Dissertation proposal:

Software Trajectory Analysis: An empirically based method for automated software process discovery

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Chapter 1

Introduction

1.1 Motivation

A *software process* is a set of activities performed in order to design, develop and maintain software systems. Examples of such activities include design methods; requirements collection and creation of UML diagrams; requirements testing; and performance analysis. The intent behind a software process is to structure and coordinate human activities in order to achieve the goal - deliver a software system successfully.

Much work has been done in software process research resulting in a number of industrial standards for process models (CMM, ISO, PSP etc. [10]) which are widely accepted by many institutions. Nevertheless, software development remains error-prone and more than half of all software development projects ending up failing or being very poorly executed. Some of them are abandoned due to running over budget, some are delivered with such low quality or so late that they are useless, and some, when delivered, are never used because they do not fulfill requirements. The cost of this lost effort is enormous and may in part be due to our incomplete understanding of software process.

There is a long history of software process improvement through proposing specific patterns of software development. For example, the Waterfall Model process proposes a sequential pattern in which developers first create a Requirements document, then create a Design, then create an Implementation, and finally develop Tests. The Test Driven Development process proposes an iterative pattern in which the developer must first write a test case, then write the code to implement that test case, then refactor the system for maximum clarity and minimal code duplication. One problem with the traditional top-down approach to process development is that it requires the developer or manager to notice a recurrent

pattern of behavior in the first place [10].

In my research, I will apply knowledge discovery and data mining techniques to the domain of software engineering in order to evaluate their ability to automatically notice interesting recurrent patterns of behavior. While I am not proposing to be able to infer a complete and correct software process model, my system will provide its users with a formal description of recurrent behaviors in their software development. As a simple example, consider a development team in which committing code to a repository triggers a build of the system. Sometimes the build passes, and sometimes the build fails. To improve the productivity of the team, it would be useful to be aware of any recurrent behaviors of the developers. My system might generate one recurrent pattern consisting of a) implementing code b) running unit tests, c) committing code and d) a passed build: $i \rightarrow u \rightarrow c \rightarrow s$, and another recurrent pattern consisting of a) implementing code, b) committing code, and c) a failed build: $i \rightarrow c \rightarrow f$. The automated generation of these recurrent patterns can provide actionable knowledge to developers; in this case, the insight that running test cases prior to committing code reduces the frequency of build failures.

Although the latest trends in software process research emphasize mining of software process artifacts and behaviors [23] [45] [39] [45], to the best of my knowledge, the approach I am taking has never been attempted. This may be partly due to the lack of means of automated, real-time data collection of fine-grained developer behaviors. By leveraging the ability of the Hackystat system [25] to collect such a fine grained data, I propose to extend previous research with new knowledge that will support improvements in our understanding of software process.

1.2 Proposed contribution

In summary, the proposed contributions of my research will include:

- the implementation of a system aiding in discovery of novel software process knowledge through the analysis of fine-grained software process and product data;
- experimental evaluation of the system, which will provide insight into its strengths and weaknesses;
- the possible discovery of useful new software process patterns.

1.3 Roadmap

This proposal has the following organization:

- Chapter 2 presents a review of the literature related to software process discovery. Methods discussed in the Section 2.1 are high-level frameworks which are used for software process inference from abstracted process artifacts. Section 2.2 presents up to date relevant progress in the mining of software repositories. Section 2.3 presents a review of research related to construction of the symbolic time-point and time-interval series and pattern discovery from a temporal symbolic data.

- Chapter 3 describes the requirements for the system and presents the current state of my Software Trajectory framework for automated software process discovery.

- Chapter 4 outlines the planned experimental evaluation of my research and presents preliminary results of the pilot study.

- Chapter 5 discusses the anticipated contributions in greater detail and presents the estimated timeline.

Chapter 2

Related work

The purpose of this chapter is to review related work in software process discovery and unsupervised temporal pattern mining. These two research areas provide a basis for my research. I am planning to use unsupervised temporal pattern mining methods for the automated discovery of recurrent behavioral patterns from the stream of low-level process and product artifacts generated by the software process. These patterns, in turn, will be used for software process discovery.

Discovery of recurrent behaviors in software process discussed in the Section 2.1. Mining recurrent evolutionary patterns from software repositories discussed in the Section 2.2. General algorithms of temporal data mining discussed in Section 2.3.

2.1 Software process discovery

Although process mining in the business domain is a well-established field with much software developed up to date (ERP, WFM and other systems), "Business Process Intelligence" tools usually do not perform process discovery and typically offer relatively simple analyses that depend upon a correct a-priori process model [52] [3]. This fact restricts direct application of business domain process mining techniques to software engineering, where processes are usually performed concurrently by many agents, are more complex and typically have a higher level of noise. Taking this fact in account, I will review only the approaches to the mining for which applicability to software process mining was expressed.

Three papers are reviewed in this section:

- Cook & Wolf in [13] discuss an event-based framework for process discovery based on grammar inference and finite state machines. The authors directly applied their frame-

work to Software Configuration Management (SCM) logs demonstrating satisfactory results.

- Van der Aalst et al. [52] demonstrate the applicability of Transition Systems and labeled Petri nets to process discovery in general. While this paper does not apply its results directly to software process, the subsequent work by van der Aalst and Rubin [45] discusses software process application.

- The third paper, by Jensen & Scacchi [23], while not presenting a pattern mining strategy, describes an interesting framework built upon an universal generic meta-model and specific to the observed processes models which are iteratively built and revised during case studies. The value of this paper is in the demonstration of the importance of the correct mapping between process artifacts and process entities as well as a demonstration of iterative, human-involved technique of process revision which is emphasizing importance of pre-existing domain knowledge in the effective pruning of the search space.

As pointed by the authors in the reviewed papers, the proposed methods have difficulties dealing with concurrency, which, in turn, is inevitable in the software process usually performed by many agents. Much successive work has been done extending reviewed approaches to the concurrent processes. Among others, Weijters & van der Aalst in [59] propose heuristics to handle concurrency and noise issues, while van der Aalst et al. in [53] discuss a genetic programming application.

2.1.1 Process discovery through Grammar Inference

Perhaps, the research most relevant to my own was done by Cook & Wolf in [13]. The authors developed a *"process discovery"* techniques intended to discover process models from event streams. The authors did not really intend to generate a complete model, but rather to generate sub-models that express the most frequent patterns in the event stream. They designed a framework which collects process data from ongoing software process or from history logs, and generates a set of recurring patterns of behavior characterizing observed process. In this work they extended two methods of *grammar inference* from previous work: purely statistical (neural network based *RNet*) and purely algorithmic (*KTail*) as well as developing their own Markovian method (*Markov*).

Process discovery, in the author's opinion, resembles the process of *grammar inference*, which can be defined as the process of inferring a language grammar from the given set

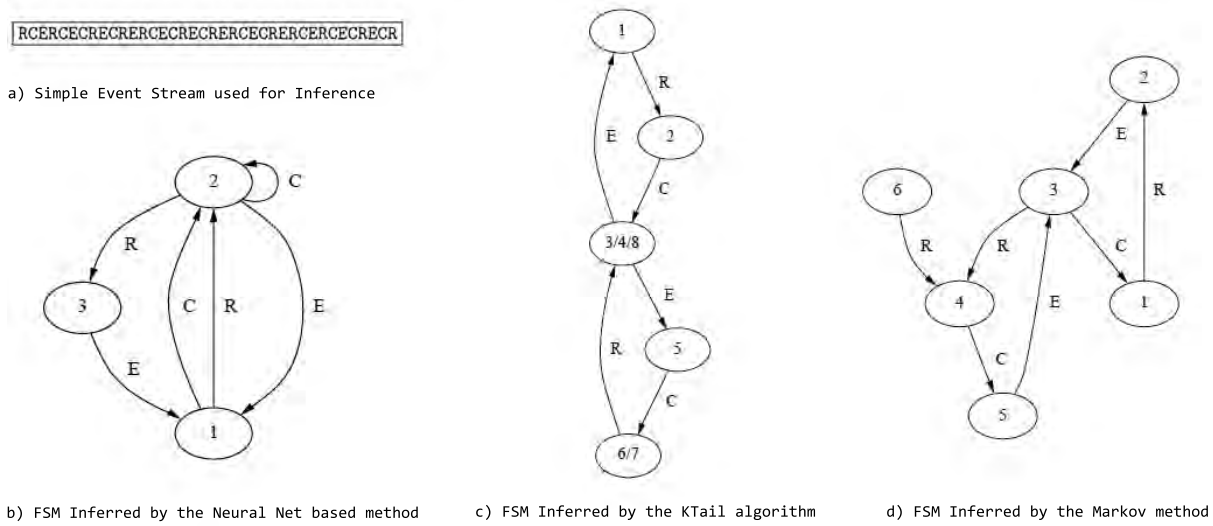


Figure 2.1: Process discovery through the grammar inference: panel a) a sample event stream (simple process involving three types of events: Edit, Review, and Checkin); and FNA results obtained by applying three methods of process discovery from Cook & Wolf [13].

(sample) of sentences in this language. In the demonstrated approach, words of the language are atomic events of the dynamic process, whether sentences built from such words, are describing the behavior of a process. Consequently, the inferred grammar of that language is the formal model of the process. Cook & Wolf expressed such grammars as Finite State Machines (FSMs) and implemented a software tool for the mining of the software process. This tool was successfully tested in an industrial case study.

The first method extended by the authors, the neural-network based grammar inference, RNet algorithm, defines a recurrent neural network architecture which is trained by the sequences of events. After training, this neural net is able to characterize a current system state by looking on past behavior. The authors extract the FSM from the trained neural network by presenting different strings to it and extracting the hidden neurons activity through observations. Due to the nature of Neural Net, closely related activation patterns are clustered into the same state; therefore, by noting the current pattern, the input token, and the next activation pattern, transitions are recorded and compiled into the inferred FSM.

The second method investigated, is a purely algorithmic KTail method, which was taken from the work of Biermann & Feldman [7]. The idea is that a current state is defined by what future behaviors can occur from it. The *future* is defined as the set of next k tokens. By looking at a window of successor events, the KTail algorithm can build the equivalence classes that compose the process model. The authors extensively modified the original KTail

algorithm improving the folding in the mined model making to make it more robust to noise.

The Markov based method developed by the authors is based on both algorithmic and statistical approaches. It takes to account past and future system behavior in order to guess the current system state. Assuming that a finite number of states can define the process, and that the probability of the next state is based only on the current state (Markov property), the authors built a n^{th}-order Markov model using the first and second order probabilities. Once built, the transition probability table corresponding to the Markov model is converted into FSM which is in turn reduced based on the user-specified cut-off threshold for probabilities.

The authors implemented all three of these algorithms in a software tool called DaGama as a plugin for larger software system called Balboa [11]. By performing benchmarking, Cook & Wolf found that the Markov algorithm was superior to the two others. RNet was found to be the worst of the three algorithms.

Overall, while having some issues with the complexity of produced output and noise handling, the authors proved applicability of implemented algorithms to real-world process data by demonstrating an abstraction of the actual process executions and capturing important properties of the process behavior. The major backdraw of the approach, as stated by the authors, lies in the inability of the FSMs to model concurrency of processes which limits its applicability to the software development process. Later, Cook et al. in [12] addressed this limitation.

2.1.2 Incremental Workflow Mining with Petri Nets

Another set of findings relevant to my research approach was developed by Rubin et al. [45] and van der Aalst et al. [52] and is called *incremental workflow mining*. The authors not only designed sophisticated algorithms but built a software system using a business process mining framework called ProM by van Dongen et al. [54] which synthesizes a Petri Net corresponding to the observed process. The system was tested on SCM logs and while the process artifacts retrieved from the SCM system are rather high-level, the approach discussed is very promising for the modeling of software processes from the low-level product and process data.

Within the incremental workflow mining framework, the input data from the SCM audit trail information is mapped to the event chain which corresponds to the software process artifacts. The authors call this process *abstraction on the log level* which is implemented as a set of filters which not only aggregates basic events into single high-level entities but also

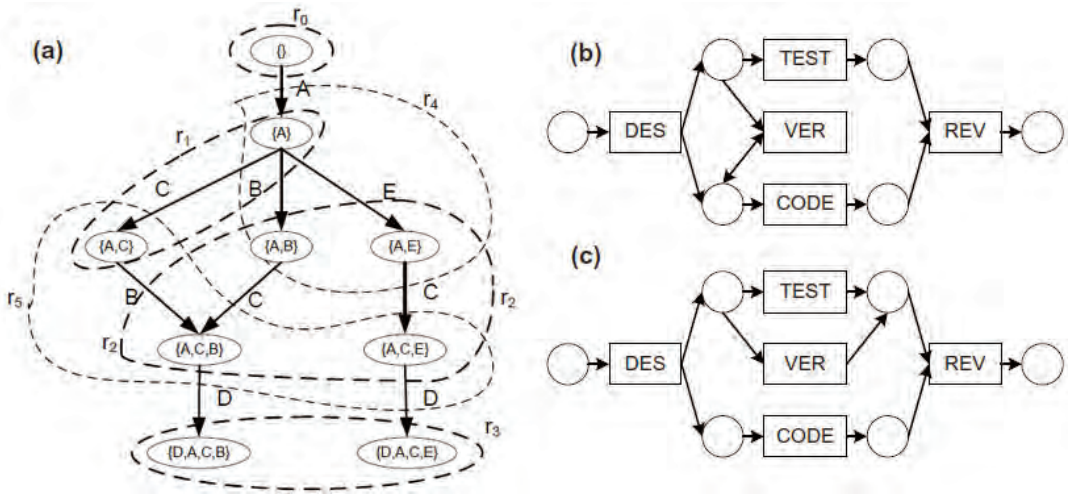


Figure 2.2: Illustration of the "Generation and Synthesis Approach" from [54]: a) Transition System with regions shown; b),c) Petri Nets synthesized from the Transition System.

removes data irrelevant to the mining process (noise).

The event chain constructed through the abstraction is then treated with the *Generate* part of the *"Generate and Synthesis"* [52] algorithm in order to generate a *Transition System* which represents an ordered series of events. This algorithm looks at the history (prefix) and the future (suffix) sequences of events related to the current one in order to discover transitions. When applied to the abstracted log information, the algorithm generates a rather large Transition System graph where edges connect to abstracted events. This transition system is then successively simplified by using various reduction strategies such as "Kill Loops", "Extend", "Merge by Output" and others; it is possible to combine these reduction strategies in order to achieve a greater simplification.

