Diagnosing Island Supplemental Material

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Chapter 1

Introduction

This is the supplemental material associated with the 6th chapter in my dissertation.

1.1 Computer Setup

These analyses were conducted in the following computing environment:

```
print(version)
```

```
x86_64-pc-linux-gnu
## platform
                 x86_64
## arch
## os
                 linux-gnu
                 x86_64, linux-gnu
## system
## status
                 Patched
## major
                 4
## minor
                 2.2
## year
                 2022
## month
                 11
## day
                 10
## svn rev
                 83330
## language
                 R
## version.string R version 4.2.2 Patched (2022-11-10 r83330)
## nickname
                 Innocent and Trusting
```

1.2 Experimental setup

Setting up required variables variables.

```
# libraries we are using
library(ggplot2)
library(cowplot)
library(dplyr)
##
## Attaching package: 'dplyr'
## The following objects are masked from 'package:stats':
##
##
       filter, lag
## The following objects are masked from 'package:base':
       intersect, setdiff, setequal, union
library(PupillometryR)
## Loading required package: rlang
p_theme <- theme(</pre>
  text = element_text(size = 28),
  plot.title = element_text( face = "bold", size = 22, hjust = 0.5),
  panel.border = element_blank(),
  panel.grid.minor = element_blank(),
  legend.title=element_text(size=18),
  legend.text=element_text(size=14),
  axis.title = element text(size=18),
  axis.text = element_text(size=16),
  legend.position="bottom",
  panel.background = element_rect(fill = "#f1f2f5",
                                   colour = "white",
                                   size = 0.5, linetype = "solid")
## Warning: The `size` argument of `element_rect()` is deprecated as of ggplot2 3.4.0.
## i Please use the `linewidth` argument instead.
# default variables
MODEL = c('EA','IS','NMIS')
EXPERIMENTS = c('BASE-EXPERIMENTS/','MI50/','MI5000/')
SCHEME = c('TRUNCATION','TOURNAMENT','LEXICASE')
DIAGNOSTIC = c('EXPLOITATION_RATE', 'ORDERED_EXPLOITATION', 'CONTRADICTORY_OBJECTIVES'
DIMENSIONALITY = 100
cb_palette <- c('#D81B60','#1E88E5','#FFC107')</pre>
SHAPE = c(15, 16, 17)
TSIZE = 20
```

```
GENERATIONS = 50000
# data related
DATA_DIR = '/opt/Diagnosing-Island-Structures/DATA-FINAL/'
# go through each diagnostic and collect over time data for cross comparison (cc)
base over time = data.frame()
mi50_over_time = data.frame()
mi5000_over_time = data.frame()
print('over time data')
## [1] "over time data"
for(model in MODEL)
  print(model)
  for(scheme in SCHEME)
   base_dir = paste(DATA_DIR,EXPERIMENTS[1],model,'/over-time-',scheme, '.csv', sep = "", collap
   base_over_time = rbind(base_over_time, read.csv(base_dir, header = TRUE, stringsAsFactors = I
   mi50_dir = paste(DATA_DIR,EXPERIMENTS[2],model,'/over-time-',scheme, '.csv', sep = "", collap
   mi50_over_time = rbind(mi50_over_time, read.csv(mi50_dir, header = TRUE, stringsAsFactors = I
   mi5000_dir = paste(DATA_DIR, EXPERIMENTS[3], model, '/over-time-', scheme, '.csv', sep = "", coll
   mi5000_over_time = rbind(mi5000_over_time, read.csv(mi5000_dir, header = TRUE, stringsAsFactor
  }
## [1] "EA"
## [1] "IS"
## [1] "NMIS"
colnames(base_over_time) [colnames(base_over_time) == "SEL"] = 'Selection\nScheme'
base_over_time$Structure <- factor(base_over_time$Structure, levels = MODEL)</pre>
base_over_time$sel_pre = base_over_time$sel_pre * -1.0
colnames(mi50_over_time)[colnames(mi50_over_time) == "SEL"] = 'Selection\nScheme'
mi50_over_time$Structure <- factor(mi50_over_time$Structure, levels = MODEL)
mi50_over_time$sel_pre = mi50_over_time$sel_pre * -1.0
colnames(mi5000_over_time) [colnames(mi5000_over_time) == "SEL"] = 'Selection\nScheme'
mi5000_over_time$Structure <- factor(mi5000_over_time$Structure, levels = MODEL)
mi5000_over_time$sel_pre = mi5000_over_time$sel_pre * -1.0
```

```
# go through each diagnostic and collect best over time for cross comparison (cc)
base_best = data.frame()
mi50_best = data.frame()
mi5000_best = data.frame()
print('best data')
## [1] "best data"
for(model in MODEL)
  print(model)
  for(scheme in SCHEME)
    base_dir = paste(DATA_DIR,EXPERIMENTS[1],model,'/best-',scheme, '.csv', sep = "",
    base_best = rbind(base_best, read.csv(base_dir, header = TRUE, stringsAsFactors = 1
    mi50_dir = paste(DATA_DIR,EXPERIMENTS[2],model,'/best-',scheme, '.csv', sep = "",
    mi50_best = rbind(mi50_best, read.csv(mi50_dir, header = TRUE, stringsAsFactors = 1
    mi5000_dir = paste(DATA_DIR,EXPERIMENTS[3],model,'/best-',scheme, '.csv', sep = ""
    mi5000_best = rbind(mi5000_best, read.csv(mi5000_dir, header = TRUE, stringsAsFact
  }
}
## [1] "EA"
## [1] "IS"
## [1] "NMIS"
colnames(base_best)[colnames(base_best) == "SEL"] = 'Selection\nScheme'
base_best$Structure <- factor(base_best$Structure, levels = MODEL)</pre>
colnames(mi50_best)[colnames(mi50_best) == "SEL"] = 'Selection\nScheme'
mi50_best$Structure <- factor(mi50_best$Structure, levels = MODEL)</pre>
colnames(mi5000_best) [colnames(mi5000_best) == "SEL"] = 'Selection\nScheme'
mi5000_best$Structure <- factor(mi5000_best$Structure, levels = MODEL)</pre>
# get generation a satisfactory solution is found for cross comparison (cc)
base_ssf = data.frame()
mi50_ssf = data.frame()
mi5000_ssf = data.frame()
print('ssf data')
## [1] "ssf data"
for(model in MODEL)
```

```
print(model)
 for(scheme in SCHEME)
   base_dir = paste(DATA_DIR,EXPERIMENTS[1],model,'/ssf-',scheme, '.csv', sep = "", collapse = 1
   base_ssf = rbind(base_ssf, read.csv(base_dir, header = TRUE, stringsAsFactors = FALSE))
   mi50_dir = paste(DATA_DIR,EXPERIMENTS[2],model,'/ssf-',scheme, '.csv', sep = "", collapse = 1
   mi50_ssf = rbind(mi50_ssf, read.csv(mi50_dir, header = TRUE, stringsAsFactors = FALSE))
   mi5000_dir = paste(DATA_DIR,EXPERIMENTS[3],model,'/ssf-',scheme, '.csv', sep = "", collapse =
   mi5000_ssf = rbind(mi5000_ssf, read.csv(mi5000_dir, header = TRUE, stringsAsFactors = FALSE)
 }
}
## [1] "EA"
## [1] "IS"
## [1] "NMIS"
colnames(base_ssf)[colnames(base_ssf) == "SEL"] = 'Selection\nScheme'
base_ssf$Structure <- factor(base_ssf$Structure, levels = MODEL)</pre>
colnames(mi50_ssf)[colnames(mi50_ssf) == "SEL"] = 'Selection\nScheme'
mi50_ssf$Structure <- factor(mi50_ssf$Structure, levels = MODEL)
colnames(mi5000_ssf)[colnames(mi5000_ssf) == "SEL"] = 'Selection\nScheme'
mi5000_ssf$Structure <- factor(mi5000_ssf$Structure, levels = MODEL)</pre>
```

