**0.44**	**0.66**	**0.81**	**0.85**
			Edit ratio		
mean	0.68	0.56	0.55	0.54	0.57
U-test	$\hookrightarrow$	<6.9e-06	<3.6e-09	<5.1e-11	<5.1e-09
Cohen's d	$\hookrightarrow$	**0.37**	**0.46**	**0.49**	**0.55**

The edit ratio behaves similarly in comparison with the data on Mylyn, where the median changes accordingly with the number of interruptions, decreasing when there are more and reaching the maximum when there are none. An important difference is that the effect overall appears to be less pronounced in UDC and we can see it on the effect size tests shown in the Table XIV. Most of the observed effects are medium, while in the Mylyn datasets the effects were large. Note despite the differences in effect sizes, the differences are still significant.

9.2. RQ2: Relationship between duration of interruptions and productivity

The next analysis is on the effects of the size of the interruptions, considering short and prolonged interruptions.

- *short*: as with Mylyn we considered those sessions that have only short interruptions (< 12 minutes of duration). They constitute 6% of the total.
- *prolonged*: this group of sessions have at least one prolonged interruption ($\geq$ 12 minutes of duration). They constitute 93% of the total.
- *none*: this group of sessions have no interruptions. They constitute 1% of the total.

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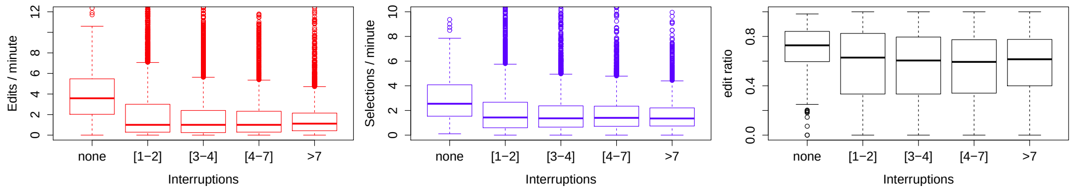

Figure 10. Boxplots showing the relation between the number of editions and selections per minute, the edit ratio, and the number of interruptions.

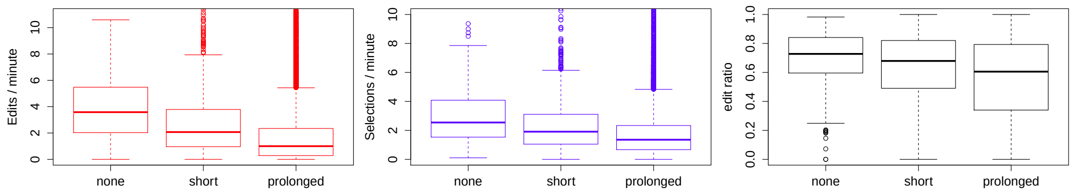

Figure 11. Boxplots showing the relation between the number of edits and selections per minute, the edit ratio and interruption duration

Again the hypothesis holds on UDC data as it did with Mylyn. We can see on the Figure 11 that with short interruptions the metrics are greater than when facing at least a prolonged one, for more time is needed to recover after a long interruption. The effect size test results in the Table XV

Table XV. Effect size and statistical significance of the relationships between edits and selection per minute, edit ratio, and duration of interruptions on UDC data

	none	short	prolonged
		Edits	
mean	3.97	2.75	1.79
U-test	$\hookrightarrow$	$<$ 2.6e-12	$<$ 2.2e-16
Cohen's d	$\hookrightarrow$	**0.48**	**0.89**
		Selections	
mean	3.10	2.37	1.78
U-test	$\hookrightarrow$	$<$ 4.3e-07	$<$ 2.2e-16
Cohen's d	$\hookrightarrow$	**0.34**	**0.68**
		Edit ratio	
mean	0.68	0.63	0.56
U-test	$\hookrightarrow$	0.01003	$<$ 4.019e-09
Cohen's d	$\hookrightarrow$	*0.21*	*0.44*

matches the previous observations on a less pronounced effect compared to the Mylyn dataset. The Cohen's *d* test results tell us that we can label the effect from medium to large and the median values act accordingly to our hypothesis and conclusions with Mylyn.

9.3. RQ3: Local relationships between interruptions and productivity

The sessions with UDC went through the same process of transformation into 10 chunks of equal time. The results on the Figure 12 shows similar (but not identical) patterns compared to the ones we observed in Mylyn.

