fc: A Package for Generalized Function Composition Using Standard Evaluation
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Abstract In this article, we present a new R package fc that provides a streamlined, standard evaluation-based approach to function composition. Using fc, a sequence of functions can be composed together such that returned objects from composed functions are used as intermediate values directly passed to the next function. Unlike with magrittr and purrr, no intermediate values need to be stored. When benchmarked, functions composed using fc achieve favorable runtimes in comparison to other implementations.

Introduction

Coding in R often reduces to running a sequence of operations in order. For instance, as part of exploratory data analysis, one might subset the first 50 rows from a data frame and then examine numerical summaries of the subset. This could be accomplished using base R for a given data frame:

```r
summary(head(iris, 50))
```

Via magrittr (Bache and Wickham, 2014), the use of a pipe operator improves readability, enabling the user to read the sequence of functions in the order of application from left to right:

```r
iris %>% head(50) %>% summary()
```

The analysis pipeline, defined by `head(50) %>% summary()`, is a sequence of functions that are run in succession. The first function uses the data object on the far left as input. Each successive function is run to completion, using the returned object from the function left of each pipe as input to the function on the right.

Over the past few years, the pipe operator (`%>%`) has become a popular means for chaining together a sequence of functions, particularly where a long chain of commands needs to be run, as often is the case with data wrangling (Wickham and Grolemund, 2016). A good deal of this popularity comes from the economy with which pipelines of functions are created. Construction of pipes often relies heavily on non-standard evaluation (NSE) (Wickham, 2014), where parsed expressions must be manipulated before their evaluation to ensure correct execution. For example, in the expression `iris %>% head(50) %>% summary()`, both the `head()` and `summary()` functions are altered so that the `iris` and output of `head()` respectively are inserted as the first function arguments. This dialect of R has seen widespread adoption due to its conciseness, enabling the user to quickly define sequences of operations to perform on data.

In this paper, we present a standard evaluation approach to chaining functions via function composition; the return of the first function becomes the argument to a second function and so on, obviating the need for storing intermediate variables and function lists. This approach, which optionally includes a slightly different pipeline syntax, is implemented in a new R package fc.

In the ensuing sections, we begin with a review of existing work in function chaining and function pipelines. We consider the fundamental differences between how pipe-forward operators are used in magrittr and fc, and show how function composition is achieved using fc. We then describe the underlying implementation of the fc package. We additionally present a number of examples that show the diverse applications of fc, including compatibility with packages like dplyr (Wickham et al., 2017); we show that runtimes are comparable and at times superior to implementations using other packages.

Background

To our knowledge, purrr (Henry and Wickham, 2017) and magrittr are the only R packages under active development that provide procedural composition of functions – namely, both packages are capable of encapsulating a specified sequence of functions within a single function. Within purrr, such encapsulating functions can be created via `compose()` and within magrittr, they are created using a pipeline with `'` in place of the data object that ordinarily precedes the first pipe operator. Despite differences in syntax, their output function bodies are actually the same – a list of functions stored in the encapsulating function in run order. Of the two packages, magrittr is by far the more commonly-used package due to its convenient pipeline syntax. Below, we give an overview of the history of pipes in R programming and then describe their use in magrittr.
A History of Pipes

The characterization of the `%>%` operator as a “pipe” may be attributed to the pipeR package (Ren, 2016); its associated syntax is inspired by Unix pipes. It may be noted, though, that `>` is not actually the pipe operator in Unix; it is the instruction operator used to route the output of a pipe to a file, including stdin, stdout, and stderr. The Unix pipe operator is denoted as `|`. Nonetheless, the convention of using `>` as a pipe is not without precedence; for example, the F# programming language denotes `|>` as the pipe-forward operator.

Along with syntactic differences, R pipes differs from Unix pipes in their design. A Unix pipe defines a sequence of applications run as different processes where the output of each application is formatted text that can be read into the next application in the “pipeline.” Text is outputted in contiguous blocks or “chunks” using files. Applications run concurrently, processing input as they become available, thereby managing memory usage (chunks are stored in the file cache and may be much smaller than the input) as well as load balancing (applications are bottlenecked by the one with the lowest throughput). Pipeline concurrency within R is supported in the iotools package (Arnold et al., 2017) but its use is primarily focused on chunked file processing and it does not support a pipe-forward operator.

