

ABSTRACT

GUO, HUI. Informative Events and Stories in Text Related to Software Development. (Under the direction of Dr. Munindar P. Singh.)

Modern software systems are deployed in sociotechnical settings, combining social entities (humans and organizations) with technical entities (software and devices). After the deployment of such software systems, users constantly interact with them, incurring events and stories regarding how the two parties behave in different scenarios. These events and stories are often captured in natural language artifacts, such as reports and reviews. A story, in the sense of natural language processing, comprises a sequence of events. In this work, we consider an event as a textual *event phrase* that describes a single action. Stories about system failures can inform developers or other responsible parties of how to improve the systems. Stories about how users behave before and after system problems can provide insights into users' expectations or the best practices to overcome the failures. Extracting and understanding the interaction stories between social and technical entities can promote the incremental improvement of software systems.

We target the extraction and understanding of informative events and stories from textual artifacts that describe the interaction between software systems and their users. This research includes three incremental components, which focus on informative events, event pairs, and stories, respectively. First, we develop LESBRE, a framework for extracting informative events from breach reports and suggesting actions based on the association between breach descriptions and corrective actions. Breach reports describe what happened during and after data breaches in the healthcare domain. Actions taken by the responsible parties afterward can be considered as lessons learned about how to prevent, mitigate, and remedy future data breaches. Second, we introduce CASPAR, a method for extracting and analyzing user-reported event pairs regarding app problems from app reviews. CASPAR collects pairs of events, the first of which describes a user action and the second of which describes an app problem triggered by the user action. These action-problem event pairs capture the essence of the bug-report type of app reviews, and provide information that helps developers maintain and improve the app's functionality and user experience. Finally, we develop SCETURE, a framework for extracting informative stories and analyzing story structures as patterns of event types in app reviews. Building on CASPAR, SCETURE targets more event types and how to sequence the events into stories. SCETURE enables the collection of stories based on story structures. We show how the different story structures seen in app reviews can help developers on their specific goals.

LESBRE discovers informative events that include useful actions promoting security in sociotechnical systems. CASPAR extracts high-quality event pairs regarding app problems from app reviews. By including both user actions and app problem events, event pairs provide richer information about how the problems occur than single events. SCETURE targets full stories in app reviews and provides a way of analyzing stories based on their structures. Extracting and analyzing stories can capture much more information residing in textual artifacts.

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Informative Events and Stories in Text Related to Software Development

by
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CHAPTER

1

INTRODUCTION

Modern software systems are deployed in sociotechnical settings, combining social entities (humans and organizations) with technical entities (software and devices). The development of such software systems is often user-oriented, decreasing cost and time with user participation and prototyping. Deployed software systems require constant maintenance and improvement. With extensive interaction with the software and other users, a user may encounter problems in scenarios where the developers have not anticipated. As time progresses and competitors emerge, users' needs and preferences on functionalities and features may shift. Developers need to pay attention to users' feedback regarding how their systems perform in the real world. However, in the setting of most current software systems, the feedback channel from users to developers is not straightforward. The knowledge about where and how to fix or improve the systems is often preserved in natural language text written by users, such as reports and reviews. Therefore, information extraction from user-generated text is imperative to software developers, analysts, and administrators.

During the interactions between users and software systems, events and stories occur regarding how the two parties behave in different scenarios. Reports and reviews of such interactions are often filled with users' interaction events and stories with the system. Analysts of such text may be interested in different kinds of events and stories based on their goals. For example, an app developer who aims to gather bugs reported in user reviews may be interested in stories about how the app behave incorrectly

and what actions the users take to trigger the incorrect behaviors. With little or no guideline on how to report such stories, users tend to generate text that is heterogeneous in content and style. Extracting informative events and stories, especially the ones that serve certain goals, is nontrivial.

A story, in the sense of natural language processing (NLP), comprises a sequence of events. Some studies define an event as an abstract object that refers to an actual incident that has taken place. Others may treat events as tuples that comprise various attributes that describe events. Since we target text about software development, we refer to an *event* in a story as a part of a sentence that describes a single action of a user, a software system, or other involved parties. We use the term *event phrase* to talk about an event as it is represented in language.

In this research, we address the extraction of events, event pairs, and stories, respectively. We target two types of text related to software development, breach reports and app reviews. In this chapter, we first describe the two targeted text sources and our motivations. We then introduce our research questions, as well as our proposed methods to address them.

1.1 Targets and Motivations

We focus on the extraction of informative events and stories from text related to the software development. We identify and target two types of textual artifacts in which the writers describe their experiences with software systems.

1.1.1 Breach Reports

The development of sociotechnical systems requires the developers to comply with existing regulations that describe the expected behavior of software and its users, particularly in domains that deal with private user information. One of the most studied regulations is the Health Insurance Portability and Accountability Act of 1996 (HIPAA) [HHS, 2003] in the healthcare domain, which is a legislation on data privacy and security regarding medical information. HIPAA restrains the behaviors of covered entities (CEs) and business associates (BAs) with regard to how health information should be stored, accessed, and disposed of. In recent years, healthcare data breaches, caused by outside attacks as well as insider misconducts, have brought HIPAA increasing prominence. US law now requires the U.S. Department of Health and Human Services (HHS) to post each breach of unsecured PHI affecting 500 or more individuals [HHS Breach Portal, 2016]. Example 1 provides an example report (with edits to remove names and dates) of the violation of HIPAA. We number the sentences for clarity. This report includes actions taken by the responsible party after the breach, usually under the guidance or supervision of the authorities. Such reports sometimes include actions that other parties, such as Office for Civil Rights

(OCR), took after the breaches.

Example 1

1. The covered entity (CE) experienced a cyberattack that resulted in unauthorized access to several of its websites.
2. The hackers were then able to access databases containing the protected health information (PHI) of 2,860 individuals due to a website coding error.
3. The compromised PHI included clinical, demographic, and financial information.
4. The CE provided breach notification to HHS, affected individuals, and the media.
5. Following the breach, the CE modified the coding error, moved all databases containing PHI to its internal secure network, implemented a new software patch management policy, and activated a new firewall and new logging and monitoring systems.
6. OCR obtained documented assurances that the CE implemented the corrective action steps listed above.

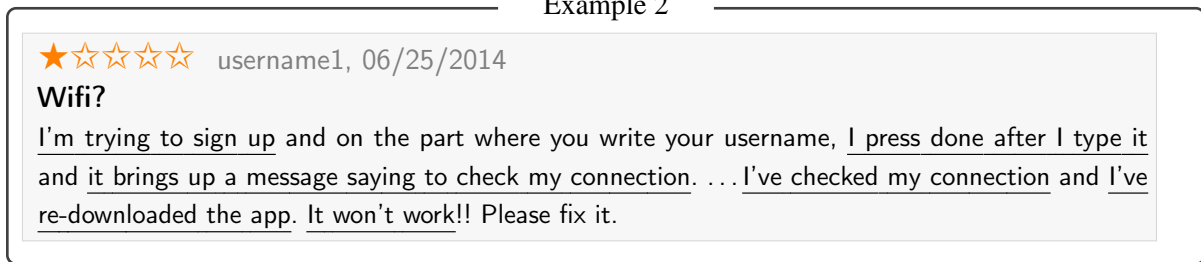
Such breach reports include informative events and stories that describe cases where deployed systems fail, or are maliciously or accidentally misused [Matulevičius et al., 2008; Sindre and Opdahl, 2005]. Breach reports can help security analysts understand regulations by providing instances where regulations are violated. Additionally, a breach report typically lists the actions taken by the responsible parties subsequently in responsible to the breach as individual events. These events, such as *moving databases to internal secure network* and *activating a new firewall* in this example, can be considered as “lessons learned” from past failures, as well as suggestions for other covered entities as to how to prevent, mitigate, and remedy similar future breaches [Liu et al., 2015; Riaz et al., 2016].

The extraction of informative events from breach reports helps gather valuable knowledge regarding the prevention and recovery of data breaches in the healthcare domain. The extracted actions can be considered as security requirements for related software systems and, if properly suggested, can provide insightful assistance to other covered entities regarding HIPAA compliance.

1.1.2 App Reviews

Application distribution platforms, such as Apple App Store and Google Play Store, provide critical pathways for users to provide feedback to app developers in the form of ratings and reviews [Pagano and Maalej, 2013]. App reviews not only serve as de facto deployment reports for an app, but also express users' expectations regarding the app. We observe that app reviews often carry deeper knowledge than is traditionally mined. Specifically, we have found that a user's review of an app often tells stories about how the user interacted or attempted to interact with the app. Users describe their intentions, actions, and reactions with regards to the apps' functionalities, as well as the behaviors of the apps. Example 2 shows an app review snippet for the Snapchat app¹ from Apple App Store, which describes a user-app interaction story, consisting of several events (marked with underlines).

Example 2



We notice that user stories in app reviews are of great structural heterogeneity. Developers with different goals for information extraction may focus on different types of stories. For example, we find that the most common type of stories in negative reviews are bug reports where the users describe problems of the apps as well as the users' actions that trigger them. The extraction of informative stories from app reviews can help developer pinpoint how to improve their apps.

However, story extraction from user-generated text is challenging. In natural language text, especially app reviews where proofreading is limited, it is not uncommon for the writers to describe events out of their sequential orders or include multiple stories in one piece of text. Understanding the relation between events is imperative for effective story extraction.

¹<https://apps.apple.com/us/app/snapchat/id447188370>

1.2 Research Questions

The objectives of this research include the extractions and understanding of informative events and stories from software development related text. We target the extraction and understanding of stories progressively. Accordingly, we identify the following three research questions:

RQ_{event} How can we effectively extract targeted events from text?

Story-rich text related to software development, such as reports and reviews, may contain a large variety of events. A basic task for information extraction from such text is the extraction of events of targeted types. Informative events that contain useful actions describe what has previously been done and therefore provide insight into the common practices in certain scenarios. We address **RQ_{event}** to investigate the effective method of extracting useful actions from breach reports and app reviews. This task is difficult as the identification of useful actions may require domain knowledge.

RQ_{pair} How can we effectively extract targeted event pairs from text?

Research on the extraction of informative event pairs is lacking. Certain types of event pairs, such action-problem pairs from app review, hold valuable information. Collecting such event pairs is an important information extraction task of practical significance. We address **RQ_{pair}** to investigate the effective extraction process to find the targeted event pairs. This extraction task is nontrivial in that the relations between the targeted events may rely on the meanings of events rather than their syntactic features.

RQ_{story} How can we effectively extract targeted stories from text?

Stories in software-related text are typically more complex than individual events or event pairs. As storytellers, users do not follow a fixed template. Instead, they tell stories with different structures for different purposes. Developers with different goals need to know what kind of stories they should focus on. We address **RQ_{story}** to find the effective solution for collecting targeted stories. The task of extracting informative stories for different analysis goals is challenging. Different from event pairs of a fixed pattern, longer stories in natural language text may be diverse in styles. The relations between events should be investigated to guarantee that the extracted stories are coherent.

1.3 Contributions

We address our research questions through three projects, which we detail in this section.

1.3.1 LESBRE: Learning Lessons from Breach Reports

We develop LESBRE, a framework for extracting informative events from breach reports and suggesting useful actions based on the lessons learned. First, LESBRE classifies the sentences in a breach report into breach description, useful event, and neither. Second, LESBRE extracts descriptive phrases from the breach description sentences, and verb phrases from the useful events with NLP techniques. Third, LESBRE suggests actions by ranking the useful actions based on their association with the descriptive phrases and their frequency.

Commonly performed actions can be considered as norms. For example, a breach event involving *laptop* and *stolen* is frequently followed by actions like *filing a police report*. By considering the concurrences of descriptive phrases and corrective actions, LESBRE is able to suggest useful actions that are most commonly performed in similar previous stories.

1.3.1.1 Background

Previous empirical work shows that the knowledge contained in regulations and breach reports are closely connected [Kafali et al., 2017]. Corrective events in the HHS breach reports are often covered by the HIPAA regulation. Therefore, knowledge extraction from breach reports provides insight into HIPAA compliance. In our previous study, we have shown that crowdsourcing can be leveraged to obtain security requirements from breach reports [Guo et al., 2020]. We propose ÇORBA, a methodology that leverages human intelligence via crowdsourcing, and extracts requirements from textual artifacts in the form of regulatory norms. With proper design of a crowdsourcing project, ÇORBA is able to glean high-quality requirements from breach reports as well as HIPAA regulation clauses. LESBRE complements ÇORBA by leveraging fully automated methods for the identification of useful actions, as well as adding the support for action suggestion based on breach descriptions.

1.3.1.2 Research Questions

LESBRE addresses the modified version of $\mathbf{RQ}_{\text{event}}$, as well as an additional research question for action suggestion.

$\mathbf{RQ}_{\text{event}}$ How can we effectively extract informative events that provide insights to similar entities from breach reports?

$\mathbf{RQ}_{\text{suggest}}$ How can we suggest actions to potential covered entities based on breach descriptions and common practices?

By answering **RQ_{event}**, we determine LESBRE’s performance in gathering useful actions from breach reports, compared to a heuristics-based baseline. Best practices described in breach reports can be considered as suggestions for future practices and a great supplement to legal requirements. By answering **RQ_{suggest}**, we investigate how the extracted lessons from previous failures can help prevent or remedy similar future breaches.

1.3.2 CASPAR: Collecting and Analyzing Stories of Problems in App Reviews

We develop CASPAR, a method for collecting and analyzing user-reported mini stories regarding app problems from app reviews. Specifically, we target the action-problem pairs in negative app reviews that act as bug reports that would help developers in better maintaining and improving their apps’ functionality and user experience.

CASPAR abstracts event pairs from stories in reviews. By extending and applying natural language processing and deep learning, CASPAR extracts ordered events from app reviews, classifies them as user actions or app problems, and collects action-problem event pairs. In addition, CASPAR builds and trains an inference model with the extracted event pairs to predict possible app problems for different use cases.

1.3.2.1 Background

Post-deployment user feedback, an important facet of user involvement in software engineering, requires developers’ close investigation as it contains important information such as feature requests and bug reports [Ko et al., 2011; Pagano and Bruegge, 2013]. We have found that a user’s review of an app, especially one with a negative rating, often tells a mini story about how the user interacted or attempted to interact with the app. This story describes what function the user tried to bring about and how the app behaved in response. We define a *action-problem* pair as such a pair of events in which an app problem (an event) follows or is caused by a user action (an event). Such event pairs describe where and how the app encounters a problem. Therefore, these pairs can yield specific suggestions to developers as to what scenarios they need to address.

1.3.2.2 Research Questions

CASPAR addresses the modified versions of **RQ_{pair}**, specific to the action-problem pairs in negative app reviews. In addition, CASPAR addresses a research question regarding the event inference based on the extracted event pairs.

RQ_{pair} How effectively can we extract app problem stories as action-problem pairs from app reviews?

RQ_{infer-pair} How effectively can an event inference model infer app problems in response to a user action?

By answering **RQ_{pair}**, we determine CASPAR’s performance in automatically extracting action-problem pairs, compared to manual annotations. By answering **RQ_{infer-pair}**, we can determine CASPAR’s practical value in (1) linking user actions and app problems, as well as (2) inferring possible app problems that may happen after a user action.

1.3.3 SCHETURE: Understanding Structures of User Stories in App Reviews

To address **RQ_{story}**, we develop SCHETURE, a framework for analyzing story structures in app reviews and collecting app reviews that follow the targeted story structures. We propose the task of obtaining structures of user stories in app reviews, and collecting stories based on their structures. We aim to help developers understand user-app interaction stories, and more easily collect useful reviews based on targeted types of stories.

SCHETURE offers a novel tool of systematically analyzing and collecting structured user stories from app reviews. App reviews are home to a cornucopia of interesting user stories that are heterogeneous in structure, making their understanding and information extraction difficult for app developers. SCHETURE summarizes straightforward event-type structures of user stories, enabling developers to access the stories in which they are interested. SCHETURE also identifies events or event sequences of specific types from these user stories, helping a developer extract information that is valuable for the improvement of their app’s functionality, performance, and use experience. With proper substructures for searching, stories retrieved by SCHETURE are significantly more helpful than average. In addition, SCHETURE is able to find common story structures and substructures in user stories, bringing novel and deep understanding on app reviews.

1.3.3.1 Background

We define a story *structure* as a sequential pattern of event *types* of a story. The event types of relevance are the following. We define user *intention* as a verb phrase that describes the user’s need or expectation of bringing about a functionality or app behavior. A user *action* event describes how the user interacts with the app, sometimes based on the user’s intention. The most common type of events in app reviews is an app *behavior*, describing how an app acts, usually caused by or in response to a user action. This event type also includes an app’s lack of behavior when a behavior is expected. In negative reviews, an app behavior is typically a problem where the app behaves unexpectedly or erroneously, and the described user actions provide details regarding the scenario where the problem occurs. Also, a user may evince a

reaction to an app’s behavior. A reaction can be a forced action by the app’s behavior, an attempt to solve a problem, or the act of departing from the app, e.g., deleting the app or switching to a competitor app. In addition, reviewers may narrate *context* events, providing supporting information to the points they want to make. We call these five types of events *target* events, while others are *nontarget* and not considered parts of the story structures.

User-app interaction stories may be unique to each user, so the stories users tell may follow different structures. The story in Example 2 exhibits a structure of $\langle \text{intention} \rightarrow \text{action} \rightarrow \text{behavior} \rightarrow \text{reaction} \rightarrow \text{behavior} \rangle$ (IABRB). A review may contain multiple stories, and a story may include multiple events with the same type. A *substructure* is a sequential pattern that is part of a story structure, e.g., $\langle \text{intention} \rightarrow \text{action} \rangle$ or $\langle \text{behavior} \rightarrow \text{reaction} \rangle$. A substructure can represent a sequence of events that constitute a meaningful snippet within a complete interaction story.

Stories with different structures may be of interest to developers with different goals for information extraction. Developers who wish to glean bug reports may focus on stories with structures like $\langle \text{action} \rightarrow \text{problem} \rangle$, as we show in CASPAR. Stories with an $\langle \text{intention} \rightarrow \text{action} \rangle$ structure may provide insights into users’ mental model and expectations when using the app. A collection of $\langle \text{problem} \rightarrow \text{reaction} \rangle$ stories for an app may help its developers understand the user retention situation.

1.3.3.2 Research Question

SCHETURE addresses $\mathbf{RQ}_{\text{story}}$ by investigating the different story structures in app reviews. To this end, SCHETURE addresses the following research questions.

$\mathbf{RQ}_{\text{extract}}$ How effectively can we extract events and determine their types in app reviews?

$\mathbf{RQ}_{\text{relate}}$ How effectively can we identify relations between events, so that we can order and combine them into stories?

$\mathbf{RQ}_{\text{collect}}$ What kind of story structures and substructures are the most common in app reviews?

First, we address $\mathbf{RQ}_{\text{extract}}$ again, with more event types that are common in app reviews. Second, by addressing $\mathbf{RQ}_{\text{relate}}$, we investigate the method of combining events into meaningful stories based on their relations. After the first two steps, we have identified the stories and the types their events, i.e., the story structures, in the app reviews. Extracting stories is simply a pattern matching task. We address $\mathbf{RQ}_{\text{collect}}$ to investigate the common story structures in app reviews, as well as the relation between story structures and developers’ goals.

1.4 Organization

The rest of the paper is organized as follows.

Chapter 2 describes LESBRE and some related work. LESBRE addresses $\mathbf{RQ}_{\text{event}}$ in the setting of breach reports. In this chapter, we show how the extraction of informative events helps learning lessons from past failures and suggesting actions to prevent and remedy future ones.

Chapter 3 introduces CASPAR. CASPAR addresses $\mathbf{RQ}_{\text{event}}$ and $\mathbf{RQ}_{\text{pair}}$ in the setting of app reviews. CASPAR targets a specific type of event pairs, action-problem pairs, and shows how such extraction can help developers pinpoint the problems of their apps.

