Trust in Motion: Capturing Trust Ascendancy in Open-Source Projects using Hybrid AI

Huascar Sanchez  
Computer Science Laboratory  
SRI International  
.huascar.sanchez@sri.com

Briland Hitaj  
Computer Science Laboratory  
SRI International  
.briland.hitaj@sri.com

Abstract—Open-source is frequently described as a driver for unprecedented communication and collaboration, and the process works best when projects support teamwork. Yet, open-source cooperation processes in no way protect project contributors from considerations of trust, power, and influence. Indeed, achieving the level of trust necessary to contribute to a project and thus influence its direction is a constant process of change, and developers take many different routes over many communication channels to achieve it. We refer to this process of influence-seeking and trust-building as trust ascendancy.

This paper describes a methodology for understanding the notion of trust ascendancy and introduces the capabilities that are needed to localize trust ascendancy operations happening over open-source projects. Much of the prior work in understanding trust in open-source software development has focused on a static view of the problem using different forms of quantity measures. However, trust ascendancy is not static, but rather adapts to changes in the open-source ecosystem in response to new input. This paper is the first attempt to articulate and study these signals from a dynamic view of the problem. In that respect, we identify related work that may help illuminate research challenges, implementation tradeoffs, and complementary solutions. Our preliminary results show the effectiveness of our method at capturing the trust ascendancy developed by individuals involved in a well-documented 2020 social engineering attack. Our future plans highlight research challenges and encourage cross-disciplinary collaboration to create more automated, accurate, and efficient ways to model and then track trust ascendancy in open-source projects.

Index Terms—trust ascendancy modeling, dynamic developer activity embeddings, influence pathway trajectories

I. INTRODUCTION

Achieving the level of trust necessary to contribute to a project is a ubiquitous construct of how open-source software development works [26], [35] and one of the most prevalent objectives [30] in the general developer population in social coding platforms like GitHub and Stack Overflow. Achieving this trust is a dynamic process of change [11] that is inherently political [13], and developers take many different routes over many communication channels to influence its formation [2], [9], [13], [35], [37]. We refer to this process of influence-seeking and trust-building as trust ascendancy. Much of the prior work in understanding trust and its ascendancy in open-source projects has focused on a static view of the problem using scale measurements (e.g., [3], [15], [24], [38]). However, trust ascendancy is not static. Instead, it adapts to changes in the ecosystem in response to developer role changes, new functionality, new technologies, and so on. Automatically tracking this socio-technically stimulated dynamism thus requires dynamic developer behavior models. This paper is a first attempt to articulate and study this issue.

We consider the problem of capturing the motion dynamics of trust ascendancy inside open-source software (OSS) projects using dynamic developer activity models. These motion dynamics are reflected in the way trust is periodically developed inside projects in response to either socio-technical stimuli (e.g., social influence, role changes, code contributions) or to periodic changes in the context of individual activities, such as reporting a bug, that are intended to help potential contributors build a reputation and eventually become project committers (see the case study of a “successful socialization” in Ducheneaut [13]). Understanding the context in which actions are performed as well as tracking when (e.g., time of day) this context changes can give us a global picture of the influence pathways formed inside a project. Here, an influence pathway is a potential conduit for influence to flow inside a project and a schedule. The context of an activity embodies the semantic associations between the activity and other activities that were performed around the same schedule.

Arguably, influence is the main driver for building trust inside networked social environments [37] like OSS projects. The structure of these networks is usually “black-boxed,” and to exert any influence in them, potential contributors need to progressively make this network structure more visible [13]. A goal of the current effort is to bridge the gap mentioned earlier, namely, that research on understanding trust and its ascendancy tends to be based on static accounts. Consistent with this goal, we introduce a hybrid approach that combines the strength of unsupervised machine learning with the flexibility of self-supervised machine learning, and generalize it to sequential data collected from real-world software projects.