magrittr Pipes and Non-Standard Evaluation

When used with functions, magrittr’s pipe-forward is an infix operator collecting the sequence of functions to be applied to an input data object. NSE alters each function call in the pipeline so that it can be evaluated in the standard way and its return value can be (1) returned if it is the last function call or (2) sent to the next function in the sequence of functions defined by the pipeline. Continuing with our opening example, we can create a function using magrittr as follows:

```r
head_summary <- . %>% head(50) %>% summary()
```

The new function, `head_summary()`, can be examined via:

```r
> unclass(head_summary)
function (value)
  freduce(value, _function_list_)
<environment: 0x7fab1e3518c0>
```

We see that `head_summary()` is a function that calls `freduce()` on the input and the sequence of functions stored in the `head_summary()` function environment named `_function_list_`, seen below:

```r
> environment(head_summary)[["_function_list"]]
[[1]]
  function (.)
  head(., 50)

[[2]]
  function (.)
  summary(.)
```

Both `head()` and `summary()` are altered in the call to pipe-forward. Each gets wrapped in a function taking `.` as an argument; `.` serves as the first argument in `head()` and `summary()` within the wrapper functions.

The arguments to pipe-forward (e.g. `head(50)` and `summary()`) are syntactically valid; they can be parsed to create a valid expression. They are not semantically valid because the user must provide `x` and object arguments to `head()` and `summary()` respectively for successful execution (assuming the base R implementations of both functions). NSE turns syntactically valid but semantically invalid expressions into new syntactically and semantically valid expressions.

Functionally, the pipe-forward provides both partial multivariate function composition, where the input arguments are the return of other functions, as well as partial multivariate function valuation, where an argument is set to a constant (e.g. setting `n` to 50 in `head()`). However, we have already seen that it does not compose functions in the expected way. Otherwise, `head_summary()` ought to be defined similarly to:

```r
function(.
{
  summary(head(., 50))
}
```
Instead, head\_summary() keeps track of the sequence of functions, applying the input to the first function and the return of the first function to the first argument of the second function. The resulting output, when applied to a data object, is equal to what would be achieved using function composition.

**Partial Function Composition and Valuation with fc**

Inspired by magrittr, the fc package provides partial multivariate function composition and valuation where resulting functions are true compositions of the inputs. Composed functions send the result of one function directly to a subsequent function without intermediate values. Code analysis finds unbound variables (variable names with no associated value) and includes them as variables in returned function.

For convenience, a pipe-forward operator is included in the package and can be thought of as an application of the more general functionality. The resulting implementations from either of these function-composing approaches tend to be more readable and easier to debug compared to that of magrittr.

**The fc() function**

The primary function in the fc package is fc(), which simultaneously allows for partial function composition and valuation. The first argument to fc() could either be an existing function in the environment or an anonymous function. Any following arguments must be named arguments to this function. For example, we can create a new function that uses partial function valuation to display the first 50 rows of a dataset with:

```r
head50 <- fc(head, n=50)
```

The return function has a single argument `x`, inherited from the `head()` function. The function `head50()` consists of:

```r
function (x) {
  head(x, n = 50)
}
```

In order to perform function composition, multiple fc() calls could be used in a nested manner:

```r
summary50 <- fc(summary, object=fc(head, n = 50)(object))
```

Or, `head50()` could be defined separately, and we could rewrite:

```r
summary50 <- fc(summary, object=head50(object))
```

The signature of the returned function consists of: (1) parameters in the formals of the function passed to fc() that are not assigned as well as (2) the unbound symbols in the expressions passed as arguments to fc(). As a result, the signature of the return function can be specified differently than that of the function it takes as its first argument. For example, if we wanted the signature of `summary50()` to be a single variable called `x`, then we could specify:

```r
summary50 <- fc(summary, object=head50(x))
```

with function definition given by:

```r
function (x) {
  summary(object = head50(x))
}
```

All arguments to fc(), except the first, must be named. This decision was made to minimize confusion that may occur when associating expressions with arguments in the mixed named/positional argument setting. The fc() function also does not promote unbound argument-function variables to arguments of the returned function. This is because some functions distinguish between a default argument and an argument with a default argument that is not passed an input at run-time.
Default and Passed Arguments

One function making the distinction between default and passed arguments is `matrix()`, whose signature is

```r
> matrix
  function (data = NA, nrow = 1, ncol = 1, byrow = FALSE, dimnames = NULL)
...
```