Chapter 4 presents SCHEPURE. SCHEPURE address $\mathbf{RQ}_{\text{event}}$ and $\mathbf{RQ}_{\text{story}}$ also in the setting of app reviews. SCHEPURE targets more event types than CASPAR, and investigates how events are combined into stories.

Chapter 5 concludes this research and proposes possible future work.

CHAPTER

2

EXTRACTING TARGETED EVENTS

We address **RQ_{extract}**, the extraction of informative events in the setting of breach reports published by the U.S. Department of Health and Human Services (HHS). HHS is legally required to publish details of breaches of protected health information (PHI) affecting 500 or more individuals. A report of such a data breach includes actions taken by the responsible party after it, which are typically norms that can inform other parties of how to prevent, mitigate, or recover from similar future breaches. Our research aims to aid security analysts and software developers in extracting useful actions from breach reports and suggesting actions based on breach descriptions. To this end, we propose **LESBRE**, a methodology of extracting knowledge from textual artifacts. First, **LESBRE** identifies sentences that contain informative events with a classifier. We leverage crowdsourcing to obtain a training set for this classification task. Second, **LESBRE** extracts useful actions as well as descriptive phrases from the informative sentences using NLP techniques. Descriptive phrases are phrases that describe the detail of a breach. Useful actions are cations in response to the breach, and can be considered as security requirements and lessons learned from the stories. Finally, **LESBRE** suggest actions based on descriptions of the breach which the responsible party wishes to prevent or remedy. We stress the importance of preserving and extracting knowledge in breach reports, and hope to draw closer attention from requirements researchers, users of software systems, as well as writers of this kind of reports.

2.1 Introduction

The development of sociotechnical systems requires the developers to comply with existing regulations that describe the expected behaviors of software and its users, particularly in domains that deal with private user information. Existing studies [Breux and Antón, 2008; Ghanavati et al., 2014; Hashmi, 2015; Maxwell and Antón, 2009; Siena et al., 2012] model or extract information from such regulatory documents to help with the elicitation of requirements for developers or compliance checking for legal purposes.

One of the most studied regulations is the Health Insurance Portability and Accountability Act of 1996 (HIPAA) [HHS, 2003] in the healthcare domain, which is a legislation on data privacy and security regarding medical information. Regulatory text is often abstruse and unclear as to requirements. Breaches are frequently caused by social (user misbehavior) and technical (flaws in software) violations. Breach reports [HHS Breach Portal, 2016; Murukannaiah et al., 2017; Verizon, 2016], often legally mandated, describe cases where deployed systems fail, or are maliciously or accidentally misused [Matulevičius et al., 2008; Sindre and Opdahl, 2005], and suggest actions to prevent, mitigate, and recover from future breaches [Liu et al., 2015; Riaz et al., 2016]. Breach reports can help security analysts understand regulations by providing instances where regulations are violated. Research has shown that practices described in breach reports are highly correlated to HIPAA policies and therefore contributes to the understanding of HIPAA compliance [Kafalı et al., 2017]. Example 1 in Chapter 1 shows an example report about a breach in which HIPAA was violated.

We define *useful actions* as actions performed by previous responsible parties to prevent, mitigate, or recovery from data breaches. For example, Example 1 describes the actions of the covered entity (CE) after the breach, such as *modifying the coding error* and *activating a new firewall*, which are useful to other CEs to prevent similar breaches. These actions are described as useful events that have taken place in the report. The goal of our research is to aid analysts and software developers in extracting useful actions from breach reports regarding legal, security, and privacy requirements. We aim to find the common practices in the healthcare domain to prevent and remedy data breaches, and suggest actions to other covered entities toward compliance of related regulations.

In a previous study of ours [Guo et al., 2020], we propose ÇORBA, a methodology that leverages human intelligence via crowdsourcing to obtain requirements by extracting and connecting key elements from regulations and breach reports. We adopt the concept of norms [Barth et al., 2006; Hao et al., 2016; Kafalı et al., 2017; Singh, 2013; Von Wright, 1999] to formalize regulations and breaches (as violations of norms). Norms (here, deontic norms including commitments, authorizations, and prohibitions) provide a compact, yet expressive formalization. Breach reports describe the actions that the responsible parties are expected to perform, as well as actions they are prohibited from performing. With carefully designed

crowdsourcing assignment, we are able to extract such actions and obtain high-quality requirements as a set of regulatory norms to provide a structured yet compact presentation for practitioners.

Crowdsourcing offers a scalable solution to the hard problem of norm extraction from breach reports. However, the results of ÇORBA are natural language annotations provided by crowd workers, and cannot be directly leveraged for automated methods. Without automated methods, we need to apply ÇORBA on all of the breach reports to extract all useful information from the dataset, which is impractical and inefficient, since there are many similar breaches. To mine the common practices during data breaches may require the repetitive application of ÇORBA on breach reports with similar features.

We propose LESBRE, a framework for supervised extraction of useful actions from breach reports and action suggestion based on breach descriptions. First, LESBRE trains a classifier to determine what kind of information a sentence provides, the description of the breach, informative events, or neither. Second, LESBRE extracts informative phrases in the sentences using natural language processing (NLP) techniques. Finally, LESBRE considers the coexistence of the phrases for action suggestion. As described in Chapter 1, LESBRE addresses the following research questions:

RQ_{event} How can we effectively extract informative events that provide insights to similar entities from breach reports?

RQ_{suggest} How can we suggest actions to potential covered entities based on breach descriptions and common practices?

By answering **RQ_{event}**, we determine LESBRE’s performance in gathering useful actions from breach reports, compared to a heuristics-based baseline. By answering **RQ_{suggest}**, we investigate how the extracted lessons from previous failures can help prevent or remedy similar future breaches. LESBRE contributes to the research on breach reports and requirement engineering by (1) automatically extracting useful actions commonly performed by previous responsible parties of data breaches, and (2) suggesting actions to covered entities of HIPAA based on the features of the breaches they wish to prevent or remedy.

2.2 Background

We now introduce the details of HHS breach reports, our previous study on norm extraction from them, and other research in the area of knowledge extraction from security related artifacts.

2.2.1 HHS Breach Reports

The Health Insurance Portability and Accountability Act of 1996 (HIPAA) [HHS, 2003] is one of the most studied regulations regarding data privacy and security in the healthcare domain regarding medical

information. HIPAA applies to covered entities (CEs) and business associates (BAs). A covered entity is required to notify the U.S. Department of Health and Human Services (HHS) if a breach of unsecured protected health information (PHI) affects 500 or more individuals. HHS is in turn required to post the breach on its website [HHS Breach Portal, 2016], including the details of the breach, such as the type, location, and date, as well as the subsequent investigation. Once the investigation concludes, the HHS typically includes a description of the breach, or breach report, that includes the major events during the whole process in natural language text.

As of April of 2021, there are more than 3,000 breaches posted on the HHS website, 60% of which include natural language descriptions, i.e., breach reports. Each breach report comprises of 6.4 sentences. Currently, there are no guidelines as to how these breach reports ought to be written. Not all breaches include reports, and some breach reports are of different styles. However, as shown in Example 1, a breach report typically includes the following types of sentences, in similar order.

Breach description : Sentences that describe the events during the breach, including the type of the breach and the number of affected individuals;

PHI detail : A sentence that describes the types of PHI involved, such as names, dates, and financial information;

Notification : A sentence that describes the notification events of the responsible parties, including notification to HHS and the affected individuals;

Corrective events : Sentences that describe what the responsible parties subsequently did to recover from, mitigate, or prevent the current and future breaches;

Others : Other sentences, such as actions performed by the Office for Civil Rights (OCR) of HHS.

In this research, we target only breach descriptions and corrective events. Breach descriptions describe the type and detail of a breach, as well as the responsible parties. Sentences about the corrective events are of great variety, and provide rich information regarding how to comply with HIPAA to prevent or remedy similar breaches. Since all covered entities are required to notify HHS and the affected individuals in case of a data breach, the notification sentence typically does not provide additional information regarding whom to notify.

2.2.2 Our Previous Study

In our previous study, we propose ÇORBA, a methodology that leverages human intelligence via crowd-sourcing, and extracts requirements from textual artifacts in the form of regulatory norms [Guo et al., 2020]. We have evaluated ÇORBA on HIPAA and HHS breach reports.

A *norm* in the particular sense we adopt here is a directed relationship between a *subject* (the party on whom the norm is focused) and an *object* (the party with respect to whom the norm arises) that regulates their interactions [Singh, 2013]. Each norm also specifies an *antecedent*, the conditions under which the norm is effective, and a *consequence*, the conditions that fully satisfy the norm. A set of norms describes the social architecture of a sociotechnical system. We consider three types of norms: commitments (c), authorizations (a), and prohibitions (p). A *commitment* means that its subject is committed to its object to bringing about the consequent if the antecedent holds. An *authorization* means that its subject is authorized by its object to bring about the consequent if the antecedent holds. A *prohibition* means that its subject is prohibited by its object from bringing about the consequent if the antecedent holds.

Norm extraction from breach reports, therefore, requires the extraction and identification of each element of a norm. ÇORBA specifies the effective workflow for such extraction. We design a crowdsourcing project with carefully constructed questions for each element, and ask crowd worker to extract the elements based on their understanding of what the responsible parties should take or should have taken to prevent or mitigate the breach. We design a method for evaluating the performance of each work. ÇORBA requires the deployment of multiple iterations of crowdsourcing, where the organizers evaluate crowd worker’s answers and revise the questions and project settings to elicit answers of higher quality.

After the final round of responses are evaluated, the evaluators formalize norms from these responses manually as the final results of ÇORBA. Since we have designed the questionnaires in the format of norms, composing norms from the responses is straightforward.

ÇORBA is a solution for effective normative information extraction from regulations and breach reports for developers and security analysts. During our experiments, we have found that the designing of the questions are closely related to the response quality from workers. Additionally, we have identified that breach reports self-reported by end users often contain irrelevant information for security requirements engineering. Our results have shown that carefully revised breach reports can enable more effective information extraction. Whereas this finding is promising, further guidelines and templates for creating structured natural language documents would be helpful for producing good quality requirements.

ÇORBA is the first step toward scalable information extraction from breach reports and regulatory text. The resulting norms are of high quality and can be considered as security and privacy requirements for software systems in the healthcare domain. However, we have not been able to find an effective way of leveraging its results for automated methods. To scale the extraction up to larger datasets, we need to deploy more batches of the same questionnaires, which requires additional financial and time costs.

2.2.3 Related Work

Security Related Artifacts: Analyzing breaches helps analysts understand how failures, e.g., unintentional or malicious actions by the software or its users, affect compliance with applicable regulations. Gürses et al. [Gürses et al., 2008] develop heuristics for designing usable privacy interfaces in online social networks based on investigation of privacy breaches. Their analysis helps in the understanding of privacy conflicts and trade-offs revealed by such breaches, with respect to each stakeholder’s viewpoint. Kafalı et al.’s [Kafalı et al., 2017] framework compares what happened in a breach with what the regulation states. However, they do not provide a way of extracting norms from text.

Crowdsourcing: Whereas security requirements can be extracted through the analysis of policies and regulations, analyzing such natural language text is labor intensive and tedious for analysts. Crowdsourcing [Breux and Schaub, 2014; Dean et al., 2015; Getman and Karasiuk, 2014; MacLean and Heer, 2013; Patwardhan et al., 2018; Reidenberg et al., 2015; Wilson et al., 2016] of information extraction from legal text is a promising and popular approach to address this challenge. Breux and Schaub [2014] propose experiments to compare the effectiveness (accuracy and cost) of untrained crowd workers on a requirements extraction task with the effectiveness of trained experts (i.e., requirements engineers). Their task includes extracting data collection, sharing, and usage requirements from privacy policies. Breux and Schaub report that they could reduce manual extraction cost by up to 60% for some policies while preserving task accuracy, and for some policies increase accuracy by 16%, based on their ways of task decomposition. They continue using crowdsourcing, combined with NLP techniques, to extract privacy goals [Bhatia et al., 2016]. Reidenberg et al. [2015] investigate how privacy policies are perceived by expert, knowledgeable, and typical users, and did not find significant differences among them.

Text Analysis: The task of extracting useful information in a formal representation from textual documents, such as security-related textual artifacts, is of great importance. Researchers start from designing and proposing systematic methodologies for manual extraction. Breux and Antón [2008] have developed a methodology for manually extracting formal descriptions of rules, such as rights and obligations, that govern information systems from regulatory texts. They represent results from a case study on the text of HIPAA Privacy Rule. Hashmi [2015] presents a methodology for the extraction of legal norms from regulatory documents that emphasizes logical structures for reasoning and modeling to facilitate compliance checking. Systematic manual extraction methodologies are helpful for domain experts to analyze text, but may not be applicable to nonspecialists, such as typical workers in crowdsourcing projects. Also, the transition from a manual extraction process to an automated one is not straightforward and needs further investigation.

Automatically converting textual artifacts into a formal representation is challenging, and may involve

semantic comparison, summarization, and rephrasing. Riaz et al. [2014] describe a tool-assisted process that incorporates machine learning for identifying security requirements from text. They empirically derive a set of context-specific templates to translate such objectives and goals into security requirements. Slankas and Williams [2013] propose an automated process for extracting access control policies implicitly and explicitly defined in natural language project artifacts. Zeni et al. propose the NómoST tool [Zeni et al., 2018] to help users construct goal-based representation of legal requirements semi-automatically by identifying and using metadata in legal texts based on their NómoS framework [Siena et al., 2012] and GaiusT framework [Zeni et al., 2015, 2017]. Sleimi et al. [2018] propose automated extraction rules for semantic metadata based on NLP, which can help with understanding legal provisions. Current such automated methods for extracting requirements from text either require domain-specific knowledge and heuristics and therefore are costly to migrate to other domains, or do not perform end-to-end extraction. We believe that using crowdsourcing for the extraction task is more generalizable, but automated methods can be leveraged to facilitate the extraction.

2.3 Methodology

LESBRE includes three components, as shown in Figure 2.1. First, LESBRE identifies the type of each sentence in a breach report. A sentence can be a breach description, a corrective event sentence (a corrective sentence), or neither. Second, LESBRE extracts descriptive phrases from the description sentences, and useful actions from the corrective event sentences. Finally, by considering the coexistence of the phrases, LESBRE suggests the most common actions associated with the input descriptive phrases.

2.3.1 Dataset: HHS Breach Reports

We collected the information of 3,144 breaches available on the HHS website as of April, 2021. We removed the breaches without textual reports, as well as breaches with duplicated reports. We leveraged the sentence segmentation tool in spaCy¹ to break the breach reports into sentences. We kept the breach reports with five to ten sentences, as short reports tend to be duplicative or non-descriptive and long reports are often copied from external reports such as news articles.

After these preprocessing steps, there are 1,873 breach reports, with an average of 6.43 sentences per report. Table 2.1 shows the numbers of reports with different lengths.

¹<https://spacy.io/>

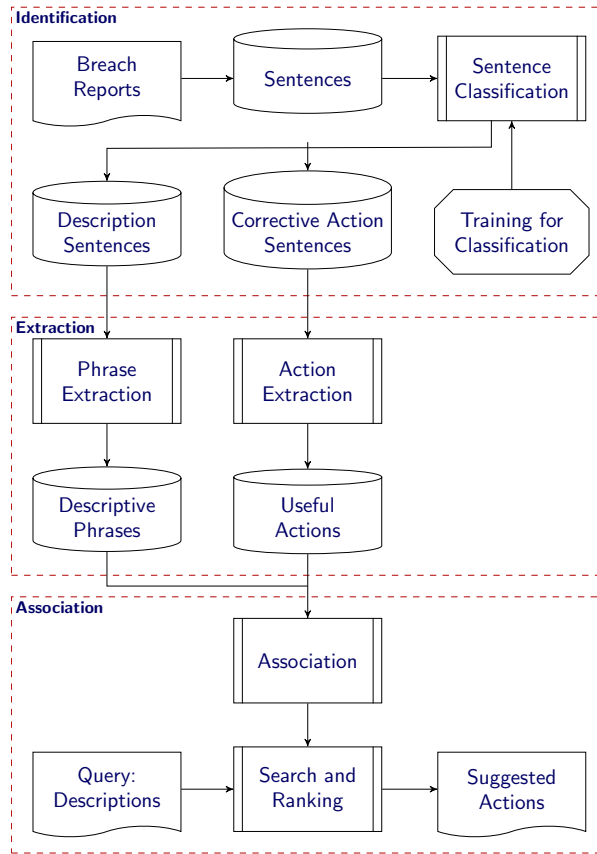


Figure 2.1 An overview of LESBRE.

Table 2.1 Number of breach reports grouped by lengths.

| Number of Sentences | Count of Reports |
|---------------------|------------------|
| 5 | 628 |
| 6 | 541 |
| 7 | 395 |
| 8 | 177 |
| 9 | 89 |
| 10 | 43 |
| Total | 1,873 |

2.3.2 Sentence Classification

First, we train a classifier to determine the type of each sentence in a report. We consider a three-class classification task, classifying each sentence into breach description, corrective sentence, or neither.

We experiment with three classification methods. First, we encode each sentence into vectors using Universal Sentence Encoder (USE) [Cer et al., 2018], and classify the vectors with a Support Vector Machine (SVM) [Russell and Norvig, 2016]. Second, we fine-tune a pre-trained BERT [Devlin et al., 2019] for the sentence classification.

As a baseline, we leverage the common structure of a breach report. We adopt keyword-based heuristics to identify the sentences about PHI detail, the notification events, and events about the OCR. For PHI details, we search for the existence of keywords like *PHI*, *involved*, and types of PHI, such as *name*, *date*, and *financial information*. For notification events, we search for the existence of the words *notification* or *notified*. For OCR events, we simply search for the mentions of the Office for Civil Rights. In a typical breach report, the sentences before the PHI details and notification events are descriptions of the breach. The sentences after them that are not OCR events describe the corrective events of the responsible parties.

Following ÇORBA, we adopt crowdsourcing to obtain a training set for this classification task. We select a set of six-sentence breach reports, each of which contains at least one notification event, and ask crowd workers to identify the type of each sentence. Specifically, we task the workers to mark the sentences that contain *useful actions*, taken by the responsible party of the breach, that other similar parties should also take, if applicable, to prevent or mitigate future breaches or to remedy a future breach if it happens. We specify that notification events and OCR events are not considered as useful or informative. The workers are also asked to mark the *events during breach* if the sentence describes the breach or events leading up to the breach. For a qualification question, we require each worker to mark the first sentence that mentions a notification event. Only workers who answer this question correctly will be paid and their answers will be kept.

We employed 500 workers to annotate 250 breach reports. Each worker was paid \$0.40 if the submission was accepted. Each sentence in a breach report received two annotations. One of our researchers acted as the tie breaker for disagreements, and provided additional annotations independently for the rejected submissions. The crowd workers achieved substantial agreement (Cohen’s Kappa = 0.693), and agreed on 79.6% of the sentences. We collected 1,500 labeled sentences after resolving the disagreements. Table 2.2 shows the number of instances in each type.

For USE+SVM and fine-tuned BERT, we randomize the order of the sentences, and choose 90% of the sentences for training and 10% for testing. For the baseline method, the original order of the sentences in each report is kept, and we measure its performance on the entire labeled dataset. We choose the

Table 2.2 Numbers of sentences with different labels in the training set.

| Sentence Type | Count |
|-----------------------------------|-------|
| <i>Breach Description</i> | 534 |
| <i>Corrective Event Sentences</i> | 448 |
| <i>Neither</i> | 518 |
| Total | 1,500 |

classifier with the highest accuracy to determine the types of all sentences in the available breach reports.

