

IPOMOEA: Intended Package Orientation using Multi-Objective Evolutionary Algorithm in R

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ABSTRACT

Programmers' lack of familiarity with what is available in packages may prompt them to reinvent the wheel. This is generally the case in any programming language, but it is a matter of madness with a language described as difficult even by professionals supporting it such as R. R Cookbook says: "But R can be frustrating. It's not obvious how to accomplish many tasks, even simple ones." IPOMOEA is a code that has been written to mitigate this problem. It helps R language developers determine how to perform a specific task, by automating the search in R site for all packages that are likely to contribute to the task implementation. After that, IPOMOEA determines a partial set of results to be the intended package using multi-objective evolutionary algorithm NSGA-II. Not only does it specify the intended package, but also it helps orient programmers and manage packages.

1 INTRODUCTION

It goes without saying that R (R Core Team, 2017) is a powerful language. It is an effective tool for statistical processing. Furthermore, it has been armed with thousands of packages thanks to the efforts of armies of developers for more than twenty years now (Smith (2017)). However, the programmers' lack of familiarity with what is available in those packages may prompt them to reinvent the wheel. This is generally the case in any programming language, but it is a matter of madness with a language described as difficult even by professionals supporting it. Let's quote what is stated in the preface of R Cookbook by Teetor (2011), in which the author says: "But R can be frustrating. It's not obvious how to accomplish many tasks, even simple ones."

IPOMOEA is a code that has been written to mitigate this problem. It helps R language developers determine how to perform a specific task, by automating the search in R site for all packages that are likely to contribute to the task implementation. After that, IPOMOEA determines a partial set of results to be the intended package using multi-objective evolutionary algorithm (MOEA) NSGA-II Deb et al. (2002). Not only does it specify the intended package, but also it helps orient programmers and manage packages.

2 MODEL

IPOMOEA front-end (Figure 1) has two steps. The developer should provide the keyword. The intended package could be any one that implements a function named after that keyword. IPOMOEA then indulges in automatic search of the R site, as if RSiteSearch() is called. This is possible thanks to Namazu search engine Namazu Project (2011). Then a file, named after the entered keyword, shall be created for storing the results locally. Namazu ranks the result set based on significance using a smart algorithm Inoue et al. (2005).

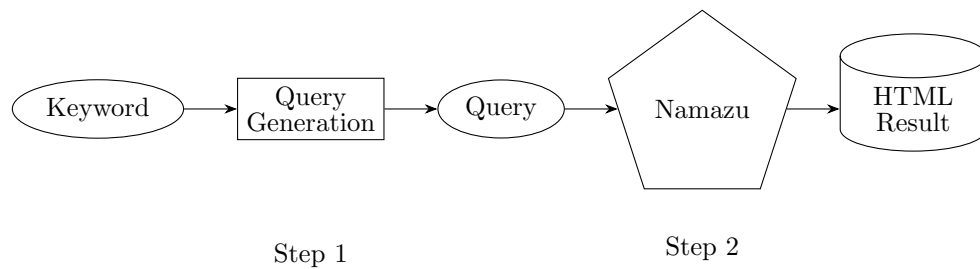


Figure 1. IPOMOE Front-end

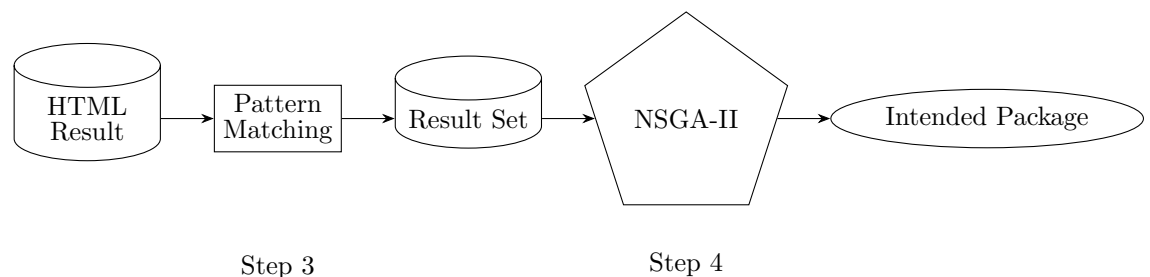


Figure 2. IPOMOE Back-end

IPOMOE back-end (Figure 2) has two steps too. IPOMOE harvests all packages, functions within, and their ranks from HTML results provided from Namazu. Namazu generates results in a fixed format, allowing for parsing them using regular expressionsMcNaughton and Yamada (1960). The intended package is then reached based on MOEA NSGA-II Deb et al. (2002).

IPOMOE is formalized to be a minimization problem over a set of features:

$$\text{minimize } IPOMOE_{Objective}(Features) \quad (1)$$

subject to

$$IPOMOE_{Constraint}(Features) = \left(\sum_{f \in Features} f \right) - \theta \geq 0 \quad (2)$$

θ is not just a mere threshold, it is a grouping and/or discriminating factor. As there could be many candidate intended packages, grouping or discriminating them is necessary.