Chapter 2

BASE: Exploitation rate results

Here we present the results for **best performances** found by each selection scheme replicate on the exploitation rate diagnostic with our base configurations. For our base configuration, we assume that there are migrations every 500 generations, 4 islands, and a ring topology. When migrations occur, we swap two individuals (same position on each island) and guarantee that no solution can return to the same island. Best performance found refers to the largest average trait score found in a given population. Note that performance values fall between 0.0 and 100.0.

2.1 Analysis dependencies

```
library(ggplot2)
library(cowplot)
library(dplyr)
library(PupillometryR)
```

2.2 Truncation selection

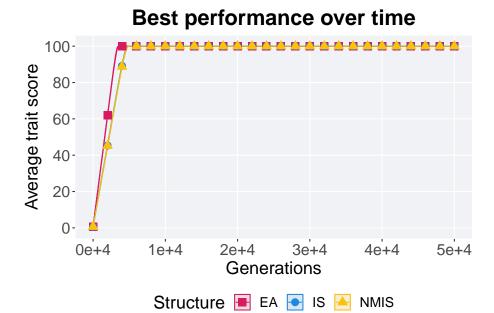
Here we analyze how the different population structures affect truncation selection (size 8) on the exploitation rate diagnostic.

2.2.1 Performance over time

```
lines = filter(base_over_time, Diagnostic == 'EXPLOITATION_RATE' & `Selection\nScheme` == 'TRUNCA
group_by(Structure, Generations) %>%
```

```
dplyr::summarise(
            min = min(pop_fit_max) / DIMENSIONALITY,
            mean = mean(pop_fit_max) / DIMENSIONALITY,
            max = max(pop_fit_max) / DIMENSIONALITY
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color 
      geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
      geom_line(size = 0.5) +
      geom_point(data = filter(lines, Generations %% 2000 == 0), size = 2.5, stroke = 2.0,
      scale_y_continuous(
           name="Average trait score",
            limits=c(-1, 101),
            breaks=seq(0,100, 20),
            labels=c("0", "20", "40", "60", "80", "100")
      ) +
      scale_x_continuous(
           name="Generations",
            limits=c(0, 50000),
            breaks=c(0, 10000, 20000, 30000, 40000, 50000),
            labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
      ) +
      scale_shape_manual(values=SHAPE)+
      scale_colour_manual(values = cb_palette) +
      scale_fill_manual(values = cb_palette) +
      ggtitle("Best performance over time") +
      p_theme
```

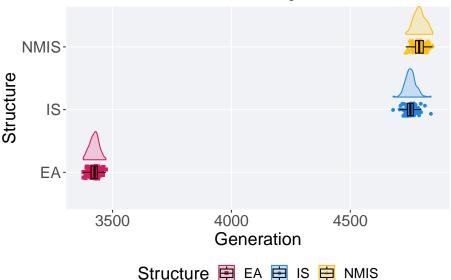
^{##} Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.
i Please use `linewidth` instead.



