DETECTION OF FLOSS VERSION RELEASE EVENTS FROM STACK OVERFLOW MESSAGE DATA

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April 1, 2020

ABSTRACT

Topic Detection and Tracking (TDT) is a very active research question within the area of text mining, generally applied to news feeds and Twitter datasets, where topics and events are detected. The notion of "event" is broad, but typically it applies to occurrences that can be detected from a single post or a message. Little attention has been drawn to what we call "micro-events", which, due to their nature, cannot be detected from a single piece of textual information. The study investigates micro-event detection on textual data using a sample of messages from the Stack Overflow Q&A platform in order to detect Free/Libre Open Source Software (FLOSS) version releases. Micro-events are detected using logistic regression models with step-wise forward regression feature selection from a set of LDA topics and sentiment analysis features. We perform a detailed statistical analysis of the models, including influential cases, variance inflation factors, validation of the linearity assumption, pseudo $R^2$ measures and no-information rate. Finally, in order to understand the detection limits and improve the performance of the estimators, we suggest a method for generating micro-event synthetic datasets and use them identify the micro-event detectability thresholds.

1 Introduction

Topic detection and tracking has been an active research question for at least two decades [1]. It focuses on identification and detection of events in text data, like news feeds and Twitter. News articles or tweets in these datasets can be classified as related or not related to the event. The considered events and topics typically include natural disasters, traffic jams, local concerts, celebrity-related events, etc. [2]. The common feature of these events is that they are followed by an observable response from the community, from which the event can be detected. In the context of this study, these events are labeled as big events.

Textual data in Software Engineering (SE) are present, among others, in the form of Question & Answer (Q&A) platform communications - Reddit and Stack Overflow (SO) to name two examples. These platforms have a large impact on the field because they are commonly queried for code snippets and solutions during the software development process. An alternative to the manual search is text mining. It has been used to better understand the influence of the Q&A platforms on the SE as well as to improve the coding practices [3].

Research Gap  In the literature people usually address events which can be detected from a single unit of text. We define micro-events as events, not causing a pronounced response from the community and requiring multiple posts to be detected. The important difference between reactions to the events in the Q&A platforms and the news feeds is that the posts in the Q&A platforms require domain knowledge and human intelligence to be labeled as related or not related to the event.

None to little research has been done on the event detection in the field of SE messages data, especially, for the case of micro-events in the noisy forum-like data.
Research Question We investigate, how to detect the micro-events on the basis of the noisy community reactions on the example of Stack Overflow (SO) Questions and Answers platform. The null and alternative hypotheses are defined in the Methodology section.

We have used the SO textual communications to detect the reactions of the developer community to Free/Libre Open Source Software (FLOSS) version release events. Additionally, using the synthetic data (more details below), we have defined the properties of the reactions making the events detectable. Version releases of Django and Selenium packages play the role of micro-events. 3 types of the releases - patches, minor and major updates, were obtained from the libraries.io dataset.

Contribution We propose a Natural Language Processing (NLP) pipeline for detecting Software Engineering micro-events in noisy forum-like data.

We perform a feasibility analysis of the approach across a broad range of scenarios. Such elements as a set of considered features (predictors), type and length of the detection time window, and type of events are investigated.

Lastly, we propose a domain-agnostic synthetic data generation model, allowing to generate synthetic forum-like messages with a controlled strength of the community response. The approach allows to understand better the scenarios, in which the micro-events can be successfully detected.

2 Background

This section describes basic concepts which we build upon in our method, described in the Method Section.

Distance metrics for text data A core of the NLP methods are distance measures for words, sentences and texts. Jaccard similarity [4], Cosine similarity, Euclidean distance, Averaged Kullback-Leibler (KL) divergence, etc. [5] are the most common distance measures in Natural Language Processing (NLP). There is a more computationally intensive approach, taking into account the semantic word meanings - Word Mover’s Distance (WMD) [6]. In the study we use KL divergence measure as a well-established and computationally efficient method of computing distances between the distributions. Also, a Jaccard similarity is used to compute the differences between messages and is considered the most appropriate for the considered case. Other measures are provided as possible alternatives, however, they should be adapted to the setting.