This work complements existing work by providing better mapping and understanding of the multiple influence pathways taken by developers to progressively open this “black-box,” thereby enabling them to contribute to the project.
When we look at existing work in language evolution detection using word embeddings [1], [12], [17], [20], [29], [41], we observe the power of word embeddings at capturing evolving semantic associations between words across time and also at allowing for cross-pollination between the NLP and other application domains (e.g., [4], [8], [10], [24], [33]). In general, these models accurately model the distribution of an object (e.g., words, security alerts) based on the surrounding objects in terms of low-dimensional vector representations.

In building on this prior work, we are interested in learning dynamic developer activity embeddings for evolving influence pathways recovery. These embeddings will capture, in a fashion that resembles how dynamic word embeddings infer embedding trajectories over time, the temporal dependence between concrete developer actions performed within OSS projects. This will give us a natural backtrace trajectory of the influence pathways taken by potential contributors. Figure 1 shows a concrete example of how we can use the dynamic developer activity embeddings to reveal distinctly novel influence trajectories that summarize a 2020 social engineering attack against the Linux Kernel [7].

The revealed trajectories show the potentially influenced maintainers and the attackers’ trust ascendency operations across both time and subsystems. The objective of each operation was to build trust and then to poison the Linux Kernel with vulnerabilities (the “hypocrite commits” patches [39]). The sections that follow provide details of the case study we explored to highlight the challenge, as well as the methods and data we used to recover these dynamic trajectories.

II. CASE STUDY: HIGHLIGHTING CHARACTERISTICS OF THE CHALLENGE

The techniques described in this paper should apply to thousands of significant OSS projects. We considered many projects, but narrowed the list of case studies to the Linux Kernel and its accepted patches case study below.

Case Study: The Linux Kernel and its accepted patches. The Linux Kernel (LK) development process is well known, documented, and researched [14], [19]. However, some actions of contributors or maintainers often diverge from this process. One of these actions is accepting patches. Studying why a technical change happens is as important as modeling either the rejection or the oversight of design changes (e.g., [27]), particularly if the acceptance is rooted in both social and technical influence. To provide a control comparison, we will model the influence pathways that have led to the integration of controversial changes such as the hypocrite commits [39]. Could this event be indicative of an intrinsic susceptibility to socio-technical influence in general OSS projects?

We rely on the high level of transparency offered by the kernel and the wealth of signals available in its development process to learn a dynamic model of developer behavior.

\[1\] Manipulated directly or indirectly in response to other maintainers’ actions.

Fig. 1: A 2D t-SNE projection of three trust ascendency trajectories across a 14-week time window (08/2020 – 11/2020). Red dots represent attackers’ behavior, green dots with a red ring represent maintainers’ behavior, purple dots represent the behavior of other aliases used by the attackers, labels are action abbreviations, and blue lines represent the trajectory of attackers’ trust ascendency. Maintainers’ distance to these trajectories is an indicator of trust development with attackers’ actions.
III. METHODOLOGY

In this section, we describe our methodology for answering the question of trust ascendency in OSS projects.

The basics of our methodology are thus: We consider a large OSS project as a case study to highlight the characteristics of the challenge. This case study project experienced an important code change that was associated with a form of social influence, and each case was well documented and widely discussed. Because of the heterogeneity of the types of contributors (e.g., domain experts, hackers, superficial contributors, vandals) who can participate in a large project, we expect the developer data to be scattered or noisy. To address this issue, we formulate our exploration task as a process of identifying a subset of general types of developer activity that best explain the data. In that regard, we use unsupervised machine learning to extract general activity types and then generalize them to sequential data. Having done that, we use self-supervised machine learning to generate properly aligned temporal embeddings of developer activities.

A. Activity-based Analysis of Developer Activity Data

To capture the motion dynamics of trust ascendency in the kernel, we need to understand first its activity space and any inter-relations that hold among them. To this end, we consider a snapshot of its development history, pulled directly from the Linux Kernel mailing list (LKML). This snapshot contains timestamped information pertaining to concrete developer actions (e.g., submitting a patch, acknowledging a submitted patch) in the LKML, in a 2019-2021 time window. Furthermore, the collected patch emails should have at least one email reply in the LKML and at least 50 words (or at least one sentence) in their email body, persuade its recipients to accept them and be sent by a human (i.e., a non bot).