2.3.3 Extraction of Informative Phrases

For each breach report, we have identified the sentences that either are descriptive of the breach or contain corrective events as to how the responsible parties remedied the current breach and attempted to prevent similar future breaches. However, the classified sentences cannot be directly leveraged for action suggestion, because (1) the sentences do not exactly describe other similar breaches and (2) the corrective sentences describe past events and are not actionable.

In this step, we leverage NLP techniques, including part-of-speech tagging and dependency parsing, to extract informative phrases from the targeted sentences.

Part-of-speech (POS) tagging Part-of-speech (POS) tagging [Santorini, 1995] is a process that marks a word in a sentence with a tag corresponding to its part of speech, based on its context and properties. POS tagging is commonly provided in NLP libraries. We leverage POS tagging to identify verbs in a sentence, as each event phrase must contain a verb. Common POS tags for verbs include VB for the base form, VBD for past tense, and VBG for gerund or present participle.

Dependency parsing Dependency parsing [de Marneffe and Manning, 2008] is the process of analyzing the grammatical structure of a sentence. For each word in the sentence, a dependency parser identifies its *head* word and how it modifies the head, i.e., the dependency relation between the given word and its head. The dependency relations identified in a sentence define a dependency-based parse tree of the sentence.

Descriptive phrases of breaches In breach description sentences, we consider a phrase as informative and descriptive if it is of one of the following types. We leverage part-of-speech tagging to identify the words, and dependency parsing for noun phrases.

Adjective : describes a feature of an entity or an item involved in the breach, such as *unencrypted*, *internal*, and *external*;

Adverb : describes an action of the responsible party before or during the breach, such as *erroneously*, *inadvertently*, and *impermissibly*;

Noun or noun phrase : refers to an entity or an item involved in the breach, such as *laptop*, *business associate*, and *phishing scheme*;

Verb : refers to an action or an event within the breach, such as *hack*, *stolen*, and *access*.

Useful actions In sentences that contain corrective events, we consider the verb phrases performed by the responsible parties. We first identify the target verbs in these sentences, and find their children in the dependency parse tree as the extracted verb phrases. Note that not all verbs in the informative vents lead actionable verb phrases. For example, in *following OCR's investigation, the BA improved its code review process to catch the system error that caused this incident*, there are four verbs, namely, *follow*, *improve*, *catch*, and *cause*. While *improve* and *catch* lead useful actions, *following OCR's investigation* and *causing this incident* are not actionable items that can be considered as lessons learned from this incident. After manual examination, we collect 62 common verbs that are not indicative of useful actions, including *follow* and *cause*, and ignore them when extracting verb phrases from informative events. We use the lemma of a target verb when keeping its verb phrase so that the verb phrase reads as an action, e.g., *improve its code review process*.

2.3.4 Action Suggestion

For action suggestion, we leverage the association between descriptive phrases and useful actions by considering their coexistence in breach reports. In this step, the input is a list of descriptive phrases of the breach, such as *laptop* and *stolen*, and the output is a list of useful actions that can help prevent, mitigate, or remedy a breach with such descriptions, such as *report the theft to the law enforcement* and *encrypt all laptops*.

Weighting the Actions First, we identify the breach reports that match the input descriptive phrases. If a breach report matches one of the input phrases, we increase its weight by one level of magnitude. If it matches more input phrases, more weight will be given. Second, we traverse all breach reports. For each report, we count the weighted occurrences of each useful action, modified by the weight of the report. Thus, if a breach report matches the descriptive phrases, the actions in it will be given more weights. Finally, we rank all useful actions by their weighted occurrences. The top ranked actions will be the suggested actions, as they appear more frequently in the breach reports matching the input descriptions. Note that, if there is no input, all breach reports will receive the same weight. The useful actions will be ranked by their actual occurrences in all breach reports.

Similarly, we can rank all possible descriptive phrases by their association with the input phrase. Such ranking can help the selection of descriptive phrases.

It is worth noticing that the descriptive phrases may differ in terms of their descriptiveness. Common phrases, such as *patient information* and *breach incident*, may not provide as much information as uncommon ones like *clinical trial information* and *cyberattack*. Therefore, we discount the weights of common phrases (appearing in more than 80 breaches) by half.

Clustering The same action may not be described exactly the same in different breach reports. For example, the phrases *encrypt all mobile media*, *encrypt all mobile devices*, and *encrypt mobile devices* refer to the same action. They should be counted as the same action for the ranking. We need to cluster the extracted phrases such that the phrases in each cluster refer to the same action. We encode the extracted phrases into vectors using Universal Sentence Encoder, and cluster them based on their cosine similarity. Extracted phrases with cosine similarity higher than a threshold will be considered as the same action. First, we adopt DBScan, a density-based clustering method, to find cluster the verb phrases such that each verb phrase in a cluster is cosine similar to at least one other verb phrase. However, not all verb phrases in a cluster are similar to each other. For each cluster determined by DBScan, we adopt K-Means to cluster the verb phrase further. We choose the smallest parameter K for each cluster such that each verb phrase in a cluster is cosine similar to the center of the cluster. This process can be time-consuming, especially with large K parameters, but we need only to run this clustering once for all extracted verb phrases. We run DBScan first to accelerate the process of finding the proper K.

For each cluster, we choose a verb phrase that is the closest to the center, as the representative verb phrase for the cluster.

Similar Descriptive Phrases Additionally, using exact matching for descriptive phrases may limit the number of relevant breach reports. For example, if the input phrase is *laptop*, breach reports about *mobile devices* may also be relevant for action suggestion. Thus, for each descriptive phrase, we identify similar phrases based on cosine similarity of their average Word2Vec vectors [Mikolov et al., 2013]. When determining the weight of a breach report, we add its weight if it matches a similar phrase to the input phrase, based on cosine similarity between the matched phrase and the input phrase.

2.4 Results

We now show the results for sentence classification, phrase extraction, and action suggestion.

Sentence classification Table 2.3 shows the accuracy of each classification technique for the three-class sentence classification.

It is noteworthy that the baseline performed well, as most of the breach reports selected for annotation

Table 2.3 Accuracy of sentence classification.

| Classifier | Accuracy |
|-----------------|----------|
| USE+SVM | 94.0% |
| Fine-tuned BERT | 94.7% |
| Baseline | 86.2% |

follow the common style. However, since there is no regulation or rule about how breach reports should be written, we cannot guarantee that the heuristics work for all future breach reports. SVM and BERT yield similar results. We adopt the fine-tuned BERT to determine the types of all sentences in the available breach reports. Although SVM and BERT yield similar results, we observe that BERT outperforms SVM when applied to unseen sentences that are semantically different from the ones in the training set. Table 2.4 shows the distribution of each sentence type in the final dataset.

Table 2.4 Distribution of sentence types in breach reports.

| Sentence Type | Count |
|-----------------------------------|---------------|
| <i>Breach Description</i> | 4,176 (35.1%) |
| <i>Corrective Event Sentences</i> | 3,911 (32.8%) |
| <i>Neither</i> | 3,819 (32.1%) |
| Total | 11,906% |

Phrase Extraction Based on the results from the previous step, 1,733 breach reports contain sentences that describe the breaches. We extracted 26,092 unique descriptive phrases from these sentences. The most common phrases include *employee*, *electronic*, *stolen*, and *business associate*.

From the 3,911 sentences that contain corrective events, we extract 8,799 verb phrases. The most common verbs include *implement*, *retrain*, *sanction*, and *revise*. We cluster these verb phrases based on their cosine similarity to each other, such that the minimum cosine similarity between each verb phrase and the center of the cluster is a threshold of 0.75. We identified 4,770 clusters, representing 4,770 different useful actions. The most common actions include *retrain the staff*, *implement additional administrative and technical safeguards*, and *sanction the responsible employee*.

Action Suggestion We have built a tool for action suggestion based on the association-based method. The tool is available at <https://hguo5.github.io/ActionSuggestion/>. Figure 2.2 shows the top

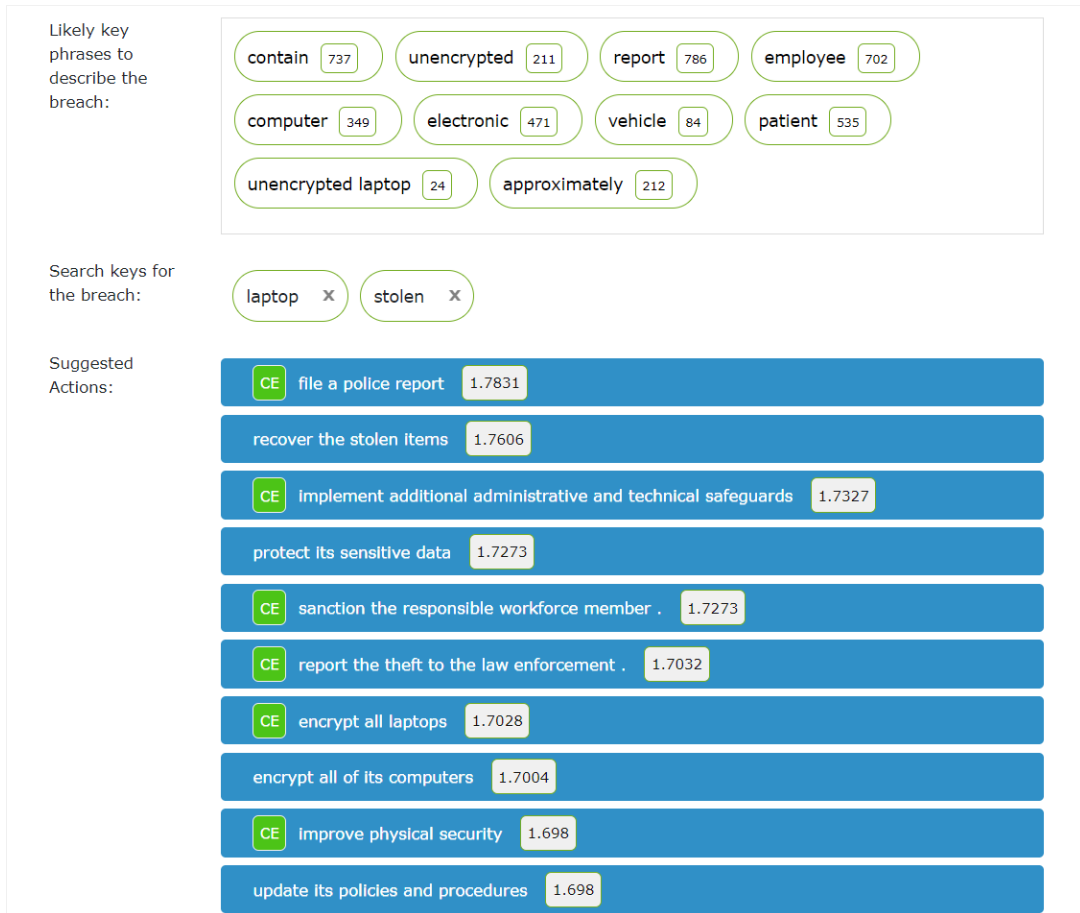


Figure 2.2 An example of action suggestion.

ranked actions for the input phrases. The number after each phrase represents its frequency or weight based on its association to the input phrases.

2.5 Discussion

We presented LESBRE, a framework for the extraction of useful actions from breach reports and action suggestion based on breach descriptions. We now discuss its merits and limitations.

2.5.1 Merits

Previous studies have stressed the importance of information extraction from breach reports for understanding HIPAA compliance and requirements engineering [Guo et al., 2020; Kafali et al., 2017].

However, the automated information extraction from breach reports is lacking. LESBRE is the first method designed for this purpose, as well as action suggestion based on what has previously done in similar scenarios.

Event Extraction Text related to software development includes informative events that describe how software systems and their users behave in the real world. LESBRE shows the importance of event extraction from such text. Breach reports are filled with common practices in the healthcare domain regarding the protection of health information. The actions frequently taken by previous practitioners in case of data breaches can be considered as lessons learned from past failures as well as security requirements for similar parties in the healthcare domain, and provide ample supplement for the understanding of the HIPAA regulation.

Action Suggestion LESBRE suggestions actions by ranking the possible actions based on their associations with the descriptive phrases of a breach. Actions that have been performed more often by previous responsible parties in similar breaches will be ranked higher than other rare actions. Commonly taken actions can be considered as norms, and should be treated as security requirements for other covered entities to prevent and remedy similar breaches.

2.5.2 Limitations

LESBRE is not without limitations.

Sentence classification Even though there are not rules or guidelines regarding how breach reports are written, the available reports generally follow a common style, in which different sentences possess distinctive features. Our classifiers, along with a heuristic-based baseline, perform well for the sentence classification task, with a relatively limited training set. However, with time progresses, other breach report writers may take on different styles. In the current breach report database on the HHS website, a few breach reports clearly do not follow the style described in Section 2.2.1. For example, some breach reports are simply news articles, which are much longer and include various types of sentences, such as quotes from the responsible parties and OCR. Our classifiers may not perform well on sentences that are semantically and syntactically different from the examples in our training set. Our previous study [Guo et al., 2020] has shown that well-organized breach reports promote the extraction of useful information. We wish to call for and contribute to the adoption of guidelines for breach reporting.

Action Suggestion LESBRE suggests actions based on the coexistence of breach descriptions and useful actions. For example, the action of *encrypting laptops* is frequently performed in breaches that mention *unencrypted laptops*, and therefore should be considered as a norm for other breaches with the same descriptive phrase. However, coexistence does not necessarily imply correlation. A breach report may

contain multiple independent descriptive phrases, and various actions may be taken by the responsible parties accordingly. Currently, the breach reports are not long, and the descriptions for each breach is limited. A breach typically involves one type of violation, such as improper disposal or unauthorized access. Our action suggestion tools works well as the actions taken in each breach show good correlation to the breach descriptions. If the breach reports evolve in style in the future, with much more complex descriptions about the breach, we may need to conduct further investigation on the cause relations between the breach events and corrective events.

Moreover, association-based action suggestion requires the descriptive phrases to have appeared in past breach reports, which may not always be the case. We mitigate this limitation with the usage of similar phrases to the input. The support for unseen breach descriptions is a good direction for future work.

2.5.3 Action Suggestion with Event Inference

As a preliminary study, we have investigated event inference in breach stories for the purpose of suggesting actions based on the description of a breach [Guo et al., 2018]. If we consider only the breach description sentences and the sentences that contain informative events, breach reports can be considered as short stories comprised of events that are related to each other. Understanding the narrative structure of the breach stories helps the inference of the follow-up events to a breach event, and therefore can be leveraged for action suggestion.

The Story Cloze Test [Mostafazadeh et al., 2016] is a popular test for story understanding. The task is to generate a natural language ending to a preceding sequence of sentences to complete a story. A model for the test should be able to learn the common progression of events in the training set, and predict the correct following events to the preceding events. The Story Cloze Test is performed on ROCStories [Mostafazadeh et al., 2017], a dataset of five-sentence stories about everyday life. For each story, the first four sentences are used as input, and the task is to predict the fifth sentence correctly. The ROCStories dataset is similar to breach reports in that breach reports (1) are composed of similar numbers of sentences and (2) the ending of a reports, i.e., the corrective actions, is related to the preceding events that describe the breach.

Recent work has demonstrated that recurrent neural networks (RNNs) with Long Short-Term Memory (LSTM) [Hochreiter and Schmidhuber, 1997] architectures are powerful models for complex tasks on sequential data, such as online handwriting recognition [Graves et al., 2007], speech recognition [Graves et al., 2013], and translation [Sutskever et al., 2014]. LSTM networks have been shown to yield superior performance for the Story Cloze Test [Srinivasan et al., 2018]. We evaluate their performance in inference of embedded vectors that represent sentences in a chain of vectors. For sentence embedding, we adopt

Paragraph Vector (PV) [Le and Mikolov, 2014], also known as Doc2Vec, which has been proven to have excellent performance in representing the meanings of documents, and achieves state-of-the-art results in text classification, information retrieval, and sentiment analysis [Ai et al., 2016; Dai et al., 2014].

We aim at the task of inferring the held-out event, in the form of a sentence, given a sequence of context sentences in a story. By embedding sentences into vectors and capturing the progression of these vectors using LSTM networks, we intend to find common semantic flow in stories. The proposed model produces the most probable vector for the held-out sentence, which we use to rank all possible answers by their cosine similarity to it. To evaluate the prediction model, we measure its performance on two datasets. Our results show that it significantly outperforms the baseline of using average word vectors.

Our method takes N sentences and produces the prediction for the held-out sentence, e.g., the next $(N + 1)$ st sentence in the story. We can repeat this process and obtain a chain of events. The prediction of such event chains is useful in that they represent a common progression of stories, which can be interpreted as lessons learned from the past, based on the nature of the training data. To accomplish this task, we train multiple models that take different numbers of inputs. For example, the i th model takes i input vectors and predicts the $(i + 1)$ st vector. The i inputs combined with this predicted output are the input for the $(i + 1)$ st model.

We manually examined all predicted follow-up requirements for a testing set, and found that 60% of the predictions were plausible and 35% matched what was reported. Figure 2.3 shows the predicted events for an example input. The actual follow-up events are also included.

As shown in this example, the predicted events can be considered as suggested corrective actions for the described breach event. The predicted events not only are mostly plausible, but also include corrective actions that are not mentioned in the actual report.

This work is limited in certain ways. First, the breach report dataset is small and may not be suitable for deep learning methods for story understanding. The trained model can only perform well on the type of breaches that have happened enough times in the past. Second, our model only learns the sequential ordering of similar sentences in the training set, and does not examine the causal relationships among the events and their actors. The performance of our method is sensitive to the representativeness of the training set. It is unable to infer surprising events or endings that are not common in the training set. Third, the model is not a full event inference model as it can only predict existing events in the data set. Finally, breach descriptions tend to be long sentences with detailed information that may not have been accurately or completely captured by the sentence vectors. For example, some actions that a CE might take depend on whether a business associate (BA) was involved in the breach. Breach stories can differ considerably between *CE losing laptops* and *BA of CE losing laptops*, even though the breach descriptions may be semantically similar.

Despite its limitations, event inference on breach stories has the potential of suggesting actions based

| |
|--|
| <p>DESCRIPTION: Two laptop computers with questionable encryption were stolen from the CE's premises.</p> |
| <p>Predicted Events</p> |
| <p><i>p</i>₁ The CE filed a police report to recover the stolen item.</p> <p><i>p</i>₂ The CE replaced its building alarm and installed bars on the windows.</p> <p><i>p</i>₃ The CE revised its existing policies to ensure its vendors enforce appropriate security measures to protect ePHI.</p> <p><i>p</i>₄ The CE implemented mandatory encryption for all mobile devices.</p> |
| <p>Actual Follow-up Events</p> |
| <p><i>a</i>₁ The CE reported the theft to law enforcement.</p> <p><i>a</i>₂ The CE worked with the local police to recover the laptops.</p> <p><i>a</i>₃ The CE developed and implemented new policies and procedures to comply with the Security Rule.</p> <p><i>a</i>₄ The CE placed an accounting of disclosures in the medical records of all affected individuals.</p> |

Figure 2.3 Inferred events to follow a breach description event.

on the semantic relations between the breach descriptions and the corrective actions. Further investigation is needed for more accurate and reliable event inference in the context of breach stories.

2.6 Conclusions and Future Work

We presented LESBRE, a framework for event extraction from breach reports and action suggestion based on breach descriptions. LESBRE leverages natural language processing techniques as well as text classification to extract the descriptive phrases of a breach and useful actions taken by the responsible parties in responsible to the breach. LESBRE suggests useful actions by ranking them based on their associations to the breach descriptions. LESBRE is the first work on the automated extraction of useful actions from breach reports. Action suggestions are useful to other covered entities for the prevention and recovery of potential future breaches.

Future work includes the investigation of breach reports and sentences of various styles, as well as the causal relation between the corrective actions and breach events. The extraction of useful actions from other software development related text, such as logs and news articles, may need further research. The understanding of causal relations between the different events in a story can help suggest apropos actions that are semantically related to the input breach descriptions.