Event detection methods An alternative approach to detecting events is topic modeling. One of the most common methods for that is LDA topic modeling [7], where changes in the topics within the time window might indicate the event. Usually different types of dynamic or temporal LDA are used [8] for this purpose. To our knowledge, LDA was never applied for detecting micro-events.

One of the significant issues in the event detection topic is reproducibility and methods comparison. The reasons for the issues is lack of standardisation of the datasets and loose understanding of the notion of an event. The most accessible dataset is Twitter. However, analyses are typically restricted to subsets of the data by topic, hashtags, location, language or other rules [9]. We are making the best effort to ensure reproducibility and transparency of the conducted study.

3 Related Research

Initially TDT was limited to detecting and following events in news streams. Later the area has benefited from the Twitter data [10]. Currently these two streams are being developed in parallel with a certain overlap in methods and approaches [11]. The section gives an overview of the event detection settings. Additionally, we name the event attributes, which are usually considered to introduce the notion of event. Finally, we describe the field of research, which uses an approach similar to the one proposed in the paper.

There are two general types of event detection exist:

- Retrospective Event Detection (RED) - analysis of the data from the past to discover new, unknown events
- New Event Detection (NED) - usually done in an online fashion with a stream of the data.

The field is very broad and there are various definitions of the events in the literature. Their classification can be done by the set of properties:

- Topic - there are topic-specific and general events distinguished.
• Geographic location - there are events, relevant for particular locations, like traffic information, concerts, etc. and less location-specific events, like financial reports, online entertainment project releases, etc.
• Time scale - depending on the event, it might take from hours to weeks and months.
• Reaction - not every event is followed by a reaction in the data source. There might be different reasons for that, but depending on the methodology, it may be treated differently.

The event detection approaches may be described as Feature Pivot or Document Pivot [11]. The first one involves a certain representation of documents/posts/messages within a time window with changes in the representation indicating the event. The Document Pivot focuses on classification of the documents as related or not related to a particular event.

As a rule, the NED methods can be assigned to one of the categories:

• Supervised Clustering
• Semi-supervised Clustering
• Unsupervised Clustering
• Anomaly Detection

The event-detection community usually uses single message labeling, where each message can be labeled as related or not related to the event [11]. While collective events, such as flu epidemics, require multiple posts for detection, the preliminary post labeling is usually performed [12], distinguishing them from the events considered in the study. In this paper we depart from this approach by detecting events without a need of labeling individual messages.

Multiple instance learning (MIL) is usually used when the labels of the dataset are partially available. MIL has been used in a range of domains, like object detection [13], audio event detection [14], text categorization [15], etc. In the MIL setting the data are split into subsets. The subset containing no positive instances is labeled as negative and subsets having at least one positive entry - as positive. The classification in this setting usually involves per-instance classification either in a sequential way, using attention [16] and convolution neural networks [17], or in an independent way, using simpler estimators like SVMs [18]. After the per-instance classification there is a pooling procedure, summarizing the output [14]. MIL uses a similar to the proposed in the paper approach by considering multiple instances as bags. However, it operates under the assumption that the elementary entries can be labeled, which is not the case in our setting.

The micro-events, which are sometimes addressed in the Topic Detection and Tracking community can still be detected from a single text entry [19, 20, 21]. Moreover, no studies were made on micro-event detection in the domain of Software Engineering and Stack Overflow Q&A platform dataset in particular.

4 Method

To support the reliability and reproducibility of the study, we have pre-registered the experiments on the Open Science Framework (osf.io). A pre-registration implies stating upfront the hypothesis, aims, methods and a state of the data collection of an experiment. While the pre-registrations are relatively uncommon for the field of Computer Science and, especially, Machine Learning, it has been accepted as a good practice for evidence-based methods [22] and commonly used in psychology [23].

The method has been pre-registered on the Open Science Framework[1]. The significance level for this study is $\alpha = .05$. The multiple comparisons are accounted for using the Holm-Bonferroni correction. Each type of events is considered as a separate experiment family. We apply the corrections when judging about the significance of the models or model features - each case is explicitly mentioned in the Results section.

Also, we have made the data and the code of the study available via Zenodo[2].

The section describes the aims of the project, its sampling strategy and the methods used. The statistical pipeline of the study is illustrated in Figure 1.

4.1 Aim

In order to formalize the research question, the null and alternative hypotheses were formulated.