At the last step of the incremental workflow mining approach, Transition Systems are used to *Synthesize* labeled Petri nets (where different transition can refer to the same event) with the help of *"regions theory"* [14]. As with the Transition System generation, the authors investigate many different strategies of Petri nets synthesis, showing significant variability in the results achieved. (see Figure 2.2).

The significant contribution of this research is in the generality of the method. It was shown that by tuning the "Generate" and "Synthesize" phases it is possible to tailor the algorithm to a wide variety of processes. In particular, as mentioned before, Rubin et al. successfully applied this framework to the SCM logs analysis.

```
Term: report
  Known Actions: testing, defect reporting, logging
  Known Agents: none
  Known Resources: whitepapers, test results, web
    server logs, defects, feature requests
  Known Tools: defect repository, test suite
```

Figure 2.3: Example of the reference model mapping from [23].

2.1.3 Reference model for Open Source Software Processes Discovery

Jensen & Scacchi in [23] take a somewhat different approach from the previously discussed research efforts. The authors are follow a top-down approach and do not try to build a software process model from available process artifacts. Instead, they try to develop a software process *reference model* by iteratively refining mapping between observed artifacts and the model entities.

The proposed software process *reference model* is a layer which provides a mapping from the underlying recognized software process artifacts into a higher level software-process meta-model by Mi & Sacchi [40]. The iterative revision of the reference model vocabulary of mapped terms (Figure 2.3) is performed through case studies. During such a study, the observed process artifacts such as SCM logs, defect reports and others are queried with terms from the reference model pulling correlated artifacts which are revised and curated by the process expert and lead to the further revisions of the terms taxonomy on the next iteration.

In the relation to my research, I am envisioning the application of such iterative "meta-model driven approach" for characterization of the discovered recurrent patterns with unknown generative phenomena. The creation of the low-level recurrent patterns taxonomy through successive mapping into the meta-model assures from a "nonsense patterns" discovery.

2.2 Mining software repositories

According to Kagdi et al. [27] the term *mining software repositories (MSR)* "... has been coined to describe a broad class of investigations into the examination of software repositories." The "software repositories" here refer to various sources containing artifacts produced

by software process. Examples of such sources are version-control systems (CVS, SVN, etc.), requirements/change/bug control systems (Bugzilla, Trac etc.), mailing lists archives and social networks. These repositories have different purposes but they support a single goal - a software change which is the single unit of the software evolution.

In the literature, *software change* defined as an addition, deletion or modification of any software artifact such as requirement, design document, test case, function in the source code, etc. Typically, software change is realized as the source code modification; and while version control system keeps track of actual source code changes, other repositories track various artifacts (called *metadata*) about these changes: a description of a rationale behind a change, tracking number assigned to a change, assignment to a particular developer, communications among developers about a change, etc.

Researchers mine this wealth of data from repositories in order to extract relevant information and discover relationships about a particular evolutionary characteristic. For example, one may be interested in the growth of a system during each change, or reuse of components from version to version. In this section I will review some MSR research literature which is relevant to my research and based on the mining of temporal patterns from SCM audit trails.

2.2.1 Mining evolutionary coupling and changes

One of the approaches in MSR mining relevant to my research is built upon mining of the simultaneous changes occurring in software evolution. This type of mining considers changes in the code within a short time-window interval which occur recurrently. Such changes are revealing logical coupling within the code which can not be captured by the static code analysis tools. This knowledge allows researcher and analysts predict the required effort and impact of changes with a higher precision.

Mining of evolutionary coupling is typically performed on different levels of code abstraction: Zimmermann et al. in [64] discuss mining of version archives on the level of the lines of source-code using annotation graphs; Ying et al. in [62] discuss mining of version archives for *co-change* patterns among files by employing association rule mining algorithm, and refining results by introducing *interestingness* measure, which based on the call and usage patterns along with inheritance; Gall et al. in [51] use a window-based heuristics on CVS logs for uncovering logical couplings and change patterns on the module/package level. Kim et al. in [33] taking a different approach by mining *function signature change* and introducing kinds of signature changes and its metrics in order to understand and predict future evolution

patterns and aid software evolution analysis.

The fine-grain mining of changes on the level of lines of source code is usually implemented with the use of *diff* utilities family which report differences between versions of the same file. For capturing temporal properties the sliding-window approach is used if mining CVS logs, while Subversion is able to report co-changed filesets (*change-sets*). Use of the information extracted by parsing issue/bug tracking logs and developer comments from version control logs allows to capture co-occurring changes with higher precision.

What is common among all this work is that while researchers use different sources and abstraction levels of information, they are extracting only the relevant to a specific question data (using filters and taxonomy mappings) and compose data sets suitable for KDD algorithms. In order to refine and classify (prune) reported results, various support functions proposed.

The main contribution of this type of mining is in the discovery of patterns in software changes which are improving our understanding of the software and allowing estimation of effort and impact of new changes with higher precision.

2.2.2 Ordered change patterns

A step ahead in the analysis of co-occurring changes in source code entities was shown by Kagdi et al. in [28]. The authors investigated a problem of mining ordered sequences of changed files from change-sets. Six heuristics (*Day, Author, File, Author-date, Author-file, and Day-file*) based on the version control transaction properties were developed and implemented. Abstracted sequences were mined with Apriori algorithm (see 2.3.10) discovering recurrent sequential patterns. The authors proposed a higher specificity and effectiveness of such approach to software change prediction than by using convenient (un-ordered) change patterns mining.

2.2.3 Usage patterns

Another interesting approach for MSR, relevant to my work, is the mining of usage patterns proposed by Livshits & Zimmermann in [38]. In this work, the authors approach a problem of finding violations of application-specific coding rules which are ultimately responsible for a number of errors. They designed approach to find "surprise patterns" (see Subsection 2.3.7) of the API and function usage in SCM audit trail by implementing a preprocessing of the functional calls and mining aggregated data with a customized Apriori algorithm (see 2.3.10)

implementation. By considering past changes and bug fixes, authors were able to classify patterns into three categories: *valid patterns*, *likely error* patterns, and *unlikely* patterns. Candidate patterns found with Apriori algorithms were considered to be a valid pattern if they were found a specified number of times and an unlikely patterns otherwise. Similarly, if a previously labeled as valid pattern was later violated a certain number of times, it was considered as an error pattern. The authors validated their approach on mining publicly available repositories effectively reporting error patterns.

2.3 Temporal data mining

My research in software process discovery mainly rests on the mining of recurrent behavioral patterns from a representation of software processes as a temporal sequences of events performed by individual developers or automated tools with or without concurrency. As we saw in the previous sections of this Chapter, it is possible not only to infer the known high-level processes from observing low-level artifacts, but also to discover novel processes through the use of a unsupervised process mining techniques.

In my research, the collection of development artifacts is performed by Hackystat, a framework for automated software process and product metrics collection and analysis. The event streams provided by Hackystat are very rich in information. They provide temporal data about atomic events, such as invoking of a build tool or performing a test, along with a great variety of process and product metrics such as cyclomatic complexity of the code, or amount of effort applied to software development and many other. It is possible to retrieve other very low-level artifacts such as buffer transfers within the IDE editor or background compilation activities. All of these artifacts characterize the dynamic behavior of a software process in great detail.

In order to perform analyses in my system, I am extracting the necessary process data with a desired granularity from the Hackystat and converting it into a symbolic representation by performing a direct mapping based on the taxonomy of events or by approximating telemetry streams (time-series) with Piecewise Aggregate Approximation (section 2.3.1) and Symbolic Aggregate approXimation (section 2.3.2). This symbolic representation of the observed software processes are used in the Software Trajectory analyses which build upon Symbolic Temporal Data Models (section 2.3.4), Temporal Concepts (section 2.3.3) and Temporal Operators (section 2.3.6).

Section 2.3.7 defines *temporal patterns* of *motif* and *surprise* along with discussing rel-

evant pattern search algorithms and data structures used for the indexing. Section 2.3.10 presents AprioriAll algorithm for unsupervised pattern mining.

2.3.1 Piecewise Aggregate Approximation (PAA)

According to Yi & Faloutsos [61], most of the prior research in the time series indexing was centered around the Euclidean distance (L_2) applied to time sequences, where the method proposed by the authors enable efficient multi-modal similarity search. Supporting the claim, the authors explain some of pitfalls of previously published spectral-decomposition methods such as DFT, DCT, SVD etc. whose core algorithm employs Euclidean distance based metrics over a set of transform coefficients is shown to be inefficient over other distance functions.

The proposed method performs a time-series feature extraction based on segmented means. Given a time-series X of length n transformed into vector $\bar{X} = (\bar{x}_1, ..., \bar{x}_M)$ of any arbitrary length $M \leq n$ where each of $\bar{x}_i$ is calculated by the following formula:

$$\bar{x}_i = \frac{M}{n} \sum_{j=n/M(i-1)+1}^{(n/M)i} x_j \tag{2.3.1.1}$$

This simply means that in order to reduce the dimensionality from n to M, we first divide the original time-series into M equally sized frames and secondly compute the mean values for each frame. The sequence assembled from the mean values is the PAA transform of the original time-series. It was shown by Keogh et al. that the complexity of the PAA transform can be reduced from $O(NM)$ (2.3.1.1) to $O(Mm)$ where m is the number of sliding windows (frames). The satisfaction of the transform to a bounding condition in order to guarantee no false dismissals was also shown by Yi & Faloutsos for any L_p norms and by Keogh et al. [30] by introducing the distance function:

$$D_{PAA}(\bar{X}, \bar{Y}) \equiv \sqrt{\frac{n}{M}} \sqrt{\sum_{i=1}^{M} (\bar{x}_i - \bar{y}_i)} \tag{2.3.1.2}$$

and showing that $D_{PAA}(\bar{X}, \bar{Y}) \leq D(X, Y)$.

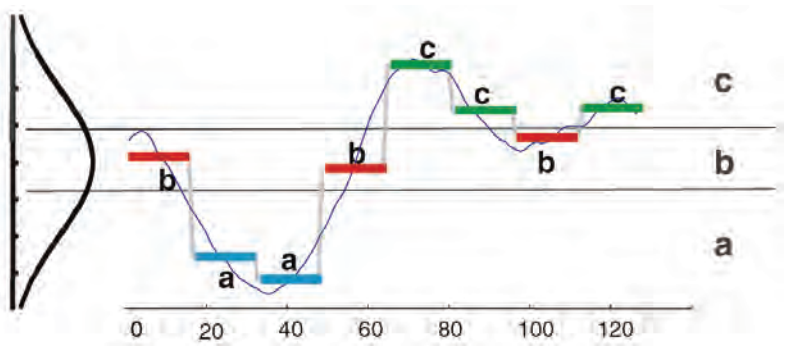


Figure 2.4: The illustration of the SAX approach taken from [37] depicts two pre-determined breakpoints for the three-symbols alphabet and the conversion of the time-series of length $n = 128$ into PAA representation followed by mapping of the PAA coefficients into SAX symbols with $w = 8$ and $a = 3$ resulting in the string **baabccbc**.

2.3.2 Symbolic Aggregate approXimation (SAX)

Symbolic Aggregate approXimation was proposed by Lin et al. in [37]. This method extends the PAA-based approach, inheriting algorithmic simplicity and low computational complexity, while providing satisfiable sensitivity and selectivity in range-query processing. Moreover, the use of a symbolic representation opens the door to the existing wealth of data-structures and string-manipulation algorithms in computer science such as hashing, regular expression pattern matching, suffix trees etc.

SAX transforms a time-series X of length n into a string of arbitrary length ω, where $\omega << n$ typically, using an alphabet A of size $a \geq 2$. The SAX algorithm consist of two steps: during the first step it transforms the original time-series into a PAA representation and this intermediate representation gets converted into a string during the second step. Use of PAA at the first step brings the advantage of a simple and efficient dimensionality reduction while providing the important lower bounding property as shown in the previous section. The second step, actual conversion of PAA coefficients into letters, is also computationally efficient and the contractive property of symbolic distance was proven by Lin et al. in [36].

Discretization of the PAA representation of a time-series into SAX is implemented in a way which produces symbols corresponding to the time-series features with equal probability. The extensive and rigorous analysis of various time-series datasets available to the authors has shown that normalized by the zero mean and unit of energy time-series follow the Normal distribution law. By using Gaussian distribution properties, it's easy to pick a equal-sized areas under the Normal curve using lookup tables [35] for the cut lines coordinates, slicing the under-the-Gaussian-curve area. The x coordinates of these lines called "breakpoints" in

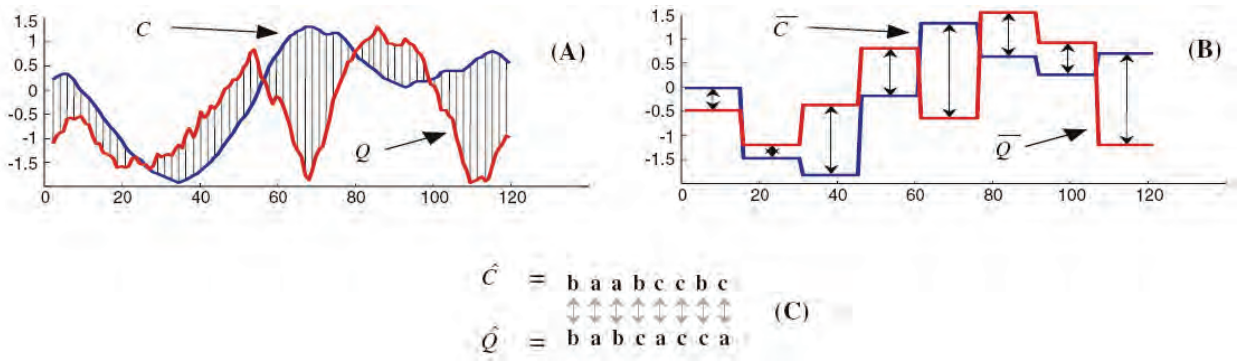


Figure 2.5: The visual representation of the two time-series Q and C and three distances between their representation: Euclidean distance between raw time-series (A), the distance defined for PAA coefficients (B) and the distance between two SAX representations (C). (The figure taken from [37] as well)

the SAX algorithm context. The list of breakpoints $B = \beta_1, \beta_2, ..., \beta_{a-1}$ such that $\beta_{i-1} < \beta_i$ and $\beta_0 = -\infty$, $\beta_a = \infty$ divides the area under $N(0,1)$ into a equal areas. By assigning a corresponding alphabet symbol $alpha_j$ to each interval $[\beta_{j-1}, \beta_j)$, the conversion of the vector of PAA coefficients $\bar{C}$ into the string $\hat{C}$ implemented as follows:

$$\hat{c}_i = alpha_j, \text{ iif } \bar{c}_i \in [\beta_{j-1}, \beta_j) \tag{2.3.2.1}$$

SAX introduces new metrics for measuring distance between strings by extending Euclidean and PAA (2.3.1.2) distances. The function returning the minimal distance between two string representations of original time series $\hat{Q}$ and $\hat{C}$ is defined as

$$MINDIST(\hat{Q}, \hat{C}) \equiv \sqrt{\frac{n}{w}} \sqrt{\sum_{i=1}^{w} (dist(\hat{q}_i, \hat{c}_i))^2} \tag{2.3.2.2}$$

where the $dist$ function is implemented by using the lookup table for the particular set of the breakpoints (alphabet size) as shown in Table 2.1, and where the singular value for each cell (r, c) is computed as

$$cell_{(r,c)} = \begin{cases} 0, \text{ if } |r - c| \leq 1 \\ \beta_{\max(r,c)-1} - \beta_{\min(r,c)-1}, \text{ otherwise} \end{cases} \tag{2.3.2.3}$$

	a	b	c	d
a	0	0	0.67	1.34
b	0	0	0	0.67
c	0.67	0	0	0
d	1.34	0.67	0	0

Table 2.1: A lookup table used by the MINDIST function for the $a = 4$

As shown by Li et al., this SAX distance metrics lower-bounds the PAA distance, i.e.

$$\sum_{i=1}^{n}(q_i - c_i)^2 \geq n(\bar{Q} - \bar{C})^2 \geq n(dist(\hat{Q}, \hat{C}))^2 \tag{2.3.2.4}$$

The SAX lower bound was examined by Ding et al. [16] in great detail and found to be superior in precision to the spectral decomposition methods on bursty (non-periodic) data sets.