As illustrated in Figure 2 this link between patch emails in LKML and commits in LK is nonexistent and thus requires an indirect provider. We circumvent this problem by probing the patchwork service according to the process described in Xu and Zhou’s paper. Overall, we collected a total of 27411 records matching our patch email criteria.

We assess the collected data using different sets of characteristics, each covering a (mail-based) software development aspect: (1) contribution, (2) exposition, and (3) administration; see Table III for a summary. These aspects are interrelated, and thus their enclosed characteristics can be assembled into descriptive action categories using Exploratory Factor Analysis (EFA) according to the process described in Cheng and Guo. In EFA language, these descriptive action categories are known as latent factors.

Formally, we are given: p, the number of characteristics (X1, X2, …, Xp); m, the number of latent factors (F1, F2, …, Fm); Xj, the representation of each characteristic as a linear function of these factors plus a residual variance (aka, latent errors) ej, with the goal of producing a model that maximizes the correlations between the characteristics (aka, observed variables) and the latent factors in Xj:

\[ X_j = l_{j1}F_1 + l_{j2}F_2 + \ldots + l_{jm}F_m + e_j \]  \hspace{1cm} (1)

where \( j = 1, 2, \ldots, p \). The factor loadings \( l_{j1}, l_{j2}, \ldots, l_{jm} \) in Equation 1 measure the strength of the correlation between characteristics and factors. The estimated values of the latent factors \( F_i, i > 0 \) are known as factor scores. By noting which characteristics are strongly associated with each factor, we can interpret the meaning of the factors in \( X_j \) and use this knowledge to identify concrete action categories.

After applying EFA to our data, we interpreted \( X_j \) to identify concrete action categories. Doing so revealed five action types: (1) Code Contribution, (2) Knowledge Sharing, (3) Patch Posting, (4) Progress Control, and (5) Acknowledgment / Response. Like Cheng and Guo’s work, we use \( X_j \)’s factor scores to extract clusters of action categories (see Figure 3). Without loss of generality, we called these categories general developer activities. Unlike their work, we generalize the factor scores to sequential data. Indeed, we represent each timestamped event in the collected data as a row vector of non-zero factor scoring coefficients and is belonging cluster as its label. Table IV provides an example of a timestamped developer activity in August of 2020.

B. Dynamic Developer Activity Embeddings

We now setup our dynamic activity model. Formally, we denote by \( S = (S_1, S_2, \ldots, S_T) \) our timestamped, labeled, sequential data, where each \( S_t \in S, t = 1, 2, \ldots, T \) is a data snapshot containing all developer activity \( Y_t \) in the \( t \)-time slice. Each \( S_t \) is arranged chronologically, and the length of the slice is a multiple of a standard time unit (e.g., weeks, months).

---

Fig. 2: Bridging the gap between LKML and LK’s codebase via Patchwork (adapted from image in [27]).

[1] https://lkml.org/
[2] Detected persuasion in emails using a transfer learning setup for Random Forest [22], trained on the Persuasion4Good dataset [36] and LKML data.
[3] https://patchwork.kernel.org/
[4] \( l_{j1} \) is the correlation weight of characteristic \( j^{th} \) on the factor 1.
TABLE I: Characteristics describing developer actions.

| Type          | Characteristic                  | Description                                                                 |
|---------------|---------------------------------|-----------------------------------------------------------------------------|
| Contribution  | Sender Experience               | #accepted patches / #submitted patches                                       |
|               | Sender Engagement               | (#new threads - #bot spam) / #sent emails                                    |
|               | Persuasive                      | Is exerting influence via persuasion?                                        |
|               | Patch Email                     | Is this email a patch email?                                                 |
|               | Bug Fix                         | Is this a bug fix patch?                                                     |
|               | New Feature                     | Is this a new feature patch?                                                 |
|               | Patch Churn                     | Is this a new patch revision?                                                |
| Exposition    | FRR Score                       | Text comprehension difficulty                                               |
|               | FKRL Score                      | Text reading grade level                                                    |
|               | Verosity                        | #words / #sentences                                                          |

