Recognizing recurrent development behaviours corresponding to Android OS release life-cycle

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***Abstract*—Android OS is an open-source Linux-based operating system for mobile devices developed by Open Handset Alliance led by Google, its SCM log was selected as a research subject for 2012 MSR Challenge. I attempted to apply a novel data mining technique based on SAX approximation and indexing of time-series with TF$*$ IDF weights in order to discover recurrent behaviors within the Android OS development process.**

By mining software process artifact trails corresponding to OMAP kernel development I was able to discover recurrent behaviors in the new code lines dynamics before and after release. By building a classifier upon these behaviors I was able to succesfully recognize pre- and post-release behaviors within the same and similar sub-projects of Android OS.

***Keywords*-Behaviors Detection, Empirical Study, Source Control System**

I. Introduction

As many other large open-source projects, Android OS was in the development for many years. Android is "an open-source software stack for mobile phones and other devices", http://source.android.com/ which is based on the Linux 2.6 monolithic kernel. Development of Android begun by Android Inc., the small startup company. In 2005 company was acquired by Google which formed the Open Handset Alliance - a consortium of 84 companies which announced the availability of the Android Software Development Kit (SDK) in November 2007. The Android OS code is open and released under the Apache License.

Git is used as a version control system for Android and source code organized into more than two hundreds of sub-projects. These organized by the function (kernel, UI, mailing system, etc.) and underlying hardware (CPU type, bluetooth communication chip, etc.). There are about two millions of change records registered in the Android SCM by more than eleven thousands of contributors within an eight years span.

By the large body of previous reserach it is shown that the change metadata is a rich source of software process and developers social characteristics. The ability of discivering of recurrent behaviors with Fourier Analysis of change events explained in [1] whether other work, such as [2] relates activity time intervals and software product quality. Thus, potentially, there is a possibility to relate the recurrent behaviors to the software product quality and to the software process efficiency. The first necessery part of a toolkit aiding such a research is an efficient mechanism of dicovering recurrent behaviors modulated by social and project-related constraints. In this paper I extend the previous research by introducing a universal framework for the temporal partitioning of software change artifacts, the data complexity reduction and for recurrent behaviors discovery.

II. Contribution

To the best of my knowledge, this work is the first attempt to study the applicability of symbolic aggregate approximation and term frequency–document frequency weight statistics to the mining of software process artifacts trails. This methodology has a number of advantages. First of all, SAX facilitates significant reduction of the large complexity (dimensionality and noise) of temporal artifacts and opens the door to application of a phetora of strings and text-mining algorithms. In turn, the TF$*$IDF statistics provides an efficient mechanism for discrimination of the signal by ranking text data. While the third component I have used - the relational database facilitates the efficient data slicing, indexing and its instant retrieval.

As an example of a possible data-mining workflow demonstrating the resolving power and correctness of the approach I present a case study of building a classifier for pre- and post-release recurrent behaviors. Whereas this classifier demonstrates a good performance within the project it was trained on with less than 20% of missclassification, it has less than 15% missclassification rate in similar Android OS kernel sub-projects.

III. Motivation

Software development is a human activity resulting in software product. The amount of time and effort needed to complete a software project and the quality of the final product are shown to be derivatives of the software process. Thus, studying software processes is one of the important areas of software engineering.

Previously it was found that software development, as many other human activities, could be successfully partitioned by the time of the day reflecting our lifestyle and habits [3] [4]. However external constraints, such as employment and management constraints [5], software release cycle, [6] and other, found to be able to significantly alter natural activity patterns. Furthermore, within open-source projects with diverse development community scattered over the globe and often following undocumented development process, the natural human activity cycles are often discarded as well as the development and release cycles are significantly altered. Thus, the only feasible way to discover an open-source software process is to analyze its artifacts trails such as SCM logs, bug and issue tracking systems and mailing lists archives. Essentially these trails are event-series where every time-stamped event has an attached set of metadata. However the complexity of this data and the precision of the process recall impose a great challenge for the researchers.

These challenges are not new to the data-mining community and an enormous wealth of methods, algorithms and data structures exist helping to overcome these issues. While some of these approaches were already implemented within the MSR framework such as finding of trends, periodicity and recurrent behaviors through the linear predictive coding and cepstrum coefficients [7], Fourier Transform [1] and coding [8], many are yet to be tried.

In this paper, I investigate the application of Symbolic Aggregate Approximation [9] and the TF∗IDF statistics [10] to the problem of discovering recurrent behaviors from software process artifacts with application to Android SCM data.

IV. Research question

In this exploratory work I am investigating the applicability of Lin&Keogh [9] symbolic approximation technique to the discovery of recurrent behaviors from SCM trails of Android OS. The research questions I am trying to resolving are:

- Which kinds of SCM data need to be collected for such analyzes?
- What is the optimal way of data representation and a data storage configuration?
- Which partitioning (slicing) is appropriate and which set of parameters one should use for SAX approximation?
- Which distance metrics serves best for measuring similarity and dissimilarity?
- What is the general mining workflow, and which parameters are crucial for result?