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[1] https://osf.io/enrd9/?view_only=0888484923dc46b2b87c90060cb8f961
[2] https://zenodo.org/record/3608827
**H₀**: An event is not followed by a change in the topic distribution/key phrases/keywords/bag-of-words, representing the community textual communications.

**H₁**: There is a change in the topic distribution/key phrases/keywords/bag-of-words, representing the textual communications of a community, after an event, relevant to the community.

In order to validate the hypotheses, the statistical sample was defined and analysed, as described in the following subsections.

### 4.2 Dataset Description and Sampling Strategy

The study sample consists of a subset of packages, related to Django web-framework, selected based on the presence of the associated discussions on SO platform and having associated event entries in the libraries.io 1.4.0 dataset. The proposed sample allowed to investigate two dataset configurations - single and multiple package-based.

We have obtained the initial list of packages from the djangopackages.org, requiring the number of associated SO posts to be at least 1% from the number of posts of Django packages. We aimed to ensure theoretical possibility of event detection for every package. To speed up the filtering, we used a GitHub stars (followers) as a preliminary filter. We did not expect a consistent flow of posts on SO, if there was less than 1000 of followers for the package. The threshold was validated empirically - we found out that event for the packages with 4000 followers the message flow is very sparse.

We downloaded a complete data dump from Stack Overflow, version June 2018, then we filtered the messages by checking the presence of the selected package names in the body and tags of the messages.

The dataset was split into training and test sets by using the first 60% of messages (chronologically) for training and the remaining 40% for test.

Throughout the paper we use the following dataset naming convention: [package][type of event][time step]. The packages can be of 3 types: Multiple (the dataset including messages of 7 different packages), Django and Selenium. The event types are major, minor and patch updates. And the time steps are either event-based or calendar week-based (c.w.).

### 4.3 Pre-processing

**Class Labels Design** From the list of release dates provided by libraries.io, three types of FLOSS version releases were considered: patches, minor and major updates. When identifying the event types, we have applied the Semantic Versioning 2.0.0 convention.

**Time Step Design** Two ways of time step generation were pursued. The first one is based on calendar weeks - every calendar week is a single time step. Events take place on any day of the time step. This approach is aimed to study prior and posterior signs of the event. If there are multiple events take place, only the most significant (major > minor > patch) is considered while labeling the time steps. The control time steps are those in which no event of any type took place.

The second time step generation is event-based. Each event happens on the day 0 of the time step. Whenever there are multiple events with less than 7 days of gap, time steps overlap (i.e. the events will share messages). As control time steps we defined the periods of 7 days without any event (of any of the three types) occurring neither within the period nor in the prior week. Because of this restrictive definition the messages of certain dates could not be used for neither type of time step and had to be dropped.

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3 Libraries.io collects, among other information, release dates of FLOSS packages.
4 https://semver.org/#semantic-versioning-200
We fixed the length of the time steps to 7 days based on the distribution of events across the time steps. It allows on average 3.5 days for a developer to relate to the event considering the calendar week granularity of the time steps, and 7 days for the event-based approach. Daily time steps were studied as well, however, they would require much faster responses from the community and a more prolific communication.

Datasets Design Two of the most discussed packages were used to generate the single-package datasets, namely Django and Selenium, 7 different packages (listed in Figure 4) were used to generate the multiple-packages dataset. Three types of updates were distinguished for the multiple-packages dataset and 2 types - for the single-package datasets. Major updates are too sparse to use them in the single-package datasets and were not considered. Finally, as explained above two different definitions of time steps were used. In total we designed 14 different dataset versions.

4.3.1 Feature Engineering - Vector Representation

Prior to applying the NLP tools, the code snippets (identified by HTML tags) were removed from the body of the messages. Initially, four techniques were applied to design the features: sentiment analysis, Bag-of-Words (BoW), LDA topic modeling and TextRank key phrases extraction. The central analysis of this paper was conducted using only LDA and sentiment analysis features because these are the most refined features types and we wanted to limit the number of variables as much as possible. The other feature spaces were investigated in the exploratory analysis.

Sentiment analysis features were generated by the NLTK python package [25], specifically using the Vader method [26]. There are 4 features generated for each message: negative, neutral, positive and compound components. The latter is a 1d representation of the sentiment. We include sentiment analysis in every feature space, due to its compactness. The sentiment features are coded as "sentiment_<component>", where the components are negative, neutral, positive and compound.