TABLE II: Timestamped and labeled factor score vector for Greg Kroah-Hartman (sender id 0)

| sender_id | sent_time  | Code Contribution | Knowledge Sharing | Patch Posting | Progress Control | Acknowledgment | label |
|-----------|------------|-------------------|-------------------|---------------|------------------|----------------|-------|
| 0         | 2020-08-20 09:35:52 | 0.83758650 | 0.00918697 | 0.00502759 | 0.19685837 | 0.25811192 | Y0   |

Fig. 3: General types of developer activity, where $Y_0$ (contributing) describes a type of sporadic activities that occasionally lead to major contributions; $Y_1$ (probing) describes a type of erratic activities that are followed by a flurry of subsequent emails; $Y_2$ (bug fixing) describes a type of periodic activities that consistently focus on small contributions like bug fixes; $Y_3$ (monitoring) describes a type of periodic activities that focus on checking progress; $Y_4$ (persuading) describes a type of lone and often controversial activities that tend to instigate, persuade, or incite changes in project direction. We use these general activities as a compass for navigating and reading the trajectories revealed by our method.

We adapted the Skipgram with negative sampling [23] (SGNS) model to construct the embeddings. This method represents each developer activity $Y_i$ in $S_t$ by two low dimensional vectors: a developer activity vector $Y_i$ and a context vector $c_t$. SGNS optimizes the vectors via stochastic gradient descent so that $\hat{p}(c_t | Y_i) \propto \exp(Y_i \cdot c_t)$, where $\hat{p}(c_t | Y_i)$ is the empirical probability of seeing $c_t$ within a fixed-length window of developer activities in $S_t$, given that it contains $Y_i$. We express this window $\mathcal{N}_m(Y_i) = \{ Y_j | |\Delta t(Y_i, Y_j)| \leq m, Y_j \in Y \}$, where $m$ is the time interval, and $Y$ is the set of all unique activities in $S$. The size of $\mathcal{N}_m(Y_i)$ and thus the number of nearby developer activities to be considered by SGNS depends upon the value of $m$. For example, $\mathcal{N}_{1hr}(Y_i)$ would return all the developer activities 4 hours away from $Y_i$ across the kernel’s subsystems. This is inspired by Shen and Stringhini’s sliding window approach [33]. Our model operationalizes the “distributional hypothesis” that developer activities occurring in the same context tend to have similar meanings, and assumes that some of them even exhibit inter-activity dependencies — e.g., they might follow, block, or depend on one another [23].

We trained our model on the entire data $S$. We followed the recommendations of Levy et al. [21] in setting the hyperparameters for SGNS, but used stochastic hyperparameter optimization to set key settings. Also, we learned embeddings of size 120, and chose weeks as the length of the $t$-time slices.

C. Aligning Dynamic Developer Activity Embeddings

Charting the trajectory of influence pathways across time requires the alignment of the $Y_i$ vectors to the same coordinate axes (aka, latent space). The low-dimensional embeddings we generated previously are naturally unaligned due to the stochastic nature of SGNS. Particularly, the training of SGNS could result in arbitrary orthogonal transformations that prevent the comparison of the same developer activity across time [16]. Like Hamilton et al. [16], we first rely on training the embeddings separately on the $S_t$, then use orthogonal Procrustes between every two adjacent $t$-time slices to align the learned low-dimensional embeddings $Y_i$. Specifically, we define a matrix of embeddings $Y^{(t)} \in \mathbb{R}^{T \times |Y|}$, learned at time period $t = 1, 2, \ldots, T$, then find a matrix $R^{(t)} \in \mathbb{R}^{T \times T}$ for mapping $Y^{(t)}$ to $Y^{(t+1)}$. $R^{(t)} = \arg\min_Q \|QY^{(t)} - Y^{(t+1)}\|_F$, subject to $Q^TQ = I$.