CHAPTER

3

EXTRACTING TARGETED EVENT PAIRS

We address $\mathbf{RQ}_{\text{event}}$ and $\mathbf{RQ}_{\text{pair}}$ in the setting of action-problem event pairs in app reviews. A review describes an app user’s interaction with an app as a story. Previous studies on app reviews focus on the classification of the entire reviews. We investigate app reviews on the event level, and focus on the extraction and inference of action-problem pairs, which describe the scenarios where expected user actions trigger unexpected app problems. To this end, we present CASPAR, a method for collecting and analyzing user-reported mini stories regarding app problems from app reviews. CASPAR abstracts event pairs from stories in reviews. By extending and applying natural language processing and deep learning, CASPAR extracts ordered events from app reviews, classifies them as user actions or app problems, and conducts inference on action-problem event pairs. It builds and trains an inference model with the extracted event pairs to predict possible app problems for different use cases. Our evaluation of CASPAR shows that it discovers high-quality event pairs regarding app problems from reviews, and infers plausible app problems for user actions. By presenting CASPAR, we demonstrate the importance and effectiveness of extracting targeted event pairs from text.

3.1 Introduction

We motivate the development of CASPAR, and introduce our research questions and contributions.

3.1.1 Motivation

As we have mentioned in Chapter 1, a user’s review of an app often tells a story about how the user interacted or attempted to interact with the app. This story, different from traditional stories that are longer and more sophisticated, includes a short sequence of events that describe what function the user tried to bring about and how the app behaved in response. Descriptions of such interactions, which we interpret as mini stories, are prominent in reviews with negative ratings. Investigating stories present in app reviews has major implications for software engineering. These stories not only serve as *de facto* deployment reports for an app, but also express users’ expectations regarding the app.

Apps, especially popular ones, receive a large amount of user reviews. Manually combing them is usually impractical. Previous research has studied the classification of app reviews, and automatically identified bug reports, saving collection time for analysts and developers. However, manually reading entire reviews to identify reports of app problems remains time-consuming. Therefore, we motivate CASPAR, a method for collecting and analyzing stories of app problems, as action-problem event pairs, from app reviews. We focus on events in app reviews. Specifically, we identify the app problem events, which further cut down reading time needed for analysts and developers.

A story of interest in this study includes at least two types of events, user actions and app problems. An app *problem* is an undesirable behavior that violates a user’s expectations. In particular, when a review gives a negative rating, the stories within it contain rich information regarding app problems. These app problems when reported on (and sometimes ranted about) by users call for a developer’s immediate attention. Negative reviews tend to act as discussion points and can be destructive to an app’s attraction and retention of users.

We define an *action-problem pair* as such a pair of events in which an app problem (an event) follows or is caused by a user action (an event). Such event pairs describe where and how the app encounters a problem. Therefore, these pairs can yield specific suggestions to developers as to what scenarios they need to address.

However, collecting and analyzing action-problem pairs from app reviews is a challenging task. First, extracting the targeted events, i.e., user actions and app problems, is nontrivial—because user-provided texts are heterogeneous and are often riddled with typos and grammatical errors. Second, users may not describe the events of their interaction with apps in a sequential order. The temporal or causal links between events should be investigated. Third, inference of event pairs is known to be a hard problem

[Rashkin et al., 2018; Zellers et al., 2018].

3.1.2 Research Questions

As we have mentioned in Chapter 1, CASPAR addresses the modified versions of $\mathbf{RQ}_{\text{pair}}$ and $\mathbf{RQ}_{\text{infer-pair}}$, specific to the action-problem pairs in negative app reviews.

$\mathbf{RQ}_{\text{pair}}$ How effectively can we extract app problem stories as action-problem pairs from app reviews?

$\mathbf{RQ}_{\text{infer-pair}}$ How effectively can an event inference model infer app problems in response to a user action?

To answer $\mathbf{RQ}_{\text{pair}}$, we investigate the performance of CASPAR in (1) classifying events as USER ACTIONS or APP PROBLEMS, and (2) identifying action-problem pairs compared to a human annotator. $\mathbf{RQ}_{\text{pair}}$ covers $\mathbf{RQ}_{\text{event}}$ as the extraction of targeted events is the first step of CASPAR.

Once event pairs are collected, analyzing them remains a big challenge. CASPAR infers app problem events based on user actions. By answering $\mathbf{RQ}_{\text{infer-pair}}$, we can determine CASPAR’s practical value in (1) linking user actions and app problems, as well as (2) inferring possible app problems that may happen after a user action.

3.1.3 Contributions

To the best of our knowledge, CASPAR is the first work on app reviews that focuses on the user-app interaction stories that are told in app reviews. From user feedback, CASPAR extracts app problems and the use cases where those problems happen. In this manner, CASPAR can assist an app’s developers in learning about its shortcomings in user experience.

CASPAR extracts app problems and the use cases where they happen from user feedback to assist developers in learning about problems in the user experience their apps provide.

In this study, we introduce and provide the first solution to the research problem of identifying and analyzing user-reported stories. CASPAR adopts NLP and deep learning, and brings the investigation of app reviews down to the event level. Instead of generating a selective set of full reviews, CASPAR yields high-quality pairs of user action and app problem events. Moreover, by linking app problem events and user actions, CASPAR can infer probable problems corresponding to a use case. A crucial meta-requirement in app development is to avoid such problems.

Our contributions include: (1) a method for collecting and analyzing stories of app problems, as action-problem event pairs, from app reviews, and (2) a resulting dataset of collected event pairs. By

presenting CASPAR, we emphasize the importance of analyzing user-reported stories regarding the usage of applications.

3.2 Related Work

Information residing in user reviews for application is crucial in maintaining and improving software. Analyzing informative reviews and prioritizing feedback have been shown to be positively linked to app success [Palomba et al., 2015]. We now introduce recent work on analyzing app reviews, which mostly involves generic NLP techniques. The task of extracting and analyzing stories in app reviews and applying event inference on those stories have not been addressed.

3.2.1 Information Extraction from App Reviews

Previous studies on information extraction from app reviews have emphasized the classification of reviews as a way of combing through the large amount of text and reducing the effort required for analysis.

Pagano and Maalej [2013] report on empirical studies of app reviews in the Apple Store. They identify 17 topics in user feedback in app stores by manually investigating the content of selected user reviews. Pagano and Maalej also find that a significant fraction of the reviews, in particular, 96.4% of reviews with 1-star ratings, include the topics of shortcoming or bug report, which could be probably mined for requirements-related information.

Maalej and Nabil [2015] classify app reviews according to whether or not they include bug information, requests for new features, or simply praises. Maalej and Nabil apply classification techniques, such as Naive Bayes and Decision Trees, with features of reviews such as bag of words, ratings, and sentiment, and achieve satisfying results. Based on their classification method, Dhinakaran et al. [2018] investigate active learning to reduce manual effort in annotation.

Panichella et al. [2015] classify user reviews based on a taxonomy relevant to software maintenance and evolution. The base categories in their taxonomy include *Information Giving*, *Information Seeking*, *Feature Request*, and *Problem Discovery*. The *Problem Discovery* type of app reviews describe app issues or unexpected behaviors. By this classification, they focus on understanding the intentions of the authors of the reviews.

Chen et al. [2014] employ unsupervised techniques for identifying and grouping informative reviews. Their framework helps developers by effectively prioritizing and presenting the most informative app reviews.

Guzman et al. [2016] investigate user feedback on Twitter, and identify and classify software-related tweets. They leverage Decision Trees and Support Vector Machines (SVMs) to automatically identify

relevant tweets that describe bugs, shortcomings, and such.

These studies focus on the analysis of entire reviews and do not look into the details that the users are describing. With the amount of available app reviews increasing, reading through reviews become more time-consuming. To reduce the time required by developers, recent research targets certain topics, and investigates user reviews on the sentence level. Jacob and Harrison [2013] retrieve sentences that contain feature requests from app reviews by applying carefully designed rules, such as keyword search and sentence structures. These rules have been informed by an investigation of the ways users express feature requests through reviews. Di Sorbo et al. [2016] summarize app reviews by grouping sentences based on topics and intention categories. Developers can learn feature requests and bug reports more quickly when presented with the summaries. Kurtanović and Maalej [2017] classify reviews and sentences based on user rationale. They identify concepts such as issues and justifications in their theory of user rationale. Using classification techniques, Kurtanović and Maalej synthesize and filter rationale-backed reviews for developers or other stakeholders.

3.2.2 Event Relations and Event Inference

App reviews contain user-app interaction stories, i.e., sequences of events related to the deployment and user experience of applications. Recent studies [Mani et al., 2006; Mirroshandel and Ghassem-Sani, 2012; Ning et al., 2018b] have applied rules and engineered features to extract temporal relations between events from texts. Other studies extract causal relations between events based on their temporal relations [Beamer and Girju, 2009; Hu et al., 2017; Hu and Walker, 2017]. These studies are usually conducted on well-edited texts, such as news articles, books, movie scripts, and blogs. Studies of event relation extraction on texts with lower quality, such as tweets and online reviews, are still lacking. We borrow ideas from these studies to extract event pair candidates from app reviews. In our work, we focus on event pairs describing app-user interactions, where a user action triggers an app problem. Note that the user action may not necessarily cause the app problem, but provides information regarding where and when the problem occurs.

Event inference is the process of inferring plausible events, follow-up or held-out, based on evidence events. Some studies target longer sequences of events [Chambers and Jurafsky, 2008; Mostafazadeh et al., 2016], and other ones target shorter ones, i.e., event pairs. Zellers et al. [2018] publish SWAG, a dataset of multiple choice questions composed by event pairs extracted from video captions. The proposed task is to select the second event from four choices based on the first event and commonsense inference. Recent studies focus on one event, and investigate its related events in different inferential dimensions [Rashkin et al., 2018; Sap et al., 2019]. CASPAR extracts user-action-app-problem event pairs, and infer plausible app problems based on user actions.

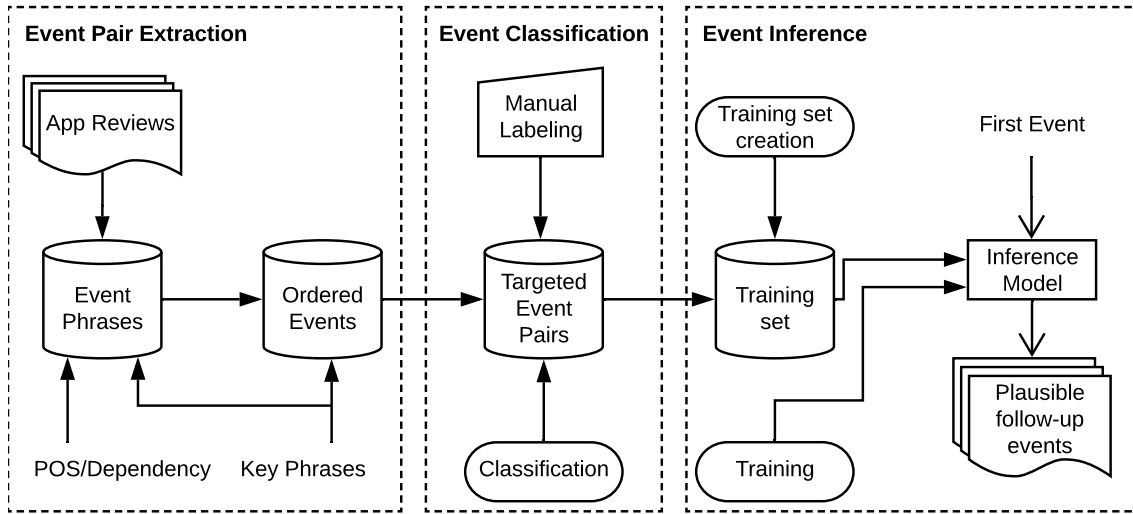


Figure 3.1 An overview of CASPAR.

Deep learning models have recently gained popularity among event inference and story understanding studies. Long Short-Term Memory (LSTM) [Hochreiter and Schmidhuber, 1997] networks are a type of recurrent neural networks that have been proven to yield superior performance on sequences of data, such as texts and stories. Srinivasan et al. [2018] target the Story Cloze Test using a straightforward bi-directional LSTM model to determine whether an event is random or the correct ending of a story. We learn from their insights when building and training the event inference model in CASPAR. BERT [Devlin et al., 2019] is a pretrained language representation model that can be fine-tuned to achieve state-of-the-art performances in numerous NLP tasks, including the event inference in SWAG. We borrow insights from their work when adopting pairs of texts as input.

3.3 Method

We now present the details of CASPAR, which consists of three steps. First, CASPAR extracts events from targeted app reviews based on heuristics and natural language processing (NLP) techniques. Second, CASPAR classifies the events and keeps the ordered pairs of user action and app problem events. Finally, CASPAR trains an inference model on the extracted event pairs, and infers app problem events given the user actions. Figure 3.1 shows an overview of CASPAR.

3.3.1 Event Extraction

Let us describe the heuristics we adopt to select targeted app reviews, focusing on details regarding the extraction of events.

When an app review reports a problem, it tends to describe the user’s interaction with the app as a story, i.e., a sequence of events. However, not all events in a review are necessarily related to each other. In this study, we focus on action-problem event pairs, each of which comprises (1) an expected user action and (2) an app problem that indicates a deviation from expected app functionality. The app problem happens after or is caused by the user action.

To make sure that the extracted events are temporally ordered and casually related, we keep only the reviews that contain temporal conjunctions, including *before*, *after*, and *when*. In addition, we consider key phrases that indicate temporal ordering, such as *as soon as*, *every time*, and *then*. Instead of processing all available app reviews, which are a large dataset, we adopt key phrase search as a heuristic and keep only the reviews that contain at least one key phrase.

App problems deviate from users’ expectations, and therefore are described in reviews with negative ratings. We collect the app reviews with negative ratings, e.g., one-star ratings, and then apply key phrase search to finalize a more refined dataset of reviews.

We then extract ordered events from these reviews using Part-of-speech (POS) and dependency parsing. We refer to an event in the text as a phrase that is rooted in a verb and includes other attributes related to the verb. To identify such event phrase, we can find the subtree rooted in the verb in the dependency-based parse tree from a dependency parser.

Note that a sentence may include multiple verbs, and some of the verbs may belong in the same event. Based on the results of dependency parsing[de Marneffe and Manning, 2008], we consider only verbs that are parsed as ROOT, advcl (adverbial clause modifier), or conj (conjunct). We choose these types of dependency relation tags because they are excellent indicators of events. Since the dependency tree rooted in a ROOT covers all the words in a sentence, we extract the ROOT event phrase from words that are not incorporated in any other event phrases. Punctuation marks at both ends of an event phrase are removed.

Thus, we take the following steps to extract ordered events from the reviews.

1. Find and keep *key sentences*, i.e., sentences that contain the key phrases, and collect the sentences surrounding them (one preceding sentence and one following sentence);
2. Extract event phrases from these sentences;
3. Order event phrases in key sentences using heuristics;

4. Collect other event phrases in the original order in which they appear in the text.

The heuristics we adopt to order the events are shown in Table 3.1, where $e_1 \rightarrow e_2$ indicates that e_1 happens before e_2 .

Table 3.1 Heuristics for events in a complex sentence.

| Sentence Structure | Event Order |
|---|--|
| e_1 , <i>before / until / then</i> e_2 | $e_1 \rightarrow e_2$ |
| e_1 , <i>after / whenever / every time / as soon as</i> e_2 | $e_2 \rightarrow e_1$ |
| e_1 , <i>when</i> e_2 | $e_1 \rightarrow e_2$, if verb of e_1 is VBG $e_2 \rightarrow e_1$, otherwise |

In the case of “ e_1 , *when* e_2 ,” e_1 happens first most of the time. However, consider the key sentence in Example 3 (for SnapChat¹).

Example 3

★★★★★ username2, 09/16/2014

Virus

I love Snapchat. Use it often. But snapchat gave my phone a virus. So I was using snapchat today when all of a sudden my phone screen turned blue and then my phone shut off for 7 HOURS. 7 HOURS. So I had to delete snapchat because it was messing up my iPhone 5c.

We add the heuristic that when e_1 is in continuous tense, i.e., the verb in e_1 is marked as VBG by the POS tagger, e_1 occurs before e_2 .

Note that the key phrases are not included within any event phrase. Instead, we label the events based on their positions relative to the key phrases. For example, if an event appears in a subclause led by *when*, it will be labeled as a *subclause* event, and the event outside of this subclause will be labeled as

¹<https://apps.apple.com/us/app/snapchat/id447188370>

main. Events that are not in a key sentence are labeled as *surrounding*. We keep these labels as context information to make the events more readable.

3.3.2 Event Classification

In this step, we classify the extracted events into *USER ACTIONS*, *APP PROBLEMS*, or *NEITHER*. To create a training set for the classification, we conducted multiple rounds of manual labeling. The details of the setup are explained in Section 3.4.

We define *USER ACTIONS* as what the users are supposed to do to correctly use the app, usually a use case designed by the developers. We define *APP PROBLEMS* as the incorrect behaviors of an app in response to the user actions (including the lack of a correct response), which do not appear to have been designed by the app developers. In negative reviews, users sometimes complain about the designed app behaviors, which we do not classify as problems. Accordingly, we disregard the types of event phrases shown in Table 3.2, without checking the context (the reviews from which they are extracted). Event phrases that fall into these categories are labeled as *NEITHER*.

Table 3.2 Types of event phrases we disregard (classify as *NEITHER*).

| Event phrase type | Example |
|---|--|
| 1. Incorrectly extracted verb phrases | — |
| 2. Users' affections or personal opinions toward the app | <i>it has made the app bad, MS OneDrive is superior</i> |
| 3. App behaviors that are designed by the developers | <i>I guess you only get 3 of the 24 levels free</i> |
| 4. Users' observations of the developers | <i>you guys changed the news feed</i> |
| 5. Users' requests of features | <i>needs the ability to enter unlimited destinations</i> |
| 6. Users' imperative requests for bug fixes | <i>fix the app please</i> |
| 7. Users' behaviors that are not related to the app | <i>I give you one-star, I contacted customer service</i> |
| 8. Events that are ambiguous without context or too general | <i>it was optional, I try to use this app</i> |

Before performing the classification, we need to convert the event phrases into a vector representation. One basic encoding method is TF-IDF (term frequency-inverse document frequency) [Salton and McGill, 1983], which we adopt as a baseline. However, TF-IDF loses information from the phrase since it

ignores the order in which the words appear. To obtain results that are more accurate, we adopt the Universal Sentence Encoder (USE) [Cer et al., 2018] to convert event phrases into vectors. USE is a transformer-based sentence embedding model that leverages the encoding subgraph of the transformer architecture [Vaswani et al., 2017]. The pretrained USE model and its variants have become popular among researchers for downstream tasks, such as text classification and clustering [Yang and Ahmad, 2019]. The USE vectors capture rich semantic information and can achieve state-of-the-art performance for these tasks.

We then adopt Support Vector Machine (SVM) [Russell and Norvig, 2016] to classify the sentence vectors into the aforementioned three classes. We adopt two separate classifiers (with probability estimate) for USER ACTIONS and APP PROBLEMS, respectively, since SVM can be applied only on binary classification. If an event is classified as both a USER ACTION and an APP PROBLEM, we choose the class with the higher probability.

Upon obtaining sequences of ordered events, each of which has been classified as a USER ACTION or an APP PROBLEM, we can extract *action-problem pairs* by selecting user actions as well as the app problems that immediately follow them.

We address **RQ_{pair}** by reporting the accuracy of the event classification, as well as the precision and recall of the event pair extraction by manually verifying the results of CASPAR applied on a small dataset of app reviews.