2.2.2 Generation satisfactory solution found

```
filter(base_ssf, Diagnostic == 'EXPLOITATION_RATE' & `Selection\nScheme` == 'TRUNCATION') %>%
    ggplot(., aes(x = Structure, y = Generations, color = Structure, fill = Structure, shape = Str
    geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.2) +
    geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
    geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
    scale_y_continuous(
        name="Generation"
) +
    scale_x_discrete(
        name="Structure"
)+
    scale_shape_manual(values=SHAPE)+
    scale_colour_manual(values = cb_palette, ) +
    scale_fill_manual(values = cb_palette) +
    ggtitle('Generation satisfactory solution found')+
    p_theme + coord_flip()
```





2.2.3Stats

3 NMIS

100

Summary statistics for the first generation a satisfactory solution is found.

```
ssf = filter(base_ssf, Diagnostic == 'EXPLOITATION_RATE' & `Selection\nScheme` == 'TRU
ssf %>%
  group_by(Structure) %>%
 dplyr::summarise(
    count = n(),
    na_cnt = sum(is.na(Generations)),
   min = min(Generations, na.rm = TRUE),
   median = median(Generations, na.rm = TRUE),
   mean = mean(Generations, na.rm = TRUE),
   max = max(Generations, na.rm = TRUE),
    IQR = IQR(Generations, na.rm = TRUE)
## # A tibble: 3 x 8
    Structure count na_cnt
                              min median mean
##
     <fct>
               <int>
                      <int> <int>
                                   <dbl> <dbl> <int> <dbl>
## 1 EA
                 100
                                   3424. 3423.
                                                3472
                                                       26.2
                          0
                             3377
## 2 IS
                 100
                             4680
                                   4752. 4754.
                                                 4839
                                                       25
```

Kruskal–Wallis test provides evidence of difference among selection schemes.

0 4733 4790. 4791.

4846

```
kruskal.test(Generations ~ Structure, data = ssf)
##
##
   Kruskal-Wallis rank sum test
##
## data: Generations by Structure
## Kruskal-Wallis chi-squared = 237.99, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = ssf$Generations, g = ssf$Structure, p.adjust.method = "bonferroni",
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: ssf$Generations and ssf$Structure
##
##
        EΑ
               TS
## IS
       <2e-16 -
## NMIS <2e-16 <2e-16
## P value adjustment method: bonferroni
```

2.3 Tournament selection

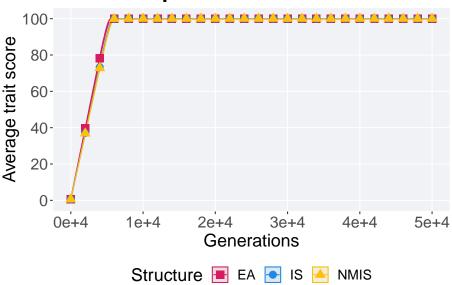
Here we analyze how the different population structures affect tournament selection (size 8) on the exploitation rate diagnostic.

2.3.1 Performance over time

```
lines = filter(base_over_time, Diagnostic == 'EXPLOITATION_RATE' &
group_by(Structure, Generations) %>%
dplyr::summarise(
   min = min(pop_fit_max) / DIMENSIONALITY,
   mean = mean(pop_fit_max) / DIMENSIONALITY,
   max = max(pop_fit_max) / DIMENSIONALITY
)
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = Structure,
   geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
   geom_line(size = 0.5) +
   geom_point(data = filter(lines, Generations %% 2000 == 0), size = 2.5, stroke = 2.0, alpha = 1.
   scale_y_continuous(
   name="Average trait score",
   limits=c(-1, 101),
   breaks=seq(0,100, 20),
```

```
labels=c("0", "20", "40", "60", "80", "100")
) +
scale_x_continuous(
  name="Generations",
  limits=c(0, 50000),
  breaks=c(0, 10000, 20000, 30000, 40000, 50000),
  labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
) +
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette) +
scale_fill_manual(values = cb_palette) +
ggtitle("Best performance over time") +
p_theme
```