2.3.3 Symbolic series, temporal models, concepts, and operators

The SAX transformation procedure described in the previous section yields symbolic time-series based on the real-valued data. Having such a symbolic representation (also called in the literature a *symbolic temporal data*) is very advantageous compared to the real-valued data due to the many algorithms available for the string processing. Moreover, having homogeneous symbolic series corresponding to low-level process artifacts combined with the symbolic event streams from the SCM or bug tracking system creates a rich data field for in-depth software process analysis. In following subsections I will review symbolic temporal data models, temporal concepts and operators.

2.3.4 Temporal data models

Mörchen aggregates much work in the field of data mining from symbolic temporal data in [41]. Two figures taken from this report (Figure 2.6) depict a hierarchy of time-points (left panel) and time-intervals (right panel) data models, concepts and operators.

While the *time-points* data model is intuitive and resembles the actual real-valued time series, the *time-intervals* temporal data model is built upon the concept of *duration* which is a repetition of the property over several time-points. *Time-intervals* are continuous groups of discrete time instants and some of the algorithms and applications operate with this

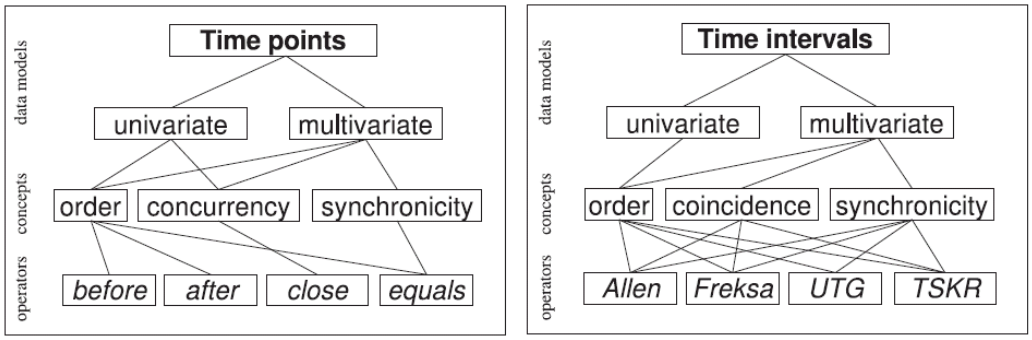


Figure 2.6: The temporal concepts and operators from [41] for both: time point and time interval data models.

data type rather than individual points. Time-intervals essentially are sets of two or more continuous points and two successive time points define a minimal interval which starts at the earlier point and continues to the latter point inclusively. Allen [4] says: "In English, we can refer times as points or as intervals..." giving next two examples: "We found the letter at twelve noon." and "We found the letter while John was away." implying temporal relations in the latter.

2.3.5 Temporal concepts

The concept of *concurrency*, as described by Mörchen, explains the closeness of two time-points in time without considering their ordering, - a coincidence of events in time is the most important property. The *synchronicity* is a special case of concurrency where events occur synchronously in time.

The *order*, and *synchronicity* concepts in the time intervals model are analogous ones in the time points model, whether the time intervals *coincidence* describes an intersection of intervals in time.

2.3.6 Temporal operators

The time point operators from the Figure 2.6: *before*, *after* and *equals* precisely define the relation of points in time. The *close* operator is a "fuzzy extension for temporal reasoning" since it encapsulates other three. Note that some threshold can be used to relax or constrain these operators, for example we can consider points equal to each other even if they are less than k time units apart.

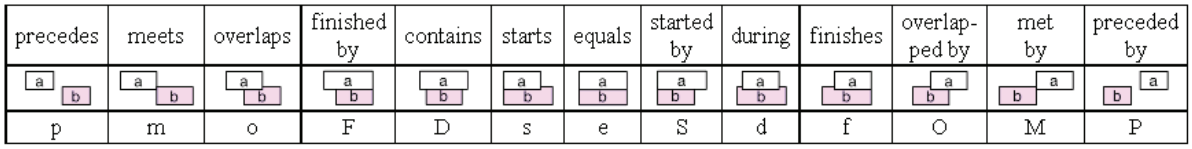


Figure 2.7: The Allen's thirteen basic relations (from [5]) sorted by the degree to which *a* begins and later ends relatively to *b*. All but *equals* can be inverted.

The Time intervals operators are more complex and have been examined by many researchers. In 1983, Allen [4] proposed thirteen basic relations between time intervals which are distinct, exhausting and qualitative. In his work Allen showed that these thirteen relationships are sufficient to model the relationship between any two intervals. Figure 2.7 depicts Allen's relations. These relations and the operations on them form *Allen's Interval Algebra*.

Despite the exhausting property of Allen's relations, while working on multimedia data analysis, Snoek & Worring [49] discovered two practical problems: first is that "in video analysis, exact alignment of start- or end- points seldom occurs due to noise... " and the second is that "two time intervals will always have a relation even if they are far apart in time...". In order to resolve these issues, the authors had to relax a set of Allen's relations and introduce a new *NoRelation* relation. This new relaxed set of 14 relations named TIME (Time Interval Multimedia Event) was built with two time-interval parameters: T_1 for the neighborhood in which impresize boundary segments considered synchronous and T_2 which assigns two intervals as *NoRelation* if they are more than T_2 time apart.

Freksa [17] proposes even more general approach for interval reasoning based on the relations between semi-intervals arguing that "semi-intervals are rather natural entities both from a cognitive and from a computational point of view". Freksa introduces ten operators (Figure 2.8) which fully exploit incomplete inferences and knowledge about events: "... we may know that a certain event Y did not start before a given event X, but we do not know if X and Y started simultaneously or if Y started after X." This approach easies representation of incomplete knowledge by simpler formulas instead of long disjunctions of Allen's algebra. Two intervals can be related by their start points with *younger*, *older* and *head to head* operators. The operators *survives*, *survived by* and *tail to tail* are defined by using end points of each interval. Based on the relation between a start point of one interval and an end point of the other *precedes*, *succeeds* and *born before death of* with inverse *died after birth of* operators defined.

Freksa combined basic operators introducing *contemporary of* relation, *younger contem-*

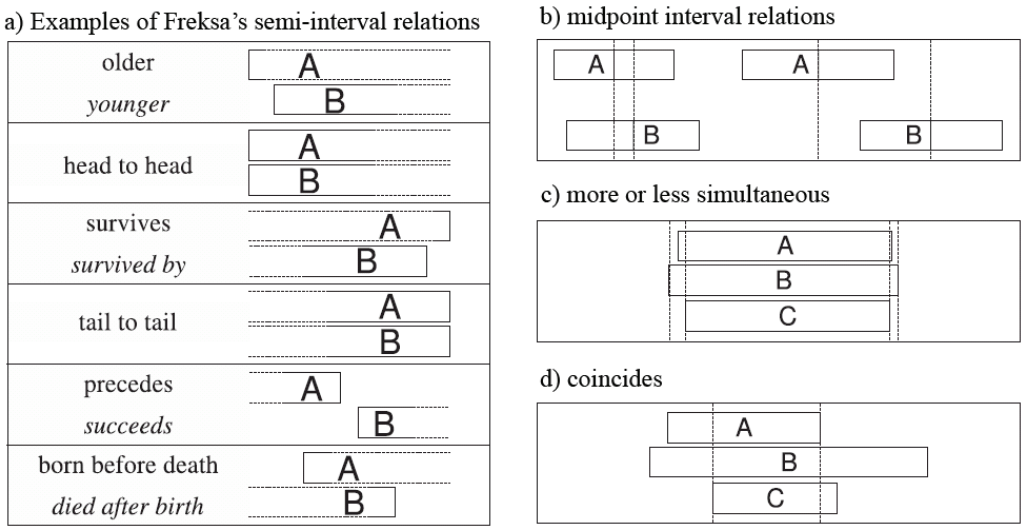


Figure 2.8: Panel a): Freksas semi-interval relations between the intervals A and B with inverse operators in italics. Panels b), c), d): Alternative interval operators.

porary of, *older contemporary of*, *surviving contemporary of*, *survived by contemporary of*, *older & survived by* and *younger & survives*.

Rainsford & Roddick in [44] implemented a system of temporal knowledge discovery based on the Freksa's relations. Later, Roddick introduced *Midpoint Interval Operators* extending Allen's and Vilain's *five-points* [55] relations with nine different *overlaps*. Two overlaps *large overlap* and *small overlap* depicted at the Figure 2.8 panel *b*. This improvement allowed the handling of coarse temporal data and data from streams.

Further extensions were proposed by Mörchen & Ultsch in the form of UTG (Unification-Based Temporal Grammar) introducing an extension to the Allen's *equals* operator with *more or less simultaneous* and *coincides* operators as shown at the Figure 2.8 panels *c* and *d*. Later, the Time Series Knowledge Representation (TSKR) hierarchical language for expressing temporal knowledge in time interval data was built by the same authors on the base of UTG [42]. It was shown that TSKR, while compared to other alternative approaches, has advantages in robustness, expressivity, and comprehensibility

2.3.7 Temporal patterns and indexing

In previous sections of this chapter I have shown the PAA and SAX algorithms for conversion of real valued time series into the symbolic representation along with symbolic temporal data models, concepts and operators. All of this is a necessary background in order to

understand approaches for unsupervised knowledge mining from a symbolic temporal data. In this section I will review sequential pattern mining algorithms from time points and time-intervals data. I will begin the review by focusing on the univariate data and then extend it to the multivariate.

Before discussing algorithms, I need to provide a formal definition of *pattern*. The essential property which defines a pattern is called *support*. Support, roughly speaking, is the frequency of occurrence of a certain pattern in the observed data. It is generally assumed that each of the possible patterns have a certain probability to be seen in the dataset just by chance, and this probability is called the *expected* probability and defines the *expected support* for the pattern. When the actual observed support (or frequency) of a pattern significantly differs from the expected one, it is called *significant support* and indicates that pattern might have some meaningful knowledge artifact attached to it. Although support different from the expected level does not guarantee usefulness or interestingness, it is used for a powerful pruning of a search space since most possible patterns will not have sufficient support. Note that there is property [56] discussed in the literature which essentially similar to support: *confidence*. Usually confidence correlates with support, i.e. greater support corresponds to higher confidence.

There are two well-established categories of patterns with significant support. The first category of patterns, frequently occurring ones (with support higher than expected), is very important in many data mining areas such as medicine, motion-capture, robotics, video surveillance, meteorology and others. Patterns from this category usually named as *repeated*, *approximately repeated* or *motifs*. The second category of patterns, contains patterns with the support lower than expected, this type of pattern is named *surprise* or *novelty* patterns. Novelty patterns also have a great value for many applications: for example it is important to detect unusual semi-repeated pattern in the ECG data diagnosing heartbeat abnormalities, or detecting unusual activity patterns in video surveillance recognizing a suspicious activity.

The temporal motif finding problem from symbolic data is very similar to one of the central problems in the field of Computational Biology [26]. Many algorithms are very similar, but, in Biology, motifs are usually *informative* and bear some information about evolutionary artifacts, which is not true in the field of time-series analysis [60].

2.3.8 Time points patterns

According to Mörchen, the most commonly searched pattern within univariate symbolic time series is order. This search for a particular order of symbols within a subsequence is called

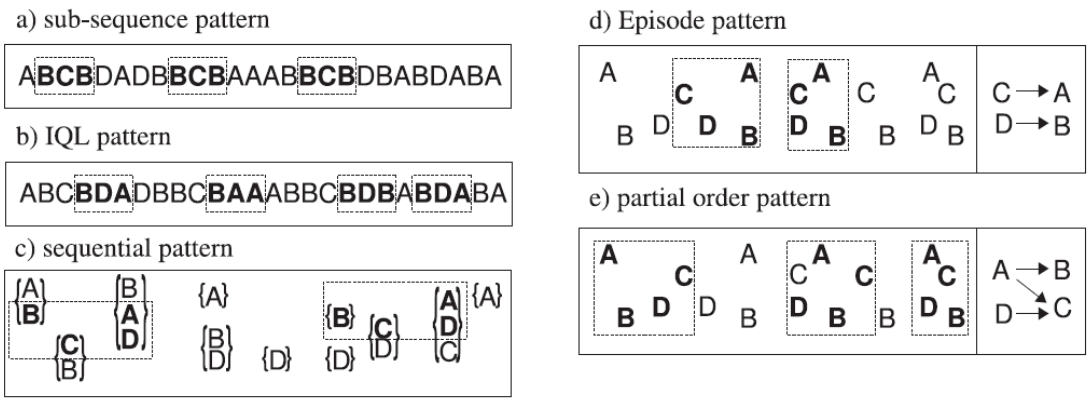


Figure 2.9: The time-points patterns as explained in [41]

sequential pattern mining [2] and does not necessarily require symbols to be consecutive.

