

# 1 Towards Mining Robust Coq Proof Patterns 56

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## 14 Abstract 69

15 To reduce the human effort involved in maintaining Coq 70  
16 formal proof scripts, we discuss the software engineering 71  
17 program repair approaches and our plan to adapt them and 72  
18 apply them to proof repair. This talk proposes a mining 73  
19 approach on a recently published Coq dataset, that aims to 74  
20 adapt established software maintenance methodologies to 75  
21 benefit the area of proof maintenance. We would appreciate 76  
22 feedback from the Coq community on our planned approach. 77

## 23 1 Introduction 78

24 Even with the advanced features of modern proof assistants 79  
25 formalizing mathematical proofs require significant human 80  
26 effort. Having invested this effort, it is essential not to be 81  
27 required to redo large parts of the proofs every time a proof 82  
28 system changes or the proof libraries are improved. The 83  
29 importance of proof maintenance has already been observed 84  
30 with the creation of the first formal proof libraries in the 85  
31 eighties [2] and formally studied in the context of LCF proof 86  
32 systems in the nineties [6]. 87

33 Usually, the responsibility for maintaining particular proofs 88  
34 stays with the original authors. However, some proof system 89  
35 communities have introduced different approaches for this. 90  
36 When a user of Isabelle wants to make a change that would 91  
37 break several people's developments, before the change is 92  
38 accepted they need to fix all broken parts of the library. 93  
39 Nevertheless, the responsibility for particular Isabelle/AFP [3] 94  
40 entries ultimately belongs to their original authors and they 95  
41 are sometimes asked to adapt their developments to the new 96  
42 versions. 97

43 Recently, Reichel et al. [14] have proposed a machine learning 98  
44 dataset for Coq intended for proof repair. Based on this 99  
45 rich dataset, we aim to bring software engineering methodologies 100  
46 that are used in software maintenance to inform proof 101  
47 engineering choices and guidelines as well as guide 102  
48 automatic program transformations, such as proof repair. It 103  
49 would be valuable to receive input from the Coq community 104  
50 on our planned methodology. 105

## 51 2 Manual Approaches to Making Proofs 106 52 Maintainable 107

53 Tactical style proofs, predominantly used in Coq formalizations, 108  
54 are convenient for proof development as they enable 109

55 Coq proof engineers to construct proofs interactively by 110  
56 applying a sequence of tactics. Such proofs are often particularly 111  
57 hard to maintain. This is because a small mismatch 112  
58 in a single step might mean that the whole later part of the 113  
59 proof requires significant adaptation. Additionally with new 114  
60 goals opened and closed by tactics, when fixing the proof 115  
61 it is necessary to figure out which parts of the tactic script 116  
62 corresponded to which part of the proof. 117

63 For this reason, explicitly stating as many sublemmas 118  
64 as possible and using them in shorter proofs helps proof 119  
65 maintainability. This approach is taken to the extreme by 120  
66 declarative proofs, where all intermediate steps are stated 121  
67 explicitly, as done for example in Isabelle/Isar [19]. In fact, 122  
68 certain kinds of tactical Coq proofs can be automatically 123  
69 translated to declarative proofs [10] where cuts are explicitly 124  
70 stated. A further study of the maintainability of such 125  
71 automatically translated proofs is necessary. A task related 126  
72 to proof maintenance is proof translation between proof 127  
73 systems, and declarative proofs are actually easier to translate 128  
74 across provers than tactical proofs [9]. 129

75 Tactical style proofs are compiled using Coq's tactic compiler 130  
76 into a low-level representation of proofs called *proof terms*. 131  
77 Proof terms can also be manually written in Coq; 132  
78 effectively constructing proofs as terms that match with 133  
79 propositions as the types of these terms. Proof terms are 134  
80 checked using Coq's kernel for correctness. As opposed to 135  
81 tactic-based proofs that can obscure the underlying proof 136  
82 structure, proof terms both reflect and give control over 137  
83 the full explicit structure of the proof. Unlike tactical-style 138  
84 proofs, which are both hard to maintain as they obfuscate 139  
85 structure and typically require active maintenance across 140  
86 versions, proof terms tend to be more robust. For instance, 141  
87 in our personal experience, we have a decade-and-a-half-old 142  
88 manual proof term style formalisation [17, Appendix A] 143  
89 that has worked across various Coq versions over the years 144  
90 without requiring *any* maintenance. Moreover, thanks to 145  
91 the explicit structure proof terms are also more amenable to 146  
92 proof transformations and proof repair [15, 16]. Proof terms 147  
93 will, therefore, serve as the basis for our proof analysis. 148