Best performance over time

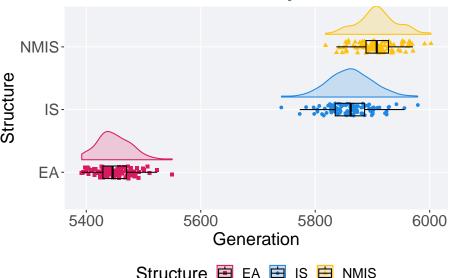


2.3.2 Generation satisfactory solution found

```
filter(base_ssf, Diagnostic == 'EXPLOITATION_RATE' & `Selection\nScheme` == 'TOURNAMEN' ggplot(., aes(x = Structure, y = Generations , color = Structure, fill = Structure, geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) + geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
```

```
scale_y_continuous(
 name="Generation"
scale_x_discrete(
 name="Structure"
)+
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette, ) +
scale_fill_manual(values = cb_palette) +
ggtitle('Generation satisfactory solution found')+
p_theme + coord_flip()
```

Generation satisfactory solution found



Structure 🖹 EA 🛱 IS 🛱 NMIS

2.3.3Stats

Summary statistics for the first generation a satisfactory solution is found.

mean = mean(Generations, na.rm = TRUE),

```
ssf = filter(base_ssf, Diagnostic == 'EXPLOITATION_RATE' & `Selection\nScheme` == 'TOURNAMENT' &
  group_by(Structure) %>%
  dplyr::summarise(
   count = n(),
   na_cnt = sum(is.na(Generations)),
   min = min(Generations, na.rm = TRUE),
   median = median(Generations, na.rm = TRUE),
```

```
max = max(Generations, na.rm = TRUE),
    IQR = IQR(Generations, na.rm = TRUE)
## # A tibble: 3 x 8
    Structure count na_cnt
                              min median mean
##
              <int> <int> <int> <dbl> <dbl> <int> <dbl>
## 1 EA
                 100
                          0 5392 5446 5449.
                                                5550 41.2
## 2 IS
                 100
                          0 5741 5862 5862. 5979 51.2
## 3 NMIS
                 100
                          0 5818 5908. 5909. 6002 39.2
Kruskal-Wallis test provides evidence of difference among selection schemes.
kruskal.test(Generations ~ Structure, data = ssf)
##
##
   Kruskal-Wallis rank sum test
##
## data: Generations by Structure
## Kruskal-Wallis chi-squared = 226.27, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = ssf$Generations, g = ssf$Structure, p.adjust.method = "bonfer.")
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: ssf$Generations and ssf$Structure
##
                IS
##
       EΑ
        < 2e-16 -
## IS
## NMIS < 2e-16 1.1e-14
##
```

2.4 Lexicase selection

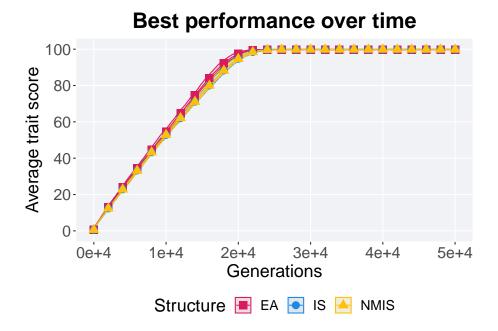
P value adjustment method: bonferroni

Here we analyze how the different population structures affect standard lexicase selection on the exploitation rate diagnostic.

2.4.1 Performance over time

```
lines = filter(base_over_time, Diagnostic == 'EXPLOITATION_RATE' & `Selection\nScheme`
group_by(Structure, Generations) %>%
dplyr::summarise(
```

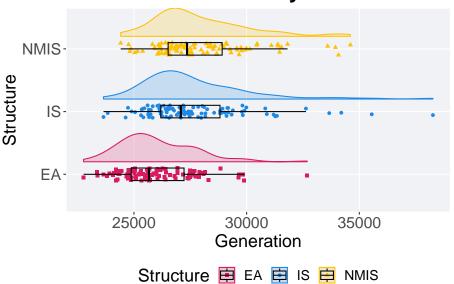
```
min = min(pop_fit_max) / DIMENSIONALITY,
   mean = mean(pop_fit_max) / DIMENSIONALITY,
   max = max(pop_fit_max) / DIMENSIONALITY
 )
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = Structure,
  geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom_line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 2.5, stroke = 2.0, alpha = 1.
  scale_y_continuous(
   name="Average trait score",
   limits=c(-1, 101),
   breaks = seq(0,100, 20),
   labels=c("0", "20", "40", "60", "80", "100")
  ) +
  scale_x_continuous(
   name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
  ) +
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle("Best performance over time") +
  p_theme
```



2.4.2 Generation satisfactory solution found

```
filter(base_ssf, Diagnostic == 'EXPLOITATION_RATE' & `Selection\nScheme` == 'LEXICASE'
  ggplot(., aes(x = Structure, y = Generations , color = Structure, fill = Structure, geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_y_continuous(
    name="Generation"
) +
  scale_x_discrete(
    name="Structure"
)+
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette, ) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Generation satisfactory solution found')+
  p_theme + coord_flip()
```





2.4.3 Stats

2 IS

3 NMIS

Summary statistics for the first generation a satisfactory solution is found.

```
ssf = filter(base_ssf, Diagnostic == 'EXPLOITATION_RATE' & `Selection\nScheme` == 'LEXICASE' & Ge
ssf %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
   na_cnt = sum(is.na(Generations)),
   min = min(Generations, na.rm = TRUE),
   median = median(Generations, na.rm = TRUE),
   mean = mean(Generations, na.rm = TRUE),
   max = max(Generations, na.rm = TRUE),
    IQR = IQR(Generations, na.rm = TRUE)
## # A tibble: 3 x 8
     Structure count na_cnt
                              min median
                                           mean
     <fct>
                      <int> <int>
                                   <dbl>
                                          <dbl> <int> <dbl>
               <int>
## 1 EA
                 100
                          0 22764 25666. 26026. 32687 2344
```

0 23649 27080. 27635. 38266 2628.

