

# PETSY: Polymorphic Enumerative Type-Guided Synthesis

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## 1 INTRODUCTION

Consider the task of implementing a function that has the following description: “If I give you a function, apply it to  $x$ . Otherwise, return  $x$  unchanged.” We can translate this function description into a Haskell type signature as follows:

$$f : \text{Maybe } (a \rightarrow a) \rightarrow x : a \rightarrow a$$

where  $f$  represents a possible function (hence the `Maybe` type), and  $x$  is of the same type that  $f$  takes in and returns. Say that we have a component `fromMaybe` that has type  $a \rightarrow \text{Maybe } a \rightarrow a$ . A possible solution to this problem is:

$$\text{applyMaybe } f \ x = \text{fromMaybe } (\backslash y \rightarrow y) \ f \ x \tag{1}$$

which either extracts the function from a `Just` and applies it to  $x$ , or applies the identity function to  $x$  when given `Nothing` (which is the same as returning  $x$  unchanged). As a component-based program, `applyMaybe` (1) is idiomatic and concise and doesn’t rely on `if-else` or pattern matching. But finding it is potentially non-intuitive.

We present **PETSY**, a tool that allows users to provide a type signature and optional examples, and get back a code snippet that consists of a composition of Haskell library functions. This allows users to speed up their programming by using our tool to synthesize small Haskell programs instead of doing it themselves. One advantage over other existing tools is that **PETSY** is able to synthesize `applyMaybe` (1) through a top-down, enumerative type-guided search algorithm.

## 2 RELATED WORK

The problem we explore is polymorphic type-guided synthesis via enumerative search. Related problems have been explored before.

**MYTH.** `MYTH` [2] already explores enumerative search for type-directed synthesis, but it does not support polymorphism or typeclasses like **PETSY** does, making it unable to synthesize `applyMaybe` (1).

**TYGAR.** `TYGAR` [1] uses Petri nets to tackle type-guided Haskell program synthesis, and is remarkable in that it also supports polymorphic types and typeclasses. However, its encoding into Petri nets reduces the type system to first-order, so programs with  $\lambda$ -abstractions are not in the space of programs that `TYGAR` can pull from.

**SYNQUID.** `SYNQUID` [3] makes use of an enumerative search approach,  $\lambda$ -abstractions, and polymorphism, but is unable to solve our running example `applyMaybe` (1). This is because its type system restricts type variables (represented here with  $\alpha$ ) from unifying with arrow types. In particular,

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Maybe  $a \rightarrow a$  cannot unify with  $\alpha_1 \rightarrow \alpha_0 \rightarrow b$ , as that would require  $a$  to unify with  $\alpha_0 \rightarrow b$ . We discuss this in depth in 3.2.

### 3 APPROACH

#### 3.1 Synthesis Problem

Our synthesis *problem* consists of a component library, a query type, and optional input-output examples. A *solution* to the synthesis problem is a Haskell code snippet that only contains applications,  $\lambda$ -abstractions, and variables (including components), and that has the desired type and works for the optionally given examples.

#### 3.2 Extending SYNQUID’s enumeration strategy

SYNQUID also solves its synthesis task via top-down enumerative search. The task it solves is similar, the only difference being that the types are not just polymorphic – they are liquid (refinement) types. Among other reasons, SYNQUID’s method of supporting refinements requires it to determine whether a type is a scalar without having to substitute its type variables. This is made possible by restricting type variables to not unify with arrow types. This, however, is only relevant in the context of refinement types, so there is no reason to have this restriction in our context.

PETSY is built on top of SYNQUID, ignoring all the refinement type logic since our synthesis task does not involve refinements. We also make the type system more expressive by letting type variables unify with arrows. This means PETSY can synthesize a wider range of programs. Defining  $::$  to mean “has type”, one concrete example is the query  $(a \rightarrow b, a) \rightarrow b$ , with components  $[fst :: \forall x. \forall y. (x, y) \rightarrow x, snd :: \forall x. \forall y. (x, y) \rightarrow y]$ . The solution is  $fst\ p\ (snd\ p)$ , which is only possible if  $\forall x. \forall y. (x, y)$  in  $fst :: \forall x. \forall y. (x, y) \rightarrow x$ , unifies with  $p :: (a \rightarrow b, a)$ . Because the type variable  $x$  needs to unify with the arrow type  $a \rightarrow b$ , PETSY is able to consider the program  $fst\ p\ (snd\ p)$  while SYNQUID cannot.

#### 3.3 Memoization (caching subproblems during enumeration)

The nature of enumerative search with iterative deepening is that many repeated subproblems are generated over the course of the search. Redoing the same subproblems wastes a lot of time. This makes memoization crucial to practical top-down enumeration, which MYTH [2] is able to solve in a monomorphic setting.