## 94 3 Software Engineering Approach to 149 95 Program Repair 150

96 Software bugs are prevalent and fixing them requires significant 151  
97 effort and resources, which in turn can substantially 152  
98 reduce developers' productivity. It can take days or even 153  
99 years for software defects to be repaired [4]. Automated bug 154  
100 detection and repair tools have been developed to help 155  
101 developers identify and fix bugs more efficiently. 156

fixing, or automated program repair (APR), is now an active and exciting research area, which engages both academia and the software industry since its practicality was first realized in 2009 [18]. Real-world defects from large programs have been shown to be efficiently and effectively repaired by APR, e.g., the Heartbleed vulnerability was correctly repaired by a recent APR approach within a matter of minutes [13]. Notably, in 2018, Facebook announced the first-ever industrial-scale APR technique, namely GetAFix [1], developed by Facebook's headquarters-based research team in Menlo Park and widely used in-house. GetAFix was directly inspired by a recent research work [12]. More recently in 2023, APR was experimentally deployed in Bloomberg [20].

With the recent advances in Large Language Models (LLMs), the once futuristic idea of APR has further become closer to reality. Multiple APR solutions have been proposed, from leveraging program analysis to pure LLM-based prompt engineering. Approaches based on program analysis, e.g., symbolic reasoning such as [11, 13], reason about program semantics to synthesize patches. Symbolic reasoning is used to infer program specifications and then program synthesis is used to synthesize repair consistent with the inferred specifications. Approaches based on LLMs, deep learning, or data mining, such as [5, 8, 12], use syntactical patterns to search for repairs. The general idea in these approaches is that bug fixes often resemble their counterparts in the past and thus learning historical bug fix patterns is helpful to repair future bugs. While both of these approaches have shown promising results, there is still much room for improvement. That is, they rely heavily on test suites to validate the correctness of patches, and thus often produce plausible patches, i.e., patches that overfit to the test suite but do not generalize. Having more comprehensive or complete specifications would help APR overcome this issue in practice.

More recently, LLMs are also adopted for proof repair [7] and have shown promising results. Different from APR, proof repair has complete specifications which helps in part avoid the patch overfitting issue. It would be interesting to see how APR techniques can be transferred to the domain of proof repair, leveraging the benefit of having complete specifications to effectively fix broken proofs.

## 4 Proposed Methodology

This project focuses on mining proof datasets to learn robust proof patterns and proof repair patterns. We hope that this can help with gaining further insights on how to write proofs that are easy to maintain as well as in guiding proof transformations; be it so proofs can be automatically rewritten to more maintainable variants or for automated proof repair. Inspired by the process used in software engineering for program repair, we plan to proceed as follows.

**Data collection** Collecting data about proof transformations and proof repair was manually done by developers

in the past. A recent Coq dataset encompasses formalisms across various Coq versions [14]. This can be used as a basis for our mining work but needs to be analysed for robust versus breaking-proof patterns.

**Repair templates mining** automatically mining proof repair templates based on the data collected. Automatic mining of proof repair templates via the collected data. Relying on the data collection of proof repairs made by human proof engineers based on existing data sets, this phase converts the proof repairs into a graph form that is amenable to graph mining techniques to mine discriminative graph patterns. This allows us to automatically mine frequently appearing repair patterns. To do so, we plan to follow the following steps.

1. We convert proofs before and after repair into abstract syntax trees (ASTs) and then represent the transformations that convert one AST to another in terms of a graph. To do this, we use tree-differencing techniques to generate the AST transformations. The tree differencing techniques originally supported traditional programming languages such as C/C++/Java. Similar differencing approaches apply to proofs.
2. We then convert the collected transformations that represent proof repairs into graphs that are amenable to discriminative graph mining techniques. We then use graph mining to automatically mine discriminative graph patterns and use the mined patterns to guide the proof repair.

**Proof repair** automatically applies the mined templates to repair proofs. This devises automated approaches to generate repairs via a feedback loop from Coq.

1. Generate repair candidates via mutations using the mined templates.
2. Validate repair candidates using Coq for feedback on the correctness of the repairs; in particular, where a repair breaks and where it succeeds.
3. Continually improve the repairs through a feedback loop until Coq accepts the repaired proof.
4. Note that by doing so, we get complete correctness guarantees for the proof by using Coq in the loop.

**Robust proof pattern mining** A similar approach to mining proof repair templates can be used to mine the dataset and identify resilient proof patterns. These can be used to guide automatic semantic-preserving proof transformations into such patterns.

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