The classical suffix tree algorithm [50] with some modifications is a standard approach for pattern discovery from string time-series according to Palopoli et al. [43]. In this paper, the authors discuss algorithms for automatic discovery of frequent patterns (*motifs*) in "exact" or "approximate" forms. There are two approaches generally used for the suffix tree building: *generative*, when algorithms generate all possible patterns and test their appearance frequency [57], and *scanning*, when a sliding window used to scan over the sequences available and construct the tree on the fly [57]. In [24] Jiang & Hamilton compare traversal strategies for suffix trees: breadth-first (BF, $O(K^2n)$), depth-first (DF, $O(Kn)$) and the heuristic depth-first (HDF) algorithms implementations for temporal data mining.

The limitation of the suffix-tree based algorithms is that the maximum length of a pattern needs to be specified upon tree construction since all sub-sequences of this length are generated or extracted from the time series with a sliding window.

Another approach, specifically designed for the *surprise pattern* finding problem, is proposed by Keogh et al. in [32]. The authors discuss methods for finding a surprise pattern from the temporal data and propose their "TARZAN" algorithm which is based upon suffix tree and Markov model, reporting surprising patterns occurring with a frequency substantially different from that expected by chance.

2.3.9 Time interval patterns

As we saw before, the duration concept is implicit in the time interval definition. Nevertheless, while defining a time-interval pattern we do not actually take into account the length

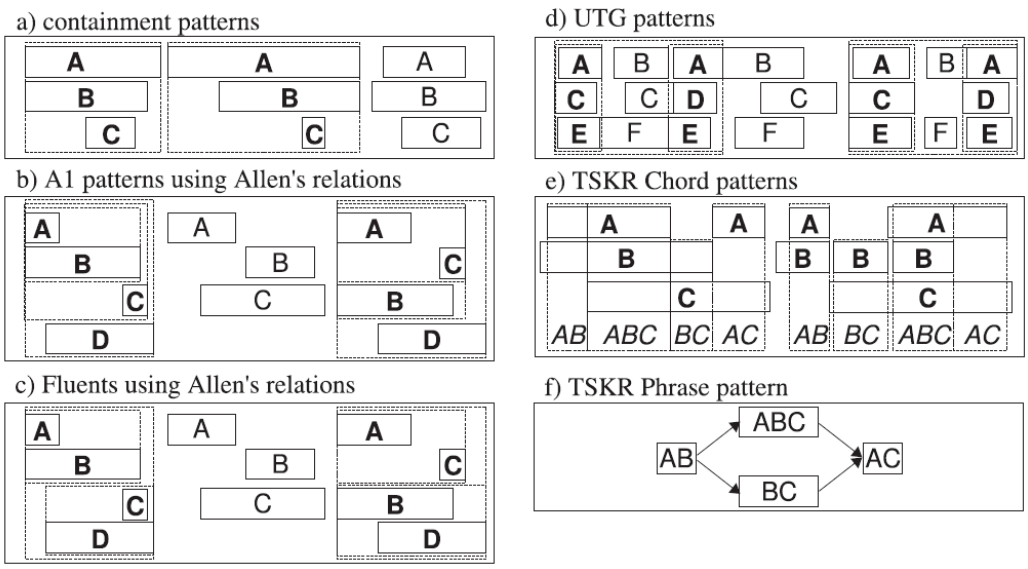


Figure 2.10: The time-interval patterns from [41]

of the interval. Interval relations are abstracted to the "border" or "mean points" relations.

Containment patterns are discussed by Villafane et al. in [56]. This type of temporal patterns has found application to many areas, for example software system log mining. In this case it is important to see what events were happening within the resource overload time interval. Another example is medicine: what was happening with the heartbeat within the period when patient's fever was high? The authors propose a method based on *containment graphs* which allows counting of the containment frequency based on a lattice. The authors designed a naive algorithm of the graph traversal performed incrementally by the path-size and have shown satisfiable results considering their limitations in computational power. One of the limitations found is that it yields different patterns describing the same temporal events. An example of containment patterns is shown at Figure 2.10 panel *a*, this figure is borrowed from [41].

Allen's relations are used in many of the approaches to mining of time-interval patterns. In [29], Kam & Fu considered interval-based events where duration is expressed in terms of end-points relations and designed a category of *A1* temporal patterns based on Allen's relations. However, Kam and Fu restrict the search space to the right concatenations of intervals corresponding to existing patterns and limit the depth of the patterns. Depending on time-interval consideration order, this approach yields different patterns describing same events, for example on the Figure 2.10 panel *b*: left pattern is *(((A starts B) overlaps C) overlaps D)* whether right one is *(((A before C) started by B) overlaps D)*.

Fluents, another type of time-interval patterns based on the Allen's algebra, were introduced by Cohen in [9] to address the problem of unsupervised learning of structures in time series. The formal definition given by the authors states that "Fluents are logical descriptions of situations that persist, and composite fluents are statistically significant temporal relationships between fluents." Sliding window and Apriori algorithms are used in this work. The *Fluent learning algorithm* designed by the authors was applied to the robot motion data collected by sensors and helped in the discovery of temporal patterns indicating persistent robot behavior along with problems with robot's sonar system. This algorithm suffers from the same problem as A1 - it reports variations of the same pattern as different patterns. The authors had to remove "the set of variants" manually before presenting results.

Höppner, in [22], demonstrates an approach to association rules mining through the use of *state sequences*. State sequences based on pairwise relations between all temporal intervals according to Allen. A sliding window is used to generate sub-sequences and the duration of the pattern over consecutive sliding windows is used to quantify the pattern support value. This information is then used in the Apriori algorithm for pattern discovery. The experimental validation of the algorithm on the weather dataset shows the ability of the approach to yield meaningful patterns.

UTG relations were used in some work for temporal interval patterns mining (Figure 2.10 panel *d*), but according to Mörchen [41], it was "criticized for the strict conditions relating interval boundaries". UTG rules place restrictions on the intervals, requiring the start and end of the intervals in the pattern to be almost simultaneous. Also, lacking the ability to express the concept of coincidence, UTG-based methods found somewhat limited application. However, Guimarães in [20] shows targeted application of UTG-based linguistic knowledge representation to the discovery of sleep-related breathing disorders. Results of this study allowed doctors to improve diagnosis, and moreover, led to the discovery of previously unknown recurrent behaviors among patients.

Unlike UTG, *TSKRpatterns* provide support for a partial order and allow inclusion of the sub-intervals into the pattern. This makes them more expressive than UTG and Allen's relations. *TSKR Chord* patterns shown at the Figure 2.10 panel *e* are mined with the CHARM [63] algorithm extended with a support function that counts the duration of the pattern occurrence [41]. *TSKR Phrase* patterns, in turn, are built upon the partial order of the several Chords (2.10 panel *f*), and provide greater sensitivity and selectivity for temporal patterns mining.

Large 3-sequences	Candidate 4-sequences after join	Candidate 4-sequences after pruning
$\{1,2,3\}$	$\{1,2,3,4\}$	$\{1,2,3,4\}$
$\{1,2,4\}$	$\{1,2,4,3\}$	
$\{1,3,4\}$	$\{1,3,4,5\}$	
$\{1,3,5\}$	$\{1,3,5,4\}$	
$\{2,3,4\}$		

Table 2.2: Illustration of AprioriAll algorithm generative function by Agrawal & Srikant [2]. 4-sequences candidates are generated from 3-sequences by join and pruned in turn.

2.3.10 Apriori algorithm

I have mentioned several applications of the Apriori algorithm while reviewing temporal patterns mining from symbolic time-points and time-interval series. The family of Apriori algorithms was proposed in 1995 by Agrawal & Srikant [2]. These algorithms are based on the naive *apriori association rule* stating that *any sub-pattern of a frequent pattern must be frequent*.

The authors has shown application of their algorithms to the mining of recurrent behavior patterns from a database of purchase transactions. They used a support function which is defined as the fraction of the customers supporting such a pattern. The problem solved in this work with the Apriori algorithm can be stated formally: "given a database of customer transactions, find the set of maximal sequences among all others that have at least user-specified support".

The naive Apriori algorithm starts by building a set of maximal sequences by finding all "candidate" patterns of size 1 with a support value that is greater or equal to the specified minimum. On the next step, the algorithm generates a successive set of candidate patterns by extending each of the candidate patterns by 1, and testing it against the database for sufficient support. The algorithm iterates over this second step, until it terminates when no further extension is possible, yielding a set of maximal sequences. While being simple, and proven to produce a correct solution, the naive approach is extremely inefficient due to the high time cost of the database scanning phase (which is the product of an amount of time needed for a single pass over the database and the number of generated candidates).

The significant improvement of the generative function and the scanning speed over the naive approach is the main contribution of Agrawal & Srikant. First, they designed a clever generative function which efficiently prunes the search space by excluding non-existing se-

quences of length $n+1$ just by looking at the existing set on sequences of length n. Second, the authors' implementation of the database scanning leverages the use of efficient intermediate in-memory index (built with a hash-tree and conducts breadth-first search). is to transform (shrink) the database of transactions during each step. During this transformation each of the individual transactions within single sequence is replaced by the "set of all *litemsets* contained in that transaction. If a transaction does not contain any *litemset*, it is not retained in the transformed sequence." The "*litemset*" here refers to the item set with a minimum support.

AprioriAll, AprioriSome and DynamicSome by Agrawal & Srikant were the very first algorithms for sequential pattern mining built upon the Apriori principle. While being far more efficient than a naive implementation, they still require many passes over the database while testing candidate sequences. Many other algorithms based on this implementation were proposed. In 1996 Srikant & Agrawal extended their original work with GSP (Generalized Sequential Pattern) algorithm. GSP allows time constraints and relaxes the definition of transaction; additional improvement was achieved by use of the knowledge of taxonomies which prunes search space by excluding non-interesting sequences. Wang et al. in 2001 proposed a GSP-based MFS (Mining Frequent Sequences) [58] algorithm based on the concept of *pre-large sequences* which further reduces the amount of rescanning.

Chapter 3

Software Trajectory: a software process mining framework.

As we saw in Chapter 2, it is possible to infer and successively formalize software process by observing its artifacts, and in particular, recurrent behavioral patterns. The problem of finding such patterns is the cornerstone of my research. My approach to this problem rests on the application of data-mining techniques to symbolic time-point and time-interval series constructed directly from the real-valued telemetry streams provided by Hackystat.

To investigate the requirements for a software tool that aids in the discovery of recurrent behavioral patterns in software process, I am designing and developing the "Software Trajectory" framework. A high-level overview of the framework is shown in Figure 3.1 and resembles the flow of the "Knowledge Discovery in Database" process discussed by Han et al. in [21]. As shown, the data collected by Hackystat is transformed into a symbolic format and then indexed for further use in data-mining. The tools, designed for data-mining, have a specific restrictions placed on the search space by domain and context knowledge in an attempt to limit the amount of reported patterns to useful ones. I am planning to design a GUI in a way that will allow easy access and modification of these restrictions.

3.1 Current state of development

I started development of the Software Trajectory framework in early 2008 by designing a user interface for visual comparison of multi-variate time series. I called this package "TrajectoryBrowser" and called its results "Software Trajectory Analysis". The idea was to visualize software project metrics as a set of trajectories in 3D space, as opposed to the

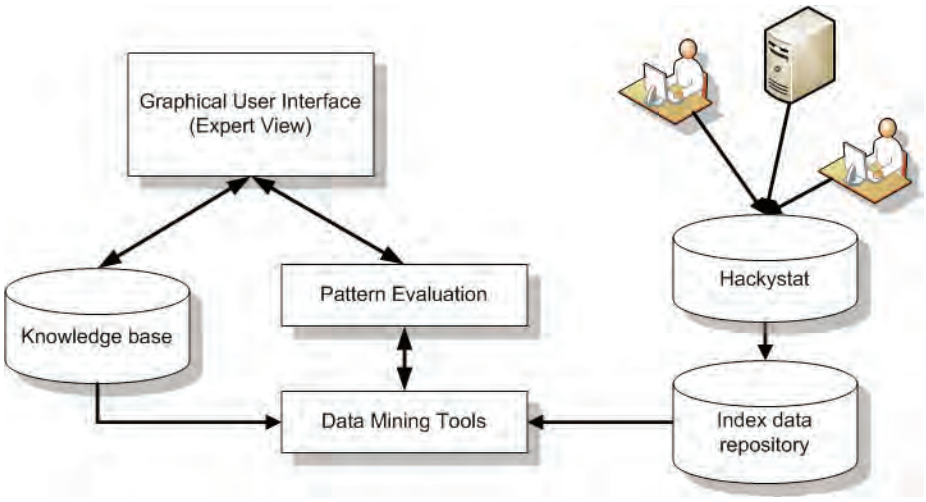


Figure 3.1: The high-level system overview. Software engineering process and product data are collected and aggregated by Hackystat and then used to generate temporal symbolic indexes. Data mining tools constrained by software engineering domain knowledge are then used for unsupervised patterns discovery. The GUI provides an interface to the discovered patterns and aids in investigation of a discovered phenomena.

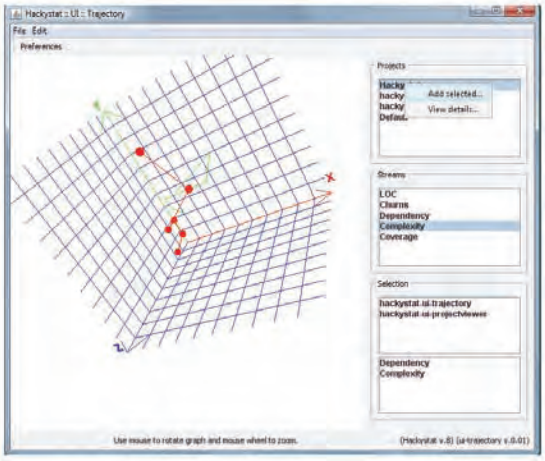
traditional 2D representation. The first *TrajectoryBrowser* was an ad-hoc application based on the two technologies: Java3D for visualization and the UI, and the JADE multi-agent framework [6] for the data generation (see Figure 3.2 panels *a* and *b*). While this first version fulfilled basic requirements for visualization, allowing trajectories to be visualized, it did not provide any means for quantifying similarities between trajectories or finding similar trajectories autonomously.

In order to introduce a metric and implement an indexing of temporal features, I then started experimenting with a naive application of Euclidean distance and later with spectral decomposition of time series through DFT. Unfortunately both methods were found to be inconsistent in their results and sometimes even misleading due to the noisy and bursty nature of temporal data generated by the software process.