V. Experimental setup and methods

A. *Data collection and organization*

Two XML files were offered for the MSR challenge. These contain the most of the information obtainable from Google-hosted git source code repository as well as from bug and issue tracking system. While the issues and comment XML file contains nearly all information available in repository, the change XML provided for this challenge contains only a fraction of all of the information.

The thirteen data fields of the change trail XML file provide information about the revision tree, author and a committer identification, change message and affected targets. Since I am focusing on the mining of temporal patterns for inferring recurrent behaviors, in addition to the existing data I have collected many auxiliary data about change. By creating a local mirror and by iterating over existing commit hashes I was able to recover the auxiliary data for 68% of existing commits. The rest 32% of change information is unretrievable and belongs to legacy projects or is lost and unrecoverable due to the changes in Android repository.

For every recoverable change record I collected a summary of added, modified and deleted files as well as a summary about LOC changes: added, modified or deleted lines. All this information was stored in the database backend. Main tables of this database correspond to change and issue events; these accompanied with change target table, issue, comments and tables for contributors. Overall, the database was normalized and optimized for the fast retrieval of change and issue information using SQL language.

B. *Temporal data partitioning*

Following the previous research [2], I have partitioned the change trails by the time of the day using time windows of

- Full day, 12AM - 12AM
- Late night, 12AM - 04AM
- Early morning, 04AM - 08AM
- Day, 08AM - 05PM
- Night, 05PM - 12AM

then aggregated within these windows values for commits, added/edited/deleted lines and targets. By having such a table it takes a fractions of a second to retrieve a summary of early morning added lines for January 2007 for a particular sub-project and a group of contributors having emails with a domain “...@ibm.com”.

C. *Symbolic approximation and indexing*

SAX algorithm requires three parameters where the first is the sliding window size, second is the PAA approximation size and the third parameter is the SAX Alphabet size.

In this work I have selected three sizes for sliding window: 7 days, 14 days and 30 days as these represent an intuitive and logical intervals of a week, two weeks and a month. For the PAA reduction I choose 4 steps for 7 days window, 6 steps for a bi-weekly interval, and 10 steps for a monthly window. Finally the alphabet, I choose 3 letters for weekly window, and 5 letters for bi-weekly and monthly windows.

By applying SAX to the pre-aggregated data I have obtained their symbolic temporal representation. Do I need a figure explaining SAX transform here?

D. Token-based distance metrics

For the experiments I have selected three similarity metrics. First one is based on the SAX min distance and the Euclidean distance which applied to vector of tokens sorted by frequency observed in the aggregated symbolic stream corresponding to selected stream class, aggregation parameters, user, project and time-interval of the interest.

$$D(S,T) = \sqrt{\sum SAXdist(s_i,t_i)^2} \tag{1}$$

where $SAXdist$ is the the SAX distance based on the Normal alphabet.

As an alternative I have tried the Jaccard similarity between two sets S and T which is simply

$$J_\delta(S,T) = \frac{|S \cup T| - |S \cap T|}{|S \cup T|} \tag{2}$$

and the $TF * IDF$ similarity or which defined as a dot product

$$TFIDF(S,T) = \sum_{\omega \in S \cap T} V(\omega,S) \cdot V(\omega,T) \tag{3}$$

where

$$V(\omega,S) = \frac{V'(\omega,S)}{\sqrt{\sum_{\omega'} V'(\omega,S)^2}} \tag{4}$$

is a normalization of $TF*IDF$ (product of token frequency and inverse document frequency):

$$V'(\omega,S) = \log(TF_{\omega,S}+1) \cdot \log(IDF_\omega) \tag{5}$$

where IDF_ω is a measure of the general importance of the pattern among all users

$$IDF_\omega = \frac{|D|}{DF(\omega)} \tag{6}$$

where $|D|$ is cardinality of D - the total number of users, and $DF(\omega)$ is the number of users having ω pattern in their activity set.

VI. Clustering

While the application of the SAX distance and Jaccard similarity yields a single number allowing the use of the convenient clustering libraries such as $hclust()$ and $kmeans()$ of R for manipulation with sparse vectors produced by the $TF * IDF$ application I used $sparcl()$ R package for hierarchical clustering and my own implementation of $k - means$ clustering.

VII. Results

A. Kernel-OMAP life cycle patterns discovery

I arbitrary selected the Android kernel-OMAP as one of the large Android OS sub-projects. OMAP is a proprietary system on chips (SoCs) for portable and mobile multimedia applications based on general-purpose ARM architecture processor provided by Texas Instruments.