Latent Dirichlet Allocation (LDA) topic modeling - a fixed-dimensional vector was associated with each post. Each dimension represents the probability of the post belonging to a particular topic. The set of topics is generated from the training partition of the data and fixed for all dataset versions.

The vocabulary was built from the lemmatized messages and included bi- and tri-grams. The topic number and the topics were obtained from the training dataset. Coherence measure (c_v) was used to find the optimal number of topics. The coherence was computed for 3 random seeded models to ensure the result is not biased by the randomness. The number of topics with the maximum coherence before reaching the plateau is considered.

We used the multicore gensim package [27] implementation of the LDA algorithm.

To verify the soundness of the obtained LDA topics, we manually inspected the top 5 messages associated to each topic, ranked by the gap in the probabilities between the target topic and the next closest one.

To give a general picture of the discussions, we assigned names to the LDA topics. This was done based on the manual inspection of the top posts in each topic. The feature names are coded as "lda_topic__<topic name>".

Vector Representation The NLP representations described generate a fixed set of features for each message. To create the overall time step representation we simply averaged these features across all messages included in the time step.

As an exploratory analysis, the more complex feature space was investigated for LDA, where each topic was represented by a minimum, maximum and mean values together with the size of each topic computed as difference between maximal and minimal values.

Standardization The obtained features were standardized as $z = \frac{x - \mu}{\sigma}$, where $\mu$ is the sample average and $\sigma$ is the sample standard deviation. Both values were obtained from the training partition of the data.

4.3.2 Outliers

Outliers were capped, feature by feature, by using the Tukey method - R’s boxplot.stats() implementation was used. We obtain the capping values from the training partition of the data.

4.4 Analysis

Effect Sizes Cliff’s Delta [28] was used as an effect size measure, due to a non-normal feature values distribution. R’s Effsize package was used to compute the effect sizes. .95 confidence intervals were corrected for the multiple features.
**Feature Selection**  Feature selection was applied before model fitting by using the step-wise forward regression method with Akaike Information Criterion (AIC). The features were sorted in descending order by the Tjur pseudo $R^2$ measure, recommended for logistic regressions with a binary outcome [29]. The feature space was increased step-wise starting from 1 feature. The process terminated when the AIC increased with respect to the previous value. The feature space with the minimal AIC was selected.

**Model Fitting**  We trained Random Forest using python sklearn implementation and Logistic Regression models using R’s glm (generalized linear model) implementation. The thorough model analysis was performed only for the logistic regression algorithm due to a solid body of knowledge on model and features significance and feature contributions. The Log-Likelihood Ratio (LLR) test was performed to check the significance of the logistic regression models for the optimal feature space. We are aware of Random Forest SHAP feature importances, however, the detailed model analysis is less common. The Random Forest estimator was only evaluated in the context of the synthetic data experiments.

**Model Analysis**  The assessment of the model’s quality involved the following steps:

1. The goodness of fit was estimated using Tjur, Nagelkerke, Cox-Snell, and Adjusted McFadden pseudo $R^2$ measures.
2. Odds ratios of the model were computed and illustrated as a forest plot with the .95 confidence intervals. The intervals were corrected for the multiple comparisons. Since the data were standardized, one standard deviation change in the feature value leads to the odds ratio multiplicative change in the base probability. For example, for the base probability $p$ and the odds ratio value $d$, the change leads to the new probability of $p \times d$.
3. Variance Inflation Factors (VIFs) were computed for the models. As advised by Andy Field et al. [30], VIFs exceeding 10 indicate unreliability of the model.
4. Linearity assumption was studied by adding $\log(f) \times f$ features to the model and checking their significance [30].
5. To make sure there are no influential outliers in the fitted model, Bonferroni Outlier Test was applied to the fitted models. It allows to spot the influential cases, significantly changing the behaviour of the model. Additionally, added variable plots were built and visually assessed.

Holm-Bonferroni corrections are considered when discussing the results.

**Model Performance**  The performance of the model was evaluated using the test dataset. P-value of the no-information rate was computed using caret R package. AUC-ROC values were reported in the model summaries (Table 2).

4.5  **Synthetic Data Generation**

The sequence of steps related to the synthetic data is shown in Figure 2.