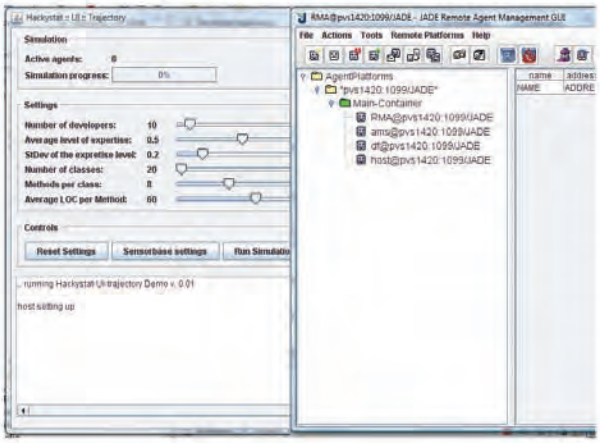
At the next iteration, inspired by its success in many applications and its robustness to noise, I implemented the Dynamic Time Warping (DTW) algorithm. This code was wrapped into the second, web-based version of TrajectoryBrowser (see Figure 3.2 panels *c*). The second version provided the user with the ability to visualize time-series intervals and quantify the similarity. Nevertheless, there was no implementation of the unsupervised similarity search provided.

In order to close this gap, I started developing an indexing module that uses sliding

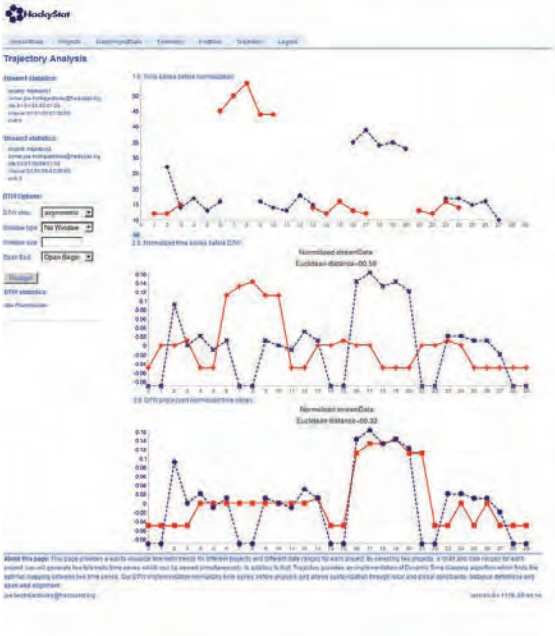
a) Java 3D based “Trajectory browser”



b) JADE based multi-agent software process simulation



c) Dynamic Time Warping implementation in Projectbrowser



d) TrajectoryBrowser showing common motifs in Telemetry streams

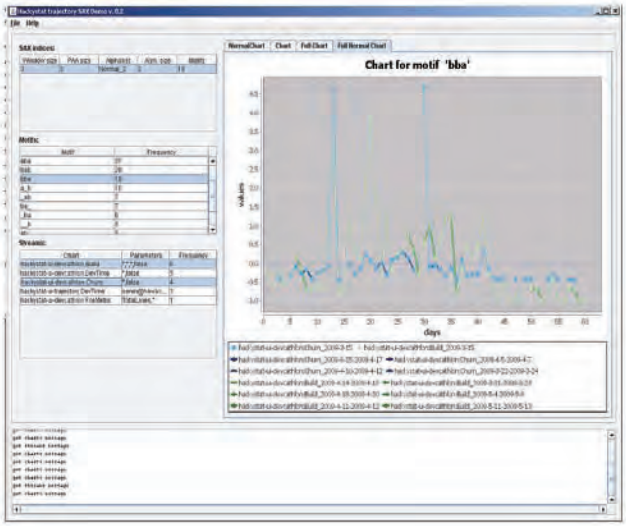


Figure 3.2: Screenshots of three versions of TrajectoryBrowser (panels a, b and d) and the software process simulation (panel b). Simulated data was used for validation in early stages.

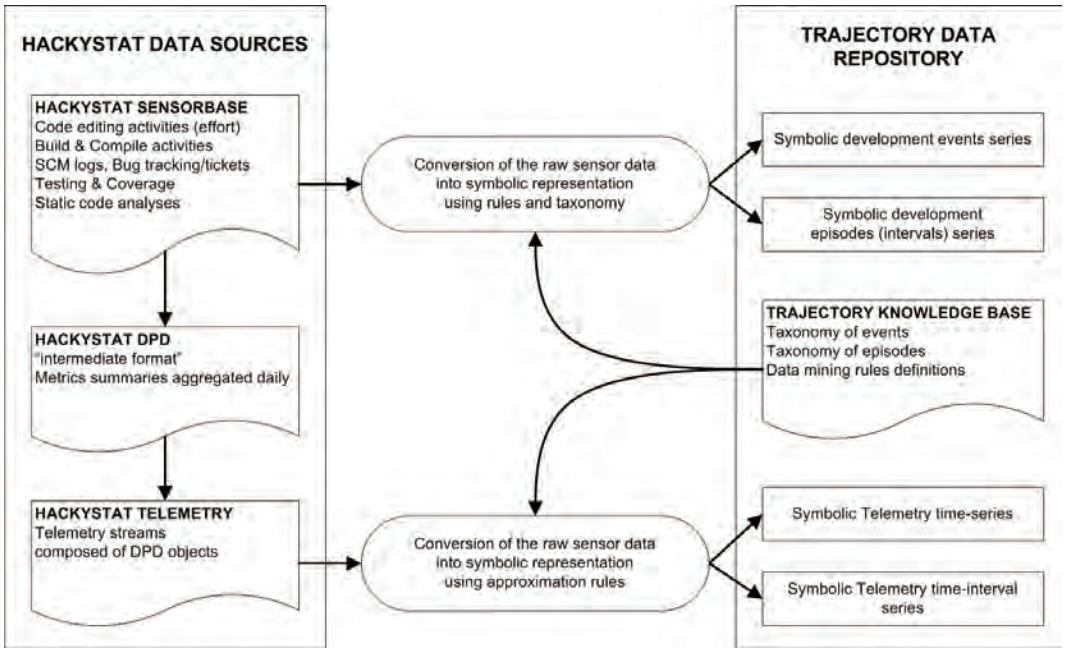


Figure 3.3: Overview of the data abstraction from the the low-level process and product artifacts collected by Hackystat (left side) to the high-level symbolic time-point and time-interval series stored in the Software Trajectory data repository.

window and DTW. While working on this, I found another promising approach for the same task: PAA and SAX (see section 2.3.1 and 2.3.2) approximations. The simplicity of these two methods allowed me to integrate them with my existed codebase almost instantly, delivering the third version of TrajectoryBrowser which I am currently using in my research. Sections 3.1.1 and 3.1.2 present the indexing mechanism and the index database design.

3.1.1 Temporal data indexing

The temporal data indexing starts with the data abstraction process shown at the Figure 3.3. Collected and aggregated by Hackystat, *raw sensor data* and derived *Hackystat Telemetry streams* are used as the data sources. Streams of individual events are retrieved from the Hackystat Sensorbase, then sorted by activity types, tokenized, and finally converted into symbolic time point (*Events*) and time-interval (*Episodes*) series by following a user-defined taxonomy mapping. By performing a user-configured PAA and successive SAX approximations, Hackystat Telemetry streams are converted into a temporal symbolic format. This symbolic data, in turn, are getting indexed and stored in the dedicated relational database for future use in data mining.

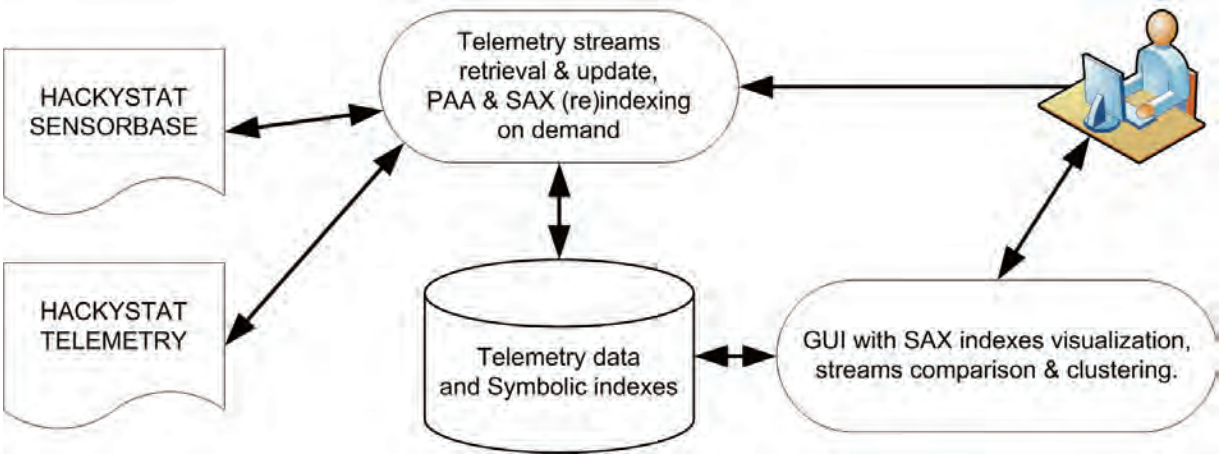


Figure 3.4: Overview of the current implementation of Software Trajectory framework.

I have not experimented with symbolic abstraction and mining of the raw sensor data yet, but this approach has a solid foundation provided by Hongbing Kou, in his thesis [34]. In his work, he was able to infer TDD behaviors by using a technique called Software Development Stream Analysis (SDSA) which is very similar to mine, except the fundamental difference in the approach: Hongbing defined TDD patterns at first and then search for them using SDSA. Within SDSA, low-level software process data was first converted into symbolic Episodes first. Next, sequences of Episodes (candidate patterns) were matched (aligned) to the set of the known TDD temporal rules (patterns), and if they were found to satisfy TDD rules (having sufficient support), the generative process was inferred as TDD.

I have implemented the indexing of Telemetry streams with a sliding window, PAA, and SAX. I am using a sliding window approach following [37] for generating a set of subsequences from a real-valued stream. Each of the subsequences is then normalized and converted into a symbolic representation with PAA and SAX. This symbolic representation and the position information is then stored in the relational database. For index manipulation and data retrieval, I am using SQL. Figure 3.4 presents the current software system overview.

3.1.2 Index database design

Figure 3.5 presents the TrajectoryDB database schema in detail. This schema was designed with two main requirements in mind. First, it must be able to hold a local copy of Telemetry streams due to the high time cost of querying Telemetry service remotely. Second, it must support KDD algorithms through optimized SQL queries. Both goals were achieved, resulting in high turn-around speed for both indexing and querying.

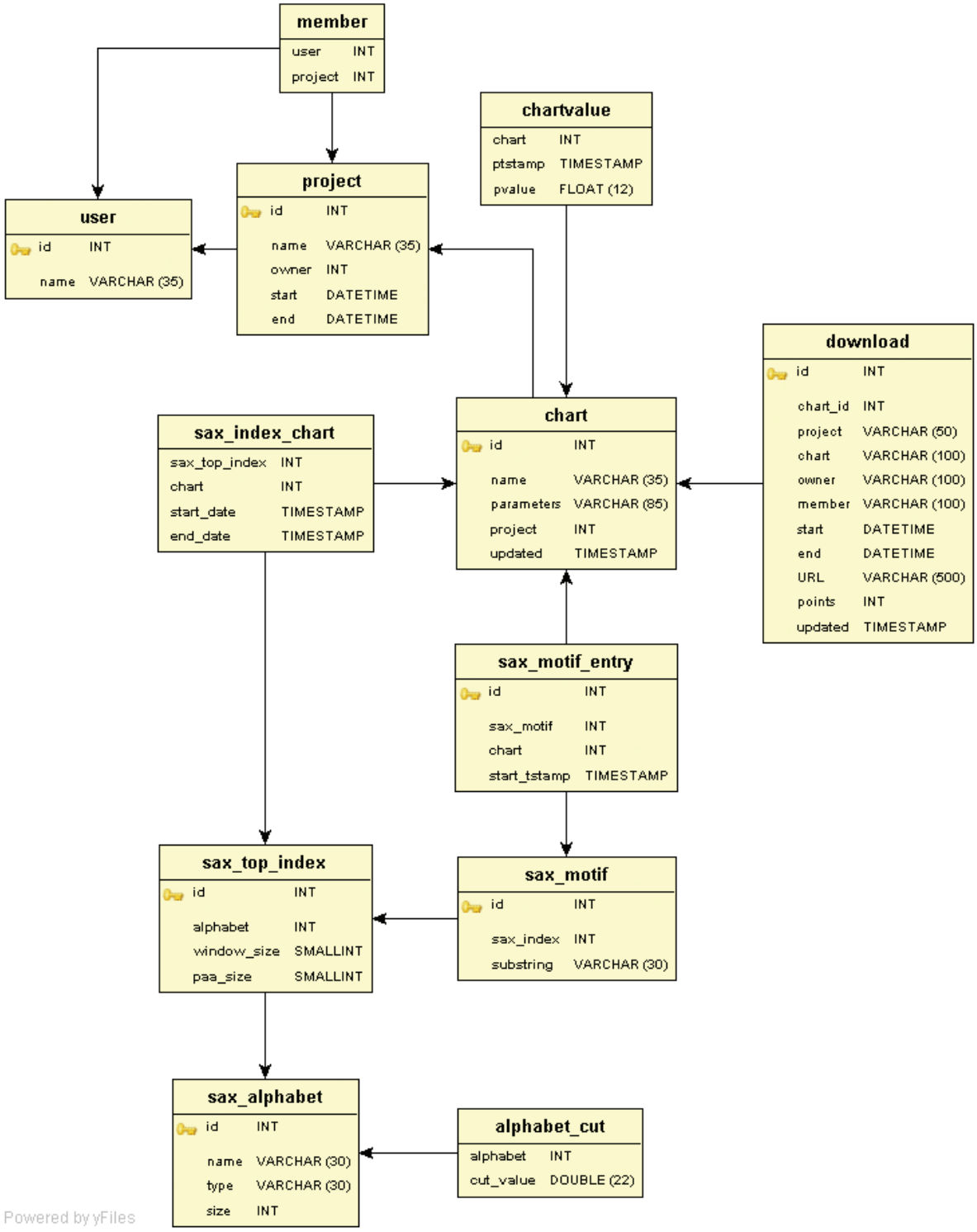


Figure 3.5: The database schema used for the Hackystat Telemetry data retrieval and indexing in the pilot project.

The current version of Hackystat is based on a Service-Oriented architecture, and in order to retrieve a Telemetry data one must query the Telemetry service over network. My initial implementation of indexing required network queries for the each of the indexing passes and was significantly affected by the network lag to my remote location and the amount of data that needed to be retrieved for each pass. To overcome this issue, I have developed a software module which provides "caching" and incrementally updates Telemetry streams data locally. The *Project, User, Member, Chart, Chartvalue* and *Download* tables (located at the upper part of the Figure 3.5) are designed to store the Telemetry data locally. The system performs incremental update of the streams over time by reading the *Download* table, which keeps track of updates.