0 24412 27358. 27906. 34604 2396.

Kruskal–Wallis test provides evidence of difference among selection schemes.

100

100

```
kruskal.test(Generations ~ Structure, data = ssf)
##
##
   Kruskal-Wallis rank sum test
##
## data: Generations by Structure
## Kruskal-Wallis chi-squared = 52.814, df = 2, p-value = 3.401e-12
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = ssf$Generations, g = ssf$Structure, p.adjust.method = "bonfer")
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: ssf$Generations and ssf$Structure
##
##
        EΑ
                IS
       3.0e-08 -
## IS
## NMIS 2.2e-11 0.24
## P value adjustment method: bonferroni
```

Chapter 3

BASE: Ordered exploitation results

Here we present the results for **best performances** found by each selection scheme replicate on the ordered exploitation diagnostic with our base configurations. Best performance found refers to the largest average trait score found in a given population. Note that performance values fall between 0.0 and 100.0. For our base configuration, we execute migrations every 500 generations and there are 4 islands in a ring topology. When migrations occur, we swap two individuals (same position on each island) and guarantee that no solution can return to the same island.

3.1 Analysis dependencies

```
library(ggplot2)
library(cowplot)
library(dplyr)
library(PupillometryR)
```

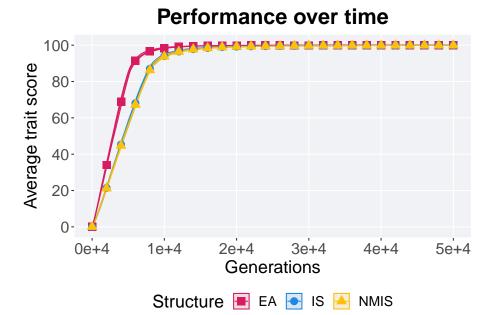
3.2 Truncation selection

Here we analyze how the different population structures affect truncation selection (size 8) on the ordered exploitation diagnostic.

3.2.1 Performance over time

```
lines = filter(base_over_time, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` == 'TRU
group_by(Structure, Generations) %>%
```

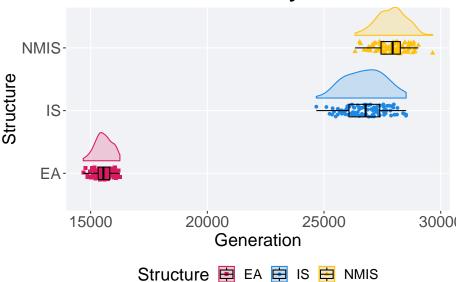
```
dplyr::summarise(
   min = min(pop_fit_max) / DIMENSIONALITY,
   mean = mean(pop_fit_max) / DIMENSIONALITY,
   max = max(pop_fit_max) / DIMENSIONALITY
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = 3
 geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom_line(size = 0.5) +
 geom_point(data = filter(lines, Generations %% 2000 == 0), size = 2.5, stroke = 2.0,
 scale_y_continuous(
   name="Average trait score",
   limits=c(-1, 101),
   breaks=seq(0,100, 20),
   labels=c("0", "20", "40", "60", "80", "100")
  ) +
 scale_x_continuous(
   name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
 ) +
 scale_shape_manual(values=SHAPE)+
 scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
 ggtitle("Performance over time") +
 p_theme
```



3.2.2 Generation satisfactory solution found

```
filter(base_ssf, Diagnostic == 'ORDERED_EXPLOITATION' & 'Selection\nScheme' == 'TRUNCATION') %>%
    ggplot(., aes(x = Structure, y = Generations, color = Structure, fill = Structure, shape = Str
    geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.2) +
    geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
    geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
    scale_y_continuous(
        name="Generation"
) +
    scale_x_discrete(
        name="Structure"
)+
    scale_shape_manual(values=SHAPE)+
    scale_colour_manual(values = cb_palette, ) +
    scale_fill_manual(values = cb_palette) +
    ggtitle('Generation satisfactory solution found')+
    p_theme + coord_flip()
```





3.2.2.1 Stats

Summary statistics for the first generation a satisfactory solution is found.

```
ssf = filter(base_ssf, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` == '
ssf %>%
  group_by(Structure) %>%
 dplyr::summarise(
    count = n(),
    na_cnt = sum(is.na(Generations)),
   min = min(Generations, na.rm = TRUE),
   median = median(Generations, na.rm = TRUE),
   mean = mean(Generations, na.rm = TRUE),
   max = max(Generations, na.rm = TRUE),
    IQR = IQR(Generations, na.rm = TRUE)
## # A tibble: 3 x 8
    Structure count na_cnt
                              min median
                                           mean
                                                        IQR
##
     <fct>
               <int>
                     <int> <int>
                                   <dbl>
                                          <dbl> <int> <dbl>
## 1 EA
                 100
                          0 14684 15546
                                        15554. 16254 492.
## 2 IS
                 100
                          0 24669 26780. 26767. 28518 1318.
## 3 NMIS
                 100
                          0 26330 27939 27888. 29654 825.
```