If unassigned arguments were promoted to input function arguments in a hypothetical `fc_bad()` function, then

```r
matrix_bad <- fc_bad(matrix, ncol = 3)
```

would result in a function

```r
function(data = NA, nrow = 1, byrow = FALSE, dimnames = NULL)
{
  matrix(data = data, nrow = nrow, ncol = 3, byrow = byrow,
         dimnames = dimnames)
}
```

and the following call would result in incorrect behavior, which does not produce either a warning or an error:

```r
> matrix_bad(rnorm(9))
```

This is different than the $3 \times 3$ matrix we would expect to see from the direct call `matrix(rnorm(9), ncol = 3)`. The difference comes from the fact that the direct call detects that `nrow` is missing and calculates the correct number of rows despite the fact that the default number of rows is 1 in the signature. The hypothetical `fc_bad()` function fails because the default values in the argument-function were taken as the defaults in the return function. As a result, when `fc(matrix_bad, rnorm(9))` is called, with the promoted defaults, the `matrix()` function is called with the default `nrow = 1`. Instead, we need to specify that the data argument is a return-function parameter and the `ncol` argument is 3:

```r
> matrix_3_col <- fc(matrix, data=data, ncol=3)
> matrix_3_col
  function (data)
  {
    matrix(data = data, ncol = 3)
  }
```

The composed function then operates as expected:

```r
> matrix_3_col(rnorm(9))
```

The Pipe-forward Operator

A pipe-forward operator is included in the package and can be regarded as a special case of functionality provided by the `fc()` function. This is because both the left- and right-hand-side functions provided to the pipe-forward operator take a single input (after appropriate argument modification). Therefore, the implementation of the pipe-forward operator is simply the composition of two functions, provided by the `fc()` function. As a result, contiguous, syntactically meaningful subsets of a valid `fc`-pipeline, when evaluated, result in a valid function.

```r
summary50 <- fc(head, n=50) %>% fc(summary)
```

Each entry in a `fc` pipeline should be a function class object. In the absence of other arguments to `fc()`, the last entry of the pipeline, `fc(summary)`, produces a simple wrapper function for the `summary()` function. For that reason, we can replace this last entry in the pipeline with `summary`:

```r
summary50 <- fc(head, n=50) %>% summary
```
We highlight two important distinctions between fc’s pipe-forward operator and that of magrittr. First, fc’s pipe-forward does not support a dataset as the left-hand-side argument. The magrittr package supports expressions like:

```
iris %>% head %>% summary
```
because the head() function is called, with iris as the input and the result is stored as the intermediate variable “.” by convention. This intermediate variable is then provided as the first argument to summary() in the subsequent call to the pipe-forward operator. The the pipe-forward operators have the same precedence and therefore they are parsed from left to right, according to R’s grammar. However, the equivalent expression using fc(), summary(head(x)), requires the composition of summary() to head() before application to iris. Giving precedence to later steps in the pipeline is incompatible with R’s parsing rules without the use of parentheses. As a result, the composition of function and the application of data to those functions must be separated, either calling the function as an intermediate variable

```
(head %>% summary)(iris)
```
or by creating a named function and then applying it to the data.

```
hsummary <- head %>% summary
hsummary(iris)
```

The second distinction is that the fc package does not use the same shorthand notation for modifying multiple arguments within functions. For example, in magrittr we might create a summary of the first half of a dataset as:

```
first_half_magrittr <- . %>% head(n=round(nrow(.)/2)) %>% summary
```
The head() function is altered to take half of the number of rows of the input as the argument to n, using the NSE “.” convention. With the fc package, we use fc() to explicitly create a single-input function out of head():

```
first_half_fc <- fc(head, n=round(nrow(x)/2)) %>% summary
```
yielding the function:

```
function (object)
{
  summary(object = internal_anon_func(object))
}
```
where internal_anon_func is the result of the fc expression:

```
function (x)
{
  head(x, n = round(nrow(x)/2))
}
```

Compatibility with Functions Having Expressions as Argument Names
An important caveat with fc() is that it does not support using expressions as argument names. As a result, functions like subset() cannot be called as:

```
> fc(subset, Sepal.Length > 5)(iris)
Error in fc(subset, Sepal.Length > 5) :
  All parameter arguments must be named.
```
However, subset() can work with named arguments:

```
fc(subset, subset = Sepal.Length > 5)
```
The use of expressions as function names should be used judiciously or even discouraged in since they are either executed within a specific context (for subset(), after the first argument is attach’ed) or they require defining operators on unbound variables. It should be noted though, that this restriction does not preclude fc’s use with tidyverse packages however (Wickham, 2017b); see Example 3 in the Examples section for details.
Implementation

The fc() function takes, as input, a function and a set of named arguments corresponding to those of the input function and whose values are expressions. Unbound variables in those expressions are used as input parameters to the resulting function that is returned by the fc() function. A high-level description of the steps taken is shown in Algorithm 1.