The telemetry streams indexing is performed on demand. For each of the indexes a sliding window size, PAA size, and an alphabet must be specified. Following Lin & Keogh [37], in order to investigate the sensitivity and selectivity of different approximation levels, I have conducted a number of experiments with various alphabets. Individual alphabets for each of the data streams (*Build, Coverage* etc.) and *Universal Telemetry Alphabet* (see example for five letters alphabet at the Figure 3.6, panel *a*) were built and tested for indexing. These custom alphabets, and the original SAX alphabet, based on the Normal distribution, are kept in the *Sax_alphabet* and *Alphabet_cut* tables.

The *Sax_top_index* table is a "binder" which keeps information about all indexes ever built. The *Sax_index_chart* table keeps track of all indexes built for a particular chart and a timeframe. *Sax_motif* and *Sax_motif_entry* tables separate heavyweight symbolic motifs and lightweight offset "information" reducing the database size and optimizing data analysis and retrieval.

This database schema was found optimal for easy retrieval of any kind of information needed for streams comparisons or clustering. By running a single query it is possible to retrieve a vector of most frequent motifs for each of the streams or find a set of motifs shared between streams.

3.2 TrajectoryBrowser

As mentioned before, the current version of TrajectoryBrowser was created in order to visualize telemetry streams along with temporal features found through indexing. It provides easy navigation within indexes and is capable of displaying multiple telemetry streams with highlighted features. By viewing the same motif entry across multiple streams it is possi-

ble to guess information about coincidence of entries, as an example, see Section 4.4, for sequential "growth" pattern finding experiment.

3.3 Future development roadmap

As I pointed out before, the current version of the TrajectoryBrowser and analyses do not support processing of low-level raw Hackystat data and analyses based upon them. I have already started the development of such a module along with extending the database schema for storing raw data, its approximation, and taxonomy. Once these components are in place, I will start developing data mining algorithms for Events and Episodes using the discussed temporal data mining algorithms. Once all major software pieces are in place, I will focus on the experimental evaluation of the system and improving the usability of the GUI.

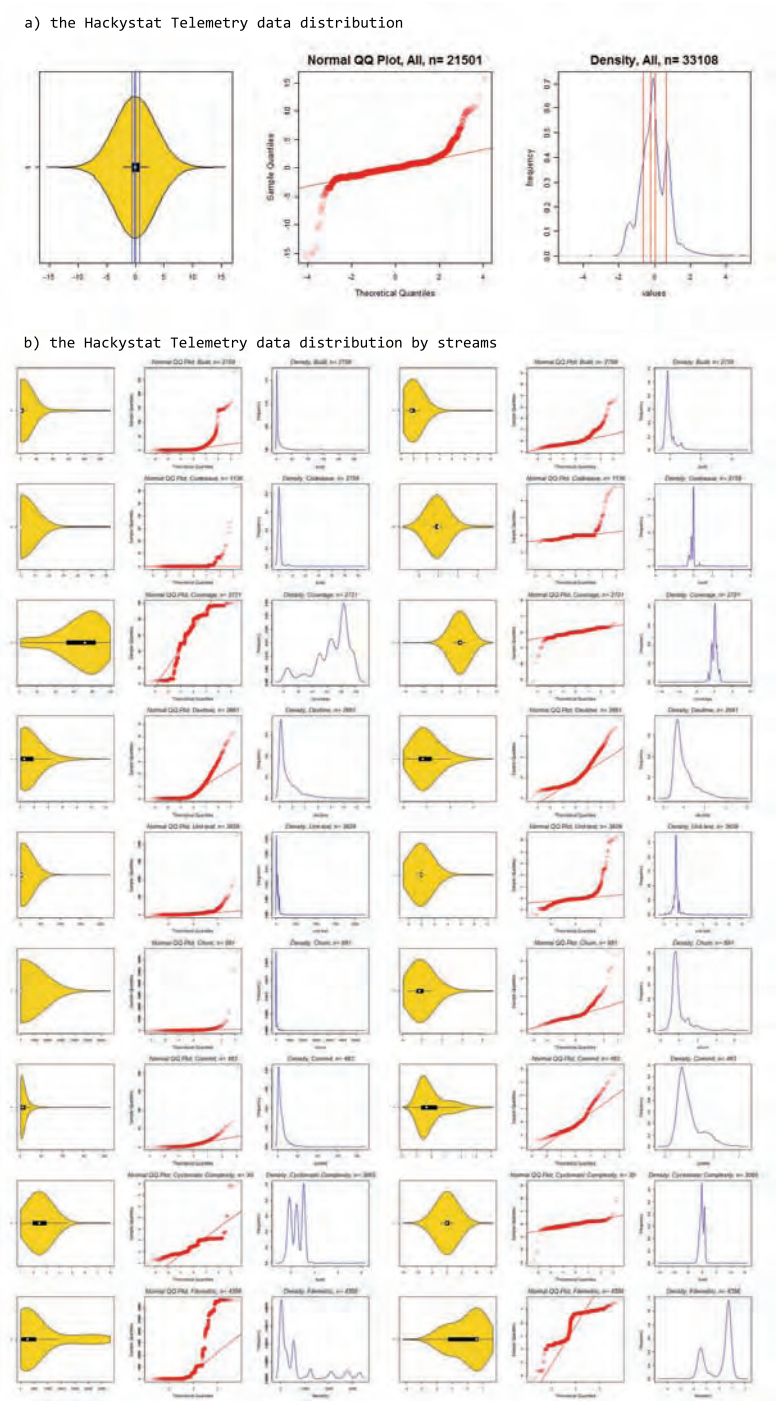


Figure 3.6: The distribution of the Hackystat Telemetry data for a sample project dataset. While individual telemetry streams (panel *b*, left three plots for each stream represent raw data, right three plots - Z-normalized data) show different data distributions, the combined and normalized data (panel *a*) close to the normal distribution. Combined data was used for creation of the *Universal Telemetry SAX alphabet*.

Chapter 4

Experimental evaluation

I propose to conduct two case studies: *Public data case study* (Section 4.5), and *Classroom case study* (Section 4.6) in order to empirically evaluate the capabilities and performance of Software Trajectory framework. These studies differ in the granularity of data used, and in the approaches for evaluation.

During my work on the pilot version of Software Trajectory framework, I began a set of small experiments in order to aid in the architectural design and algorithms implementation. In addition, these experiments helped me to outline the boundaries of applicability of my approach to certain problems in software engineering. I call these experiments the *Pilot study* and Section 4.4 discusses some of the insights yielded by this study.

My intent behind these empirical studies is to assess the ability of Software Trajectory framework to recognize well known recurrent behavioral patterns and software processes (for example Test Driven Development), as well as its ability to discover new ones. In addition, these studies will support a classification and extension of the current Hackystat sensor family in order to improve Software Trajectory's performance. It is quite possible that some of the currently collected sensor data will be excluded from the Software Trajectory datasets, while some new ones will be designed and developed in order to capture important features from the studied software development data streams.

Before proceeding with the presentation of design of these studies and approaches for evaluation, I will discuss my evaluation paradigm.

4.1 Review of evaluation strategies

In contemporary literature, research methods are categorized into three paradigms: quantitative, qualitative and mixed-methods [46]. Despite the arguments presented in the past for integrating first two methods [19], combining qualitative and quantitative methods in a single, mixed-method study is currently widely practiced and accepted in many areas of research, and in particular, in empirical software engineering [8] [48].

4.1.1 The two paradigms

The quantitative paradigm is based on positivism. The positivism philosophy presumes that there exists only one truth, which is an objective reality independent from human perception, which, in turn, means that a researcher and a researched phenomena is unable to influence this truth or be influenced by it [19]. Quantitative studies are focused on finding of this truth through extensive study of the phenomena, and often characterized with very large sample sizes, control groups etc. in order to ensure proper statistical analysis.

In contrast, qualitative study is based on constructivism [15] [19] and interpretivism [1]. Both presume the existence of multiple truths based on the one's construction of reality, as well as non-existence of such a reality prior to the investigation. Moreover, once such a reality is solely or socially constructed, it is not fixed, - it is changing over time, shaped by new findings and experiences of researcher. Techniques of qualitative studies are not meant to be applied to a large population. They rather focus on small, rich in features samples which can provide valuable information. In other words, subjects in a qualitative study are picked not because they represent large groups, but because they can articulate important high-quality information.

The assumptions behind the two approaches extend beyond just methodological or philosophical differences to the one's perceptions of reality. According to Guba et al. [19], qualitative and quantitative methods do not study the same phenomena. Applying the authors' statement to empirical software engineering, we can infer the limitations of qualitative studies by their inability to access some of the phenomena that researchers are interested in, such as prior experiences, social interactions, and the behavioral variations of individuals performing software process.

4.1.2 Mixed methods and Exploratory research

Surprisingly, the fundamental differences between the two paradigms are rarely discussed in the mixed-methods research which is based on pragmatism. The finding of truth is more important in pragmatist paradigm than the question of methods or philosophy. Researchers practicing the mixed-method approach are free to use methods, techniques and protocols which meet their purposes, and which, in the end, provide the best understanding of the research problem. This unifying logic in understanding of studied phenomena regardless of approach, is central to mixed methods.

While the three discussed paradigms at least assume the existence of a problem and provide the outlines for methods of data collection and design of a study, sometimes a clear statement of a problem is missing from research. In such a case, exploratory research must be conducted in order to clarify the detailed nature of the problem.

4.2 Software Trajectory approach evolution

When I started exploring Hackystat telemetry streams during the Software Engineering class taught by my present adviser Philip Johnson, I realized the "coolness" of software process metrics visualization for providing insights into software process. By using the web interface of Hackystat, I was able to pull and visualize various telemetry streams reflecting my development. Working in the class, I compared metrics of my software process to ones from my team members. Performing such analyses, and discussing their results enabled us to improve our individual and team software processes, which resulted in excellent grades.

After joining CSDL, I started my research by exploring the boundaries of telemetry visualization and telemetry analyses, and finding possibilities for improvements. At that point of time, I was working on two problems: improving the visualization of telemetry streams and introduction of metrics for quantitative comparison of telemetry streams (trajectories). While working on these two problems, I realized that the real problem I am trying to solve lies beyond the reach of these two. The problem is that the user is not provided with enough details about their software process to be able to perform comparative analyses of two projects (two software processes). I am envisioning the solution of this problem through the extension of Hackystat analyses with the ability to discover detailed features from software process.

In other words, by conducting *exploratory research* of visualization tools and techniques as well as designing "flexible enough" metrics appropriate for telemetry streams comparison, I have realized the importance of understanding of the generative software process. This

knowledge about performed software process, inferred from the set of collected artifacts, is crucial in the process improvement and in the comparative analysis of software projects.

Once I was able to clearly formulate this problem, I have started another exploratory study - my pilot study. By performing this exploration of the tools and techniques for software process mining and inference, I am trying to build my own toolkit which will allow me to approach the next problem - the problem of quantifying of software process through the discovery of recurrent behaviors.

4.3 Software Trajectory case studies and evaluation design

The proposed public data case study is based on the use of publicly available Software Configuration Management (SCM) audit trails of the big, ongoing software projects such as Eclipse, GNOME etc. Mining of SCM repositories is a well-developed area of research with much work published [18]. SCM repositories contain coarse software product artifacts which are usually mined with a purpose of discovering of various characteristics of software evolution and software process. I am using a mixed-method approach in this study. In the first phase of this study, I plan to perform SCM audit trail data mining following published work and using Software Trajectory as a tool in order to discover confirmed patterns in software process artifacts, and thus quantitatively evaluate Software Trajectory's performance when compared to existing tools. In the second phase, I will develop my own pre-processing and taxonomy mapping of software process artifacts into temporal symbolic series. By using this data and Software Trajectory framework, I plan to develop a new approach for SCM audit trail mining and possibly discover new evolutionary behaviors within software process. These discovered knowledge will be evaluated through the peer-reviewed publication submitted for the annual MSR challenge [18].

The classroom case study is based on a more comprehensive data set. This data will be collected by Hackystat from Continuous Integration and from individual developers and will contain fine-grained information about performed software process. The approach I am taking in this study is very similar to the public data case study. I will develop my own taxonomy for mapping of software process artifacts into symbolic temporal data and will apply Software Trajectory analyses to this data in order to discover recurrent behaviors. In turn, these discovered knowledge will be evaluated through interviewing for usefulness and meaningfulness. Results of interviewing will be used to improve Software Trajectory and

will constitute part of my thesis and following publication.

Both case studies are exploratory in nature. At this point of my research, I can only see that the properties of my approach and its current implementation in the Software Trajectory framework appear to be very promising. The wealth of developed techniques for temporal symbolic data mining and recent development of SAX approximation allow me to overcome many computational limitations in existing approaches for mining of software process artifacts. The current implementation of Hackystat provides the ability to capture fine-grain software product and process metrics providing a richness of data, which, potentially, might reveal new insights. Current research in software process discovery indicates the overall feasibility of proposed goals in the discovery of unknown recurrent behaviors in software process.

Nevertheless, there is no prior knowledge about application of these techniques to software process mining. Moreover, at this stage of my research, it is impossible to foresee if new recurrent behaviors will be discovered or their meaningfulness or usefulness for real world applications. For this reason I am undertaking a constructivism paradigm in my research [15], and will develop knowledge about the applicability of my approach to software process mining during the development of Software Trajectory framework and its empirical evaluation. By designing, developing, deploying and observing a software system, and by conducting interviews and surveys, I will gain the desired experience and knowledge.

But it is possible that this part of my research will fail, and I will not be able to discover any meaningful novel knowledge about software process. If so, I will apply every effort to investigate and explain the pitfalls of my approach to the domain of software process data mining. It may be that failure is due to the specificity of domain, or due to the insufficiency of the information enclosed in the collected artifacts, or maybe due to inefficiency of augmented methods. Through thorough analyses of failed experiments and collection of feedback, I will outline boundaries of the approach taken in this work and appropriate avenues for future development.

4.4 Pilot study

In order to demonstrate the ability of Software Trajectory to perform telemetry indexing and temporal recurrent patterns extraction, I have conducted two experiments which provide insights in the use of the motif frequencies and software process event taxonomies.