**Memoization map.** We organize our memoization map as follows:

$$\text{goal type and desired program size} \implies \{ \text{solutions at the given size} \}$$

**Complications with polymorphism – type variable clashes.** If we allow both memo keys and program types to contain polymorphic type variables (which Petsy does), memoization becomes difficult to implement. When synthesizing function arguments, we need to know their desired type and therefore the type of the function. In polymorphic settings, though, getting this information is non-trivial. Say, for instance, that our memo map contains a mapping

$$(\alpha_1 \rightarrow \text{Int}) \text{ at size } 1 \implies \{ \text{length} :: [\alpha_2] \rightarrow \text{Int} \}$$

One possible solution is to simply retrieve the stored type from the map itself,  $[\alpha_2] \rightarrow \text{Int}$ . This, however, will cause type clashes at retrieval time. When we originally store the program  $\text{length}$ ,  $\alpha_1$  and  $\alpha_2$  are fresh type variables. But when we retrieve this in a later context,  $\alpha_1$  and  $\alpha_2$  might already be in use for something else, and by using the stored type we’d be unintentionally linking these existing type variables with the type of  $\text{length}$ . To overcome this clash, we ignore the stored type and *infer the type* of the retrieved program from scratch upon retrieval instead.

Table 1. TYGAR vs. PETSy

N	Name	Query	TYGAR	PETSy
1	test	Bool -> a -> Maybe a	8.0 s	6.0 s
2	firstJust	a -> [Maybe a] -> a	18.4 s	6.5 s
3	mapEither	(a -> Either b c) -> [a] -> ([b], [c])	4.8 s	3.2 s
4	mapMaybes	(a -> Maybe b) -> [a] -> Maybe b	8.0 s	5.2 s
5	mergeEither	Either a (Either a b) -> Either a b	3.8 s	181.5 s
6	map	(a->b)->[a]->[b]	2.1 s	3.7 s
7	repl-funcs	(a->b)->Int->[a->b]	1.1 s	1.2 s
8	mbAppFirst	b -> (a -> b) -> [a] -> b	3.2 s	9.5 s
9	resolveEither	Either a b -> (a->b) -> b	4.0 s	10.3 s
10	multiApp	(a -> b -> c) -> (a -> b) -> a -> c	6.9 s	9.6 s
11	singleList	a -> [a]	7.7 s	4.4 s
12	head-last	[a] -> (a,a)	257.3 s	12.0 s
13	firstMatch	[a] -> (a -> Bool) -> a	6.0 s	6.9 s
14	rights	[Either a b] -> Either a [b]	1.9 s	2.6 s
15	firstKey	[(a,b)] -> a	1.5 s	3.4 s
16	firstRight	[Either a b] -> Either a b	4.4 s	9.6 s
17	zipWithResult	(a->b)->[a]->[(a,b)]	268.1 s	10.8 s
18	applyNtimes	(a->a) -> a -> Int -> a	30.2 s	18.0 s
19	mbElem	Eq a => a -> [a] -> Maybe a	3.7 s	295.6 s
20	flatten	[[[a]]] -> [a]	4.7 s	1.4 s

We also normalize memo key type variables, making the first one  $\beta_0$ , the second one  $\beta_1$ , and so on. This saves space by mapping semantically equivalent goal types, like  $\alpha_0 \rightarrow \text{Int}$  and  $\alpha_1 \rightarrow \text{Int}$ , to the same key,  $\beta_0 \rightarrow \text{Int}$ .

## 4 RESULTS

We evaluated PETSy on 20 benchmarks that we took from TYGAR’s [1] paper. We used the same set of 130 components in all experiments. Because TYGAR’s search space was most similar to ours, we chose to compare PETSy with TYGAR. The results can be found in Table 1.

**Analysis.** PETSy and TYGAR are comparable. While there are some tests that PETSy does much *better* in – #12 and #17 – and some tests that PETSy does much *worse* in – #5 and #19 – both tools perform about equally well (within a few seconds) on the other benchmarks.

These results are quite encouraging. For one, since PETSy takes advantage of  $\lambda$ -abstractions and TYGAR doesn’t, PETSy is more expressive and therefore searches through more programs, yet is still competitive. We also have only implemented the most basic form of memoization, and plan to improve upon it to make PETSy even faster (see [Future Work](#)).

**Quality of Results.** For the most part, both TYGAR and PETSy returned the same programs. If they didn’t return the same program (because PETSy found a solution using  $\lambda$ -abstractions), the programs were equivalent, so there is no significant difference in program quality between the two tools.

## 5 FUTURE WORK

Our memoization tool is still very basic and we think there are multiple ways in which we can improve upon what we have:

- (1) Re-organize our memo map to store programs first based on size, and then find programs based on query. This would make lookup much faster.
- (2) Take advantage of sub-typing in the memo keys so that the same programs aren’t stored multiple times. For example, all programs in goal  $\text{Int} \rightarrow \text{Int}$  should be in goal  $\alpha_0 \rightarrow \text{Int}$ . When we lookup  $\alpha_0 \rightarrow \text{Int}$ , we could first look at  $\text{Int} \rightarrow \text{Int}$  and then move on to other programs that are more general.

## REFERENCES

- [1] Zheng Guo, Michael James, David Justo, Jiaxiao Zhou, Ziteng Wang, Ranjit Jhala, and Nadia Polikarpova. 2020. Program synthesis by type-guided abstraction refinement. *Proc. ACM Program. Lang.* 4, POPL (2020), 12:1–12:28. <https://doi.org/10.1145/3371080>
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