The median of editions and selections per minute are greater in sessions without interruptions, and the editions are more common than selections. Sessions with only short interruptions show a level of edit activity similar to selection activity overall, but with a tendency to rise overtime (except a drop in the last segment). When facing at least one prolonged interruption we can see the metrics drop in comparison with short interruptions and the selections are now more frequent than the edit events. This agrees with the results with Mylyn on this point.

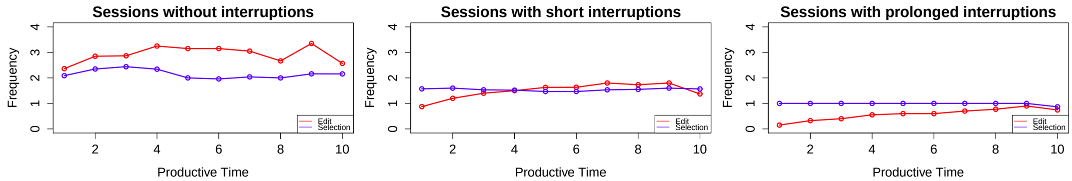

Figure 12. Global representation of a session with: no interruptions (top); only short interruptions (middle); and at least one prolonged interruption (bottom).

As for the observation that activity was overall higher in the middle of the session we do see this for sessions without interruptions. For sessions with interruptions, selection activity appears to be constant over time, while edit activity appears to rise over time with a slight drop at the end.

On a local analysis around the interruptions, we can see a similar interesting behavior of the edition and selections metrics as we observed with Mylyn. In the Figure 13 we show the frequency of editions and selections around the interruptions, specifically 30 minutes before and after. We observed that close to the interruption the frequency of editions and selections drastically drop, and in a radius of around 10 minutes both metrics are below the overall median. This phenomenon is also visible on the same version of this plot with Mylyn, agreeing that the activity of programming gradually decreases before the interruption and takes several minutes to restore the intensity of work above the median. Similarly than for Mylyn, we can see that the edits pass below the selections events near the interruption.

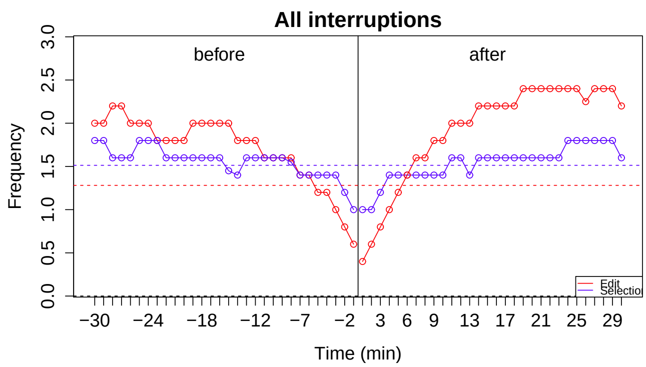

Figure 13. Local effect of an interruption in the user activity.

After this, we separated the interruptions in three categories: those with positive effects afterwards, those a with negative effect and those with no clear effect. Both positive and negative interruptions have a proportion of 44% each of all the interruptions, and the neutrals stand with the 12%, and they are similar to the proportions on Mylyn. The results are in the Table XVI.

The table XVI show a similar pattern on negative, positive and neutral interruptions in comparison with the results on Mylyn. After a positive interruption both metrics tend to increase at a high rhythm. In contrast, when facing the effects of a negative interruption the metrics take longer to reach the median. We can see that once separated in categories, the effect appear to be even more drastic on UDC data than they appear on Mylyn data.

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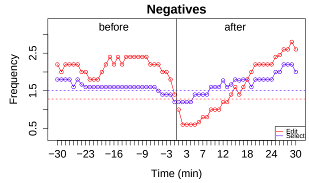
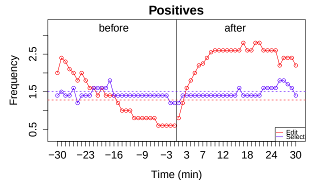
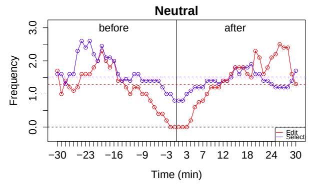
Table XVI. Local Effect of Interruption.

effect	pattern
negative (44%): when the frequency of edit events decreases after the interruption	
positive (44%): when the frequency of edit events increases after the interruption	
neutral (12%): when there is no well defined effect before or after the interruption	

10. RQ4: RECOVERY TIME AFTER AN INTERRUPTION

10.1. Edition and selections during recovery time

The amount of information we have in Usage Data Collector allows us to analyze more specific sections on a programming session. We further investigated the immediate activities after an interruption that we name the *recovery time*, which is a time period taken by the programmer to resume the interrupted work. We could not do this with Mylyn data, since the process involves a lot of filtering of interruptions, which left us with too few data points to analyze.