Kruskal–Wallis test provides evidence of difference among selection schemes.

```
kruskal.test(Generations ~ Structure, data = ssf)
##
##
   Kruskal-Wallis rank sum test
##
## data: Generations by Structure
## Kruskal-Wallis chi-squared = 231.88, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = ssf$Generations, g = ssf$Structure, p.adjust.method = "bonferroni",
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: ssf$Generations and ssf$Structure
##
##
        EΑ
               TS
## IS
       <2e-16 -
## NMIS <2e-16 <2e-16
## P value adjustment method: bonferroni
```

3.3 Tournament selection

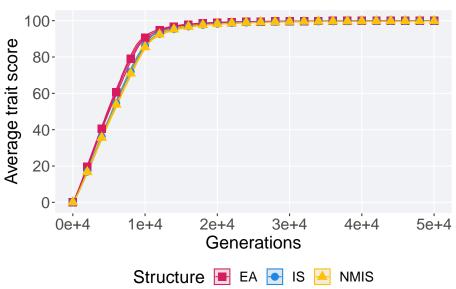
Here we analyze how the different population structures affect tournament selection (size 8) on the ordered exploitation diagnostic.

3.3.1 Performance over time

```
lines = filter(base_over_time, Diagnostic == 'ORDERED_EXPLOITATION'
group_by(Structure, Generations) %>%
dplyr::summarise(
   min = min(pop_fit_max) / DIMENSIONALITY,
   mean = mean(pop_fit_max) / DIMENSIONALITY,
   max = max(pop_fit_max) / DIMENSIONALITY
)
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = Structure,
   geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
   geom_line(size = 0.5) +
   geom_point(data = filter(lines, Generations %% 2000 == 0), size = 2.5, stroke = 2.0, alpha = 1.
   scale_y_continuous(
   name="Average trait score",
   limits=c(-1, 101),
   breaks=seq(0,100, 20),
```

```
labels=c("0", "20", "40", "60", "80", "100")
) +
scale_x_continuous(
  name="Generations",
  limits=c(0, 50000),
  breaks=c(0, 10000, 20000, 30000, 40000, 50000),
  labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
) +
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette) +
scale_fill_manual(values = cb_palette) +
ggtitle("Performance over time") +
p_theme
```

Performance over time

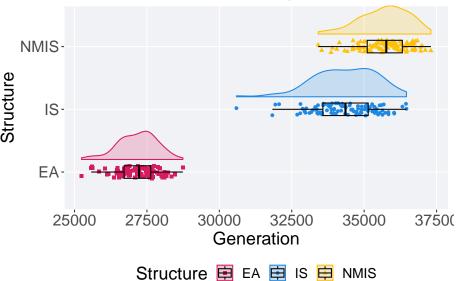


3.3.2 Generation satisfactory solution found

```
filter(base_ssf, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` == 'TOURNAL ggplot(., aes(x = Structure, y = Generations, color = Structure, fill = Structure, geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) + geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
```

```
scale_y_continuous(
   name="Generation"
) +
scale_x_discrete(
   name="Structure"
)+
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette, ) +
scale_fill_manual(values = cb_palette) +
ggtitle('Generation satisfactory solution found')+
p_theme + coord_flip()
```

Generation satisfactory solution found



3.3.2.1 Stats

Summary statistics for the first generation a satisfactory solution is found.

```
ssf = filter(base_ssf, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` == 'TOURNAMENT'
ssf %>%
group_by(Structure) %>%
dplyr::summarise(
  count = n(),
  na_cnt = sum(is.na(Generations)),
  min = min(Generations, na.rm = TRUE),
  median = median(Generations, na.rm = TRUE),
  mean = mean(Generations, na.rm = TRUE),
```

```
max = max(Generations, na.rm = TRUE),
    IQR = IQR(Generations, na.rm = TRUE)
## # A tibble: 3 x 8
    Structure count na_cnt
                              min median
                                            mean
                                                   max
##
               <int> <int> <int> <dbl> <dbl> <int> <dbl>
                          0 25242 27228. 27172. 28742 921.
## 1 EA
                 100
## 2 IS
                 100
                          0 30589 34356. 34349. 36461 1564.
## 3 NMIS
                 100
                          0 33412 35764 35692. 37306 1213
Kruskal-Wallis test provides evidence of difference among selection schemes.
kruskal.test(Generations ~ Structure, data = ssf)
##
##
   Kruskal-Wallis rank sum test
##
## data: Generations by Structure
## Kruskal-Wallis chi-squared = 229.49, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = ssf$Generations, g = ssf$Structure, p.adjust.method = "bonfer.")
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: ssf$Generations and ssf$Structure
##
##
        EΑ
                TS
        < 2e-16 -
## IS
## NMIS < 2e-16 2.8e-16
##
```

