GP4P4: Enabling Self-Programming Networks

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Abstract—Recent advances in programmable switches have enabled network operators to build high-speed customized network functions. Although this is an important step towards self-* networks, operators are now faced with the burden of learning a new language and maintaining a repository of network function code. Inspired by the Intent-Based Networking paradigm, we propose a new framework, GP4P4: a genetic programming approach able to autonomously generate programs for P4-programmable switches directly from network intents. We demonstrate that GP4P4 is able to generate various small network functions in up to a few minutes; an important first step towards realizing the vision of ‘Self-Driving’ networks.

I. INTRODUCTION

The concept of Self-Driving Networks, analogous to the concept of Self-Driving Cars, has been a Utopian dream in the field of computer networks. That ultimate goal of running a network that behaves solely based on our intent is rapidly coming in reach through fast advances in the domains of network programmability and artificial intelligence [1], [2].

The introduction of the network programming language P4 [3], which allows for data-plane programmability, has enabled network operators to construct high-speed network functions customized to their own needs. However, this does require them to create and maintain a large library of network function code, which is prone to human error. Moreover, the move from P4_14 [4] to P4_16 [5] introduced major code-breaking changes to the language. As languages keep evolving, to remain up to date, a network operator would need to adjust his entire catalog of P4 programs.

In [6], the authors proposed an intent-based programming framework for P4, which can automatically create and install P4 programs using a library of P4 templates. Although this is a step in the right direction and simplifies the process of changing network functionality on the fly, it shifts the problem of maintaining a catalog of P4 programs to maintaining a catalog of P4 templates.

To avoid these problems entirely, we propose to leave the programming of the network to the network itself by enabling it to automatically generate data-plane code based on sets of less complex, human-readable rules or intents. These programs can then be used as templates to create larger, more complex programs or directly installed in the network. As a proof of concept, we present GP4P4, a framework that allows operators to modify their network functionality near instantaneously without modifying any code themselves. We believe this framework is an important first step towards a future where self-programming networks can fully program and adapt themselves to their current goals and circumstances with minimum intervention by network operators.

Machine-learning has recently been applied within the control-plane (see [7]) and to boost the performance of network functions (e.g., [8], [9], [10]), but the utilization of machine learning techniques to generate network functions themselves has yet to be considered. Also, a few position papers on self-driving networks have appeared [11], [12], [13], [14], [8], but again a concrete framework that enables the network to program itself is missing.

Our main contributions are: (1) GP4P4 itself, a framework for automatically generating P4 programs using techniques adapted from Linear Genetic Programming (LGP). LGP is a machine-learning technique to “evolve” an initially randomized population of programs towards satisfying an objective function [15]; (2) An evaluation module required to make LGP suitable for dataplane programmability. Our proposed evaluation module evaluates programs by creating synthetic network traces and simulating the output of P4 programs on these traces. In this regard, GP4P4 is fully self-sufficient and does not depend on any external network traces or physical switches; (3) Proof-of-Concept experiments demonstrating the efficacy of GP4P4.

II. GP4P4

Figure 1 gives a high-level overview of GP4P4. Behavioral rules – the intents of the network operator – lie at the base of our framework. They are analyzed to obtain the P4 building blocks that the framework uses to create P4 programs, as well as for evaluating the programs during and after their generation. In the inner loop, GP4P4 evolves programs using LGP. If the best of these programs satisfies all behavioral rules, GP4P4 presents this program as the solution. If not, it reboots the population of P4 programs and restarts the inner loop. This process continues until a solution has been found.

A. Behavioral Rules

We describe combinations of network functions as a set of behavioral rules on packet attributes (headers and metadata). If these rules are followed for each packet, we say that the P4 program is valid. In contrast to P4 programs themselves, these rules describe the intended outcome of a program, and not its methodology. In other words, these rules can be seen as a low-level description of the intents of a network operator.

In GP4P4, behavioral rules are expressed in the form of IF-THEN predicates connecting packet input conditions to output
We see these rules as a type of low-level intents, in between natural language high-level intents and P4 code itself. Thus, although they can be easily created by network operators themselves, behavioral rules could also be generated by natural language processors as an intermediary step between natural language and P4 code, allowing these processors to generate P4 code through GP4P4.