3 IMPLEMENTATION

IPOMOE code is publicly available ?. First of all, it makes sure the MCO package (Mersmann et al., 2014) is available. It is the package that provides `nsga2()` function, implementing NSGA-II Deb et al. (2002). MCO will be installed if it is not already installed.

```
if (!require("mco")) install.packages("mco")
```

Then the developer should provide the keyword. It happened to be

```
%
```

```
%
```

```
\begin{lstlisting}
```

```
ipomoea_keyword <- 'dickey-fuller'
```

IPOMOEAE then indulges in automatic search of the R site, as if RSiteSearch() is called. This is possible thanks to Namazu search engine Namazu Project (2011). Then a file, named after the entered keyword, shall be created for storing the results locally.

```
ipomoea_search <- readLines(paste('http://search.r-project.org/cgi-
bin/
namazu.cgi?query=', ipomoea_keyword))
ipomoea_file <- paste(".ipomoea.", ipomoea_keyword, ".html")
```

Namazu generates results in a fixed format, allowing for parsing them using regular expressionsMcNaughton and Yamada (1960). For example, the cardinality of result set can be extracted using the following pattern.

```
ipomoea_total_pattern = 'Total<!--HIT-->([<]*)<!--HIT-->'
```

Using grep(), gregexpr(), and gregexpr(), IPOMOEAE extracts the cardinality of result set, which happened to be:

```
48
```

Result set per se can be extracted using:

```
ipomoea_result_set_pattern = '<dl>(.*</dl>'
```

Namazu ranks the result set based on significance using a smart algorithm Inoue et al. (2005). To harvest all packages, functions within, and their ranks from the results:

```
ipomoea_packs <- c()
ipomoea_funcs <- c()
ipomoea_ranks <- c()

for (ipomoea_line in ipomoea_resultLines){
  if(startsWith(ipomoea_line, ipomoea_dt)){
    ipomoea_pack <- get_lib_func_score(ipomoea_package_pattern,
    ipomoea_line)
    ipomoea_func <- get_lib_func_score(ipomoea_function_pattern,
    ipomoea_line)
    ipomoea_rank <- get_lib_func_score(ipomoea_rank_pattern,
    ipomoea_line))

    if(!startsWith(ipomoea_func, "00")){
      ipomoea_func_fullname<- paste(ipomoea_pack, "::", ipomoea
      _func, sep='')

      ipomoea_packs <- c(ipomoea_packs, ipomoea_pack)
      ipomoea_funcs <- c(ipomoea_funcs, ipomoea_func_fullname)
      ipomoea_ranks <- c(ipomoea_ranks, as.numeric(ipomoea_rank
      ))
    }
  }
}
```

All the magic is in the meticulously tweaked patterns. The pattern to extract ranks is:

```
ipomoea_rank_pattern <- "<dt>[^()]*[() score:(.*)]</dt>"
```

Top results and their associated scores/ranks are depicted in Figure 3.

To convert the problem into a minimization one, all ranks should be subtracted from the maximum one:

```
ipomoea_max_rank <- max(ipomoea_ranks)
ipomoea_min_rank <- min(ipomoea_ranks)
ipomoea_inverted_ranks <- ipomoea_max_rank - ipomoea_ranks
```



Figure 3. Top results and their associated scores/ranks.

Then the implementation of formalization (Equation 1 and Equation 2). For a matter of simplification, let us limit the feature set to just 2 of them, namely the ID, and the rank/score.

```

102 ipomoea_objective <- function(ipomoea_features) {
103   if(is.wholenumber(ipomoea_features[1])) { ipomoea_features }
104   else { c(as.double(floor(ipomoea_features[1])+1), ipomoea_
105     features[2]) }
106 }
107 ipomoea_constraint <- function(ipomoea_features) {
108   sum(ipomoea_features) - ipomoea_theta
109 }

```

Then, the time is ripe to call MCO package (Mersmann et al., 2014) that provides nsga2() function Deb et al. (2002), setting its parameters, and calling it.

```

112 library(mco)
113
114 ipomoea_theta <- 5
115
116 ipomoea_generations<-100
117 ipomoea_dimension_1_lower_bound <-1
118 ipomoea_dimension_1_upper_bound <- length(ipomoea_ranks)
119 ipomoea_dimension_2_lower_bound <- 0
120 ipomoea_dimension_2_upper_bound <- max(ipomoea_inverted_ranks)
121
122 ipomoea_intended_packs <- nsga2(ipomoea_objective, 2, 2,
123   generations= ipomoea_generations,
124   lower.bounds=c(ipomoea_dimension_1_lower_bound, ipomoea_dimension
125     _2_lower_bound),
126   upper.bounds=c(ipomoea_dimension_1_upper_bound, ipomoea_dimension
127     _2_upper_bound),
128   constraints=ipomoea_constraint,
129   cdim=1)

```

Candidate intended package(s) at $\theta = 5$, $\theta = 7$, and the extreme case at $\theta = |ResultSet|$ are shown in Figure 4, Figure 5, and Figure 6 respectively.