![Figure 2: Synthetic dataset, sequence of steps.](image)

We generated a synthetic dataset with an objective of understanding, what strength of the reactions in the textual communications is reliably detectable.

The synthetic data generation process is the following:

1. Generate background messages;
2. Generate event-related messages;
3. By mixing messages from (1) and (2) we create time steps with positive labels;
4. We take messages from (1) to create negatively labeled time steps;
Certain assumptions were made to generate the synthetic dataset. We assumed that only a fraction of messages is relevant to an event, this fraction represents the strength of the reactions. The ratio of positive to negative time steps was set to .25 to mirror the considered real-world scenarios.

4.5.1 Deep Learning Text Generator

The posts were generated using a small version of GPT-2 OpenAI neural network [31] with 117M neurons. The original pre-trained version of GPT-2 was fine-tuned on the multiple packages sample of Stack Overflow data.

Background messages The background messages (ones having no relation to an event) were generated from an empty context.

Event-related messages In order to generate event messages, we propose a model to inject events into the data. The community values are represented by 3 compounds: rules, people and products (Fig. 3). Changes in any of these compounds might lead to changes in the community communications. These are abstract entities, individual for every community.

The event-related messages are generated from a set of seed phrases, used as a context for the generator network.

The seed phrases are designed on the basis of the real-world dataset, used for the generator fine-tuning. Entities representing the three compounds have to be identified in the dataset. To do that, we used a Word2vec model [32], fitted on Google News dataset. We have taken the closest 1.7k nouns for each of the components. Since we were interested in changes, we have taken 1k closest verbs representing addition and removal operations. The phrases were obtained by concatenating the obtained nouns with the verbs. For the generation we have used randomly chosen 100 seed phrases. NTLK POS tagger was used for the part of speech identification.

4.5.2 Generator Optimization

To ensure maximum similarity between the synthetic and real world datasets, the softmax temperature and top_k parameters of the generator were optimized. These parameters affect the properties of the generator output distribution.

The following two metrics were used to assess the similarity between message corpora:

1. The pair-wise Jaccard similarity [33] between the posts, which is used in Natural Language Processing in different variations [34].

2. The Kullback-Leibler divergence was used for quantitative comparison of the distance distributions, as a well-established method for distributions comparison [35, 36, 37].

Since it is not feasible to compute the pair-wise distances between all individual messages, random samples of 500 posts were taken from the data and the measurement was repeated 30 times to get the standard deviations of the result. We also made sure that further increase of the random sample size does not change the optimization outcome.

To our knowledge, there is no unified framework for assessing the synthetic texts quality. However, it is common to consider such measures as Fluency, Novelty, Diversity and Intelligibility of the generated entries [34]. Generating the data for a particular purpose, we have taken two properties - Novelty and Diversity, which can be accessed for the synthetic and the real world datasets.
| Package                  | Number of posts |
|-------------------------|-----------------|
| Django                  | 475760          |
| Selenium                | 210498          |
| Sentry                  | 60874           |
| Django-rest-framework   | 24852           |
| celery                  | 20864           |
| Hypothesis              | 19401           |
| Gunicorn                | 14602           |
| **Total (unique)**      | **826851 (777812)** |

Table 1: Numbers of posts per package after filtering by the package name in the post’s tag or body. The total number of posts in the Stack Overflow platform data dump of 06/2018 is 65049182.

Based on the equations in [34], Novelty defines the distance between the synthetically generated and the real world datasets. Diversity of the dataset can be measured as novelty between two samples of the same dataset. Fluency and Intelligibility cannot be directly measured from the defined metrics, consequently were not used in our study.

With this understanding, we have applied the measures to our case:

- Novelty: a sample of the synthetic data is assessed against the sample of the real world data. The metrics value should be as small as possible. Ideally it should be equal to the Diversity of the real world dataset.

- Diversity: a sample of the synthetic data is assessed against a different sample of the synthetic data. The metrics value should be as close as possible to the same measure applied to the real world dataset.

The optimization process was performed separately for the event-related and background messages. Then, a single set of parameters was chosen to generate all the messages in order to preserve the consistency of the dataset and avoid the process of differentiating between the positive and negative entries to become trivial.