The example in Figure [1] shows the evolution of three contribution activities $Y_0$ performed by individuals involved in the Hypocrite Commits incident, under the aliases like
we found their behavior to be similar to the behavior of the other two.

This section outlines how we can structure coding platforms present substantial new scientific and technical challenges. To address the dynamics issue, we use self-supervised training in concert with Temporal Graph Networks [28], a dynamic graph processing model to capture the motion dynamics of people’s practices, tools, actions, and code can be influenced in OSS projects; and (3) capturing the dynamism of influence operations through their shifts in language, activity, and contexts linked downstream to source code evolution and integrity. To resolve scalability issues, we will limit our processing to only the most interesting activity traces (exemplars) and will use stochastic hyperparameter optimizers to speed up learning and data mining tasks. To resolve diversity issues, we rely on the high level of transparency of social coding environments and their social media connections (e.g., GitHub, Stack Overflow, Twitter) to generate a diversity of signals through which developers’ practices, tools, actions, and code can be influenced. To address the dynamics issue, we use self-supervised training in concert with Temporal Graph Networks [28], a dynamic graph processing model to capture the motion dynamics of trust ascendancy without requiring embedding alignments.

IV. FUTURE PLANS

We position this work as an ideal influence pathway discovery, filtering and selection method for signaling emergent trust ascendancy operations in OSS projects.

Charting trust ascendancy trajectories and their patterns with agility, accuracy, and effectiveness at the scale of social coding platforms present substantial new scientific and technical challenges. This section outlines how we can structure our research to account for and address emerging issues. The basics of our future plans are thus: (1) scaling to large volumes of socio-technical traces we can introspect to discover and visualize influence trajectories while avoiding information overload and unnecessary and complex, CPU-cycle-intensive data related operations; (2) capturing the relationships and complexities of new case studies, paying close attention to the collection of a diversity of signals through which developers’ practices, tools, actions, and code can be influenced in OSS projects; and (3) capturing the dynamism of influence operations through their shifts in language, activity, and contexts linked downstream to source code evolution and integrity. To resolve scalability issues, we will limit our processing to only the most interesting activity traces (exemplars) and will use stochastic hyperparameter optimizers to speed up learning and data mining tasks. To resolve diversity issues, we rely on the high level of transparency of social coding environments and their social media connections (e.g., GitHub, Stack Overflow, Twitter) to generate a diversity of signals through which people’s practices, tools, actions, and code can be influenced. To address the dynamics issue, we use self-supervised training in concert with Temporal Graph Networks [28], a dynamic graph processing model to capture the motion dynamics of trust ascendancy without requiring embedding alignments.

REFERENCES

[1] R. Bamler and S. Mandt, “Dynamic word embeddings,” in *International conference on Machine learning*. PMLR, 2017, pp. 380–389.
[2] N. Bettenburg, A. E. Hassan, B. Adams, and D. M. German, “Management of community contributions,” *Empirical Software Engineering*, vol. 20, no. 1, pp. 252–289, 2015.
[3] F. Calefato, F. Lanubile, and N. Novielli, “A preliminary analysis on the effects of propensity to trust in distributed software development,” in *2017 IEEE 12th international conference on global software engineering (ICGSE)*. IEEE, 2017, pp. 56–60.
[4] C. Chen, Y. Tao, and H. Lin, “Dynamic network embeddings for network evolution analysis,” *arXiv preprint arXiv:1906.09860*, 2019.
[5] J. Cheng and J. L. Guo, “Activity-based analysis of open source software contributors: Roles and dynamics,” in *2019 IEEE/ACM 12th International Workshop on Cooperative and Human Aspects of Software Engineering (CHASE)*. IEEE, 2019, pp. 11–18.
[6] D. Child, *The essentials of factor analysis*. A&C Black, 2006.
[7] K. Cook, “Report on University of Minnesota Breach-of-Trust Incident,” May 2021, accessed: 2022-05-01. [Online]. Available: https://lkml.org/lkml/2021/5/5/1244.
E. Rossi, B. Chamberlain, F. Frasca, D. Eynard, F. Monti, and S. Mahdavi, S. Khoshraftar, and A. An, “dynnode2vec: Scalable dynamic network embedding,” in 2018 IEEE international conference on big data (Big Data). IEEE, 2018, pp. 3762–3765.