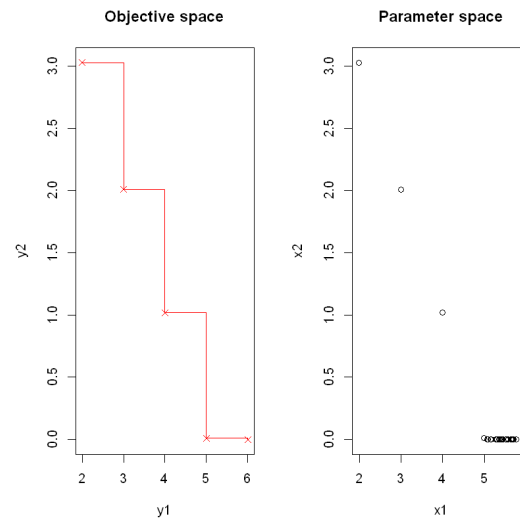


Figure 4. Candidate intended package(s) at $\theta = 5$

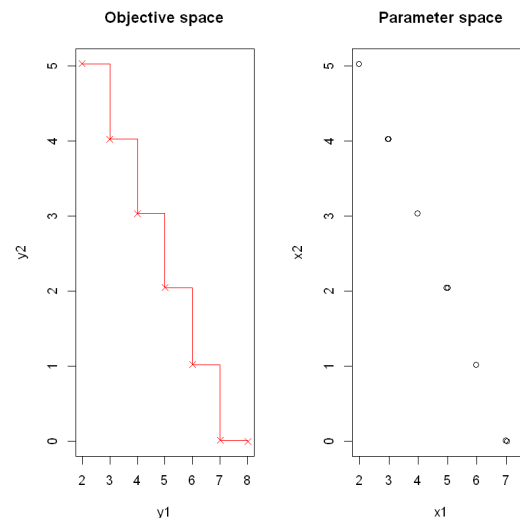


Figure 5. Candidate intended package(s) at $\theta = 7$

132 Note that candidate intended package(s) is/are distilled spatially at the zeroth level, and
 133 temporally after *ipomoea_generations* iterations. Note also that the intended package actual ID
 134 needs to be adjusted before calling it.

```
135 ipomoea_intended_pack_all_ids <- ipomoea_intended_packs["value"]
136 ipomoea_intended_pack_inverted_id <- ipomoea_intended_pack_all_ids[
137   ipomoea_generations]
138 ipomoea_intended_pack_actual_id <- length(ipomoea_ranks)
139   - ipomoea_intended_pack_inverted_id +
140     1
141 ipomoea_intended_function = ipomoea_funcs[ipomoea_intended_pack_
142   actual_id]
```

143 Then came the automatic installation of the intended package(s):

```
144 ipomoea_unique_packs <- unique(ipomoea_packs)
```

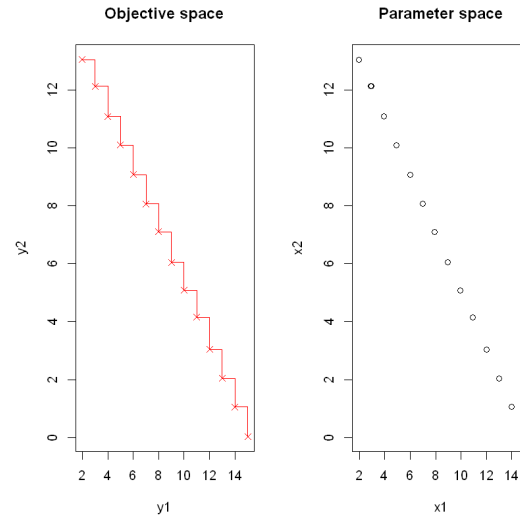


Figure 6. Candidate intended package(s) at $\theta = |ResultSet|$

```

145 ipomoea_intersection_packs <- (ipomoea_unique_packs %in% installed.
146   packages())[, "Package"]
147 ipomoea_uninstalled_packs <- ipomoea_unique_packs[! ipomoea_
148   intersection_packs]
149 if(length(ipomoea_uninstalled_packs)>0) install.packages(ipomoea_
150   uninstalled_packs)

```

151 4 SUMMARY AND DISCUSSION

152 IPOMOE front-end has two steps: query generation out of a keyword, and automatic search of
 153 the R site, as if RSiteSearch() is called thanks to Namazu search engine Namazu Project (2011).

154 IPOMOE back-end has two steps too: harvesting all packages, functions within, and their
 155 ranks from HTML results provided from Namazu using regular expressions, before reaching the
 156 intended package using MOEA NSGA-II Deb et al. (2002).

157 Basic orientation is provided by the automatic installation of the intended package(s).

This is ongoing project. Incorporating extra-features for selection criteria is a must to
 meet developers' preferences. Advanced orientation is highly admired. Possible orientation
 may consider displaying examples of use cases.

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