3.4 Lexicase selection

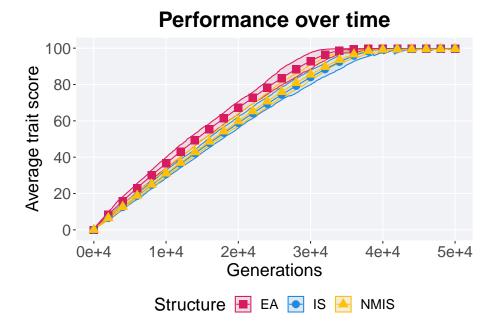
P value adjustment method: bonferroni

Here we analyze how the different population structures affect standard lexicase selection on the ordered exploitation diagnostic.

3.4.1 Performance over time

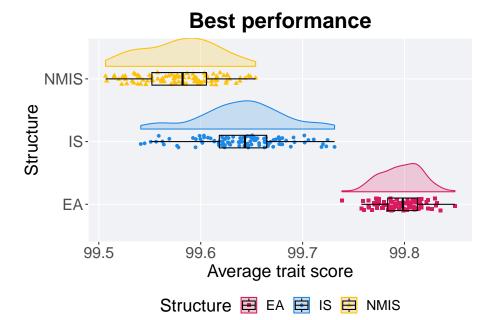
```
lines = filter(base_over_time, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nSchen
group_by(Structure, Generations) %>%
dplyr::summarise(
```

```
min = min(pop_fit_max) / DIMENSIONALITY,
   mean = mean(pop_fit_max) / DIMENSIONALITY,
   max = max(pop_fit_max) / DIMENSIONALITY
 )
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = Structure,
  geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom_line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 2.5, stroke = 2.0, alpha = 1.
  scale_y_continuous(
   name="Average trait score",
   limits=c(-1, 101),
   breaks = seq(0, 100, 20),
   labels=c("0", "20", "40", "60", "80", "100")
  ) +
  scale_x_continuous(
   name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
  ) +
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle("Performance over time") +
  p_theme
```



3.4.2 Best performance

```
filter(base_best, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` == 'LEXIC.
  ggplot(., aes(x = Structure, y = VAL / DIMENSIONALITY, color = Structure, fill = Str
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = '
  geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_y_continuous(
   name="Average trait score"
  ) +
  scale_x_discrete(
   name="Structure"
  )+
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette, ) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Best performance')+
 p_theme + coord_flip()
```



3.4.2.1 Stats

3 NMIS

Summary statistics for the first generation a satisfactory solution is found.

```
performance = filter(base_best, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` == 'LF
performance %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
   na_cnt = sum(is.na(VAL)),
   min = min(VAL, na.rm = TRUE) / DIMENSIONALITY,
   median = median(VAL, na.rm = TRUE) / DIMENSIONALITY,
   mean = mean(VAL, na.rm = TRUE) / DIMENSIONALITY,
   max = max(VAL, na.rm = TRUE) / DIMENSIONALITY,
    IQR = IQR(VAL, na.rm = TRUE) / DIMENSIONALITY
## # A tibble: 3 x 8
     Structure count na_cnt
                              min median
                                          mean
                                                         IQR
     <fct>
                      <int> <dbl>
                                   <dbl> <dbl> <dbl>
                                                       <dbl>
               <int>
## 1 EA
                 100
                             99.7
                                     99.8
                                           99.8
                                                 99.8 0.0291
## 2 IS
                 100
                             99.5
                                     99.6
                                           99.6
                                                 99.7 0.0465
```

99.6

99.6

99.7 0.0535

Kruskal–Wallis test provides evidence of difference among selection schemes.

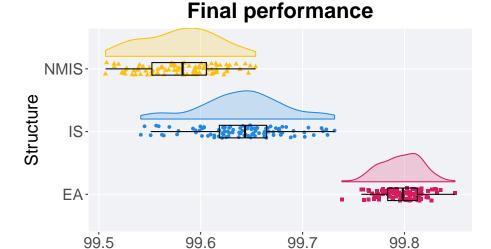
99.5

100

```
kruskal.test(VAL ~ Structure, data = performance)
##
##
   Kruskal-Wallis rank sum test
##
## data: VAL by Structure
## Kruskal-Wallis chi-squared = 235.04, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = performance$VAL, g = performance$Structure, p.adjust.method =
                     paired = FALSE, conf.int = FALSE, alternative = '1')
##
##
  Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: performance$VAL and performance$Structure
##
##
        EΑ
               TS
## IS
        <2e-16 -
## NMIS <2e-16 <2e-16
##
## P value adjustment method: bonferroni
```

3.4.3 Final performance

```
filter(base_over_time, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` == '.
  ggplot(., aes(x = Structure, y = pop_fit_max / DIMENSIONALITY, color = Structure, fi
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = '
  geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_y_continuous(
   name="Average trait score"
  ) +
  scale_x_discrete(
   name="Structure"
  )+
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette, ) +
  scale_fill_manual(values = cb_palette) +
 ggtitle('Final performance')+
 p_theme + coord_flip()
```