The optimal configuration was chosen based on the Novelty and Diversity of the event-related and background messages. In the optimization we have treated the quantitative improvements in both measures equally. The consensus set of parameters was expected to have the least Novelty and Diversity differences between the synthetic and the real world data. Changes were 1 order smaller for the Novelty of the event-related messages in comparison to the background messages. Changes were of the same order in both message types for the Diversity. The observation we have made is that .1 decrease of the softmax temperature led to a significant divergence between the synthetic and the real world data properties. Based on our observations, we have chosen the softmax temperature of 1.0 and top_k of 400.

### 4.6 Deviations From The Pre-registration

After the first tests with the multiple packages dataset, we decided to simplify the task and run the classification on the single package datasets. However, at that point we could not train a reliable classifier even with the suggested optimization and transfer learning approaches.

This made us switch to the formal statistics approach to study the reasons behind the obtained results. Later we have designed the synthetic data generation method and successfully used the synthetic data in the transfer learning setting, as well as studied the detectability thresholds of the reactions to the micro-events.

### 5 Results

#### 5.1 Data Sample

For the single package experiments we focused on Django and Selenium, as they account for around 85% of the messages. Table 1 shows the packages (and number of associated messages) included in our sample. Moreover, Figure 4 represents chronologically the events associated to these seven packages. Black strips at the top part of the figure represent the events. We provide this figure to support the reproducibility of the study.

The posts before 27 July, 2015 belong to the training set, after the date - to testing one.
Figure 4: Sample of the posts and the events per package for the available time range. The number of posts is provided in a per-time-step fashion. The packages are stacked vertically. The drawdowns take place in the New Year’s Eve periods.

Table 2: Summary of all the dataset configurations. Log-Likelihood Ratio (LLR) test p-values together with the Tjur $R^2$ and Adjusted McFadden (Adj. MF) $R^2$ are used to choose the best fitted model. Event-based multiple packages datasets were not considered due to violation of the independence condition of the logistic regression model. Based on the goodness of fit, we have chosen Django calendar week patch updates dataset to show the detailed analysis. The LLR test results are considered in multiple comparison corrections - for that reason the exact values are shown.

5.2 Results on the SO Datasets

Results of the logistic regression models From all the studied dataset configurations we reveal a detailed statistical analysis of the best fitted model. It was chosen on the basis of the goodness of fit - Adjusted McFadden and Tjur $R^2$ measures. We did not consider multiple packages datasets with event-based time steps due to their potential violation of the independence assumption of the logistic regression. This is discussed more in detail in the next section.

In general the results of this first set of models were poor as reflected by the majority of models not able to obtain AUC scores much better than 0.5. To further analyze these results and understand the limitations of these models we will in the next sections focus on a particular dataset as case study: Django dataset, calendar week, with patch updates.

Effect Sizes As a model-agnostic feature analysis, we build a forest plot of the effect sizes as shown in Figure sorted by the range of the confidence intervals (CI). We have found out that the feature values are distributed non-normally. Computing the effect sizes, we have chosen the Cliff’s Delta measure, which has no feature distribution constraints. The error bars illustrate the 95 CI’s to get an idea about the significance of the features beyond the considered sample. At this point, there are only 3 significant features - Web Elements LDA topic, File Directories LDA topic and neutral sentiment measure.
**Model Fitting Analysis**

We have fitted the logistic regression model and computed its descriptive statistics. There are 4 features in the feature space. However, only 2 of them are significant - Web Elements LDA topic and File Directories LDA topic. Also, based on Tjur $R^2$ one can see that around 10% of the variance is explained, other $R^2$ measures support that statement. Overall, we can see that the pseudo $R^2$ values do not show any anomalies. Considering the Holm-Bonferroni correction for the particular type of event (6 comparisons, rank = 3), the Log-Likelihood test outcome is significant, telling us that the overall model is significant.

