RESEARCH STATEMENT

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I specialize in the field of software engineering. Since software, including AI, is now ubiquitous, it is of vital importance that we improve how we build software systems. My primary research goal is to **enhance developer productivity** through **automated approaches designed to leverage human knowledge**.

Guided by this overaching aim, I have designed **human-centric, data-driven** techniques addressing important software engineering challenges, including **program analysis** and **software evolution**. My research investigates how to use human feedback as well as the artifacts produced by engineers following software development processes. My work explores and takes advantage of advances in the intersection of Artificial Intelligence and Software Engineering. In my Ph.D. and postdoc research, I developed approaches to automate tasks that are error-prone for humans, including the prevention and detection of software defects.

My work has been published in highly reputable venues, including ICSE, FSE, ASE, and TSE. Papers from my research has been nominated for ACM SIGSOFT Distinguished Paper Awards. My work has real-world, practical impact. It has uncovered vulnerabilities leading to the assignment of over 20 CVEs. The solutions developed as part of the industrial collaboration were deployed by our industrial partner, Veracode, to assist its security researchers. This instills confidence in the potential of my research agenda to have significant impact in the future.

Current Research

My research helps software developers in detecting bugs, preventing them, as well as improving program analyses/models. I have made innovative contributions for learning code patterns for code search and transformation, postprocessing the outputs of static analyzers, and for managing the software supply chain. These innovations can be conceptualized using three qualities:

- Active Learning with Human Feedback
- Task-Specific Abstractions
- Software Development Process-Aware Techniques

Active Learning for Software Engineering – soliciting and learning from human inputs

Designing solutions with a *human in the loop* establishes human-automation trust and increases the steerability of automated approaches.

Code Patterns. I developed ALP [11] and SURF [15], which infer and refine code patterns for searching for source code containing bugs related to API (Application Programming Interfaces) misuses. ALP expresses the constraints for human labelling as a logic program, and solves it to inform its queries to the human user, leading to close to 10% improvements in its effectiveness over existing techniques. To reduce the human effort required, SURF guides human users with what-if analyses to provide feature-level feedback for refining the inferred pattern. We evaluated SURF through a user study and found improvements of 20% in correctness and 30% in time saved.

Static Analysis. In studies for filtering false alarms from static analyzers, I found methodological errors that led to overoptimistic results reported by another team of researchers [9]. Subsequently, we worked together to put together a new solution that reestablishes state-of-the-art results [17]. The work demonstrates that even in low-resource settings, rather than obtaining more data, it is more important to "reflect more on that data".

Effort Reduction in Human Inspection. To provide feedback, human users face significant cognitive demands. Human cognition and effort is therefore a bottleneck in Active Learning. In my ongoing research, I developed Inspector, which allows users to identify and filter high quality data when generating a large synthetic dataset. To inspect warnings from static analyzers, I have going work on the development of a tool, which combines the use of inductive logic programming to infer conditions under which false alarms occur, and infers a code pattern representing the root cause of a false alarm (i.e., code structurally challenging for a precise analysis).

Designing task-specific abstractions

Effective abstractions allow us to *simplify and manage complex problems.*

Code Patterns. I developed Coccinelle4J [14], a program matching and transformation tool. Coccinelle4J extendis the Coccinelle tool, which is widely adopted for C systems software, including the Linux kernel. The tool uses a code representation that captures a range of relationships between program elements on the control-flow graph, allowing developers to precisely describe a code transformation. This tool is the foundation that several tools for matching and transforming programs is later built on.

Static Analysis. For improving a call graph analysis, often used as an upstream component to support other analyses, I guided the development of AutoPruner [4], an approach combining traditional static analysis with large language models of code, to prune errors in a call graph. This leads to improvements of 13% in identifying false positives.

Dynamic Analysis. I developed SkipFuzz [12] for fuzzing deep learning libraries. Through the course of the fuzzing campaign, SkipFuzz refines its model, expressed as a disjunction of conjuctions of logical predicates, of inputs accepted by each library function. This model informs the fuzzer's selection of inputs. The model was carefully designed to be sufficiently expressive to support its ability to make predictions about different inputs – following the model, inputs identified as similar should produce the same test outcomes when used in fuzzing. Avoiding the selection of inputs with the same outcomes reduces redundancy, and uncovers more vulnerabilities.

Software development process-aware techniques

Since software is *engineered* through rigorous and systematic processes, data generated through its development are informative and can enable powerful techniques.

Code Patterns. To mine API migration patterns for the Android API, I guided the development of AndroEvolve [1, 2], which exploits the development practices within the Android SDK to support backwards compatibility. This allows us to identify a single code update pattern from a large space of candidate patterns.