3.3.3 Event Inference

The goal of conducting event inference on the extracted event pairs is to infer possible app problems, i.e., unexpected app behaviors, based on an expected user action. Developers can preemptively address possible issues to ensure application quality. We propose treating this event inference task as a classification problem. Given a pair of ordered event, $\langle e_u, e_a \rangle$, where e_u is a USER ACTION and e_a is an APP PROBLEM, the classifier determines whether e_a is a valid *follow-up event* to e_u or a *random event*. Thus, the classes for each entry are ORDERED EVENT PAIR and RANDOM EVENT PAIR. We define this type of classification as *event follow-up classification*.

We conduct negative sampling to train a classifier for event follow-up classification. Negative sampling is the process of generating negative observations in scenarios where they are not provided explicitly. The extracted event pairs can be kept directly as positive examples. To create negative instances of event pairs, we compose an event pair by randomly choosing an app problem for each user action.

In addition to encoding an event into a vector using sentence encoding techniques, we can convert a event phrase into a list of word vectors. Converting words into vectors require a word embedding technique. *Word embedding* is the collective name for models that map words or phrases to dense

vectors of real numbers that represent semantic meanings. Popular word embedding techniques include Word2Vec [Mikolov et al., 2013] and GloVe [Pennington et al., 2014].

We experiment with the following classification models.

Baseline: We adopt SVM for this classification problem. As a baseline, we first convert each event into a vector using TF-IDF, and then concatenate the vectors of the two events in an event pair, and train an SVM classifier on the concatenated vectors.

USE+SVM: We convert each event into a vector using USE, and then concatenate the USE vectors of the two events in an event pair. We then train an SVM classifier on the concatenated vectors.

Bi-LSTM network: We concatenate the tokens in the two events, separated by a special token, [SEP], convert the concatenated tokens to a sequence of word vectors, and train a bidirectional LSTM network for the classification of the sequences of vectors.

Training set improvement: If we have a large amount of duplicate or similar app problem events, a random event is likely to be similar to the actual follow-up, which can impair the accuracy of the classification. We can improve the training set by choosing dissimilar events when composing the negative examples. We consider the following two methods of choosing events for negative examples.

- **Clustering.** We cluster all app problem events into two groups based on cosine similarity, and select an event for the negative example from the cluster that is different from that of the follow-up event.
- **Similarity threshold.** When choosing an event as a negative example, we calculate its similarity to the follow-up event. The similarity score should be lower than a threshold. We adopt cosine similarity between the vectors produced for the events, and report the performance of the classifiers using thresholds 0.50 and 0.25, respectively.

The trained classification models can be leveraged for inferring app problems that can follow or be caused by a user action. For a given user action, e_u , we can rank all possible app problems, e_a^i , by the model’s confidences of the pair $\langle e_u, e_a^i \rangle$ being an ORDERED EVENT PAIR. The top-ranked app problems can be treated as the results of event inference.

Our observations show that many app problems are similar to each other, for which a classifier should yield similar probabilities. To diversify the inferred events, we choose a similarity threshold, and enforce that the cosine similarity between any two inferred events should be below this threshold.

We address $\mathbf{RQ}_{\text{infer-pair}}$ by reporting the accuracy of the event follow-up classification, and manually verify the plausibility of inferred app problem events.

3.4 Results

To evaluate CASPAR, we need a dataset of app reviews and their ratings. We collected 5,867,198 reviews of 151 apps from 2008-07-10 to 2017-09-15, by crawling the app reviews pages on Apple App Store.² As we mentioned in Section 3.3, we focus on reviews with negative ratings. In our experiment, we focused on the 1,220,003 reviews with 1-star ratings. In addition, we applied key phrase search to further filter the dataset. The total number of targeted reviews is 393,755. Table 3.3 lists the key phrases and the count of reviews that contain each of them. Note that some reviews contain multiple key phrases.

Table 3.3 Counts of negative reviews with key phrases.

| <i>after</i> | <i>as soon as</i> | <i>before</i> | <i>every time</i> | <i>then</i> | <i>until</i> | <i>when</i> | <i>whenever</i> | <i>while</i> | Total |
|--------------|-------------------|---------------|-------------------|-------------|--------------|-------------|-----------------|--------------|---------|
| 77,360 | 7,603 | 55,630 | 53,341 | 81,338 | 42,823 | 152,568 | 8,563 | 25,237 | 393,755 |

The following experiments are conducted on this refined dataset of negative reviews that contain these key phrases. We will release these reviews, the extracted events, and the action-problem pairs upon publication.

3.4.1 Event Extraction

Following the steps described in Section 3.3, we extract 1,308,188 events from the reviews. We adopt the Python spaCy library³ for tokenization, part-of-speech tagging, and dependency parsing of the app reviews. The resulting distribution of event labels is shown in Table 3.4.

Table 3.4 Numbers of extracted events with different labels.

| Event label | Count |
|--------------------|-----------|
| <i>main</i> | 396,365 |
| <i>subclause</i> | 385,396 |
| <i>surrounding</i> | 526,427 |
| Total | 1,308,188 |

²<https://apps.apple.com/us/genre/ios/id36>

³<https://spacy.io/>

The events listed in Table 3.5 are extracted from the review in Example 2. Note that the events have been ordered based on the heuristic regarding *when*.

Table 3.5 Events extracted from Example 2.

| ID | Event label | Event phrase |
|-------|--------------------|--|
| e_1 | <i>Surrounding</i> | I ’m going to look for another weather app |
| e_2 | <i>Subclause</i> | (<i>when</i>) I try to scroll thru cities |
| e_3 | <i>Main</i> | It hesitates |
| e_4 | <i>Surrounding</i> | I ’m so irritated with this fact alone . . . |

3.4.2 Event Classification

We conducted three rounds of manual labeling with three annotators that are familiar with text analysis and app reviews. The three annotators were asked to label each extracted event as a USER ACTION, an APP PROBLEM, or NEITHER, as described in Section 3.3. For each round, we randomly selected extracted events from the results in the previous step. In the first two rounds, each annotator labeled all events in a subset, followed by the annotators resolving their disagreements through discussion. In the third round, each event was labeled by two annotators, and the disagreements were resolved by labeling the events as NEITHER. We consider this resolution acceptable, as the NEITHER events are not considered in the event inference task.

Manual labeling. Table 3.6 shows the Cohen’s kappa for each round of manual labeling between each two annotators before resolutions.

Table 3.6 Pair-wise Cohen’s kappa for manual labeling.

| Round | Count | Cohen’s kappa |
|-------|-------|---------------------|
| 1 | 100 | 0.630, 0.502, 0.603 |
| 2 | 100 | 0.607, 0.542, 0.572 |
| 3 | 1,200 | 0.614 |

Considering there are three classes (so agreement by chance would occur with a probability of 0.333), the results show that the annotators had moderate to good agreement over the labels before their

discussions. After excluding some events that were identified by the annotators as having parsing errors or being too short, the resulting dataset contains 1,386 labeled events. Table 3.7 shows the distribution of this dataset.

Table 3.7 Distribution of the manually labeled dataset.

| Event type | Count |
|-------------|-------|
| USER ACTION | 401 |
| APP PROBLEM | 383 |
| NEITHER | 602 |
| Total | 1,386 |

Classification. We adopt the Universal Sentence Encoder in TensorFlow Hub⁴ to encode each event phrase into a vector. Each USE vector is of size 512. As described in Section 3.3, we train two SVM classifiers for a three-class classification. We adopted the SVM implementation of scikit-learn,⁵ which provides an estimate for the probability of a classification. One SVM classifies an event into USER ACTION or other; the other SVM classifies an event into APP PROBLEM or other. For a given event, e , the first SVM yields a probability, u , of e being a USER ACTION, and the second SVM yields a probability, a , of e being an APP PROBLEM. We adopt the following formulae to convert these probability estimates into a three-class probability distribution. Each tuple below is of the form, P_{NEITHER} , P_{ACTION} , and P_{PROBLEM} , which represent the probability estimates of event e being NEITHER, a USER ACTION, or an APP PROBLEM respectively.

If $u \geq 0.5$ and $a \geq 0.5$,

$$P(e) = \left(\frac{2(1-u)(1-a)}{2-u-a+2ua}, \frac{u}{2-u-a+2ua}, \frac{a}{2-u-a+2ua} \right)$$

If $u \geq 0.5$ and $a < 0.5$,

$$P(e) = \left(\frac{1-u}{1+a}, \frac{u}{1+a}, \frac{a}{1+a} \right)$$

If $u < 0.5$ and $a \geq 0.5$,

$$P(e) = \left(\frac{1-a}{1+u}, \frac{u}{1+u}, \frac{a}{1+u} \right)$$

⁴<https://tfhub.dev/google/universal-sentence-encoder-large/3>

⁵<https://scikit-learn.org/stable/>

If $u < 0.5$ and $a < 0.5$,

$$P(e) = \left(\frac{0.5}{0.5 + u + a}, \frac{u}{0.5 + u + a}, \frac{a}{0.5 + u + a} \right)$$

The purpose of this exercise is to convert two probability estimates into a three-class probability distribution via continuous transformation while preserving the results of the original classifiers. An event is classified into the class with the highest probability after this transformation.

We use 90% of the dataset for training and 10% for testing. We report the performance arising from 10-fold cross validation for each classifier. The results are shown in Table 3.8.

Table 3.8 Accuracy of event classification.

| Classification | TF-IDF | USE |
|---|--------|-------|
| USER ACTIONS vs. Others | 81.2% | 86.9% |
| APP PROBLEMS vs. Others | 80.2% | 86.4% |
| USER ACTIONS vs. APP PROBLEMS vs. NEITHER | 71.2% | 82.0% |

We then apply the trained classifiers to the entire dataset of extracted events. Table 3.9 shows the results for the events extracted from Example 2.

Table 3.9 Event classification for events in Example 2.

| ID | Event phrase | $P_1(e)$ | $P_2(e)$ | Prediction |
|-------|--|--------------|--------------|-------------|
| e_1 | I 'm going to look for another weather app | 0.212 | 0.057 | NEITHER |
| e_2 | I try to scroll thru cities | 0.939 | 0.022 | USER ACTION |
| e_3 | It hesitates | 0.034 | 0.705 | APP PROBLEM |
| e_4 | I 'm so irritated with this fact alone ... | 0.036 | 0.080 | NEITHER |

Event pairs. All adjacent and subsequently ordered action-problem event pairs are then collected for event inference. For example, $\langle e_2, e_3 \rangle$ in Table 3.9 is collected accordingly. The total number of extracted event pairs is 85,099. Additional examples (some paraphrasing to save space) for the same app can be found in Table 3.10.

Table 3.10 Extracted event pairs for the Weather Channel.

| User Action | App problem |
|---------------------------------------|------------------------------------|
| (after) I upgraded to iPhone 6 | → this app doesn't work |
| (as soon as) I open app | → takes me automatically to an ad |
| You need to uninstall app | → (before) location services stops |
| (every time) I try to pull up weather | → I get "no data" |
| (whenever) I press play | → it always is blotchy |
| (when) I have full bars | → Always shows up not available |
| I updated my app | → (then) it deleted itself |

To evaluate the effectiveness of CASPAR in extracting action-problem pairs, we selected a random sample of 200 app reviews of rating 1, and asked a human annotator to manually extract such event pairs. Of these 200 reviews, only 63 contain at least one key phrase that we have adopted. Based on whether an event pair has been identified, we compose two confusion matrices for this study, one for all reviews and one for reviews with key phrases only, as shown in Table 3.11.

Table 3.11 Manual verification of CASPAR extraction results.

| | | All reviews | | Reviews w/ key | |
|--------|-----------|-------------|-----------|----------------|-----------|
| | | Human | | Human | |
| | | ID-ed | Not ID-ed | ID-ed | Not ID-ed |
| CASPAR | ID-ed | 13/200 | 1/200 | 13/63 | 1/63 |
| | Not ID-ed | 32/200 | 154/200 | 19/63 | 30/63 |

If we consider the human results as the ground truth, CASPAR has an overall accuracy of 83.5%, a precision of 92.9%, and recall of 28.9%. Of the 45 reviews in which the human annotator has identified event pairs, 32 reviews (71.1%) contain at least one key phrases. We discuss these results in Section 3.5.

3.4.3 Event Inference

We divide the extracted pairs into a training set (90%) and a testing set (10%). We report the accuracy of each method for the event follow-up classification.

To convert each token into vectors, we adopted one of spaCy's pre-trained statistical models for En-

glish, en_core_web_lg⁶, with GloVe vectors [Pennington et al., 2014] trained on Common Crawl⁷ data. Each GloVe vector is of size 300. We implemented the bidirectional LSTM network using TensorFlow.⁸ The size of the hidden layers is 256. An Adam Optimizer [Kingma and Ba, 2015] with learning rate of 0.0001 is used to minimize the sigmoid cross entropy between the output and the target. We trained the model for 20 epochs with batch size of 1.

To improve the quality of the training set, we adopted two types of rules during negative sampling, namely, clustering and similarity threshold. For clustering, we adopted KMeans in scikit-learn to divide all app problem events into two clusters ($k = 2$) based on their cosine similarity. For the similarity threshold method, when choosing a random event as a negative example, the cosine similarity between that event and the follow-up event is restricted to be below the threshold. We experiment with thresholds of 0.5 and 0.25, respectively, and report the performance of the classification. All cosine similarity calculations are conducted on the USE vectors of the events.

The results are shown in Table 3.12. The training set column identifies the method for constructing the negative examples.

Table 3.12 Accuracy of classification of event pairs.

| Classifier | Negative Sampling Strategy | Accuracy |
|--------------------|----------------------------|----------|
| Baseline | Random | 55.3% |
| USE+SVM | Random | 66.0% |
| Bidirectional-LSTM | Random | 67.2% |
| Baseline | Clustering | 58.5% |
| USE+SVM | Clustering | 67.8% |
| Bidirectional-LSTM | Clustering | 67.8% |
| Baseline | Similarity < 0.5 | 60.7% |
| USE+SVM | Similarity < 0.5 | 68.1% |
| Bidirectional-LSTM | Similarity < 0.5 | 69.1% |
| Baseline | Similarity < 0.25 | 72.9% |
| USE+SVM | Similarity < 0.25 | 82.8% |
| Bidirectional-LSTM | Similarity < 0.25 | 79.6% |

⁶<https://spacy.io/models/en>

⁷<http://commoncrawl.org/>

⁸<https://www.tensorflow.org/>

| |
|--|
| <p>USER ACTION: I try to scroll thru cities Ground truth: it hesitates Inferred APP PROBLEMS:</p> |
| <p>Unanimously judged plausible</p> |
| <p>a_1 it says there is an error a_2 it loads for what seems like forever a_3 it tells me the info for my area is not available a_4 the app crashes a_8 it reset my home location</p> |
| <p>Conflicting judgments</p> |
| <p>a_6 it rarely retrieves the latest weather without me having to refresh a_9 it goes to a login screen that does not work</p> |
| <p>Unanimously judged implausible</p> |
| <p>a_5 the radar never moves , it just disappears a_7 I rely heavily on it & for the past month , it says temporarily unavailable a_{10} Radar map is buggy – weather activity stalls , appears , then disappears</p> |

Figure 3.2 Inferred app problem events to follow-up a user action (threshold = 0.75).

For event inference, the input should be a USER ACTION. We rank all possible APP PROBLEM events by their probabilities of being a valid follow-up of the input, and consider the top-ranked ones as the results of the event inference. We choose a similarity threshold of 0.75 to diversify the inferred events. We consider only app problems extracted from reviews of the same app as the input.

Figure 3.2 shows the top-10 app problem events for the user action *I try to scroll thru cities* by the trained bidirectional LSTM network (trained with improved training set with Similarity < 0.25). The inferred event *it loads for what seems like forever* presents the most similar meaning to the ground truth.

We ask three human annotators to independently label each of these output app problems events based on whether it is plausible that it follows or is caused by the user action. All three annotators labeled a_1 , a_2 , a_3 , a_4 , and a_8 as plausible (50%), and a_5 , a_7 , and a_{10} as implausible (30%). They disagreed over the other two events.

3.5 Discussion

We presented CASPAR, a method for collecting and analyzing app problem stories in user-generated app reviews. We now discuss its merits and limitations.

3.5.1 Merits

Previous studies have been focused on text analysis of app reviews on the review level, the results of which are collections of reviews that require further investigation by developers. CASPAR dives deeper to the event level, and can extract and infer app problems, which can help developers improve their applications by addressing and avoiding the problems.

App problem event pairs. By extracting and collecting action-problem pairs from app reviews, CASPAR presents application problems that require attention to the developers in a readable way. The extracted event pairs describe the apps' unexpected behaviors as well as the context in which they occur, i.e., the users' actions that have triggered them. CASPAR can be applied selectively, such as to reviews for certain apps over a specified period of time, so that the extracted event pairs are more appealing to a particular audience of developers. By answering RQ_{pair} , we have shown that CASPAR extracts targeted event pairs effectively, and the classification of event types yields high accuracy.

Event inference. By conducting inference on the extracted event pairs, we endeavor to establish a connection between user actions and app problems. Inferring possible app problems based on a user action can help developers preemptively avoid problems or failures of user experience. By addressing $RQ_{\text{infer-pair}}$, we have shown that CASPAR yields satisfactory performance when determining whether an app problem is random or a valid follow-up of a user action. In addition, CASPAR generates plausible follow-up app problems to user actions.

3.5.2 Limitations

CASPAR is not without its limitations.

Key phrases. We target only those app reviews that contain certain selected key phrases that indicate the temporal ordering of events. Using key phrase search helps limit the size of the resulting dataset. We use these key phrases because we need the extracted events to be temporally and causally related. Further investigation on how to extract related events is required, which we leave to future work. In fact, during the manual verification of the performance of event pair extraction, the human annotator identified event pairs that are linked by key phrases like *ever since*, *if*, and *any time* that were missing from our list. Experimenting with key phrases that indicate conditional or causal relations, such as *if* and *because*, is a

promising direction. Additional key phrases may be found in a semi-supervised fashion.

Text quality. CASPAR extracts events using a part-of-speech tagger and a dependency parser, which are not reliable when the texts have typos, missing punctuation, or grammatical errors. During the manual verification, human annotators have identified event pairs that CASPAR is not able to parse. For example, one review says *App is now crashing everyone I tap a story*, where the typo causes CASPAR to miss the event pairs. Consider the review in Example 4 (for The Weather Chanel).

Example 4

★☆☆☆☆ username3, 05/01/2014

Terrible

Worse than ever. They took an amazing weather app & turned it into crap! U add a location it's automatically added to favorites. Very annoying & time consuming when u are traveling to delete locations. Very busy presentation & not as user friendly. Not a big fan, thanks for NOTHING on the new update!

CASPAR identifies the underlined sentence as one event, which is classified as NEITHER, since the sentence is missing a conjunction. However, the human annotator can easily identify the two events in this sentence. We estimate the quality of user-generated texts, or the lack thereof, is the most important reason for the low recall of CASPAR in extracting event pairs. Our future work includes extraction methods that counter the errors of the employed parser.

Manual labeling. Regarding manual event classification, the annotators achieved only moderate to good agreement, and the agreement does not improve with additional iterations and discussions. We have excluded data points on which the annotators disagreed by labeling them as NEITHER, which limited the number data points available for event inference.

We identify the following reasons for the disagreement among annotators. First, user-generated texts are prone to typos and grammatical errors, which cause a parser to produce erroneous events. For example, one common challenge is the omission of proper punctuation. The key sentence in Example 4 is extracted as one event which can be both user action and app problem. Second, events have been stripped out of context—some of them may lose critical information. For example, the event *reset my phone* is usually a user action, but the annotators could not be sure without context. Example 5 shows the entire review (for Messenger⁹).

⁹<https://apps.apple.com/us/app/messenger/id454638411>

Example 5

★★★★★ username4, 01/22/2016

Great but.....

This is a great app. But it has been crashing before it can load. Reset my phone, got the new update for iOS and it just keeps crashing. Not sure if I'm the only one with this problem.