We established the recovery time as the 15 minute period after an interruption, without considering the time consumed by the interruption itself. The length of the period was chosen according to the observations by Solingen et al. [40].

It was required to make a selection of those interruptions which had a period afterwards of at least 15 minutes before another interruption. After this query we obtained 5,684 valid interruptions from a total of 110,077.

From those valid interruptions, we split the time after the interruption occurred into two phases:

- *recovery time*: the period after the interruption of 15 minutes in length.
- *after recovery time*: the period after the recovery time until the next interruption.

The recovery time was split in three phases of 5 minutes each, and the after recovery time into the following phases:

- *before interruption*: the period of 10 minutes before the next interruption.
- *peak*: the time between the recovery time and the before interruption phase.

Splitting the recovery phase into three phases allows us to analyze in detail the evolution of productivity and identify the immediate activities after the interruption, which will be helpful later. On the other hand, the before interruption phase represents the time where the productivity drops just before the next interruption, as seen in the results of the last research question. The peak phase is where the productivity should be reaching its maximum, as the programmers are not taking actions to retake the lost mental model or preparing for an interruption. The Figure 14 shows how the time after the interruption was split into phases.

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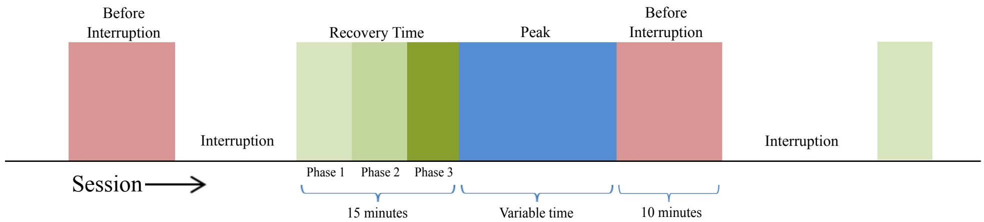

Figure 14. Graphic showing how the time after an interruption was split.

The duration of the peak varies among the also called working spheres, as mentioned by Gonzalez and Mark [5]. On average, the peak lasts for 12 minutes, while the maximum registered is of 145 minutes. The distribution of duration of the peak is reported in Table XVII.

Table XVII. Quartiles of the distribution of the duration of the peak phase.

	25%	50%	75%
quartile	3.38	8.05	16.31

We can see in the Figure 15 the evolution of the metrics through the phases. The three metrics show a tendency to increase and reach a maximum between the last phase of the recovery time and the peak of the session. Moreover, the fall of the productivity on the last minutes before the next interruptions agrees with the observations on the local analysis of the time around an interruption. From this we can conclude that the first five minutes after an interruption and the moment before the next one are the are the phases where productivity is more affected, while the phases around the peak are where the productivity is more favorable.

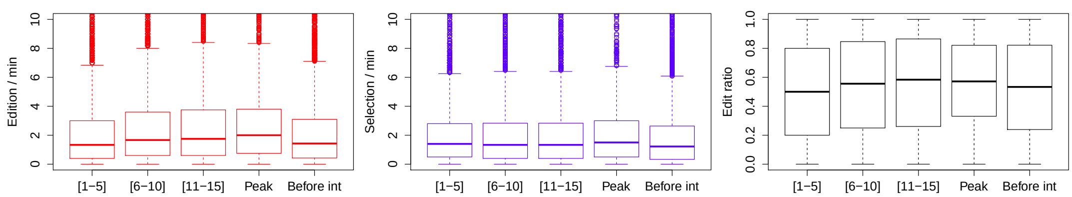

Figure 15. Boxplots showing the detailed evolution of editions, selections and edit ratio during recovery time and after recovery time.