Managing Software Dependencies. To automate the workflow of security researchers maintaining vulnerability databases, I guided the development of Chronos [5], Hermes [7], and Midas [6], collaborating with our industrial partners, including Veracode and Huawei. These techniques are designed following careful analysis of the limitations of state-of-the-art techniques, which are addressed by incorporating domain knowledge of software development processes. Next, to help developers assess the importance of a library vulnerability, I led the development of the Test Mimicry [13] technique. This performs evolutionary test case generation for a client program that depends on the library. Compared to the results of a static call graph analysis, inspecting a test case that reproduces the same program state reached by the library test case presents developers with more useful information about the exploitability of a library vulnerability.

Large Code Models. I contributed to CC2Vec [3], a distributed representation learned from code changes and their commit logs. This led to state-of-the-art performance on multiple downstream task, following my assessment of an older embedding model that could not generalize to different tasks [10]. I contributed to Compressor [8], which enables large code models (400+ MB) to be compressed into small models (3 MB), allowing their deployment on regular developer's laptops, with a negligible trade-off in model accuracy.

Future Research Plans

My research vision is to develop better human-in-the-loop techniques, which offer many advantages. My research has shown the promise of Active Learning for building more powerful, human-centered solutions.

In the short-term, I plan to develop better active learning techniques by addressing shortfalls I observed during my research. I plan to explore improvements in a) what types of knowledge and feedback are solicited, as well as b) how the tools obtain the information or help human users in providing these feedback. Looking forward to the long term, I hope to lead a rethinking of automated assistants that work with software engineers.

Better Active Learning for improving developer productivity

My research has shown that automating developer activities benefit from the incorporation of human feedback and knowledge. Still, there is room to improve by expanding on the types of information utilized by active learning approaches. I will investigate multiple modalities of feedback (e.g., natural language text, code, screenshots of running applications), which, in appropriate contexts, can be more easily provided by a human user. Advances in deep learning have made it possible for models to combine information from multiple forms of modalities. I plan to to take advantage of these advances and investigate how to synergize feedback of different modalities interactively with a human user.

To reduce the significant amount of effort demanded from human users, I am eager to explore solutions involving the combination of symbolic techniques, such as logic programs, and neural methods. Symbolic techniques allow us to instill a strong inductive bias, allowing certain classes of subproblems to be solved with a much weaker requirement for data. On the other hand, neural methods, e.g., large language models, allow classes of subproblems with an abundance of data to be easily solved. Carefully designing a neurosymbolic approach would allow active learning techniques that are effective without too heavy a labelling burden on a human user.

One particular domain I would like to investigate is vulnerability detection. In practice, software engineers in industry employ handwritten static analysis rules, e.g. CodeQL rules, for detecting vulnerabilities. These tools produce large amounts of false alarms and are challenging to scale up to more complex analyses. In research, scientists have proposed methods of using deep learning for vulnerability detection. These tools are opaque and are difficult to interpret by human practitioners. I believe that a middle-ground can be achieved through Active Learning – interpretable static analysis rules can be inferred using deep learning models by using simple yet expressive abstractions designed to take advantage of lightweight human feedback.

Better Active Learning from improved program comprehension

Soliciting feedback effectively can be challenging because it relies on human users to accurately provide them. While active learning already strives to minimize the number of labels needed from a human annotator, my research has uncovered that this still imposes heavy cognitive demands on the human user. This points at the need to design better automated techniques to support human comprehension.

For reducing the cognitive demands required for active learning techniques, my plan involves the design and development of tools for enhancing program comprehension. Many powerful tools in the research community, such as fault localizers, fuzz testers, and model checkers, can already help human users in discovering both useful and surprising information about their programs. However, on their own, human users find it difficult to interpret these analyses as these tools are rarely made to be accessible. I aim to build techniques that make these tools and their analyses accessible for non-experts. For example, developers would benefit from techniques that provide explanations in natural language text that interprets and combines these analyses. With this information at their disposal, users can provide more informed and valuable feedback for Active Learning.

My work has also utilize artifacts and data generated during the software development process. These artifacts and data would also be useful to a human user for program comprehension. I plan to investigate ways of using rich metadata about each program to help human users debug and understand code.

Long-term: The Software Engineer's Apprentice

The research paper, The Programmer's Apprentice [16], written in 1982 (over 40 years ago!), predicted programming assistants today. The Programmer's Apprentice was envisioned to be an aspirational tool that communicates with programmers, assisting them in automatic programming. Today, programmers have embraced tools, such as ChatGPT, communicating with them to write and edit code.

A software engineer does more than write code. Software engineers debug, maintain, and deploy code. They work on challenging tasks including investigate bug reports, disclose and assess the impact of vulnerabilities, ensure that legal and privacy requirements are satisfied. These error-prone tasks are where developers need help in. I will work towards building the aspirational Software Engineer's Apprentice, which should *collaborate* with engineers in *challenging* aspects of software development. I will investigate the most effective methods through which developers can communicate with an automated assistant, how an assistant can optimally assist developers in obtaining and interpreting information, and how an assistant can effectively use developer feedback.

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