Third, there are always unforeseen cases where annotators may disagree. For example, the event *switching between apps doesn't make anything faster* can be interpreted as an app problem or irrelevant.

Action-problem pairs. CASPAR targets only those event pairs that describe single iterations of user-app interaction. However, this type of interaction does not cover all scenarios of app problems. Some app problems may occur without users' actions. In fact, most app reviews that describe bug reports do not describe in detail the users' actions that caused the unexpected behaviors. We did not focus on such reviews. Although such reviews may mention serious problems that need developers' attention, they do not provide insightful information for developers to address the problems.

Meanwhile, user-app interaction may include a longer sequence of events than just a pair. For example, the review in Example 5 describes multiple user actions, none of which seemed to have caused the observed problem. However, this review does report a bug that requires developers' attention. The information contained in this review is also potentially useful to the developers.

Many app reviews additionally describe user expectations, user reactions to app problems, or misuses of the apps. We leave the extraction of other formats of user-app interaction to future work.

Event inference. The proposed classification of event pairs yields moderate results. One major reason is that there are quite a few duplicate app problems. For example, the events *app crashed* and *app freezes* are common occurrences. A random app problem, which counts as a negative instance, is likely to be semantically similar to the actual app problem. We have proposed methods to improve the training set, which has improved the performance of the classifiers evaluated.

Homogeneity among extracted events interferes with inference of app problems. The top-ranked events can be similar to each other. To mitigate this problem, we have excluded app problems that are similar to event phrases that are already inferred.

A second possible reason for the moderate performance is that the training set is fairly small, especially for a deep learning model. As we mentioned above, CASPAR adopts fairly strict key phrase search to ensure the quality of extracted pairs. We have collected 85,099 event pairs for 151 different apps, which may not be large enough for the bidirectional LSTM network. We plan to apply CASPAR on app reviews from other application distribution platforms to extract and collect more event pairs. We will

also investigate other reliable techniques for the extraction, as future work.

Third, we have simplified event inference to an event follow-up classification, which limits the inference to app problem events that have been reported. To fully infer follow-up events of user actions, we may need to build more sophisticated inference models, such as sequence to sequence models [Sutskever et al., 2014]. We leave the investigation of such models to future work.

3.5.3 Threats to Validity

The first threat is that our annotators may lack the expertise in the software development of iOS applications. Our annotators are familiar with or experts on concepts of NLP and machine learning, but they may not possess enough experience in industry, which may have affected their disagreement over the labels.

Second, all of our labeling and training have been conducted on reviews with 1-star ratings from Apple’s App Store. Our work may not be generalizable to other reviews where the descriptions of apps’ behaviors are not limited to app problems.

Third, in the event inference step, we improve the training set by imposing certain rules regarding the random event. However, we adopt USE vectors for the clustering and calculating similarity, which may have affected the performance of the classification models that leverage the same vectors. We can mitigate this threat by using a different sentence embedding technique for the creation of the training set.

3.6 Conclusions and Future Work

We presented CASPAR, a method for extracting, collecting, and analyzing app problem stories, as action-problem event pairs. CASPAR adopts heuristics and classification and effectively extracts ordered event pairs. By extracting and collecting such app problem instances, CASPAR helps developers by presenting readable reports of app issues, which require their attention. CASPAR extracts high-quality action-problem pairs with a high precision. In addition, CASPAR trains an inference model with the extracted event pairs, leveraging NLP techniques and deep learning models, and infers possible follow-up app problems based on user actions. Such inference allows the developers to preemptively address possible app issues, which helps ensure the quality of the applications.

By presenting CASPAR, we emphasize the significance of conducting research into user-reported stories in app reviews. These stories, though not without typos and grammatical errors, are valuable deployment logs reported by real users of the applications. Extracting structured stories from user-generated texts and making practical use of them remain challenges that call for deep thinking and more investigations.

Future work includes applying more heuristics for event pair extraction, exploring extraction methods that rely less on parsers, studying other types of user-app interaction, and investigating other suitable models for the event inference task.

CHAPTER

4

EXTRACTING TARGETED STORIES

We address RQ_{story} in the setting of user-app interaction stories in app reviews. A developer’s motivations in mining app reviews include three major goals: understanding app problems, user retention, and user expectation. We understand an app review as telling one or more stories of how a user interacted with the app. As storytellers, users do not follow a fixed template. Instead, they tell stories with different structures for different purposes. To report bugs, reviewers describe context, their actions, and apps’ problems. To express expectations, they talk about their intentions and reactions to apps’ behaviors. We investigate how the different story structures seen in app reviews can help developers on their specific goals.

We propose SCHEPURE, a framework for analyzing story structures as patterns of event types in app reviews. SCHEPURE provides a novel method of profiling and collecting app reviews. SCHEPURE extends CASPAR by targeting stories of any lengths. First, SCHEPURE extracts and classifies events in user-app interaction stories from app reviews, similar to LESBRE and CASPAR. Second, SCHEPURE automatically determines the sequential relations between the extracted events via heuristics and a machine learned model, and combines the related events into stories. Third, SCHEPURE enables collecting stories based on their structures. Via an empirical study, we show that stories retrieved by SCHEPURE are more helpful to developers with certain goals than randomly selected stories.

4.1 Introduction

Users of mobile apps tell stories of user-app interactions in app reviews [Guo and Singh, 2020]. We have found that user stories in app reviews are of great structural heterogeneity. Users describe their intentions, actions, and reactions with regards to the apps’ functionalities, as well as the behaviors of the apps. With different experiences users encounter, the structures of user stories notably differ from each other. The analysis of these structures can help developers improve app quality and user experience by understanding users’ expectations, the way they use the apps, and the scenarios where the apps fail to meet their expectations.

As we mentioned in previous chapters, we consider a *story* as a sequence of events ordered by their occurrence, which is a common practice in the area of natural language processing (NLP). In the context of information extraction from app reviews, there are several types of events that are of great importance. Consider the example review in Example 2 in Chapter 1. The underlined events are of different types.

CASPAR considers only user *actions* and app problems. A user *action* event describes how the user interacts with the app, sometimes based on the user’s intention, such as *I press done* in Example 2. In this work, we consider general app *behavior* events instead of *problems*, which is the most common type of events in app reviews. A behavior event describes how an app acts, usually caused by or in response to a user action. This event type also includes an app’s lack of behavior when a behavior is expected. As we find in the previous chapter, in negative reviews, an app behavior is typically a problem where the app behaves unexpectedly or erroneously, and the described user actions provide details regarding the scenario where the problem occurs.

We extend CASPAR by considering three more types of events in app reviews. A user may evince a *reaction* to an app’s behavior. A reaction can be a forced action by the app’s behavior, an attempt to solve a problem, or the act of departing from the app, such as *re-downloading the app* in Example 2. In addition, reviewers may narrate *context* events, providing supporting information to the points they want to make, such as the models of their phones or events about their operating systems. We call these five types of events *target* events, while others are *nontarget*.

We define a story *structure* as a sequential pattern of event types of a story. We consider the *target* events, and not the *nontarget* event, as parts of the story structures.

User-app interaction stories may be unique to each user, so the stories users tell may follow different structures. The story in Example 2 exhibits a structure of $\langle \text{intention} \rightarrow \text{action} \rightarrow \text{behavior} \rightarrow \text{reaction} \rightarrow \text{behavior} \rangle$ (IABRB). A review may contain multiple stories, and a story may include multiple events with the same type. A *substructure* is a sequential pattern that is part of a story structure, e.g., $\langle \text{intention} \rightarrow \text{action} \rangle$ or $\langle \text{behavior} \rightarrow \text{reaction} \rangle$. A substructure can represent a sequence of events that constitute a meaningful snippet within a complete interaction story.

Stories with different structures may be of interest to developers with different goals for information extraction. Developers who wish to glean bug reports may focus on stories with structures like $\langle \text{action} \rightarrow \text{problem} \rangle$ [Guo and Singh, 2020]. Stories with an $\langle \text{intention} \rightarrow \text{action} \rangle$ structure may provide insights into users’ mental model and expectations when using the app. A collection of $\langle \text{problem} \rightarrow \text{reaction} \rangle$ stories for an app may help its developers understand the user retention situation.

We propose the task of obtaining structures of user stories in app reviews, and collecting stories based on their structures. We aim to help developers understand user-app interaction stories, and more easily collect useful reviews based on targeted types of stories. To this end, we propose SCHEPURE, a framework for analyzing story structures in app reviews and collecting app reviews that follow the targeted story structures. SCHEPURE addresses the following research questions.

RQ_{event} How effectively can we extract events and determine their types in app reviews?

RQ_{relate} How effectively can we identify relations between events, so that we can order and combine them into stories?

RQ_{collect} What kind of story structures and substructures are the most common in app reviews?

Accordingly, SCHEPURE includes three steps. First, SCHEPURE leverages NLP techniques to extract events from app reviews and classify their types, similar to LESBRE and CASPAR. Second, we adopt heuristics and train classification models to learn the relations between events, and automatically identify the sequential order of events in a story. Finally, based on the extracted stories and their structures, SCHEPURE enables the search of app reviews and user stories by their story structures. We conduct frequent pattern mining to most frequent story structures and substructures in app reviews.

We address **RQ_{event}** and **RQ_{relate}** by reporting SCHEPURE’s accuracy in classifying event types and identifying event relations. We address **RQ_{collect}** by presenting the common story structures and substructures that SCHEPURE has mined from the user stories in app reviews. Additionally, to prove the effectiveness of SCHEPURE, we conduct a small-scale human study, and ask annotators to rate the helpfulness of a set of short stories toward the understanding of app problems, user retention, and user expectation. This set of stories includes stories with certain substructures, retrieved by SCHEPURE, as well as random stories.

SCHEPURE offers a novel tool of systematically analyzing and collecting structured user stories from app reviews. App reviews are home to a cornucopia of interesting user stories that are heterogeneous in structure, making their understanding and information extraction difficult for app developers. SCHEPURE summarizes straightforward event-type structures of user stories, enabling developers to access the stories in which they are interested. SCHEPURE also identifies events or event sequences of specific types from these user stories, helping a developer extract information that is valuable for the improvement of their

app's functionality, performance, and use experience. With proper substructures for searching, stories retrieved by SCHEURE are significantly more helpful than average. In addition, SCHEURE is able to find common story structures and substructures in user stories, bringing novel and deep understanding on app reviews.

4.2 Related Work

Research on app reviews has been moving from applying generic natural language processing (NLP) techniques on entire reviews to extracting specific information with greater finesse. This study targets useful events and stories the users report in app reviews. We now introduce related work on app review analysis and event relations.

4.2.1 App Review Analysis

Although app reviews may include valuable information for app developers, not all app reviews are informative [Maalej et al., 2016]. Earlier studies targeted the identification and classification of useful reviews, leveraging text classification techniques on entire reviews. Maalej and Nabil [2015] introduce four types of app reviews, i.e., bug reports, feature requests, user experiences, and text ratings, and classify app reviews using NLP techniques. Ciurumelea et al. [2017] define a taxonomy of specific categories regarding mobile apps, such as performance, resources, battery, and memory. Based on this taxonomy, they leverage NLP techniques to classify reviews, as an automatic method for organizing reviews. Instead of targeting all reviews, McIlroy et al. [2016] argue that reviews with negative ratings i.e., one-star or two-star ratings, are more related to negative issues. They apply multilabel classification to identify with what issues a negative review is associated. Dąbrowski et al. [2019] adopt text classification techniques to retrieve reviews based on the features. Their tool helps developers analyze users' requests and sentiment on different features of the apps.

Identifying reviews that contain useful information saves time on manual filtering for developers, but taking advantage of the large amount of whole reviews remains cumbersome. Recent work focuses on the extraction of useful information in a compact form. Di Sorbo et al. [2016] introduce a summarizer for user reviews that can condense the information residing in the large amount of reviews a popular app receives. Such a summarizer substantially reduces the analyzing time for developers. Jha and Mahmoud [2019] automatically capture non-functional requirements (NFRs) in different categories like performance and usability from app reviews. Truelove et al. [2019] leverage topic modeling to identify user issues, such as connectivity, timing, and updates, in app reviews for Internet of Things (IoT) systems. Guo and Singh [2020] extract user-action app-problem event pairs from app reviews. The collected mini stories are easy

to read and analyze for a developer who wish to fix their app’s problems.

4.2.2 Event Relations

We target user stories described in app reviews, which are sequences of events. Unlike traditional stories, app reviews include a large amount of text that is not part of a story, and may not describe events sequentially. To combine related events into stories, we need to determine the relations between events, such as their sequential order. We now introduce studies on the topic of event relations.

Earlier studies target temporal relations of events based on how they appear in text, using heuristics or unsupervised methods. Mani et al. [2006] use rules and axioms to infer the temporal relations between event. Mirroshandel and Ghassem-Sani [2012] extract temporally related events from news articles with event features such as tense, polarity, and modality, as well as event-event features, such as prepositional phrases. Ning et al. [2018b] facilitate the extraction of temporal relations with a knowledge base of such relations collected from widely available sources such as news articles. Causal relations between events can be extracted based on events’ temporal relations. Hu and Walker [2017] extract frequent event pairs from movie scripts, and infer their *causal potentials* [Beamer and Girju, 2009] by comparing the frequencies of a pair and its reverse pair. Based on similar ideas, Hu et al. [2017] extract and infer fine-grained event pairs that are causally related from blogs and film descriptions. Ning et al. [2018a] propose a framework that jointly reason about and extracts temporal and causal relations between annotated events from texts, and improve the extraction of both relations from text.

Recent studies strive to understand the relations between events at a deeper level and with less reliance on context. Rashkin et al. [2018] investigate the intents and reactions of a single event, and publish Event2Mind, a dataset of 25,000 events along with commonsense intents and reactions collected via crowdsourcing. ATOMIC [Sap et al., 2019] extends Event2Mind by incorporating more *inferential dimensions* along which follow-up or preceding events can be inferred, and includes commonsense knowledge for 24,000 base events. Both of these studies have proposed models to infer events based on their relations. BERT [Devlin et al., 2019] is a popular transformer-based language model that provides a solution for next sentence prediction (NSP): to predict whether a second sentence is the next sentence of the first. Even though BERT’s NSP model cannot be directly used to predict the relations between events, it shows that concatenation is a viable way of dealing with two input sentences. We borrow ideas from the above studies, and adopt both heuristics and classification models to determine the relation between two events.

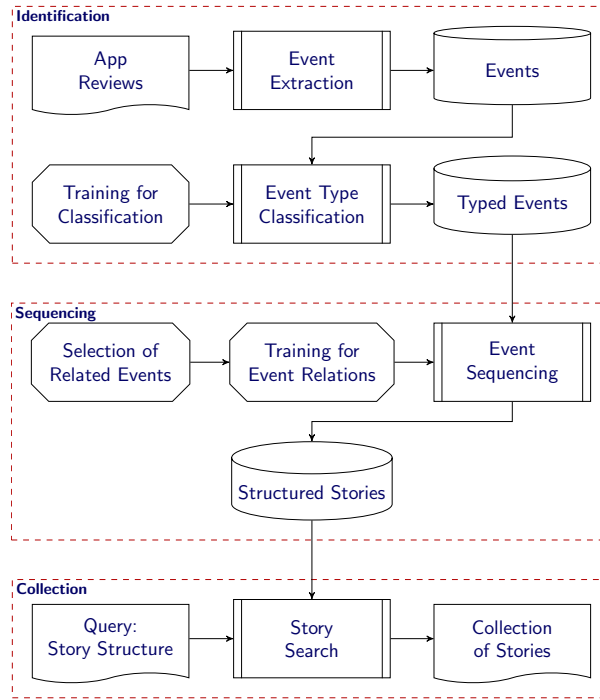


Figure 4.1 An overview of SCHETURE.

4.3 Method

SCHETURE includes three components, as shown in Figure 4.1. First, SCHETURE extracts events from targeted app reviews and identifies their types. SCHETURE adopts natural language processing (NLP) techniques for the extraction, and trains the classification model based on human annotations. Second, SCHETURE combines heuristics and a classification model to determine the relations between two events. Events are ordered and sequenced to form structured stories. The classification model is trained on related event pairs that are selected based on the heuristics. Third, SCHETURE enables the search on the structured stories, and collects the target stories based on the query. In addition, we present SCHETURE’s method of mining frequent story structures and substructures in this section.

4.3.1 Dataset: Targeted App Reviews

Continuing the data collection process in the previous chapter, we collected 7,679,543 reviews, including text and star ratings, received by 182 apps from the period of 2008-07-10 to 2019-02-04, by crawling the

app reviews pages on Apple App Store.¹ Table 4.1 lists the counts of reviews with different ratings.

Table 4.1 Number of reviews grouped by ratings.

| Rating | Count | Included in our analysis |
|--------|-----------|--------------------------|
| ★☆☆☆☆ | 1,620,505 | Yes |
| ★★☆☆☆ | 498,437 | Yes |
| ★★★☆☆ | 579,175 | No |
| ★★★★☆ | 1,037,368 | No |
| ★★★★★ | 3,944,058 | No |

Based on the intuition that behaviors that are unexpected by users or developers are more informative to developers than the designed behaviors, we focus on stories in negative reviews, namely, one-star and two-star reviews [Guo and Singh, 2020; McIlroy et al., 2016; Pagano and Maalej, 2013]. Therefore, the total number of targeted reviews in our study is 2,118,942.

4.3.2 Event Identification

To identify target events from app reviews, we extract event phrases from the reviews using NLP techniques, and determine the type of each extracted event through classification. We conducted manual labeling to build a training set for the classification model.

4.3.2.1 Event Extraction

We define an *event* as something described by an *event phrase* [Guo and Singh, 2020; Rashkin et al., 2018; Sap et al., 2019] in an app review, namely, a piece of text (typically a sentence or a clause) rooted in a target verb [de Marneffe and Manning, 2008]. Similarly to our previous event extraction process, we adopt *Part-of-Speech (POS) tagging* and *Dependency parsing* to extract event phrases. We adopt the POS tagger and dependency parser implemented in spaCy² to extract event phrases.

4.3.2.2 Manual Labeling

To determine the types of the extracted events, we need a training set of labeled events to train a classifier. We consider the following five types of events as *target* events, and all other events are classified as the

¹<https://apps.apple.com/us/genre/ios/id36>

²<https://spacy.io/>

NONTARGET type (**N**):

(I) INTENTION: The user intends to fulfill a need or bring about an app behavior. We assume that as of the reference time of the utterance, the user has not taken an action or achieved the intention.

(A) ACTION: The user takes or tries taking an action within the app. As of the reference time of the utterance, the user has taken at least part of the described action.

(B) BEHAVIOR: The app exhibits a behavior, typically in reaction to the user’s action. The behavior can be a non-behavior, such as “app does not respond to user’s action.”

(R) REACTION: The user reacts to an app behavior, including attempts to solve a problem and being forced to take an action in response to a problem.

(C) CONTEXT: Other contextual events that are related to the above types. They are typically mentioned to support the reviewer’s claim.

The classification of certain events, such as REACTION, may rely on the context in which they appear. Thus, during the annotations, an annotator is shown the event phrase along with the text covering its preceding and following events.

User-generated stories are a hodgepodge of events, and determining event types can be challenging. In Table 4.2, we list guidelines for some commonly seen event themes that are difficult to classify. However, we leave the final verdict to the annotators.

Based on this classification, we conducted a small-scale investigation on a dataset of 300 randomly selected events. The number of events in each type is shown in Table 4.3. It is notable that the distribution of event types is skewed.