1) NAT Example: Consider the example situation in Figure 2. Switch S1 connects two networks, inside and outside. We want to install a “static source Network Address Translation (NAT)” network function on the switch that automatically replaces the source destination IP address of host H1 in inside, 192.168.1.1, with 10.0.0.10 in any outgoing packet, and the destination IP address 10.0.0.10 with 192.168.1.1 in any incoming packet. The IP addresses of all other packets should be left unchanged. To determine if packets are from inside or outside, we can match on their input port (pkt_in.port_num); packets arriving at port 0 are moving from inside to outside, and packets arriving at port 1 are moving from outside to inside. Figure 3 shows the resulting 2 behavioral rules for this network function.

**B. Program Generation**

In Genetic Programming (GP), an initially randomized population of programs is gradually evolved to satisfy an objective function by selection and reproduction, similarly to the biological concept of natural selection. To move through the search space, reproduced programs are randomly modified by mutation and/or crossover operations.

An important concept in GP is that of the phenotype versus the genotype. The phenotype is the program itself, while the genotype is an internal lower-level representation of the program that is more suitable for GP. Given a genotype, we can directly construct the phenotype by de-encoding this representation. In practice, GP has three major genotype representations: (1) linear, (2) tree-based, and (3) graph-based. In a tree-based approach, programs permanently branch after every IF-statement. Thus, this representation is more likely to evolve nested IF-statements than successive IF-statements. The graph-based approach does not suffer from this “problem,” but
limits our ability to perform crossover\(^1\). Crossover is vital for creating programs that satisfy our behavioral rules, as it allows a program that satisfies one rule to “merge” with a program that satisfies another rule to, hopefully, create an offspring that satisfies both rules. As we want to be able to evolve programs with both nested and successive IF-statements, as well as to make use of crossover, we use Linear Genetic Programming (LGP) in GP4P4. LGP evolves sequences of primitives of an imperative programming language. Each of these primitives represents a snippet of code in the phenotype program. In GP4P4 each primitive corresponds to a basic one-line declaration in P4, such as `src_ip = 10.0.0.10;`. We assume a set of XML is transformed to the GP4P4 primitive

```
if(a == b && b == c) {
    ...
}
```

To construct GP4P4 primitives, P4 declarations are simplified and written in prefix notation. For example, the P4 declaration `var3 = var5;` is transformed to the GP4P4 primitive `ASSIGN(var3, var5).` Although P4 declarations are normally written in infix notation, it is easier to encode genes in prefix format. The if-then statement `if() { }` is cut into two primitives, corresponding to `if() { and }`. In addition, we restrict these primitives to two input registers, and create a separate primitive for each possible comparison operator: `IF_EQ(a, b)` for `if (a == b)`, `IF_NEQ(a, b)` for `if (a != b)`, and `ENDIF` for `}.

We do not allow any other control-flow statements, such as the else statement. Although this choice of primitives is rather limited, it still supports a wide range of possible declarations, albeit in the form of multiple primitives. For example, `if(a == b & & b == c) {` is represented as `IF_EQ(a, b), IF_EQ(b, c).`

P4 allows for a wide array of possible memory locations, metadata values and packet headers. Including all these possibilities as registers would severely hamper the ability of GP4P4 to evolve programs into the right direction. Thus, GP4P4 automatically extracts all registers from the behavioral rules themselves. A packet attribute or constant is included as a register if and only if it is used in at least one of the behavioral rules.

As an optimization step, we categorize each attribute and constant by its data type, such as integer, string, Boolean, or IP address. We then limit the registers each primitive is allowed to access by type. This reduces the search space and ensures each primitive + register combination translates to correct P4 code.

2) **Initial Population:** To initialize the inner loop, we generate a population of \( N \) syntactically correct programs of primitives with a length between \( \min \_len \) and \( \max \_len \). To construct each program, GP4P4 first randomly picks a program length between \( \min \_len \) and \( \max \_len \). Then, it randomly generates this number of primitives, randomly selects valid registers for each primitive, and puts the primitives in sequence. This process is repeated every time the inner loop is restarted.

3) **Selection and Reproduction:** Within each iteration of the inner loop, GP4P4 holds two tournaments between \( t_r \times N \) randomly selected programs, where \( t_r \) is the tournament size ratio. The program with the highest fitness value of each tournament (or winner) is chosen for reproduction, while the bottom \( n_r \) programs (or losers) of each tournament are chosen to be replaced by the offspring of the two winners. In LGP, the new set of programs created by replacing the losers by the offspring of the winners is called a new generation. The inner loop continues the process of generating new generations until it either finds a valid program or reaches a pre-set generation limit.