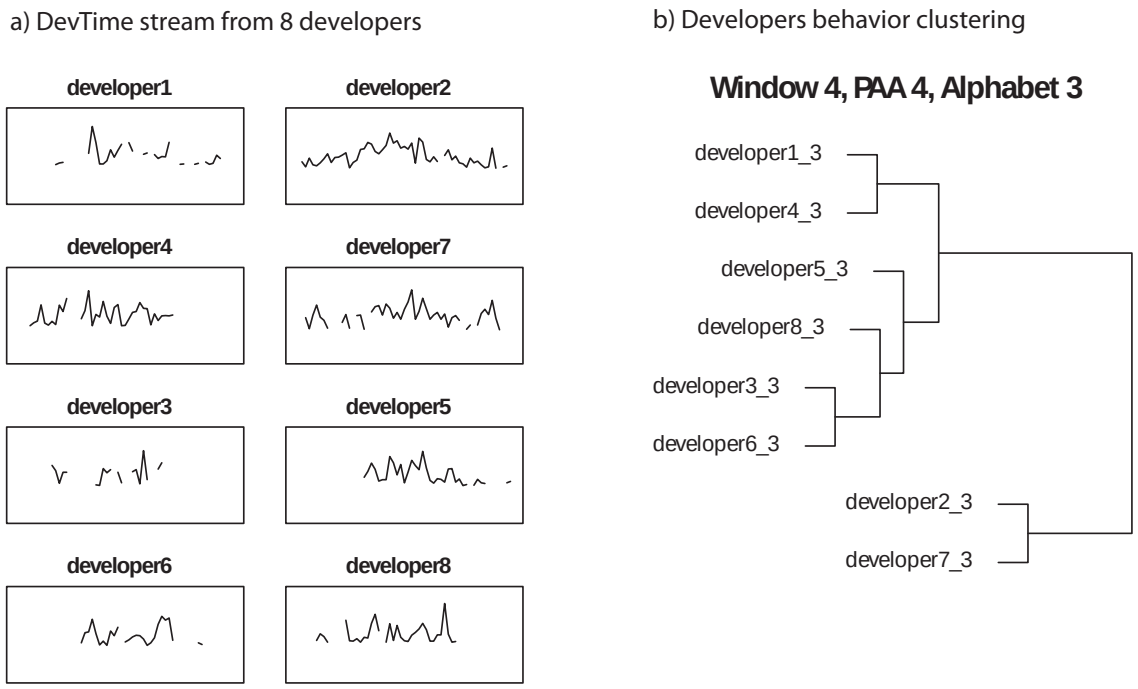


Figure 4.1: Clustering of developers behavior using symbolic approximation and vectors of motif frequencies. This analysis captured similar development behavior among developers. Developers #2 and #7 were consistent (no bursts observed) in both, coding and measuring effort during whole time interval, while all others can be characterized with bursty, inconsistent effort.

4.4.1 Clustering of the Hackystat Telemetry streams

The main purpose of the this study was to evaluate the ability of PAA and SAX approximations and indexing to capture a temporal specificity of telemetry streams through the discovery of recurrent temporal patterns. Knowing about the frequently misleading results of a time-series clustering [31], I did not expect to capture many interesting facts, nevertheless the results were encouraging.

The data used in this study was collected from student users of Hackystat during Spring, 2009. This dataset represents Hackystat metrics collected during sixty days of a classroom project by eight students. The following clustering experiments were conducted using the distance between vectors of motif frequencies extracted by indexing of telemetry streams:

- Clustering of software process related telemetry streams collected from individual developers. I was able to group developers with similar behavioral patterns within clusters, which indicates the feasibility of the classification approach. Figure 4.1 depicts results of this analysis.

- Clustering of software product-related telemetry streams by using motif frequencies. I was able to group telemetry streams, but while these groups look intuitively meaningful, the close examination of the stream features suggests that this grouping happened due to the similar temporal behavior on the short stretches. This result, while proving the correctness of approach, indicates it's limitation, pointing that instead of using just motif frequencies, some temporal ordering should be taken into account. Figure 4.2 displays results of this analysis.

4.4.2 Sequential patterns search

The second pilot study, focusing on discovery of sequential patterns, was conducted using real data from my own concurrent development of two software projects. While working on the Software Trajectory framework, I made the decision to split the code into two parts: an algorithm implementation library that I named JMotif, and user-interface part called TrajectoryBrowser. While this decision simplified development, it introduced a dependency of TrajectoryBrowser on the JMotif API. As a result of iterative and incremental pattern in my development, I changed the JMotif public API three times, which consequently involved extensive refactoring in the ProjectBrowser code. This dependency can be clearly seen from observing DevTime streams at Figure 4.3 panel *a*.

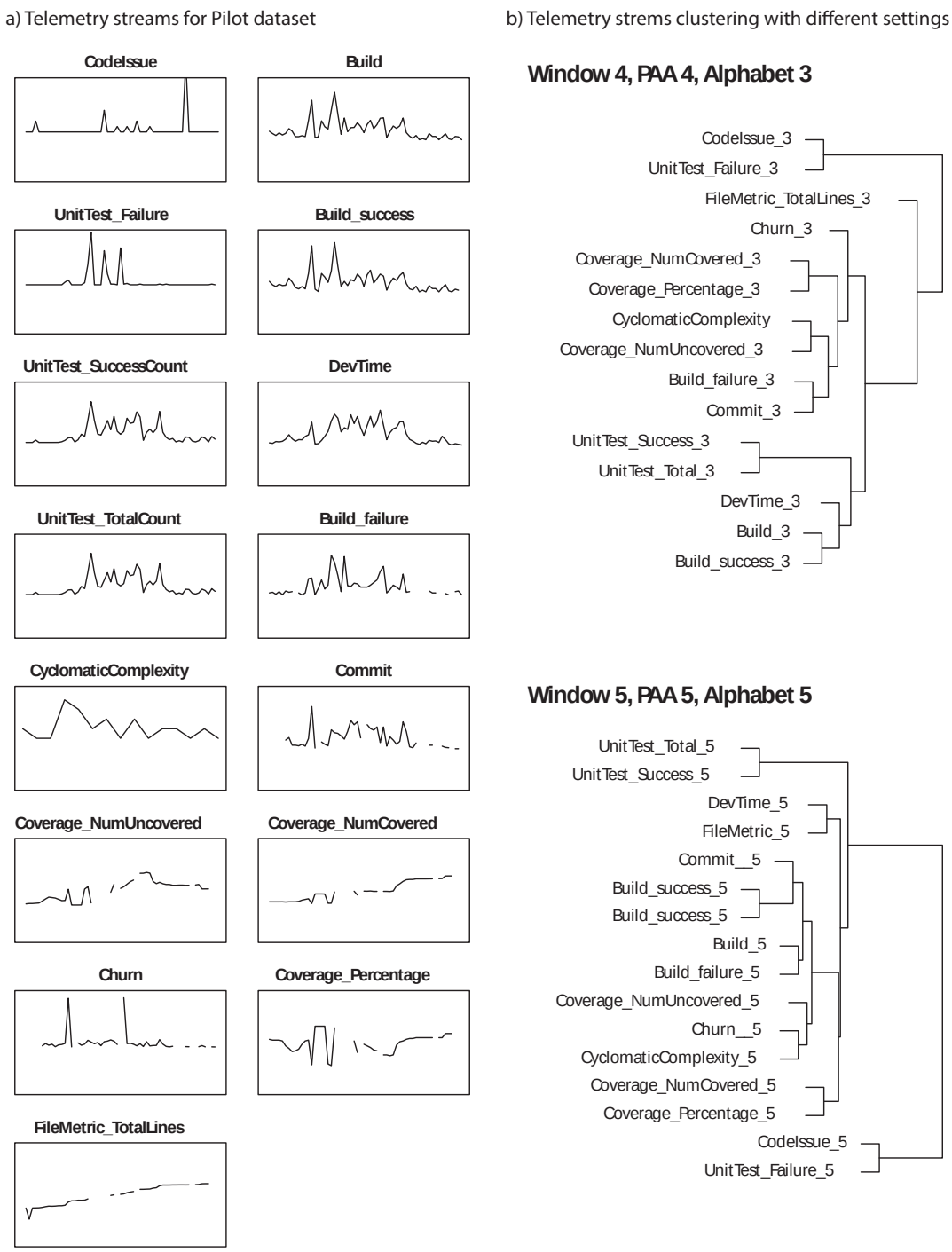


Figure 4.2: Clustering of telemetry streams for classroom pilot dataset using symbolic approximation and vectors of motif frequencies. While it seems to be meaningful to find correlation between *UnitTest_Failure* and *CodeIssue* streams unit test, this grouping happened due to the similarity of behavior pattern - short, high amplitude bursts; but note, there is no correlation of features in time .

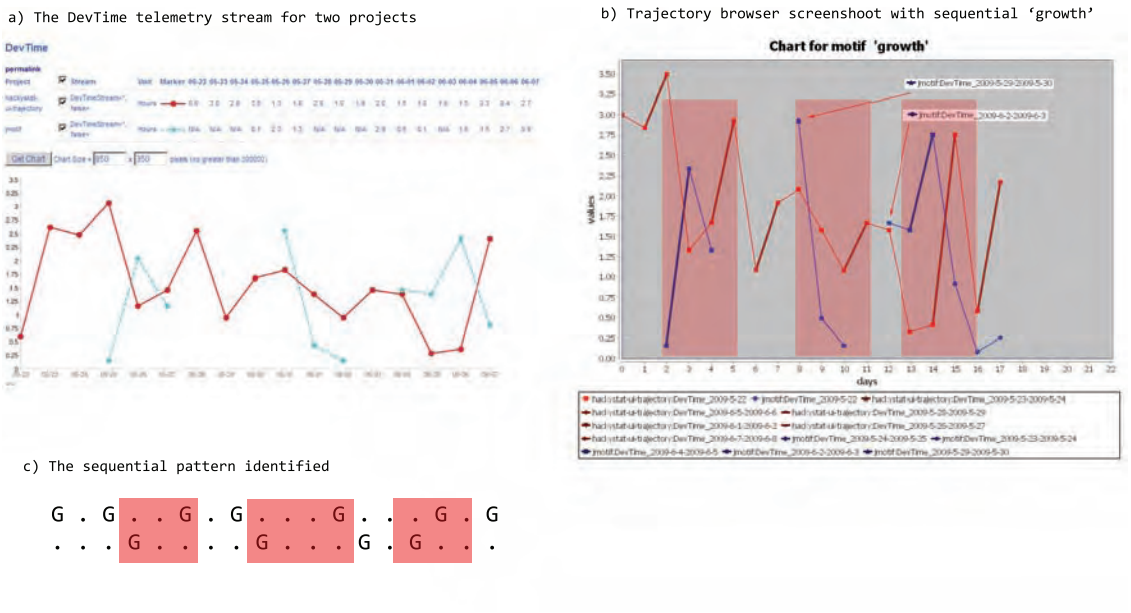


Figure 4.3: The illustration of finding of sequential *growth pattern* in two DevTime telemetry streams. Panel *a*: The Hackystat ProjectBrowser showing telemetry streams. Panel *b*: the TrajectoryBrowser showing same telemetry streams along with identified pattern. Panel *c*: the symbolic representation of streams with highlighted pattern.

In order to capture this dependency pattern in two Telemetry streams, representing the daily amount of development time spent on the TrajectoryBrowser and JMotif projects, I defined a synthetic *growth pattern* as the large positive delta value between previous and current day effort. By transforming Telemetry streams with this simple rule in the symbolic form, I obtained a two dimensional symbolic time series, where letter G represents a growth pattern, see Figure 4.3 panel *c*. I defined a formal rule for *sequential growth* pattern as the pattern like $G_{JMotif} \rightarrow G_{TrajectoryBrowser}$ where distance between these Gs is less than three days. By application of this rule I identified a pattern which exactly corresponds to my experience.

While this experiment was designed with a purpose and does not provide any value in the dependencies discovery, the "sequential growth" pattern and past effort information can be used in the estimation of effort needed for requested software changes.

4.5 Public data case study

I plan to evaluate my research and its results through the mining of publicly available software configuration management (SCM) repositories. The goal of this experiment is to

assess the ability of my approach to reproduce already published results, which will indicate the correctness of approach taken, along with the ability to compare the performance of Software Trajectory to other tools. If I can find novel patterns within this data with my approach, it will provide additional evidence for the utility of my research.

As the main source of the data, I am planning to use public SCM repositories whose mining is traditionally used in the "MSR Challenges" [18] and published in proceedings of "IEEE International Conference on Mining Software Repositories". The GNOME project SCM data will be used in the 2009 challenge, Eclipse repositories were used in 2008 and 2007; PostgreSQL and ArgoUML in 2006. Two primary temporal data sets are usually offered for use: one is the CVS repository audit trail and second one is the bugs and issues tracking information. The following MSR challenge topics I found relevant to my research:

- Approaches, applications, and tools for software repository mining.
- Analysis of change patterns to assist in future development.
- Prediction, characterization, and classification of software defects based on analysis of software repositories.
- Techniques to model reliability and defect occurrences.

My approach will be based on the approximation of the artifacts from SCM repositories into symbolic series using "SCM trail taxonomy" and successful indexing of this symbolic data.

For example, in order to find "ripple effect" patterns in software change, I will construct a set of symbolic time-points and time-interval series which will represent all code changes in time by pre-processing change metadata from issue tracking system and actual changes in version control by using sliding window. Once data will be extracted and saved locally, for time-points symbolic data I will construct a series for each of the software packages (like `eclipse.swt.layout.*`, `org.eclipse.swt.widgets.*`, etc.) where symbolic data represents a change occurred in the package. For time-interval symbolic data I will use the duration when a change request was "open" to construct series representing concurrent order and dynamics of changes. By applying Software Trajectory analyses, I expect to discover something like "the change requested in package A class b usually results in changes in package A class c and package B class d" and it takes $Ab_t + Ac_t + Bd_t$ time to finish these changes. In turn, this information can be used to estimate the time and effort of newly requested software changes as well, as to identify changes that more likely to induce bugs and fixes and should be avoided. By adding the information about developers working on fixes, it is

also possible to design an expert system which will suggest assignment of newly reported bug reports or feature request to a particular developer(s).

In addition to the public SCM, there are various public data hosted by the "PROMISE software engineering repository" [47] which contains two kinds of data: the software product datasets used for the building of the predictive software models, and some "universal" data sets representing SCM repository transaction. Most of these datasets were also used for a number of publications and I am planning to evaluate my framework by attempting to reproduce these results.

4.6 Classroom study

In order to evaluate Software Trajectory performance in the discovery of well known and novel recurrent behavioral patterns in software process, I am planning to conduct two classroom case studies followed by survey of participants (Section 6.1).