| Predictor                  | Estimate | Std. Error | Z-value | Pr(>|z|) | VIF |
|----------------------------|----------|------------|---------|---------|-----|
| (Intercept)                | -3.97    | 0.45       | -8.77   | < .001  |     |
| lda_topic__Web_Elements    | 0.56     | 0.26       | 2.15    | .032    | 1.14|
| lda_topic__File_Directories| 0.76     | 0.31       | 2.50    | .012    | 1.16|
| sentiment Neutral          | 0.60     | 0.35       | 1.71    | .087    | 1.01|
| lda_topic__Objects_Queries | 0.49     | 0.29       | 1.71    | .087    | 1.01|

| Descriptive Statistics     | Value    |
|----------------------------|----------|
| Observations               | 325      |
| Log Likelihood             | -42.270  |
| AIC                        | 94.540   |
| Corrected AIC             | 94.728   |
| LLR Test p-value          | .0014    |
| Null model base prob.     | .196     |
| Tjur $R^2$                | .118     |
| Adj. McFadden $R^2$       | .060     |
| Cox-Snell $R^2$           | .054     |
| Nagelkerke $R^2$         | .201     |

Table 3: Logistic regression model fit with its descriptive statistics. The model was fitted on Django package, patch update events, calendar week time steps dataset, with the update events as a dependent variable. The subset of features was selected using a step-wise forward regression with AIC.
LDA Topics Interpretation  The LDA was optimized on the training dataset and 14 topics had the maximum coherence $C_v$ score before reaching plateau. In this study we interpret in detail only the significant predictors of the model.

Web Elements LDA topic - the topic describes various interactions with web elements, like positioning buttons, searching for CSS/HTML elements, discussing technical details of extracting information from web-pages. The top 5 characteristic words extracted from the LDA model are: page, use, element, click, html. Taking the Holm-Bonferroni correction into account (4 comparisons, $rank = 2$), the feature becomes insignificant.

File Directories LDA topic - the topic contains messages on the operations with files and filesystems, like accessing, storing and downloading. The top 5 characteristic words extracted from the LDA model are: file, image, directory, folder, path. Taking the Holm-Bonferroni correction into account (4 comparisons, $rank = 1$), the feature stays significant.

We compute the odds ratios of the model (Fig. 6) to describe the contribution of each feature to the model output. The error bars show the .95 confidence intervals. Since the data are standardized, one standard deviation change in the feature value leads to the event probability change multiplicative the feature’s odds ratio. Both significant features have odds ratios around 2. Assuming the initial base probability equals to the null model (.196), the standard deviation increment in any of the two features would lead to the event probability of .39.

Validating Model Assumptions  The Logistic Regression algorithm assumes there is a linear relation between the feature and the class labels. We assess it through the feature interactions. For the considered dataset configuration, none of the interactions were significant in the model - the linearity criterion is satisfied. None of the Variance Inflation Factors (VIFs) cross the threshold of 10 (Table 3), meaning there are no unnecessary features in the model. Bonferroni Outlier Test did not discover any outliers with the p-value below .05, meaning that the model is reliable.

| Measure             | Value |
|---------------------|-------|
| Accuracy            | .914  |
| Accuracy Lower      | .857  |
| Accuracy Upper      | .953  |
| Accuracy Null       | .921  |
| Accuracy P-Value    | .686  |
| McNemar P-Value     | .006  |

Table 4: Validation of the Django, calendar week granularity, patch updates dataset logistic regression model.

From the no-information rate (Table 4) one can see that the model is not significant on the validation dataset. We do not provide the F1-score performance measures due to ambiguity when choosing the optimal threshold - that is why only AUC-ROC values are shown in the models summary in Table 2.

Other Feature Spaces  In exploratory analysis we also evaluated the performance of the TextRank and Bag-of-Words NLP representations. However, using these did not improve the performance of the models. As their dimensionality is around 2 orders larger in comparison to the LDA feature space, these would make the models susceptible to the curse of dimensionality [38]. Moreover, the large number of features makes the statistical analysis application limited. Hence we decided not to include them in the full analysis.
Figure 7: Performance of a Random Forest (RF) and Logistic Regression (LR) estimators versus the fraction of the event-related messages. The experiments were conducted on a synthetically generated dataset. The performance results are an average over 15 randomly initialized dataset instances. The illustrated p-values are obtained from the permutation tests (1000 permutations) and are the maximums over the 15 random initializations. The error bars show the .95 confidence intervals for the random initializations.

5.3 Results on the Synthetic Data

Generator Optimization The optimized configuration was used to generate 1109150 background messages and 154680 event-related messages.