Each of the \( 2 \times n_r \) offspring is created in pairs of two:

1) Duplicate both winners
2) Perform a crossover between both offspring with probability \( P_c \)
3) Mutate offspring 1 with probability \( P_m \)
4) Mutate offspring 2 with probability \( P_m \)

We compute and store the fitness value of each program as soon as it is created. This way, we reduce the number of fitness

\(^1\)Combining information from two parent programs to create new offspring.
values that need to be computed every iteration from $t_r \times N$ to $2 \times n_v$.

4) **Mutation**: To mutate a program, GP4P4 first selects a random index $i$ in the program. Then, with equal probability, it either adds a new random primitive to the program at $i + 1$, removes the current primitive at $i$, or replaces the current primitive at $i$ with a new random primitive. Random primitives are generated in the same way as described previously in Section II-B2, with a few notable exceptions: To help evolve the program towards satisfying new rules, we generate new random if-then primitives with a higher probability than other primitives. GP4P4 selects a new, random if-then primitive with probability $P_d$ and a non-if-then primitive with probability $1 - P_d$. In addition, to prevent new if-then primitives from dropping the fitness level of the program, GP4P4 adds an ENDIF() primitive directly after every new if-then primitive it adds to a program. Similarly, when removing an if-then or ENDIF() primitive, GP4P4 also removes the corresponding ENDIF() or if-then primitive.

5) **Crossover**: To perform a crossover between two programs, GP4P4 randomly selects a unit of code of both programs and swaps these units with each other. In GP4P4, a unit is either a single non-if-then primitive or a sequence of primitives starting with an if-then primitive and ending with its corresponding ENDIF() primitive. By only swapping valid blocks of code, we ensure that the resulting two programs remain syntactically valid.

**C. Program Evaluation**

The evaluation module plays a critical role in GP4P4, as it guides the evolution of programs in the right direction, as well as checks if a program satisfies all behavioral rules. A good evaluation function should evaluate, in fine granularity, how close a program is to satisfying all rules and express this in a numerical value. In the case of P4 programs, this is not a straightforward process, as programs may seemingly satisfy a rule for one packet, while breaking it for another. Figure 4 gives an overview of the evaluation module.

First, the **Trace Generator** generates a synthetic network trace of packets and output conditions based on the behavior rules supplied to the framework. Then, the **Switch Simulator** simulates the program and processes the network trace. For each packet in the trace, the simulator counts the number of packet output attributes that satisfy the behavioral rules. Finally, the total number of these valid output attributes over all packets in the trace, $A_p$, is normalized to obtain the fitness value, $F_p$, by dividing it by the total number of packets in the network trace, $N$, times the number of output attributes per packet, $A_p$: $F_p := \frac{A_p}{N \times A_p}$.

1) **Trace Generator**: If a behavioral rule contains multiple expressions combined with OR, it is important that the final program is valid for all possible cases. Thus, the Trace Generator first splits the IF statement of each behavioral rule into its disjunctive normal form and creates a separate rule for each of its clauses. In addition, to ensure the program does not modify any attributes if it does not match any rules, the Trace Generator also adds the complement of all behavioral rules as a default rule.

For each of these created rules, the Trace Generator creates $k$ packets. Packet input attributes are created in a semi-randomized fashion to match the IF conditions of the rule, while the output attribute conditions are directly taken from the THEN conditions of any rule that match the randomly-created packet. By creating packets for each rule, we ensure that the fitness evaluation function evaluates programs on each rule as well. To reduce computation time, the same network trace is re-used throughout the inner and outer genetic programming loops. Thus, the Trace Generator is only run once, just before starting the outer genetic programming loop.

2) **Switch Simulator**: Compiling a program to P4, and then running the program on a real or emulated switch can take a significant amount of time. We propose running and evaluating each program on a simulated switch instead, while guaranteeing the same output/fitness as a real switch.

To save time, the simulator (written in Python) runs directly on the sequence of primitives (the genotype) described in Section II-B instead of on P4 code (phenotype). When simulating a program, the Switch Simulator first initializes a new list of registers, as described in Section II-B1. It then “runs” the program on each packet of the network trace by

1) Copying the packet attributes to the corresponding registers.

2) Interpreting the GP4P4 primitives line by line, reading and modifying the register values whenever required.

3) Copying the output packet attributes from the corresponding registers.

The fitness value of the program is then determined by counting the total number of satisfied output conditions, $A_p$, and dividing this value by the total number of output conditions, $N \times A_p$.