The studies will be conducted in two Software Engineering classes during the Fall'09 semester (ICS 413 and ICS 613) and one software engineering class (ICS 414) during the Spring'10 semesters taught by Dr. Philip Johnson at the University of Hawaii. ICS 413 and ICS 414 are for undergraduate students, and ICS 613 is for graduate students. By curriculum design, students will be required to collect metrics and perform analyses on their own data in order to develop understanding of software metrics and improve their software development process. About 20 - 30 students are expected to participate in the study.

By the beginning of the data collection in the Fall'09 class I am planning to implement a data extraction, transformation and indexing engine, and begin the first phase of the classroom study. This engine will perform unsupervised recurrent behaviors discovery on the daily basis. By the end of the class I will administer interviews to collect students feedback about Software Trajectory analyses. The questionnaire will cover questions concerned about Software Trajectory analyses performance and usability. Another important question will be the students' perception of whether or not Software Trajectory analyses is a reasonable approach to software process discovery, analysis and improvement in "real world" settings. The experience collected during the first phase of the classroom study will be used in the improvement of the Software Trajectory analyses and in the design of the TrajectoryBrowser user interface.

By the beginning of the data collection in the Spring'10 class I am planning to release a next version of the Software Trajectory analyses framework incorporating experience from

the first classroom study. The second classroom study will be very similar to the first one in the flow.

4.6.1 Classroom study design

As explained before, during the classroom study the software product and process data will be collected from continuous integration as well as from individual students by Hackystat. This data will be converted into a symbolic representation and analyzed with Software Trajectory. Once Software Trajectory identifies strongly supported ("candidate") patterns, they will be analyzed by me.

The support function I am considering for this study will be a product of two metrics: the first one is based on the support function from the AprioriAll algorithm and will quantify the fraction of participating students demonstrating the pattern, and the second one is based on the total frequency of the pattern appearance. The reason for using two components is that the classroom "sampling space" is limited to only twenty students and it is likely that there will be "non-shared" strong patterns - ones that observed only within a data collected from the single student.

I understand that this choice of the support function introduces a bias into my analyses by focusing too much on subjective patterns which might be too specific to the observed individuals or classroom curriculum settings. Here I am compromising between the ability to capture recurrent behaviors at all and the usefulness and significance of captured behaviors. As I said, at this point of my research it is impossible to foresee the cognitive impact of observing and understanding of discovered patterns and guess where I should draw the support function threshold. By iteratively reviewing Software Trajectory results and collecting relevant feedback from students through the instructor, I plan to improve the Software Trajectory knowledge base in order to prune reported patterns to only useful and meaningful ones. This ability to communicate with students and iteratively improve the system design is crucial for in-process knowledge development and overall experiment success.

I am planning to perform two types of analyses: an individual developer behavioral software process analysis (personal software process discovery) and a "collective software process" analysis.

Symbolic abbreviation of Events	Description
CI	code implementation event, corresponds to the new code entry
CR	code refactoring event, includes renaming or deleting of functional units, and buffer transactions
CD	debugging event
CCS	successful compilation event
CCF	unsuccessful compilation event
UTS	successful unit test run
UTF	unsuccessful unit test run
CM	code commit to version control
CU	code update from version control
CAS	code analysis success event, corresponds to a successful invocation of one of the code analysis tools
CAF	code analysis failure event, corresponds to a unsuccessful invocation of one of the code analysis tools
CCP	positive delta in the code size (churn)
CCN	negative delta in the code size (churn)

Table 4.1: Taxonomy of the Symbolic Events to be used in the classroom evaluation of Software Trajectory analyses.

4.6.2 Personal software process discovery

For this type of experimental validation, I plan to perform Software Trajectory analyses using Hackystat data collected from individual developers. The data collected by Hackystat from each of developers will be aggregated into symbolic streams of two types: symbolic Events series and symbolic Episodes series:

- Symbolic Events series. This dataset will consist of the thirteen types of Events listed in Table 4.1. These Events represent a set of essential code-development activities which will constitute a multivariate symbolic time-point series for further analyses through data mining. The goal of these analyses will be to discover recurrent behavioral patterns in the sequence of activities by an individual developer.

- Symbolic Episodes data. This dataset will consist of the fifteen types of Episodes listed in the table 4.2. These Episodes represent a set of code-development activities which intended to capture dynamic recurrent behavioral patterns.

The goal of the Event series analysis is to build a taxonomy of symbolic software process patterns corresponding to one of the behaviors such as test-driven design or the more traditional test-last design.

In contrast to the analysis of symbolic Events series, which treats the process as a set of sequential activities, the analysis of symbolic Episodes series is intended to support discovery of overlapping, dynamic patterns. For example, I might find that an unsuccessful unit testing episode is usually happening within a code refactoring episode.

By combining Events and Episodes in the analyses I might discover that during code implementation, unit tests are usually successful but accompanied with decreasing test coverage. Also, I expect to be able to infer a developers' "reaction" patterns. For example, as a reaction to the continuous failure of unit tests, one might start broad refactoring of the code with the goal of reducing its complexity.

4.6.3 Team-based software process discovery

Traditionally students in the class work in groups. It will be interesting to see whether the "team-based behavior" and corresponding recurrent behavioral patterns are different from those in the personal software process. For the "team-based software process" recurrent behavioral pattern discovery I plan to summarize individual developer streams by combining overlapping Events and Episodes of same activities. It is hard to guess at this time whether

Symbolic abbreviation of Episodes	Description of metric
CI	code implementation episode, corresponds to new code entry events
CR	code refactoring episode, includes renaming or deleting of functional units, and buffer transactions
CD	code debugging episode, corresponds to debugging events
CCS	successful code compilation episode, corresponds to two or more successful compilation events
CCF	unsuccessful code compilation episode, corresponds to two or more unsuccessful compilation events
UTS	successful unit test episode, corresponds to two or more successful unit-test events
UTF	unsuccessful unit test episode, corresponds to two or more unsuccessful unit-test events
TCG	code test coverage growth, corresponds to a positive delta between at least three code coverage analysis tool invocations
TCD	code test coverage decrease, corresponds to a negative delta between at least three code coverage analysis tool invocations
CSG	code size growth, corresponds to a positive delta between at least three code size analysis tool invocations or three commits
CSD	code size decrease, corresponds to a negative delta between at least three code size analysis tool invocations or three commits
CCG	code complexity growth, corresponds to a positive delta between at least three complexity analysis tool invocations
CCD	code complexity decrease, corresponds to a negative code complexity delta between at least three complexity analysis tool invocations
CAS	"clean code development" episode, corresponds to at least three successful code analysis tools invocations
CAF	"unclean code development" episode, corresponds to at least three unsuccessful code analysis tools invocations

Table 4.2: Taxonomy of the Symbolic Episodes to be used in the classroom evaluation of Software Trajectory analyses.

or not these aggregated streams will be more or less noisy than individual streams, but in any case the application of the Software Trajectory analyses might lead to interesting findings. For example, I might infer a "programming session" episodes through the high fraction of synchronous (overlapping) development events between team members, or identify role separation by analyzing each student's development/commit patterns.

Chapter 5

Summary and Future Directions

5.1 Contribution

The main contribution of my research to the software engineering and software process community is the development and evaluation of a previously unexplored approach to discovering of recurrent behaviors in software process through the temporal data mining of low-level process and product artifacts.

The knowledge developed through the experimental work, and evaluation of the approach taken, will be another contribution of my research. By performing these experiments, I also hoping to discover new patterns in software process and software evolution thereby improving our knowledge about it.

The software framework and data mining toolkit which I will develop for my research will be integrated with the existing family of Hackystat tools and made available as open source, thus contributing to the software-engineering community.

5.2 Estimated Timeline

By the beginning of the Fall'09 semester, I plan to design a taxonomy and implement a low-level software process artifact abstractions into a symbolic representation for the classroom experiments. The current database schema will be extended for storing these data and indexes. Immediately after that, I will proceed with the implementation of fundamental algorithms for sequential patterns mining from the time-points and time-interval data. My goal is to have a first-generation data model and KDD toolkit to be available for use before in-class development starts.

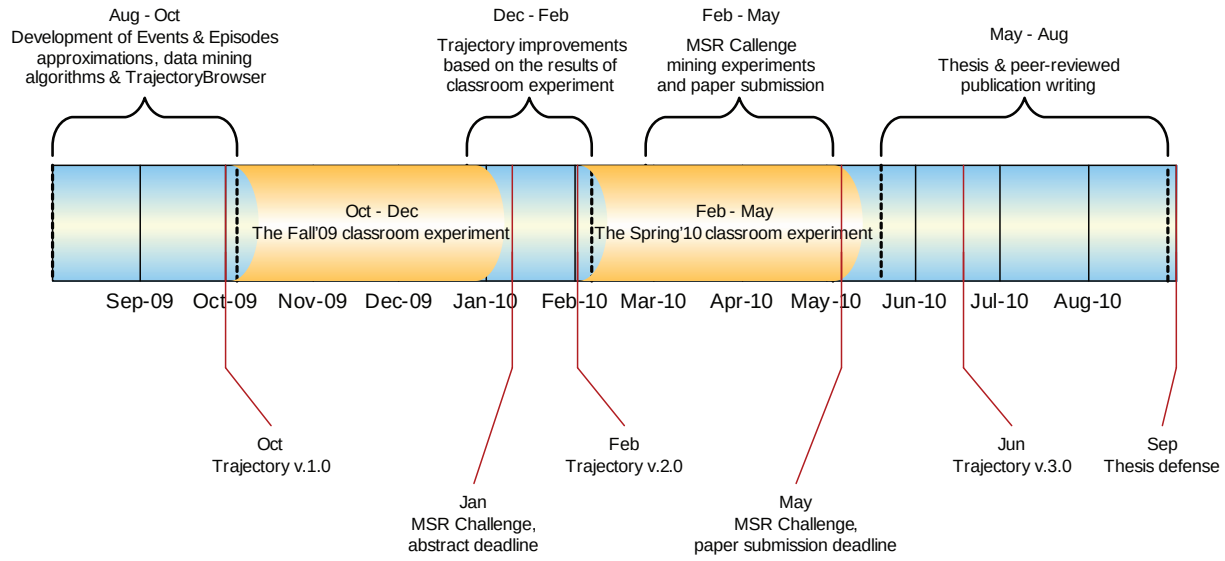


Figure 5.1: Proposed Software Trajectory development timeline.

Based on the Fall'09 classroom experiment experience, I will extend and fine-tune my system for the Spring'10 software engineering class, during which I plan to evaluate a final version of my system. The results of these two classroom experiments, the description of designed methods and developed software will constitute a peer-reviewed publication which I plan finish by Summer'10.

The MSR Challenge 2010 is announced to happen early May'10. I plan to design SCM data mining toolkit and perform pilot experiments by early January'10 submitting an abstract. If abstract will be accepted, I will prepare and submit a research paper following the Challenge timeline.

I plan to be working on my thesis during Fall'09, Spring'10 and Summer'10 semesters. During the Fall'10 semester I plan to finish my work and defend the dissertation.

Chapter 6

Appendices

6.1 Classroom case study interview design

I plan to conduct at least one classroom interview session evaluating Software Trajectory framework. I am targeting senior-level undergraduates and graduate students as my primary responders. These interviews will be conducted under approved by Committee on Human Subjects application: *CHS #16520 - Evaluation of Hackystat*. By performing interviews, I expect to collect evidence about the ability of Software Trajectory framework to capture recurrent behaviors from software process performed on the team and individual level. My secondary goal is the evaluation of the significance of these behaviors for software process understanding and improvement.

I plan to administer interviews during the last week of instructions. I will select responders demonstrating recurrent behaviors by balancing two factors: first is to cover as much various discovered patterns as possible, and second is to cover patterns demonstrated by the most of students. Taking in account the possible students' concern about final grading, I am crafting my interview questionnaire in order to make it as neutral as possible. The current version of the interview questionnaire is presented further.

The first three questions are designed to assess the respondents' level of education, area of expertise, and knowledge of software development patterns. The fourth question elicits a general discussion to the classroom experience and the respondents' opinion about the software processes they performed and I observed. By introducing my research in greater detail at this point, and by walking through the last three questions I will try to encourage responder to discuss with me my findings. Depending on the responders' reaction and willingness to continue, I will finish the interview after two to five iterations over observed

patterns.

The interviews will be tape-recorded, later they will be transcribed, coded, and analyzed. I am not very familiar with a methodology of developing of coding procedures yet, moreover, at this point of time it is impossible to foresee any of the results of Software Trajectory analyses. Thus, interview coding scheme will be constructed after interview-discussed ("candidate") patterns will be identified.

6.1.1 Software Trajectory evaluation interview questionnaire

1. What is your level of education and major?
2. Do you have any previous experience with software development?
3. Do you aware about recurrent behaviors (philosophies/approaches/styles) in the software development? If so, which ones can you recall?
4. Did you ever follow any of the formal approaches or styles in your own, professional, or the classroom development?
5. By applying Software Trajectory framework I was able to capture a behavioral pattern P which looks like $P_1 \rightarrow P_2 \rightarrow ....$ My interpretation of this is .... . Does my interpretation of this recurrent behavior match your own understanding of your development behavior?
6. Is there another interpretation of this pattern that you believe more accurately reflects your behavior?
7. When you think about this pattern, can you think of changes you might want to make to your development behaviors based upon it?

6.1.2 Software Trajectory consent form

Thank you for agreeing to participate in our research on software process discovery. This research experiment is being conducted by Pavel Senin as a part of his Ph.D. research in Computer Science under the supervision of Professor Philip Johnson.

As a part of this research experiment, you will be asked to provide a feedback about automatically discovered behavioral patterns in your software development process. These patterns will be automatically discovered by Software Trajectory framework which applies data mining techniques to the telemetry streams collected by Hackystat. The primary goal of this research is to evaluate the ability of Software Trajectory to discover and classify recurrent behavioral patterns; while the secondary goal is to assess the usefulness of discovered behaviors.

The data that we collect will be kept anonymously, and there will be no identifying information about you in any analyses of this data.

Your participation is voluntary, and you may decide to stop participation at any time, including after your data has been collected. If you are doing this task as part of a course, your participation or lack of participation will not affect your grade.

If you have questions regarding this research, you may contact Professor Philip Johnson, Department of Information and Computer Sciences, University of Hawaii, 1680 East-West Road, Honolulu, HI 96822, 808-956-3489. If you have questions or concerns related to your treatment as a research subject, you can contact the University of Hawaii Committee on Human Studies, 2540 Maile Way, Spalding Hall 253, University of Hawaii, Honolulu, HI 96822, 808-539-3955.

Please sign below to indicate that you have read and agreed to these conditions.

Thank you very much!

Your name/signature

Cc: A copy of this consent form will be provided to you to keep.

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