T. Mikolov, I. Sutskever, K. Chen, G. S. Corrado, and J. Dean, “Distributed representations of words and phrases and their compositionality,” Advances in neural information processing systems, vol. 26, 2013.

F. Nagle, D. Wheeler, H. Lifshitz-Assaf, H. Am, and J. Hoffman, “Report on the 2020 foss contributor survey,” The Linux Foundation Core Infrastructure Initiative, 2020.

D. Richle, “Analysis of ignored patches in the linux kernel development,” Ph.D. dissertation, Friedrich-Alexander-Universität Erlangen-Nürnberg, 2019.

M. Rudolph and D. Blei, “Dynamic embeddings for language evolution,” in Proceedings of the 2018 world wide web conference, 2018, pp. 1003–1011.

W. Scacchi, “Free/open source software development,” in Proceedings of the the 6th joint meeting of the European software engineering conference and the ACM SIGSOFT symposium on The foundations of software engineering, 2007, pp. 459–468.

D. Schneider, S. Spurlock, and M. Squire, “Differentiating communication styles of leaders on the linux kernel mailing list,” in Proceedings of the 12th International Symposium on Open Collaboration, 2016, pp. 1–10.

N. Segev, M. Harel, S. Mannor, K. Crammer, and R. El-Yaniv, “Learn on source, refine on target: A model transfer learning framework with random forests,” IEEE transactions on pattern analysis and machine intelligence, vol. 39, no. 9, pp. 1811–1824, 2016.

Y. Shen and G. Stringhini, “ATTACK2VEC: Leveraging temporal word embeddings to understand the evolution of cyberattacks,” in 28th USENIX Security Symposium (USENIX Security 19). Santa Clara, CA: USENIX Association, Aug. 2019, pp. 905–921. [Online]. Available: https://www.usenix.org/conference/usenixsecurity19/presentation/shen

V. S. Sinha, S. Mani, and S. Sinha, “Entering the circle of trust: developer initiation as committers in open-source projects,” in Proceedings of the 8th Working Conference on Mining Software Repositories, 2011, pp. 133–142.

G. Von Krogh, S. Spaeth, and K. R. Lakhanji, “Community, joining, and specialization in open source software innovation: a case study,” Research policy, vol. 32, no. 7, pp. 1217–1241, 2003.

X. Wang, W. Shi, R. Kim, Y. Oh, S. Yang, J. Zhang, and Z. Yu, “Persuasion for good: Towards a personalized persuasive dialogue system for social good,” arXiv preprint arXiv:1906.06725, 2019.

Y. Wang and D. Redmiles, “The diffusion of trust and cooperation in teams with individuals’ variations on baseline trust,” in Proceedings of the 19th ACM conference on Computer-Supported Cooperative Work & Social Computing, 2016, pp. 303–318.

D. Wermke, N. Wöhler, J. H. Klemmer, M. Fourné, Y. Acar, and S. Fahl, “Committed to trust: A qualitative study on security & trust in open source software projects,” in Proceedings of the 43rd IEEE Symposium on Security and Privacy, IEEE S&P 2022, May 22-26, 2022. IEEE Computer Society, May 2022.

Q. Wu and K. Lu, “On the feasibility of stealthily introducing vulnerabilities in open-source software via hypocrite commits,” Proc. Oakland, page to appear, 2021.

Y. Xu and M. Zhou, “A multi-level dataset of linux kernel patchwork,” in 2018 IEEE/ACM 15th International Conference on Mining Software Repositories (MSR). IEEE, 2018, pp. 54–57.

Z. Yao, Y. Sun, W. Ding, N. Rao, and H. Xiong, “Dynamic word embeddings for evolving semantic discovery,” in Proceedings of the eleventh acm international conference on web search and data mining, 2018, pp. 673–681.