Algorithm 1 High-level Pseudocode for the fc() function

1: procedure FUNCTION COMPOSE(func,...)
2: fc_ret_env ← the parent environment.
3: if func is a call to Function Compose or anonymous function then
4: func ← the evaluated func expression
5: fc_ret_env ← a new environment
6: func is stored in fc_ret_env
7: if Any ... arguments are not named then
8: return an error
9: if Any ... arguments are Function Compose statements then
10: evaluate them and keep them in fc_ret_env
11: ret_fun_body ← the name of func with parameters defined by the ... arguments.
12: ret_fun_sig ← the unbound arguments in each of the ... expressions.
13: Return the function defined by ret_fun_sig, ret_fun_body, and ret_fun_env

The first argument may be a named function, an anonymous function, or a call to the fc() function. If it is either an anonymous function or a call to fc(), then the argument is evaluated and should result in a function. In this case, a new environment is created to hold the evaluated function. This new environment will be that of the return-function. If fc() does not need to create an anonymous function, then the return-function's environment is set to the environment returned by parent.frame, the default environment when the function() function is called. Subsequent arguments, which must be named, may be expressions, including calls to fc(), which are processed in a manner similar to that of the first argument. Subsequent arguments may not be calls to anonymous function declarations.

The signature of the return function is derived by parsing the arguments of each of the expressions supplied to the ... variable. The expression tree is created using the codetools package (Tierney, 2016), finding each of the leaves of the abstract syntax tree, that are of type symbol (corresponding to unbound variables). The unique set of symbols for each of the arguments are collected to create the return-function signature. The func and ... arguments are used to generate the function body. This, along with the function signature and environment are sufficient to create the function that is returned by fc().

Examples

In this section, we present four example usages of fc. In the Comparison subsection, we show the runtimes of our composed functions in these examples as well as similar implementations using magrittr and purrr.

Example 1

In a simple example involving primitive R functions only, we take the natural log of the square root of 10. This could be done using base R as follows:

```r
log_sqrt_base <- function(x) log(x=sqrt(x))
```

We can implement the same function using fc in two ways, with or without pipes.

```r
log_sqrt_fc <- fc(log, x=sqrt(x))
log_sqrt_fc_pipe <- fc(log, x=x) %>% fc(sqrt, x=x)
```

Example 2

The next example involves text processing. A common web scraping task requires processing information between HTML tags found within a character string vector. This could be done in three steps:
(1) using `grep()` to identify entries in a vector containing information, (2) using `gsub()` to extract information in those entries, and (3) cleaning up the information, say via `trimws()`. A base R composed function for this task is as follows:

```r
code_here
```

Below, we show a concrete example of an input `x` and the associated function output `search_trim_base(x)`.

```r
x <- c("<td class = 'address'>24 Hillhouse Ave.</td>",
"<td class = 'city'>New Haven</td>",
"</table>")
search_trim_base(x)
```

We can express the same function using `fc` as follows:

```r
code_here
```

There are three calls to `fc` nested together. Pipes can be used to enhance the readability:

```r
code_here
```

**Example 3**

This next example shows how `fc` can be used in conjunction with existing data wrangling packages such as `dplyr`, which natively uses NSE function chaining via `magrittr` pipes. Most of the NSE functions in `dplyr` have standard evaluation analogues that are designated with an underscore suffix. We will use these standard evaluation functions with `fc`.

In this example, we use the `nycflights13` package (Wickham, 2017a) to demonstrate how to calculate group-wise numerical summaries using `dplyr`. Below, we compare the usual `dplyr` NSE syntax to the SE syntax supported by `fc`.

```r
code_here
```

Additionally, we note that `flight_summary_fc()` and `flight_summary_fc_pipe()` can also operate on database objects hosted via `dbplyr` (Wickham and Ruiz, 2018). Specifically, instead of applying each function to an actual data frame, we could leverage the extended capabilities of `filter_()`, `group_by_()`, and `summarize_()` to operate on a data frame object.
The chunk of code below creates a database in memory from the flights data frame.

```r
my_db <- DBI::dbConnect(RSQLite::SQLite(), path = "~/memory:"
) copy_to(my_db,
   flights,
   temporary = FALSE,
   indexes = list(
      c("year", "month", "day"),
      "carrier", "tailnum"
   )
) flights_db <- tbl(my_db, "flights")
flights_db
```

flights_db is now a database object and we could run flight_summary_fc(flights_db).