As a training set for building dictionaries of pre and post-release patterns I choose three Android releases: *Android 1.0*, *Android 1.5* and *Android 2.0*. For each release in the set I selected four weeks before the release as *pre-release* and four weeks after release as *post-release* training intervals. As an additional constraint for this experiment I have selected contributors affiliated with $@android.com$ e-mail domain and a telemetry stream of $added\_lines$. After pre-generated patterns retrieval with SQL query I applied hierarchical clustering based on $TF * IDF$ similarity as a sanity test. The almost perfect clustering picture 1 indicates that there are significant differences in the pre-release and post-release weekly behaviors among selected contributors.

While hierarchical clustering is a good sanity test for the separation of data, the performance of K-means clustering is the most valuable metrics [11]. I performed k-means on the symbolic representation of data using $TF * IDF$ statistics and the Euclidean distance. Algorithm converged after two iterations separating pre- and post-release dictionaries with a single mismatch for the Android 2.0 pre-release.

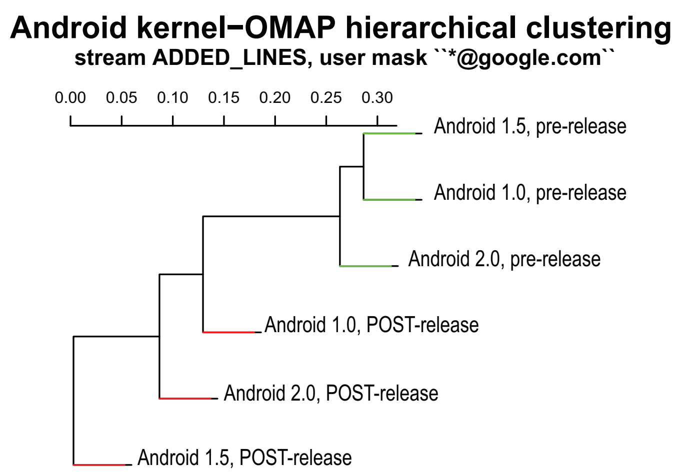


Figure 1. Hierarchical clustering of pre- and post- commit patterns.

By using centroids of resulting clusters as a basis for pre and post-release patterns I tested the classifier on the rest of Android releases for which kernel-OMAP remained an active project (some of the pre- and post- release interval contained non or only trivial patterns making them ineligible for classification). This classifier was able to successfully classify more than 81% of pre- and post-release behaviors (Table II).

Table I
PRE- AND POST-RELEASE PATTERNS, THEIR $TF * IDF$ WEIGHTS AND SAMPLE CURVES.

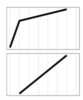
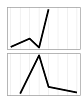
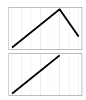
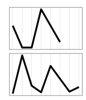
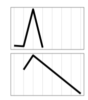
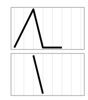
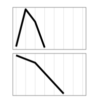
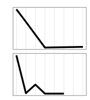
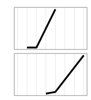
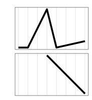
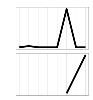
release	”bbac”	”abca”	”babc”	”bbba”	”bcaa”	”bcbb”	”ccaa”	”cbaa”	”bbcb”	”bbbb”	”bbbc”
post-2.0	0.63	0	0.63	0	0	0	0	0.39	0.24	0.06	0
post-1.0	0	0.93	0	0	0	0	0	0	0	0.09	0.36
post-1.5	0	0	0	0	0	0	0	0	0.79	0.61	0
pre-1.5	0	0	0	0.23	0.23	0.91	0	0.14	0.18	0	0.09
pre-2.0	0	0	0	0	0	0	0	0	0	1	0
pre-2.0	0	0	0	0	0	0	0.79	0	0	0.08	0.61
Sample curves corresponding to patterns											

Table II
PRE- AND POST-RELEASE DEVELOPMENT PATTERNS CLASSIFICATION RESULTS FOR KERNEL-OMAP.

Release	Classification
1.6 -pre	-
1.6 -post	+
2.2 -pre	+
2.2 -post	+
1.1 -pre	+
1.1 -post	+
2.3 -pre	+
2.3 -post	+

Release	Classification
beta -pre	+
beta -post	+
2.0.1 -pre	+
2.0.1 -post	-
2.1 -pre	+
2.1 -post	+
2.2.1 -pre	+
2.2.1 -post	-

VIII. CONCLUSIONS

The presented approach and workflow is able to recognize recurrent behaviors from software process artifact trails. Its application to Android OS kernel-OMAP subproject SCM artifact trail yielded the pre- and post-release behavior models. In particular, it was shown that error rate of recognition of releases within the same as training project is less than 20%, f

IX. ACKNOWLEDGEMENT

X. CONCLUSION

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ACKNOWLEDGMENT

The authors would like to thank... more thanks here

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