10.2. Recovery time after positive and negative interruptions

We take a closer look into the recovery time by splitting it into interruptions of positive and negative events. As expected the edit ratio is higher during recovery time after a positive interruption and the contrary is seen after a negative interruption. The Figure 16 show a comparison of both effects and the overall edit ratio considering all interruptions.

We can see that after a positive interruption the edit ratio during recovery time is much higher than after a negative interruption, which agrees with the results of the local analysis of interruptions and the observed effects on the metrics.

11. RQ5: COMMON EVENTS DURING RECOVERY TIME

To better understand the reasons of the difference between positive and negative interruptions, we did an analysis of the common events during recovery time, depending on the nature of the interruption. For this we created a new classification of events on a lower level that takes into

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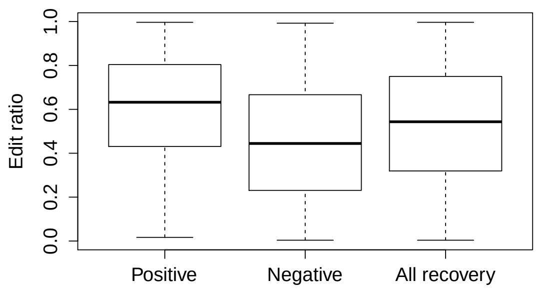

Figure 16. Boxplot of the edit ratio during recovery time after a positive or negative interruption, compared to the edit ratio overall.

consideration what kind of activity is performed by the programmer. The new classification contains the categories described in the Table XVIII. Similarly to the first classification, we followed an iterative process involving two of the authors to classify the events in these categories.

Table XVIII. New category of events.

category	description	usage (%)
clean-build	Events related to the build system (clean, build or run a project)	2.3
control	Source control events	7.6
debug	Events executed during debugging sessions	11.7
edit-text	Text edition events	19.7
file	Management of files (saving, closing, opening, etc.)	8.9
find-replace	Search and replacement of text or code entities	2.5
high-nav	High-level navigation through classes, windows and artifacts	25.9
perspective	Change of perspectives in Eclipse	4.1
refactoring	Refactoring events	5.1
search	Text or code search	2.8
text-nav	Low-level text navigation	9.4

We calculated the weighted average of every event based on the frequency of execution during the first phase of Recovery Time after a positive or negative interruption and the percentage of users that make use of that event (so that events that are used by very few users do not distort the results). The weighted average was calculated as $\bar{x} = \sum_{i=1}^{n} w_i x_i / \sum_{i=1}^{n} w_i$, where x_i is de frequency of execution of the event i and w_i is the percentage of use. This balances the average of execution for events frequently used by a small number of users, for example, the event *copyLineDown* is more frequent than the *rename* event, but the former is only used by 2.4% of the users and the latest by 25.2% of them.

To get a baseline, the same frequency calculation was made for the entire dataset, without distinction of the location of events in the session. We then compared the weighted average changes to have evidence of what kind of events are more often executed after a positive or a negative interruption. Table XIX shows the results.

After a positive interruption we can see that the more common activities are text edition, refactoring, file management and, to a lesser extent, navigation through the text. On the other hand the navigation around classes, find and replace, searches, debug, clean and build are actions more common after a negative. The navigation on the code and control version activities are more common after the Recovery Time.

We can conclude that after a positive interruption there are more assertive actions with a clear intention like refactoring a class or saving all changes; activities related to program edition. After a negative interruption there are more uncertainty and doubt judging by the activities performed like debugging, searching for text or navigating around classes; activities related to program comprehension. These categories of events agree with our previous hypothesis that positive interruptions are related to information seeking, while negative interruptions are related to actual task switches where context needs to be rebuilt afterwards.

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Table XIX. Comparison of execution after positive or negative interruptions.

category	positive	negative	all
Most common events after a positive interruption			
edit-text	**34.75**	22.35	26.62
file	**10.56**	9.53	10.01
refactoring	**1.29**	0.84	1.01
perspective	**0.38**	0.30	0.35
Most common events after a negative interruption			
high-nav	7.84	**10.14**	8.74
find-replace	1.26	**1.47**	1.11
debug	3.08	**7.81**	6.35
search	0.57	**0.96**	0.73
clean-build	0.42	**0.62**	0.56
Less common events after a positive or negative interruption			
text-nav	14.20	12.89	**16.13**
control	1.21	1.75	**1.82**

It is noticeable the relation between type of events. For example is natural to think that if there is a lot of debugging events there is also a lot of clean and build events as they are necessary to begin a debugging session. There is also a link between high level navigation and debugging because navigating into a method may take you to another class.