**Example 4**

This example illustrates how anonymous functions may be used in function composition with fc. Consider writing a function that (1) shuffles the rows of a data frame, (2) outputs the first ten rows and a subset of columns, and (3) prints a summary of each column. This could be written a number of ways using fc. We begin by examining two ways of composing functions without pipes.

```r
get_sepal1 <- fc(summary, object = fc(head, x = (function(x) {
   x[sample(1:nrow(x)),
   grep("Sepal", colnames(x))]
 }) (x), n = 10)(x))
get_sepal2 <- fc(summary, object = fc(head, x = fc(function(x, cols) {x[sample(1:nrow(x)), cols]},
   cols = grep("Sepal", colnames(x)))(x), n = 10)(x))
```

In get_sepal1(), we define an anonymous function whose result when run on the input variable x will be passed along as the primary argument for head. In get_sepal2(), we use an anonymous function as the primary argument to fc and use partial valuation to set the value of cols.

We can rewrite each of these function compositions with pipes:

```r
get_sepal1_pipe <- (function(x) {
   x[sample(1:nrow(x)), grep("Sepal", colnames(x))]
 }) %>% fc(head, n=10) %>% summary
get_sepal2_pipe <- fc(function(x, cols) {x[sample(1:nrow(x)), cols]},
   cols = grep("Sepal", colnames(x)))(x), n = 10) %>% summary
```

**Comparison**

We now compare the run speeds of Examples 1 through 4 to comparable implementations achieved using magrittr, purrr, and base R. For each example, we present code for the various implementations. The suffixes of the composed functions indicate the implementation approach:

- .base: function is created from explicitly writing out the function composition in base R.
- .purrr: function is created using purrr’s compose() function (and its partial() function, where applicable).
- .mag: function is created using magrittr, with a % in the first entry of the pipeline.

### Example 1

```r
log_sqrt_base <- function(x) log(x=sqrt(x))
log_sqrt_purrr <- compose(log, sqrt)
log_sqrt_mag <- . %>% sqrt %>% log
```

### Example 2

```r
search_trim_base <- function(v) {
   trimws(gsub(grep(v, pattern="[^/]*", value=TRUE),
   pattern=".*>(.*)<.*", replacement = \"\1\")
 )
}
search_trim_mag <- . %>% grep(pattern="[^/]*", x=., value=TRUE) %>%
   gsub(".*>(.*)<.*", "\1", x=.) %>%
```
trimws
search_trim_purrr <- purrr::compose(trimws, partial(gsub, pattern=".*>(.*)<.*",
replacement = "\\\""),
partial(grep, pattern="<[^/]*">", value=TRUE))

### Example 3
flight_summary_base <- function(x) {
  filter_(summarize_(group_by_(x, .dots = list('/quotesingle.Vartailnum/quotesingle.Var')),
  .dots = list(count = /quotesingle.Varn()/quotesingle.Var,
  dist=/quotesingle.Varmean(distance, na.rm=TRUE)/quotesingle.Var,
  delay=/quotesingle.Varmean(arr_delay, na.rm=TRUE)/quotesingle.Var)),
  .dots = list(/quotesingle.Varcount > 20/quotesingle.Var, /quotesingle.Vardist < 2000/quotesingle.Var))
}

flight_summary_mag <- . %>% group_by_(.dots = list('/quotesingle.Vartailnum/quotesingle.Var')) %>%
summarize_(.dots = list(count = /quotesingle.Varn()/quotesingle.Var,
  dist=/quotesingle.Varmean(distance, na.rm=TRUE)/quotesingle.Var,
  delay=/quotesingle.Varmean(arr_delay, na.rm=TRUE)/quotesingle.Var)) %>%
filter_(.dots = list(/quotesingle.Varcount > 20/quotesingle.Var, /quotesingle.Vardist < 2000/quotesingle.Var))

flight_summary_purrr <- compose(partial(filter_, .dots = list(/quotesingle.Varcount > 20/quotesingle.Var, /quotesingle.Vardist < 2000/quotesingle.Var)),
partial(summarize_, .dots = list(count = /quotesingle.Varn()/quotesingle.Var,
  dist=/quotesingle.Varmean(distance, na.rm=TRUE)/quotesingle.Var,
  delay=/quotesingle.Varmean(arr_delay, na.rm=TRUE)/quotesingle.Var)),
partial(group_by_, .dots = list('/quotesingle.Vartailnum/quotesingle.Var')))  