In the Switch Simulator, all primitives are assigned their own Python function. Consequently, to interpret a GP4P4 primitive, the simulator simply executes the corresponding Python function. If-then primitives form their own special case: when the simulator encounters an if-then primitive, it checks if its condition is true. If it is, the simulator continues to the next line. If not, the simulator searches for and skips forward to the corresponding ENDIF() primitive. To prevent the simulator from jumping to the end of a nested if-then block instead, it keeps track of its current depth while searching for the correct ENDIF() primitive.

**III. EXPERIMENTS**

We demonstrate GP4P4 on the 7 small network functions given in Table I. The experiments were run on an Intel Xeon CPU E5-2690 running Ubuntu 14.04.6 LTS (kernel version 3.13.0-151).

As can be seen in Figure 5, GP4P4 can generate each of the 7 network functions within 1.5 minutes. Even for the most difficult function (Router), a valid solution is usually found within 1 minute. The worst-case generation time was around 67 seconds. As network functions do not constantly
Behavioral rules

| Network trace:                          | Output conditions |
|----------------------------------------|-------------------|
| Input attributes                       | Output attributes |
| port_num | src_ip | port_num | src_ip |
| 0 192.168.1.1 | 10.0.0.10 | 0 192.168.1.0 | 192.168.1.0 |

Evaluation Function

\[ F_v = \frac{A_c}{N \times A_p} \]

**TABLE I**

| Network Function         | rules | primitives |
|--------------------------|-------|------------|
| Network Address Translation (NAT) | 2     | 3          |
| Firewall                 | 1     | 3          |
| Server Balancer          | 2     | 3          |
| Link Balancer            | 2     | 3          |
| DSCP Marker              | 2     | 3          |
| Router                   | 2     | 4          |
| Port Address Translation (PAT) | 1   | 3          |

**Fig. 4.** Evaluation module overview.

**Fig. 5.** Tukey boxplots of the generation times of 7 network functions. Each network function was generated 100 times.

need to be regenerated, this is well within acceptable limits. In fact, GP4P4 enables networks to almost immediately react to changing requirements from users or network operators, as the network can generate and install a completely new P4 program within minutes.

Next, we consider the effect of changing different parameters on the program generation time. In general, there does not seem to be a clear-cut rule for the optimal setting for all network functions. However, in all our experiments, as long as crossover was enabled, a program could still be generated within 8 minutes at worst, suggesting that it is still possible to achieve reasonable generation times even with non-optimal parameters.

Figure 6 shows the generation time of Firewall and Router versus the population size, tournament size ratio, and maximum initial program length. We chose to illustrate these network functions, because they have respectively the lowest and highest generation times, and thus presumably are respectively the easiest and most difficult to generate. The parameters were selected due to their impact on both functions.

For the 4 network functions with the lowest generation times, a population size of around 1000 seems to be near-optimal. For the other network functions, a population size of 3000 gives the best results. As we want to prioritize the generation time of more difficult functions, 3000 seems to be a good choice for the population size.

For some functions, a low tournament size ratio of at most 0.1 results in both lower generation times and generation time variance. A lower tournament size ratio allows more sub-optimal programs to evolve. Presumably, this helps increase the number of possibilities GP4P4 considers, which allows it to find valid programs more quickly.

For all network functions, limiting the maximum initial program length, max_len, to 10 significantly improved generation times. Presumably, this is because the network functions we tested are quite small and do not require many lines of code. Alternatively, it might help early programs to satisfy one specific (implicit) behavioral rule, after which these programs can be “merged” using crossover in later generations.

Figure 7 shows the impact of crossover and mutation rates on the program generation time. For all network functions except Firewall and PAT, introducing crossover significantly decreases generation times as well as generation time variance. The mutation rate only has a clear impact on the generation time of the Router network function. However, as it decreased both the average generation time and the generation time variance of Router, and does not significantly increase the generation time of other network functions, mutation is clearly worthwhile to include in GP4P4.

**IV. CONCLUSION**

The size and complexity of networks has grown formidably, making managing and programming them a daunting task. In this paper, we provide a first step towards automating this
process. Our proposed framework, called GP4P4, uses Linear Genetic Programming techniques to automatically generate and evolve a population of P4 network programs. GP4P4 evaluates these programs by simulating a P4 switch and generating a synthetic trace of network packets tailored towards effectively evaluating a specific rule-set. This not only reduces the computation time significantly, but also allows GP4P4 to generate P4 programs without relying on any external switches or network traces.

Our experiments show that GP4P4 can generate P4 programs within minutes. Although GP4P4 is currently applied to simple behavioral rules, we believe it is an important first step towards a future of self-programming networks: networks that can fully program and adapt themselves to their current goals and circumstances with minimal intervention by network operators.

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