12. DISCUSSION

Comparison of the datasets Although they represent the same kind of information both Mylyn and UDC datasets have some peculiarities that make them unique that we discuss here.

The interaction data recorded by Mylyn is the basis for a recommendation tool, and is focused on Java projects. On the other hand, the interaction data recorded by the UDC is only used for diagnostic purposes, and is much more generic. For instance, the UDC has interaction data from Java, Web, and mobile developers, and more specific roles like back-end developers, testers and C++ or PHP users.

As the UDC was installed by default on all the Eclipse distributions from 2008 to 2010, the size of the information collected is several orders of magnitude larger than the Mylyn dataset, which was collected since then on a few dozen of developers who installed it voluntarily and contributed to the Mylyn and Eclipse projects. This makes of the UDC data a better source of information to analyze phenomenons on a wide scale.

The UDC and Mylyn also offer different levels of details: while the UDC records fine-grained type of events, Mylyn records the entity that were affected by the events (Java packages, classes, and methods). On the other hand, Mylyn has essentially two types of events of interest (edits and selections), while the UDC has no information on the entities that were affected.

Comparison of the results We conducted a replication of the results of RQ1, RQ2 and RQ3 with the additional dataset. If we noted similarities in the observations accross both datasets, it is important to discuss the differences in the size of the effects that were observed: the overall effects observed were larger for the Mylyn dataset than for the UDC dataset.

The fact that all the observations go in the same direction lends us more confidence in our conclusions. However, the reduced magnitude of the effect gave us pause. We can think of several reasons for this behavior:

- The models are not directly comparable: Mylyn records edition and selection events directly, while the UDC records a broader array of user activity. As such, our classification of UDC events as edits, selections, or other, does not exactly replicate the way the Mylyn model operates. It is possible that some events are more frequent in the UDC than in Mylyn, for instance. We debated several ways to fine-tune our model of the UDC data, including

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weighting some UDC events more than others, but ultimately decided against doing so. As the models are not directly comparable, we primarily focus on intra-model comparisons.

- The (comparatively) small size of the Mylyn dataset may have favored outliers: since there is data from dozens of developers only in the Mylyn dataset, a few outliers may have affected the results. The UDC model is however based on 1,000 UDC users.
- Non-java users in the UDC: A small portion of UDC users were not primarily programming in Java; some were using C++, PHP, web frameworks, or a report generation plugin known as BIRT. These may have had an impact on the results.

13. THREATS TO VALIDITY

The main threats to the validity of our study are construct validity threats due to the operational nature of the data recorded by Mylyn and the UDC [1]. Most of them are mentioned above but recalled here for convenience.

For the Mylyn dataset, the main threat to validity is due to the exclusion of development session with aggregated information. We deemed that disaggregating the data as was done in other work [17] was not appropriate as we do not know the exact distribution of aggregated events in time, which is very important for this study. We thus elected to filter out part of the data. We have not found evidence of bias due to this but it may still be present.

Another threat comes from the metrics we use. Our choices are limited by the data recorded by Mylyn. We believe our three indicator (edits per minute, selections per minute, and edit ratio) provide a reasonable measure of productivity (especially with the addition of edit ratio, used in other work [13]). However we can not exclude that other indicators of productivity (such as actual changes [41]) may yield different results.

We defined several thresholds empirically: 8 hours of inactivity to split a session in sub-sessions, 30 minutes as the minimum duration for a session, 3 minutes for the minimum duration of a interruption and $\geq$ 12 minutes for prolonged interruptions. We also tested with other close values and obtained similar results. However, a large variation of these thresholds might significantly alter the results.

We acknowledge that our separation of sessions in short and long interruptions is not perfect, as it is based on the presence of at least one long interruption, and nothing more. Other factors present in the group of sessions with at least one long interruption may contribute to the observed effect (for instance, these sessions may also have more interruptions overall).