To sample a more balanced dataset for the final annotation, we leveraged the 300 labeled data points as a seed dataset. We first encoded each event into a vector using the Universal Sentence Encoder (USE) [Cer et al., 2018]. USE is a transformer-based sentence embedding model that has been shown to be able to capture rich semantic information of sentences. USE can achieve state-of-the-art performance for tasks like text classification and clustering [Yang and Ahmad, 2019]. We then determined the potential type of each event using k-nearest neighbors (KNN, $k = 7$), where the distance between two events is determined by the cosine similarity of their USE vectors. We randomly sampled 500 events in each type, including the NONTARGET type, resulting in a dataset of 3,000 events.

We conducted a crowdsourcing project on Amazon Mechanical Turk³ (MTurk) to obtain the labels for the types of the 3,000 events. We provided instructions for the annotation, including the definitions of

³<https://www.mturk.com/>

Table 4.2 Annotation Guidelines for some common events.

| Event Type | Event Theme |
|------------|--|
| ACTION | <i>I accidentally did something in app</i> <i>Other users did something in app that affected me</i> |
| BEHAVIOR | <i>Nothing changed/helped after I tried something</i> <i>I have to do something because of app design</i> |
| REACTION | <i>I have to do something because an app problem</i> <i>I am done with this app because of problem</i> <i>I will do something in response to problem</i> <i>I refuse to do what was asked</i> <i>I am still waiting for things to change</i> |
| CONTEXT | <i>Other people are having the same issue</i> <i>I get something (a message, a notification, etc.) from/in app (and it is not a problem)</i> <i>App is updated</i> <i>I forgot to do something</i> <i>I decided to use this app</i> <i>I used to do something about the app</i> Events about device type and OS version Contextual events about security issues |
| NONTARGET | <i>I get the developers are trying to do something</i> <i>Opinion: Developers need to do something</i> <i>Opinion: I used to love this app</i> <i>Opinion: I do not want something</i> Requests or questions Rating related events Hypothetical events |

the event types and respective examples. Each event was labeled by two different crowd workers, and the disagreements were resolved by one of the authors. The collection and public release of this dataset have been approved by our university’s Institutional Review Board (IRB). The final distribution of this labeled dataset, as shown in Table 4.3, is more balanced than that of the seed dataset.

Table 4.3 Distribution of event types in labeled datasets.

| Event Type | Seed Dataset | Final Dataset |
|------------|--------------|---------------|
| INTENTION | 23 (7.67%) | 263 (8.77%) |
| ACTION | 32 (10.67%) | 422 (14.07%) |
| BEHAVIOR | 101 (33.67%) | 741 (24.70%) |
| REACTION | 37 (12.33%) | 531 (17.70%) |
| CONTEXT | 58 (19.33%) | 472 (15.73%) |
| NONTARGET | 49 (16.33%) | 571 (19.03%) |
| Total | 300 | 3,000 |

4.3.2.3 Event Type Classification

Determining the type of an event is a six-class classification. We first convert event phrases into vectors using the USE, and then apply classification models on the vectors. The classification models that we experiment with include k-nearest neighbors (KNN), Support Vector Machines (SVM), Decision Trees (DT), and Multi-Layer Perceptron (MLP).

Additionally, as the context of an event phrase is considered in the annotation process, we experiment with classification models that leverage this contextual information. As we mentioned before, we consider the two segments of text that cover a preceding event and a following event, respectively, as the context of an event. We convert these two text segments into vectors using USE, and concatenate them to the vector of an event. The classification models are then applied to the concatenated vector.

We address $\mathbf{RQ}_{\text{event}}$ by reporting the performance of the event type classifiers. We choose the one that yields the highest accuracy and apply it on all extracted events to determine their types. The identified target events are considered in the following components of SCHEURE. Reviews that contain at least one target event are referred to as *target* reviews.

4.3.3 Event Sequencing

Of the target reviews, many describe only one event, typically a bad app behavior in negative reviews. These “simple” stories can be collected directly for analysis. However, the majority of the target reviews are “complex” and include multiple events. Although it is natural for storytellers to describe events in the order in which they happen, such *occurrence order* is not always the same as the order in which events appear in text, i.e., *discourse order*. Additionally, it is not uncommon for a reviewer to describe multiple stories in a review. Example 6 shows a review (for the Snapchat app) with large complexity. Target events and their types are marked.

Example 6

☆☆☆☆☆ username5, 06/10/2014
HATING SO MUCH LATELY!
 I HATE how in iphones you can not zoom in to record a video_{BEHAVIOR}. If you zoom in and try to record_{ACTION} it goes back to normal_{BEHAVIOR}. How ANNOYING! I also HATE how when someone sends me a conversation_{ACTION} my music will stop playing_{BEHAVIOR} because I opened what they sent me_{ACTION}. It's not a snap necessarily_{CONTEXT} it's a simple conversation_{CONTEXT}. Also my snapchat sometimes says like memory full_{BEHAVIOR} when I try to take or record a snapchat_{ACTION}. It's so ANNOYING.

This review provides three short stories, each describing a bug in the app, and the discourse orders in the last two stories are different from their occurrence orders. For example, in the second story, the order in which the events occurred was: \langle someone sends me a conversation \rightarrow I opened what they sent me \rightarrow my music will stop playing \rangle . This step seeks to determine whether two events are from the same story, and, if yes, their occurrence order. Thus, we can combine the related events into stories in their occurrence order.

We assume that events in the same sentence belong to the same story, and sentences that are separated by k ($k \geq 3$) NONTARGET events are from different stories. We adopt heuristics based on language cues to determine the orders between events from the same sentence. If there is no listed language cue between event phrases from the same sentence, we order them as they appear in the text. We include two additional heuristics for sentences that are adjacent to each other. Table 4.4 shows all the heuristics we adopt in this study (\rightarrow indicates the occurrence order between events, and [SEP] marks the sentence boundary).

Table 4.4 Heuristics to determine event relations.

| Event Order | Sentence Structure |
|-----------------------|---|
| $e_1 \rightarrow e_2$ | e_1 , before / until / then e_2 e_1 [SEP] And then e_2 |
| $e_2 \rightarrow e_1$ | e_1 , after / when / whenever / every time / as soon as e_2 e_1 , if / because e_2 |
| Separate | e_1 [SEP] Also / Additionally e_2 |

Event relation classification. These heuristics cover only a portion of the extracted events. For the remainder, we frame the event sequencing problem as a classification problem on two event phrases: given a pair of events, e_1 and e_2 , where e_2 appears after e_1 in the text, does e_2 occur before e_1 , after e_1 , or in a separate story from e_1 ? We first train a model on this event relation classification task. We then combine this model with the heuristics to determine the relation between every event and its preceding event in the text. In this fashion, we can sequence all events in a review into stories.

As a training set for such a classifier, we glean related and unrelated event pairs using the heuristics listed in Table 4.4, with the language cues removed. A classifier should be able to determine event relations based solely on the semantic meanings of the events.

We experiment on different classification methods. Since this task has two inputs, we first encode the event phrases into vectors, and then concatenate them into a large vector as the input to a classifier. We experiment with SVM and MLP for this classification. For encoding the event phrases, we experiment with USE, average GloVe [Pennington et al., 2014] vector, and average Word2Vec [Mikolov et al., 2013] vector. Alternatively, we convert each word in the two events into a vector using GloVe and Word2Vec, and employ a sequential model, Long Short-Term Memory (LSTM) [Hochreiter and Schmidhuber, 1997] network, for the classification. Moreover, BERT [Devlin et al., 2019] is a transformer-based NLP technique that supports the input being two sentences. We fine-tuned a pre-trained BERT model⁴ for the event relation classification task. We report and compare the performance of different models. The model with the highest accuracy will be chosen to sequence all extracted event phrases. The extracted stories, i.e., sequences of ordered events, will be used for the following component of SCHEURE.

We address $\mathbf{RQ}_{\text{relate}}$ by reporting SCHEURE’s accuracy on event relation classification.

4.3.4 Story Collection

In previous steps, SCHEURE is able to extract stories, i.e., sequences of events, and their structures as patterns of event types. We now describe how SCHEURE collects stories based on their structures. In this component, we make the following assumptions:

NONTARGET events do not contribute to the structure of a story, except for being separators from other stories;

CONTEXT events can appear in any part of the story in terms of story structure;

Adjacent events of the same type are potentially a coherent chain of events, and can be considered collectively.

⁴<https://huggingface.co/bert-base-uncased>

Based on these assumptions, we ignore NONTARGET and CONTEXT events in the collection process. We mark the same event type occurring in adjacent events with a plus sign. Thus, the stories in Examples 1 and 2 can be represented by the patterns in Table 4.5.

Table 4.5 Story pattern in the examples.

| Story | Review | Pattern |
|-------|-----------|----------------|
| s_1 | Example 1 | I, A, B, R+, B |
| s_2 | Example 2 | B, A, B |
| s_3 | Example 2 | A+, B |
| s_4 | Example 2 | A, B |

After converting the story structures into such patterns, we can search stories based on them. For example, if we search the pattern $\langle \text{ACTION} \rightarrow \text{BEHAVIOR} \rangle$ to gather stories about app problems caused by user actions, we would collect all four stories. If we search the pattern $\langle \text{BEHAVIOR} \rightarrow \text{REACTION} \rangle$ to understand users reactions to app behaviors, story s_1 would be retrieved.

We count the number of stories in each different structure, and present the most common ones. In our counting, if the story structure contains a repetition of event types, it is counted twice, both as a structure with and without repetition. For example, a story with the structure A+B is counted toward both the structure A+B and AB. The structure AB appears in two stories in Table 4.5, which makes it a common structure.

Each full story pattern contains one or more snippets of smaller patterns, i.e., story substructures. We investigate the most common substructures. We treat the collection of frequent story substructures as a sequential pattern mining problem. We adopt the Generalized Sequential Pattern (GSP) [Srikant and Agrawal, 1996] algorithm to mine the frequent story patterns. Similar to our structure counting process, our mining process differs from the standard GSP only in that the repetition of event types is counted twice. The pattern AB appears in all four stories in Table 4.5, and is extracted as a frequent pattern.

We address $\mathbf{RQ}_{\text{collect}}$ by presenting the most common story structures and substructures discovered by SCHEURE.

4.3.5 An Empirical Study

To show that stories with certain substructures are more helpful to developers with a particular goal, we conduct a small-scale human study to investigate the helpfulness of user stories extracted from app reviews. Leveraging SCHEURE, we collect 200 stories from app reviews for the Snapchat app with

different event patterns for searching. We retrieve 25 stories for each of the following target patterns, A+B+, C+B+, B+R+, and I+A+. We then randomly select 100 stories as a control group. Note that a story may contain multiple target patterns, including randomly selected stories. In fact, 78.0% of the stories contain at least one BEHAVIOR event.

We employ five graduate students majoring in Computer Science who are familiar with Snapchat and software development. The stories are divided among the annotators, such that each story is investigated by two people. We ask the annotators to rate each story in terms of its helpfulness toward the understanding of app problems, user retention, and user expectation. They are asked to rate the helpfulness of a story on a Likert scale, where 5 means very helpful, and 1 means not helpful at all. We report the average helpfulness scores of each target pattern toward the three developer goals. We show the effectiveness of SCHEPURE by showing the significant improvement of helpfulness scores over randomly selected stories.

4.4 Results

We applied SCHEPURE on the 2,118,942 negative reviews as described in Section 4.3.1. We address **RQ_{event}**, **RQ_{relate}**, and **RQ_{collect}** by reporting SCHEPURE’s performance and results in its three parts.

4.4.1 Event Identification

We applied the event extraction process on all reviews, and extracted 9,305,505 event phrases. Since we considered all verbs in the text, all potential event phrases are extracted. We can answer **RQ_{event}** by reporting the performance of event type classification. User generated text tends to contain a large amount of typos and grammatical errors. The text quality of app reviews did affect the performance of the dependency parser and, therefore, the event extraction. We discuss this problem in Section 4.5.

As we mentioned in Section 4.3, we considered KNN, SVM, DT, and MLP, both with (“context”) and without (“event”) the context information for the classification of event types. We report and compare their performance from a 10-fold cross validation. We adopted their implementations of scikit-learn.⁵ For each model, we experimented with different parameters, and only report the results with the best parameters. In the KNN model, $K = 7$. We adopted the RBF kernel for SVM. For decision trees, the maximum depth was seven. The intermediate layer size of MLP_{event} was 55 and that of $MLP_{context}$ was 96.

Additionally, we report the precision and recall of the event identification process by considering target events as relevant, and NONTARGET events as irrelevant. Table 4.6 shows the performance of each classification model.

⁵<https://scikit-learn.org/stable/>

Table 4.6 Performance of event type classification.

| Model | Accuracy (6-class) | Precision | Recall | F-1 Score |
|------------------------|-----------------------|-----------|--------|-----------|
| KNN _{event} | 0.661 | 0.922 | 0.951 | 0.936 |
| SVM _{event} | 0.741 | 0.956 | 0.932 | 0.944 |
| DT _{event} | 0.539 | 0.896 | 0.906 | 0.901 |
| MLP _{event} | 0.717 | 0.953 | 0.930 | 0.942 |
| KNN _{context} | 0.584 | 0.888 | 0.954 | 0.920 |
| SVM _{context} | 0.718 | 0.955 | 0.914 | 0.934 |
| DT _{context} | 0.529 | 0.894 | 0.910 | 0.902 |
| MLP _{context} | 0.720 | 0.949 | 0.932 | 0.941 |

The results show that the two SVM models and the two MLP models yield comparable results, and perform well for the identification of target events. The context information does not make notable difference in the classification. Since the other components of SCHETURE rely on the accuracy of the event type classification, we chose the model that yield the highest six-class accuracy, SVM_{event}, to classify all the extracted events for the following steps. The distribution of event types in the entire dataset is shown in Table 4.7.

Table 4.7 Distribution of event types of extracted events and simple reviews.

| Event Type | Event Count | Simple Reviews |
|------------|--------------------|------------------|
| INTENTION | 203,053 (2.18%) | 16,256 (3.42%) |
| ACTION | 658,931 (7.08%) | 31,377 (6.60%) |
| BEHAVIOR | 3,065,360 (32.94%) | 334,549 (70.37%) |
| REACTION | 591,624 (6.36%) | 35,507 (7.47%) |
| CONTEXT | 1,201,579 (12.91%) | 57,756 (12.15%) |
| NONTARGET | 3,584,958 (38.53%) | – |
| Total | 9,305,505 | 475,445 |

Of all target reviews, 373,470 (17.63%) contain no event or only NONTARGET events. These reviews mainly express a reviewer’s opinions, requests, ratings, or other information. 475,445 (22.44%) reviews contain only one target event. Table 4.7 shows the distribution of event types in these simple reviews. The next two components of SCHETURE consider only the remaining 1,270,027 (59.94%) complex reviews

that contain multiple target events, of which 733,748 (34.63%) comprise at least two different types of events.

4.4.2 Event Sequencing

As mentioned in Section 4.3.3, we adopt both heuristics and event relation classification for event sequencing. We collected 1,005,166 (32.4% of all event pairs to be determined) event pairs whose relations were determined by the heuristics, to create a training set for the event relation classification. From these event pairs, we randomly sampled 20,000 event pairs for each relation type, $e_1 \rightarrow e_2$, $e_2 \rightarrow e_1$, and Separate. We divided these 60,000 event pairs into a training set (90%) and a testing set (10%), and compare the performance of different classification models. The event relation classification performance of different models is shown in Table 4.8.

Table 4.8 Performance of event relation classification.

| Model | Accuracy |
|--------------------------|----------|
| SVM _{GloVe} | 0.737 |
| SVM _{Word2Vec} | 0.728 |
| SVM _{USE} | 0.752 |
| MLP _{GloVe} | 0.727 |
| MLP _{Word2Vec} | 0.718 |
| MLP _{USE} | 0.736 |
| LSTM _{GloVe} | 0.722 |
| LSTM _{Word2Vec} | 0.714 |
| BERT _{base} | 0.797 |

In our experiments, the fine-tuned BERT yielded the highest accuracy. Using both heuristics and this classification model, we obtained 2,500,580 stories from the 1,270,027 complex reviews from the previous step.

4.4.3 Story Collection

In this step, we only consider INTENTION, ACTION, BEHAVIOR, and REACTION events, and other events are ignored. Of the 2,500,580 stories from the previous step, 269,409 (10.8%) contain only CONTEXT events. 1,558,156 (62.3%) stories are composed of only one type of events, when ignoring CONTEXT

events. The rest 673,015 (26.9%) stories are complex stories with more than one type of event. Table 4.9 shows the most common story structures in both simple stories and complex stories. 22 structures are common in complex stories, with frequency of more than 1%.

Table 4.9 Common story structures.

| Simple Stories | | Complex Stories (freq > 1%) | | | | | |
|----------------|-----------------|-----------------------------|------------------|----------|----------------|----------|---------------|
| Length 1 | | Length 2 | | Length 3 | | Length 4 | |
| B | 855,630 (54.9%) | AB | 176,661 (26.25%) | BAB | 39,291 (5.84%) | ABAB | 8,869 (1.32%) |
| B+ | 365,361 (23.4%) | BR | 85,807 (12.75%) | BRB | 19,794 (2.94%) | | |
| R | 152,259 (9.77%) | BA | 60,310 (8.96%) | ABR | 13,030 (1.94%) | | |
| A | 88,178 (5.66%) | RB | 56,928 (8.46%) | ABA | 9,431 (1.40%) | | |
| I | 55,613 (3.57%) | AB+ | 52,817 (7.85%) | BAB+ | 7,783 (1.16%) | | |
| R+ | 25,592 (1.64%) | IB | 34,629 (5.15%) | | | | |
| A+ | 12,747 (0.82%) | B+R | 20,414 (3.03%) | | | | |
| I+ | 2,776 (0.18%) | BI | 16,091 (2.39%) | | | | |
| | | B+A | 12,858 (1.91%) | | | | |
| | | AR | 12,486 (1.86%) | | | | |
| | | RB+ | 9,943 (1.48%) | | | | |
| | | A+B | 9,815 (1.46%) | | | | |
| | | IB+ | 8,424 (1.25%) | | | | |
| | | RA | 7,793 (1.16%) | | | | |
| | | R+B | 7,249 (1.08%) | | | | |
| | | BR+ | 7,075 (1.05%) | | | | |

Most simple stories (78.3%) in app reviews describe only the apps' behaviors. Such simple behavior stories constitute 48.8% of all 2,500,580 stories in complex reviews. The most common length-two structure is $\langle \text{ACTION} \rightarrow \text{BEHAVIOR} \rangle$ for complex stories, in which an app behavior is caused or triggered by a user action.

To obtain the most common story substructures, we ran the Generalized Sequential Pattern (GSP) on the complex stories only. We retained 43 frequent patterns that appeared in more than 1% (6,730) of the complex stories, as shown in Table 4.10.

It is notable that the most frequent type of event is app BEHAVIOR, followed by user ACTION and REACTION, which is not surprising since we have targeted negative reviews. Most described app behaviors are problems, and reviewers typically describe what they did before and after these problems.