Response Strength Analysis 15 instances of the dataset were generated for the event-related message fractions in a range from .1 to .5 with a step of .05. Each dataset consisted of 335 time steps, to match the number of time steps in the SO dataset. Permutation tests were performed for all the instances and the results were plotted as a scatter plot (Fig. 7). Error bars show the .95 confidence intervals for the multiple instances of the same configuration. The maximum p-value among the instances is shown by the color. One can see that the p-values become significant starting with the .2 fraction of the event-related messages in the positive time steps. Logistic repression tends to perform significantly (statistically) better than Random Forest until the 0.35 ratio of the event-related messages. Afterwards the two algorithms perform similarly.

Based on what we have learnt on the synthetic datasets experiments and given that none of the models trained on the SO data obtained significant performance, we can assume that the fraction of event-related messages is below .2 and hence the micro-events in the considered setting are undetectable. The reason of the weaker performance of the RF is probably too small dimensionality and size of the dataset.

6 Discussion

6.1 Limitations

Time step design The event-based time steps might violate the independence assumption for the logistic regression model in case there are multiple updates of the same type taking place within the time interval of a time step. It leads to using some fraction of posts in multiple entries, making the entries dependent. The violation does not allow to rely on the logistic regression model results. However, this setting can be used in the machine learning approach with its own benefits, such as more data points and a narrower-defined setting in comparison to the calendar week-based time steps.

Nevertheless, our time step representation has less risk of encountering ethical issues because it avoids having to label individual messages and hence it can better preserve the privacy of individual message contributors.

Response lag In this work we assume that the reaction can be observed within up to 7 days after the event took place. This assumption was empirically derived from the sparsity of the events-posts as well as our understanding of the software engineering workflows. Moreover, when designing the reference time steps, one has to assume that the reaction to the most recent event is not in the data any longer. So that for the event-based time steps, we assume that the
day 8 after the event would belong to the reference time step. Depending on the available length of the time series, these assumptions can be optimized to the detriment of the time series length. This assumption becomes unrealistically strict when considering daily time steps. Our exploratory experiments on the daily time steps confirm that.

It should be noted that the two suggested time step designs are aimed at two different temporal natures of the reactions. The event-based is aimed at the posterior reactions to events, and the calendar week based is aimed at both prior and posterior. It should be taken into account when comparing the results.

NLP tools We are aware of the limitations of the sentiment analysis tools [39, 40], as well as part-of-speech recognition tools [41] applied to the SE domain. Indeed, it makes the SE texts challenging for the NLP tasks. We use the classical NLTK python package POS tagger and NLTK Vader sentiment analysis since we aim at developing the general approach. Consequently, we do not claim the state-of-art performance. There is definitely space to improve the model, which we discuss below.

When generating the event-related synthetic messages, we assume that the three community components are represented by nouns and the change operations - by verbs. Depending on the community or its language, it might not hold.

Generator fine-tuning To fine-tune the generator, we use the multiple packages post sample, which contains both event-related and not related entries. To tweak it into the generation of the two types of messages separately, we use the seed phrases, designed based on the 3-compound model. In this way we overcome the requirement of manual labeling of the messages, making the approach scalable and applicable to the content where possibilities for the manual labeling are limited.

6.2 Future Work

As it was mentioned above, the model can be improved, for example by adjusting the NLP tools to the problem. We have shown that the micro-event detection is possible in the challenging domain of SE, using the default tools, and considering the general minimalistic feature space obtained from textual data in message bodies and tags only.

Considering the improvements, there are more advanced extended LDA models, such as Author-Topic LDA, which links authors, topics, documents and words [42], LDA with Genetic Algorithm, acting on multimodal data [43], LACT acting on the source code [44], etc. [45].

7 Conclusion

The contribution of the paper is a feasibility study of the micro-events detection on the example of the FLOSS version releases. When applied to present data, the approach would enable developers to observe the event-related community interactions. On historical data, the developers would be able to make better informed decisions when choosing dependencies for their projects (i.e. identify problematic dependencies). Additionally, it would boost the feedback loop between users and the developers - the event-related interactions can help measure a release’s success.

The current study extends the research area of the event detection into micro-events. We show that it is possible to detect FLOSS version release micro-events from SO data. However, this detection is still very challenging and requires improvements in message/time step representations, models and data preparation. The experiments on the synthetic datasets help understand the limitations on the detectability of the studied micro-events. The analysis of the features contributing to our models can help understand better the nature of the predicted events, and contribute insight for the monitoring and management of the FLOSS ecosystems health.

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