The study has threats to its statistical conclusion. In particular, correlation does not necessarily implies causation: the drop in productivity may not be due to work fragmentation but to other factors (such as task difficulty). The fact that our results agree with the existing literature does help in this respect. We note that our local analysis uncovered two well-defined patterns around gaps of inactivity: ones that we hypothesize are actual interruptions (negative effect post-interruptions), and the ones that we hypothesize are more likely information-seeking activities (positive effect post-interruption). This result points to two different effects and is in need of further study; the additional evidence uncovered in the UDC does support this hypothesis, since different activities appear to take place in both types of interruptions. As stated in the introduction, we were careful not to conclude that every gap of activity is an actual interruption.

We used Cohen's d, a parametric effect size measure, as it has defined thresholds allowing easier interpretation of the results. Other effect size measures such as the common language effect size [42] or A_{12} [43] may slightly alter the discussion.

This study also has threats to external validity. The gathered data corresponds to a limited group of programmers, which use both Mylyn and Eclipse regularly. The set of evolution tasks considered is a subset of the ones present on the Eclipse bug report website. It may be biased one way or another. One source of bias is the impact of Mylyn itself: Mylyn has been shown to facilitate task switching and to increase the edit ratio of its users compared to non-users. In the context of this study, we hypothesize that Mylyn could reduce the effect of work fragmentation: in other words, the observed effects may be larger for non-users. Additional studies may alleviate these threats and

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confirm or infirm the previous hypothesis. Our additional dataset (the UDC) comes from a much larger and more varied sample of users, and does show similar behavior, which raises confidence in our results.

The same threats about the metrics, implications and statistical conclusions apply on the results observed with the UDC. Additionally, our classification of events is a possible threat, as it was based on our own criteria of what should be an Edition and Selection event. We took this liberty due to the lack of an actual pre-classification, and on the other hand the extra information available on UDC events compared to Mylyn. We took special care when establishing the classification, using an iterative process involving two authors of this paper. We also ran tests of what kind of data was recorded for specific usage scenarios of the IDE in order to better understand the nature of the dataset when particular events were unclear.

The workbench activation and deactivation events were a particular issue, for they can be executed under many circumstances. We performed live test to understand how these events work and gain confidence about their precise behavior. For instance, we found that they were reliable markers of when the user leaves and returns to Eclipse—and we used this fact to accurately detect interruptions—but we had more uncertainty on other scenarios. Therefore, we decided not count them as “system” events, and thus only use them to define an interruption or the end of a session.

14. CONCLUSIONS AND FUTURE WORK

This paper presented an empirical study on the prevalence of work fragmentation in software evolution tasks, and its relationship to developer productivity. The study was based on the Mylyn dataset of software evolution tasks, where work fragmentation is indicated by gaps of activity (interruptions) in the IDE, and productivity is measured in terms of the number of edits, selections, and the edit ratio. It was then complemented with data coming from the Eclipse Usage Data Collector (UDC) dataset, which offered us to complement our previous findings by analysing a larger sample of users, with a finer-grained classification of events.

We analyzed several thousands software evolution tasks, originating from several dozens of developers. Our global analysis found an inverse relationship between number and duration of interruptions and all three of our productivity indicators. These findings agree with the literature on information workers and software developers.

A subsequent local analysis around interruptions confirmed these results as the activity around interruptions was found to be lower than average. This analysis also found two well-defined patterns around interruptions: interruptions yielding a negative effects (consistent with a real-life interruption involving an expensive context switch), and interruptions with positive effects (consistent with information-seeking behavior). Further studies are necessary to expand on these findings.

With the Usage Data Collector dataset, we replicated our previous study to compare the results obtained with Mylyn. We found the same observations on the relationship of interruptions and productivity; even though the observed effects are less marked, we reach similar conclusions.

The UDC data also allowed us to extend our study with two additional research questions related to the recovery time after an interruption, and the two patterns of interruptions we observed.

We first analyzed the Recovery Time in detail, finding a higher productivity when the interruption is positive and we identified a positive evolution of the metrics as the programmer advances through this stage, reaching a peak of productivity between the last minutes of the Recovery Time and 10 minutes before the next interruption happens.

In addition, we found that after a positive interruption the most common events during the first minutes of the Recovery Time are those with an assertive intention such as edition, refactoring and saving files. In contrast, after a negative interruption the most common events are debugging, searching and navigation around classes, which tell us about a doubtful and uncertain behavior from the programmer. These findings support out hypotheses that positive interruptions are due to information-seeking, while negative interruptions are due to context rebuilding after an actual interruption.

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