Many longer frequent substructures are interpretable. For example, the substructure BRB potentially

Table 4.10 Frequent substructures (freq > 1%) in complex stories.

| Length 1 | | Length 2 | | Length 3 | | Length 4 | |
|----------|------------------|----------|------------------|----------|----------------|----------|----------------|
| B | 629,562 (93.54%) | AB | 294,096 (43.70%) | BAB | 67,178 (9.98%) | ABAB | 14,760 (2.19%) |
| A | 422,417 (62.76%) | BR | 161,000 (23.92%) | BRB | 34,883 (5.18%) | ABRB | 7,162 (1.06%) |
| R | 285,226 (42.38%) | BA | 157,842 (23.45%) | ABA | 30,222 (4.49%) | BABR | 7,025 (1.04%) |
| B+ | 193,518 (28.75%) | RB | 115,699 (17.19%) | ABR | 28,600 (4.25%) | BABA | 6,743 (1.00%) |
| I | 117,656 (17.48%) | AB+ | 85,970 (12.77%) | B+AB | 14,836 (2.20%) | | |
| A+ | 41,255 (6.13%) | IB | 59,579 (8.85%) | BAB+ | 13,618 (2.02%) | | |
| R+ | 37,069 (5.51%) | B+R | 44,761 (6.65%) | RBR | 13,261 (1.97%) | | |
| | | B+A | 39,033 (5.80%) | BAR | 12,690 (1.89%) | | |
| | | BI | 37,440 (5.56%) | ARB | 10,759 (1.60%) | | |
| | | AR | 37,371 (5.55%) | BIB | 10,595 (1.57%) | | |
| | | A+B | 28,471 (4.23%) | RAB | 10,536 (1.57%) | | |
| | | RA | 28,092 (4.17%) | BRA | 9,424 (1.40%) | | |
| | | RB+ | 21,953 (3.26%) | AB+R | 8,068 (1.20%) | | |
| | | R+B | 16,642 (2.47%) | B+RB | 8,050 (1.20%) | | |
| | | IA | 15,670 (2.33%) | RBA | 7,719 (1.15%) | | |
| | | IB+ | 14,580 (2.17%) | AB+A | 7,429 (1.10%) | | |
| | | BR+ | 14,382 (2.14%) | | | | |
| | | AI | 13,530 (2.01%) | | | | |
| | | IR | 13,178 (1.96%) | | | | |
| | | BA+ | 11,381 (1.69%) | | | | |
| | | A+B+ | 9,182 (1.36%) | | | | |
| | | B+I | 8,902 (1.32%) | | | | |
| | | RI | 7,525 (1.12%) | | | | |

describes a part of a story in which the app is exhibiting a problem, the user tries to fix it, but the problem persists. The substructure ABR likely describes a part of a story in which a user’s action caused an app behavior, and the user reacted to this behavior. We list some example stories (with minor edits) that contain frequent substructures in Table 4.11. Note that the patterns are based on the occurrence orders of events, not their discourse order in the text.

4.4.4 Manual Verification

We showed the 200 sample stories to our annotators, and asked them to rate the stories, on a Likert scale, in terms of their helpfulness toward the developer goals of understanding app problems, user retention, and user expectation. Each story received two scores for each of these three goals. To calculate inter-rater agreements, we considered scores of 3 or above as helpful and others as not helpful. Our annotators

Table 4.11 Example stories for some structures.

| Structure | Type | Events |
|-----------|------------------|--|
| B+ | [B] | <i>This new format is so awful</i> |
| | [B] | <i>Half the time this app “can not get weather data”</i> |
| | [N] | <i>(When) it does</i> |
| | [B] | <i>it is slow to load, difficult to navigate, and unnecessarily convoluted</i> |
| AB | [A] | <i>(when) I’m typing to another person</i> |
| | [C] | <i>& they are there</i> |
| | [B] | <i>The yellow button doesn’t always turn blue</i> |
| | [N] | <i>FIX IT SNAPCHAT!</i> |
| ABRB | [N] | <i>I love Pandora</i> |
| | [A] | <i>(even though) I just started listening to Pandora for the first time during the day</i> |
| | [B] | <i>(But often times) I’m unable to skip songs</i> |
| | [R] | <i>I’ve tried quitting and reopening. . .</i> |
| | [B] | <i>None of which work/help!!</i> |
| IABR | [N] | <i>What’s up with this?</i> |
| | [I] | <i>I want to be able to delete saved chats!!!</i> |
| | [A] | <i>(Because if) I accidentally tap a message</i> |
| | [B] | <i>(then) it becomes bolded font and saves</i> |
| | [R] | <i>(yet) I can’t unsave it!</i> |
| [N] | <i>FIX IT!!!</i> | |

achieved moderate agreements for all three goals (Cohen’s kappa is 0.441, 0.541, and 0.455 for app problems, user retention, and user expectation, respectively). We calculated the average score of each pair of annotations as the final score.

We propose the following null hypotheses on the helpfulness of stories retrieved by SCHEURE (simple problem stories are the stories with B events but no A, C, or R events):

H_{problem} Stories with A+B+, C+B+, and B+R+ patterns are the same as random stories in terms of their helpfulness toward the understanding of app problems.

H_{longer} Stories with A+B+, C+B+, and B+R+ patterns are the same as simple problem stories in terms of their helpfulness toward the understanding of app problems.

H_{retention} Stories with the B+R+ pattern are the same as random stories in terms of their helpfulness

toward the understanding of user retention.

H_{expectation} Stories with the I+A+ pattern are the same as random stories in terms of their helpfulness toward the understanding of user expectation.

Table 4.12 shows the average score of stories with each pattern, as well as random stories. As shown in this table, the null hypotheses can all be rejected with significance ($p < 0.01$).

Table 4.12 Average helpfulness scores of different stories toward different goals (p_s denotes p-value against simple problem stories; p_r denotes p-value against random stories).

| Goal | Simple Problem Stories | Random Stories | Pattern | Score | p_s | p_r |
|------------------|------------------------|----------------|---------|-------|-------|-------|
| App Problem | 3.578 | 3.435 | A+B+ | 4.163 | 0.003 | 0.000 |
| | | | C+B+ | 4.118 | 0.009 | 0.000 |
| | | | B+R+ | 4.136 | 0.005 | 0.000 |
| | | | I+A+ | 3.900 | - | - |
| User Retention | 1.689 | 1.825 | A+B+ | 1.596 | - | - |
| | | | C+B+ | 1.735 | - | - |
| | | | B+R+ | 2.652 | 0.001 | 0.005 |
| | | | I+A+ | 1.617 | - | - |
| User Expectation | 3.467 | 3.275 | A+B+ | 3.125 | - | - |
| | | | C+B+ | 3.039 | - | - |
| | | | B+R+ | 2.288 | - | - |
| | | | I+A+ | 4.133 | - | 0.000 |

4.5 Discussion and Future Work

We presented SCHETURE, a framework for analyzing the structures of user-app interaction stories in app reviews. In this section, we discuss the merits, threats to validity, and limitations of SCHETURE.

4.5.1 Merits

SCHETURE contributes to software engineering as follows.

Event type in app reviews. SCHETURE targets event types that are related to user-app interactions. Instead of investigating app reviews at the coarse review level, SCHETURE focuses on actionable items

at the event level. Identifying events of specific types can help developers quickly zoom in to find their desired information. For example, BEHAVIOR events in negative reviews typically describe unexpected problems that the users have experienced. Such events provide insights into how the apps can be maintained and improved. User INTENTION events describe the functionalities the users wish to bring about. Developers can look into such events in negative reviews to find out which functionalities in their apps are prone to error or do not meet the users' expectations.

Event sequencing in app reviews. App reviews vary greatly in length and information. A negative review may include multiple stories, mapping to different bug reports or feature requests, which should not be treated collectively. In our experiments, we found that in app reviews with more than one target event, the average number of stories per review is 1.41, and 26.6% of these reviews contained two or more stories. SCHETURE is able to identify individual stories, and sequentially order the events in them, which advances research on information extraction from app reviews.

Story structure in app reviews. SCHETURE introduces a novel way of analyzing app reviews. Previous studies on app reviews have classified app reviews by the type of information they contain. We distinguish app reviews by what kind of stories they tell. The structure of stories in an app review is a good indicator for what the review is about. Developers with specific goals should target specific types of stories. We have shown that stories retrieved by SCHETURE are more helpful than average for different developer goals, if the correct substructures are used for searching.

4.5.2 Threats to Validity

We identify the following threats to validity.

First, we targeted negative reviews. Intuitively, reviewers usually do not report the apps' normal behaviors if they satisfy the users' expectations. Our method may not be generalized well to neutral or positive reviews, where the event types and story structures may be greatly different.

Second, we obtained the training set for event type classification via crowdsourcing. The crowd workers may not be experienced enough in software engineering to determine certain events, such as contextual events that are important to the user stories. We provided detailed instructions and examples in our crowdsourcing project to mitigate this threat.

Third, we trained the event relation classification model with related event pairs that are identified with heuristics. Most event pairs in this training set are from the same sentences. Models trained on such event pairs may not generalize perfectly on event pairs that are from different sentences.

4.5.3 Limitations and Future Work

We identify the following limitations in SCHETURE as well as potential future work to address them.

Target event types. SCHETURE targets five types of events that can provide useful information to developers. However, event types in app reviews may be more diverse than five types. For example, some reviews describe what the developers did to the apps, such as updates and certain designs. Reviews for sociotechnical apps, such as Uber,⁶ may describe the actions of other users, e.g., Uber drivers, that affected the storyteller.

In addition, app BEHAVIOR is a broad type of events, and can be divided into smaller classes and examined separately. For example, app behaviors in negative reviews are often erroneous, but behaviors by design are also described as supporting information. User reactions to app problems can be attempts to solve the problems, deleting the apps, or switching to competitor apps. We defer the identification of more event types to future work.

Certain types of verb phrases are considered NONTARGET in SCHETURE but can be of interest to developers. For example, feature requests are often expressed in app reviews in the form of imperative sentences or requesting questions. Since they are not actual actions or events that can take place in a story, we do not consider them in SCHETURE. Investigating such sentences is an interesting direction for future work on app reviews.

Text quality. We extract event phrases from reviews based on a POS tagger and a dependency parser, both of which can be hindered by low-quality text. App reviews are written by regular app users, who are unlikely and not required to double-check their text. We see typos, grammatical errors, and incorrect punctuation in app reviews, all of which can affect the resulting dependency tag of a verb, and affect whether it is identified as a target verb. Figure 4.2 shows how spaCy’s dependency parsers performs on two sentences.

The first sentence is the original sentence in the review, with a comma missing. Since the word *reset* is parsed as ROOT, and *took* as its relcl (relative clause modifier), only one event is extracted. Adding back the comma enables the parser to perform correctly, recognizing *took* as the root, and two event phrases can be extracted.

In addition, we target negative reviews in this study, some of which include highly emotional expressions that are difficult to handle. For example, our dataset includes a review that repeats the word *LAG* for more than a hundred times, which causes failure for not only the parsers, but also the USE. Future work includes the investigation of extraction methods that are not based on parsers.

Classification performance. The accuracy for the six-class event type classification is acceptable for

⁶<https://apps.apple.com/us/app/uber-request-a-ride/id368677368>

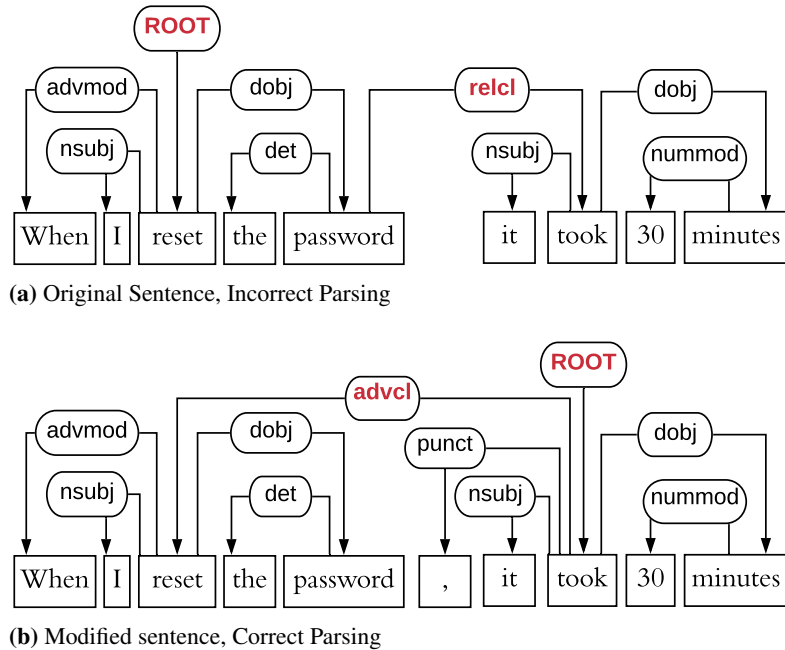


Figure 4.2 Dependency parser performance on examples.

helping app review analysis, but there is room for improvement. A possible limiting factor is the size of the training set. Since there are six classes, the number of examples per class is limited. Using a seed dataset and nearest neighbor technique, the distribution of event types in this training set is more balanced than events in actual app reviews, but is less than optimal. One possible improvement for event type classification is to target event types individually, and build a balanced training set for each event type.

Moreover, certain types of events can be similar to each other, and therefore more difficult to distinguish than others. For example, a user INTENTION, e.g., *I tried to deposit a check*, can be syntactically similar to a user ACTION, e.g., *I tried to take a picture*, which can also be similar to a user REACTION, e.g., *I tried to reinstall the app*. We posited that considering contextual information could help with the classification. However, concatenating the vectors of context and event did not yield notable improvement over event vectors only. Further investigation is needed on how to take better advantage of context information.

We have experimented only with straightforward classification models for the event relation classification, which leaves room for improvement. We mitigated this limitation by incorporating heuristics and keeping events' original orders in text when the classification model did not yield confident predictions. Determining the occurrence order of event pairs is a hard problem in natural language processing. Future

work includes the investigation of reliable ways to gather training set, as well as different language models for this task.

Substructures. We have collected and presented frequent substructures in stories, and shown that they can be used for retrieving stories by their structures. However, the implications of these frequent patterns are not yet fully understood. Previous studies [Guo and Singh, 2020] have targeted certain types of events and event patterns, such as $\langle \text{user action} \rightarrow \text{app problem} \rangle$, that are of practical significance to app developers. Further investigation is needed to determine whether or how the event type patterns are related to app development.

4.6 Conclusions

We introduced SCHEPURE, a framework for analyzing story structures in app reviews. Different user feedback, such as user expectations, bug reports, and user retention, comes in the form of differently structured stories. SCHEPURE examines the patterns of event types in user-app interaction stories described in app reviews, and proposes a novel way for collecting useful app reviews. SCHEPURE can determine event types and event relations with a good accuracy. We presented the frequent story structures and patterns that SCHEPURE has identified, and showed that stories in app reviews can be returned by their structures. SCHEPURE addresses $\mathbf{RQ}_{\text{story}}$, and shows how the extraction of informative stories from app reviews can help developers and analysts. Future work includes the investigation of additional event types, extraction methods robust against low quality text, and the improvement of event type and event relation classifications.

CHAPTER

5

CONCLUSION

In this work, we investigate the extraction and understanding of events and stories in text related to software development. Our research progresses from the extraction of informative events, to event pairs, and then to stories. We targeted two types of text, HHS breach reports and app reviews. By focusing on the events and stories, we show that such textual artifacts are a rich source of valuable knowledge regarding requirements, software problems, user expectations, and user retention.

5.1 Extracting Informative Events

We present LESBRE to address $\mathbf{RQ}_{\text{event}}$. LESBRE is a framework for extracting informative phrases and events from breach reports and suggesting actions based on the association between breach descriptions and corrective actions.

In a previous study, we propose ÇORBA, a framework of leveraging human intelligence for the extraction of security requirements from textual artifacts in the format of norms. ÇORBA shows that breach reports contain valuable lessons regarding how to prevent, mitigate, and recover from data breaches of health information in the healthcare domain, and therefore are great supplement to the understanding of compliance to regulations. However, ÇORBA calls for but does not fully address automated methods on information extraction from breach reports.

LESBRE is the first work on automated information extraction from breach reports. First, by focusing on the extraction of informative events, LESBRE is able to extract useful actions commonly taken in response to data breaches. LESBRE builds a classifier to identify the informative sentences from breach reports, and adopts natural language processing (NLP) techniques for the extraction of descriptive phrases and useful actions. Borrowing ideas from ÇORBA, LESBRE takes advantage of crowdsourcing to obtain a training set for the classification. Second, by leveraging the association between descriptive phrases about a breach and the useful corrective actions, LESBRE results in a tool for action suggestion for the prevention and compensation of similar breaches. The suggested actions are ranked by how common they are in the breach reports as well as how associated they are with the descriptions. As the actions described in breach reports are often directed and supervised by the authorities, they can be considered as common practices for the information systems in the healthcare domain.

LESBRE shows the importance of the extraction of informative events from textual artifacts, and calls for further investigation on event relations for more reliable action suggestion.

5.2 Extracting Informative Event Pairs

We present CASPAR to address $\mathbf{RQ}_{\text{pair}}$. CASPAR is a method for collecting and analyzing short app problem stories, i.e., action-problem event pairs, in user-generated app reviews. In addition to problem events, we consider the user actions that lead to them. By extracting action-problem event pairs, CASPAR is able to help developers identify valuable information regarding how to improve their apps.

Similar to LESBRE, CASPAR leverages NLP techniques, such as part-of-speech tagging and dependency parsing, to extract events from app reviews. To synthesizing action-problem pairs, CASPAR first identifies the user action and app problem events through text classification. CASPAR then determines and identifies the related action-problem pairs with heuristics. By focusing on key phrases like *when*, *before*, and *after*, we are able to determine the relations between pairs of events, and only the related event pairs are identified and collected.

In addition, we conduct a preliminary investigation on event inference on action-problem pairs. We propose the event follow-up classification to understand the relations between problem events and action events, and leverage negative sampling for the training of such classifiers. By understanding such relations, we enable the prediction of possible follow-up app problems based on user actions. This type of inference can potentially help developers preemptively avoid problems or failures of user experience.

CASPAR shows the significance of extracting event pairs of a targeted type. Short stories like action-problem pairs are one of the most common types of stories in negative reviews. They provide rich information as they describe the real-world performance of the deployed software systems. By considering event pairs instead of single events, CASPAR extracts information that is more helpful

regarding where and how developers should allocate their effort. Event pairs also enable the investigation of event relations and event inference, which contributes to the research of story understanding.

5.3 Extracting Informative Stories

We present SCHEPURE to address $\mathbf{RQ}_{\text{story}}$. SCHEPURE is a framework for analyzing story structures as patterns of event types in app reviews. App reviews are filled with users' interaction stories with the apps. Each app user's experience with an app is unique, and no two stories are the same. Therefore, it is difficult for developers and analysts to extract informative stories systematically, since there is no formal method to describe the types of stories which they wish to target. SCHEPURE provides a method for formally representing the structures of user stories, and therefore enables the collection of different types of stories based on their structures.

SCHEPURE extracts and classifies informative events from text, similar to LESBRE and CASPAR. CASPAR leverages heuristics to extract related event pairs, which limits the extraction scope. For more accurate and more general story extraction, SCHEPURE contains a component for automatically determining the sequential relations between the extracted events. This machine learned model is trained on event pairs extracted via heuristics, similar to CASPAR.

Via an empirical study, we show that developers with specific goals for app review investigation should focus on stories with different structures. The structure of a story indicates what information this story contains. SCHEPURE provides an effective solution to the extraction of informative stories based on the needs of an investigator.

5.4 Future Work

Our work mainly focuses on the extraction of useful events and stories. We have conducted preliminary investigations on the understanding of event relations and narrative structures. Our future work includes the deeper understanding of causal relations between events and more sophisticated event inference tasks.

For information extraction from breach reports, understanding event relations is a necessary next step. Our proposed framework, LESBRE, suggests actions based on the coexistence of previous corrective actions and breach descriptions in the breach reports. The resulting tool cannot suggest actions to unforeseen breach descriptions, and the suggested actions are only empirically associated but may not be causally correlated. Further research on the causal relations between the two types of events as well as event inference may enable more precise and reliable action suggestion.

We have started a new line of research on information extraction from app reviews by considering them as user-app interaction stories. We have investigated the most common event types that are

interesting to software developers and analysts. However, the stories in app reviews are more complicated than the basic event types. For example, with the blooming diversity of mobile apps and the continuous emergence of novel app functionalities, the events about app behaviors can be very different from each other. Modern apps are increasingly involving social characteristics. Events about user-user interactions are more frequently mentioned in app reviews. Research on story structures without predefined event types can be a beneficial next step. Investigations on how event inference and story understanding can benefit the information extraction from the stories app reviews are also an interesting future direction.

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