### Example 4
get_random_sepal_base <- function(x) head(x[sample(1:nrow(x)),
grep("Sepal", colnames(x))], n=10)

get_random_sepal_mag <- . %>% (function(x) x[sample(1:nrow(x)), grep("Sepal", colnames(x))]) %>%
head(n = 10) %>% summary

get_random_sepal_purrr <- compose(function(x) {
  x[sample(1:nrow(x)),
grep("Sepal", colnames(x))]
}, partial(head, n=10), summary)

Notes: In Example 3, we use the standard evaluation flavors of the dplyr functions rather than their NSE counterparts, even for use with magrittr so as to ensure a fair comparison; runtimes reflect those of the functions applied to the database object instead of the data frame. For Example 4, we previously showed multiple ways of composing functions to achieve the desired functionality via fc. For comparison purposes, we will use get_sepal1() and get_sepal1_pipe().

Each function was run 10,000 times with the same inputs. Runtimes are checked using the microbenchmark package (Mersmann, 2018). The results are summarized below.

|          | Example 1 (µs) | Example 2 (µs) | Example 3 (ms) | Example 4 (ms) |
|----------|----------------|----------------|----------------|----------------|
| base R   | 0.782(±0.01)   | 74.584(±0.317) | 4.418(±0.02)   | 0.284(±0.002)  |
| magrittr | 5.386(±0.053)  | 81.174(±0.55)  | 4.468(±0.027)  | 1.503(±0.016)  |
| purrr    | 5.486(±0.17)   | 82.399(±0.498) | 4.51(±0.027)   | 2.681(±0.022)  |
| fc       | 0.87(±0.034)   | 76.976(±0.434) | 4.445(±0.023)  | 1.498(±0.007)  |
| fc_pipe  | 2.537(±0.159)  | 77.553(±0.448) | 4.431(±0.014)  | 1.499(±0.007)  |

Table 1: Runtime comparisons for Examples 1 through 4, showing mean runtime (± standard error) across 10,000 iterations. Examples 1 and 2 runtimes are reported in units of microseconds whereas Example 3 and 4 runtimes are reported in milliseconds.

Examples 1 and 2 show fc’s superior performance when used with standard R functions. We hypothesize that fc does especially well with Example 1 because the constituent functions of log() and sqrt() are simple enough that most of the heavy-lifting done by magrittr and purrr involve parsing their NSE expressions. For that reason, when pipes are used with fc, the runtime suffers somewhat as well, albeit to a lesser extent. In Example 2, while the constituent functions are not primitive, like those of Example 1, their specified arguments involve expressions that require a fair amount of parsing.

In Example 3, had we used the NSE versions of the dplyr functions like filter(), group_by(), and summarize() for the magrittr solution, we would find that magrittr’s solution runs much faster.
This is due to clever implementation in the NSE \texttt{dplyr} functions themselves (e.g. \texttt{filter()} simply works faster than \texttt{filter()}) and not due to differences between function composition between \texttt{magrittr} and \texttt{fc}.

Example 4 compares how the various approaches fare with anonymous functions used in composition. It seems as though \texttt{magrittr} does about as well as \texttt{fc} on this front.

Overall, from the perspective of runtime, we find that \texttt{purrr} usually does as well as \texttt{magrittr}, but could at times do worse. \texttt{fc} typically does as well as \texttt{magrittr} but could be much faster.

\section*{Discussion}

In this article, we presented a new package \texttt{fc} that combines general function composition with the economy and clarity afforded by a pipeline syntax. Importantly, \texttt{fc} utilizes standard evaluation so that components of a pipeline can be directly evaluated in R. This is in stark contrast to the \texttt{magrittr} package, which (1) utilizes a pipeline syntax to chain functions without composition and (2) uses non-standard evaluation to further prioritize conciseness of syntax.

\texttt{fc}'s usage can be slightly more verbose compared to that of \texttt{magrittr}, since expressions in the \texttt{fc} pipeline are evaluated without manipulation. However, the return of the pipe is a human-readable function that is consistent with expectations given a sequence of functions defined in the pipe. Furthermore, because the result is a composed function, rather than a sequence of functions, the resulting syntax tree is easier to debug and optimize. As a consequence, \texttt{fc}'s composition provides similar performance as standard R implementations and tends to achieve better runtimes than \texttt{magrittr} and \texttt{purrr}, particularly when a pipeline is deep or is called many times.

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