Structure 🖪 EA 🛱 IS 🛱 NMIS

Average trait score

3.4.3.1 Stats

3 NMIS

Summary statistics for the first generation a satisfactory solution is found.

```
performance = filter(base_over_time, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` =
performance %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
   na_cnt = sum(is.na(pop_fit_max)),
   min = min(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
   median = median(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
   mean = mean(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
   max = max(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
    IQR = IQR(pop_fit_max / DIMENSIONALITY, na.rm = TRUE)
## # A tibble: 3 x 8
     Structure count na_cnt
                              min median
                                          mean
                                                         IQR
     <fct>
                      <int> <dbl>
                                   <dbl> <dbl> <dbl>
                                                       <dbl>
               <int>
## 1 EA
                 100
                             99.7
                                     99.8
                                           99.8
                                                 99.8 0.0291
## 2 IS
                 100
                             99.5
                                     99.6
                                           99.6
                                                 99.7 0.0465
```

Kruskal–Wallis test provides evidence of difference among selection schemes.

99.5

99.6

99.6

99.7 0.0535

100

```
kruskal.test(pop_fit_max ~ Structure, data = performance)
##
##
   Kruskal-Wallis rank sum test
##
## data: pop_fit_max by Structure
## Kruskal-Wallis chi-squared = 235.02, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = performance$pop_fit_max, g = performance$Structure, p.adjust.
                     paired = FALSE, conf.int = FALSE, alternative = '1')
##
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: performance$pop_fit_max and performance$Structure
##
##
        EΑ
               TS
        <2e-16 -
## IS
## NMIS <2e-16 <2e-16
## P value adjustment method: bonferroni
```

3.4.4 Generation satisfactory solution found

```
lex_fail = filter(base_ssf, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme`
lex_fail$Generations = 55000
lex_fail$Structure <- factor(lex_fail$Structure, levels = MODEL)</pre>
filter(base_ssf, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` == 'LEXICA
      ggplot(., aes(x = Structure, y = Generations, color = Structure, fill = Structure, sill = Structu
             geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha =
       geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
      geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
      geom_point(data = lex_fail, aes(x = Structure, y = Generations, color = Structure, f
       scale_shape_manual(values=SHAPE)+
      scale_y_continuous(
            name="Generations",
            limits=c(30000, 55000),
            breaks=c(30000, 40000, 50000, 55000),
            labels=c("3e+4", "4e+4", "5e+4", "Fail")
       ) +
       scale_x_discrete(
```

Fail

5e+4

```
name="Structure"
) +
scale_colour_manual(values = cb_palette) +
scale_fill_manual(values = cb_palette) +
p_theme + coord_flip()
NMIS-
```

Structure 🖻 EA 🔁 IS 🔁 NMIS

Generations

3.4.4.1 Stats

3e+4

Summary statistics for the first generation a satisfactory solution is found.

4e+4

```
ssf = filter(base_ssf, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` == 'LEXICASE' &
ssf %>%
 group_by(Structure) %>%
 dplyr::summarise(
   count = n(),
   na_cnt = sum(is.na(Generations)),
   min = min(Generations, na.rm = TRUE),
   median = median(Generations, na.rm = TRUE),
   mean = mean(Generations, na.rm = TRUE),
   max = max(Generations, na.rm = TRUE),
   IQR = IQR(Generations, na.rm = TRUE)
## # A tibble: 2 x 8
    Structure count na_cnt
                             min median
                                          mean
    <fct> <int> <int> <dbl> <dbl> <int> <dbl>
```

##

P value adjustment method: bonferroni

```
## 1 EA
                  100
                           0 34272 38848 38795. 42983 2814
## 2 IS
                  18
                           0 46454 48378. 48402. 49847 1929
Kruskal–Wallis test provides evidence of difference among selection schemes.
kruskal.test(Generations ~ Structure, data = ssf)
##
##
   Kruskal-Wallis rank sum test
##
## data: Generations by Structure
## Kruskal-Wallis chi-squared = 45.378, df = 1, p-value = 1.624e-11
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = ssf$Generations, g = ssf$Structure, p.adjust.method = "bonfer.")
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
##
## data: ssf$Generations and ssf$Structure
##
##
## IS 8.3e-12
```

Chapter 4

BASE: Contradictory objectives results

Here we present the results for the **satisfactory trait corverage** and **activation gene coverage** generated by each selection scheme replicate on the contradictory objectives diagnostic with our base configurations. Note both of these values are gathered at the population-level. Activation gene coverage refers to the count of unique activation genes in a given population; this gives us a range of integers between 0 and 100. Satisfactory trait coverage refers to the count of unique satisfied traits in a given population; this gives us a range of integers between 0 and 100. For our base configuration, we execute migrations every 500 generations and there are 4 islands in a ring topology. When migrations occur, two individuals are swapped (same position on each island) and guarantee that no solution can return to its original island.

4.1 Analysis dependencies

```
library(ggplot2)
library(cowplot)
library(dplyr)
library(PupillometryR)
```

4.2 Truncation selection

Here we analyze how the different population structures affect truncation selection (size 8) on the contradictory objectives diagnostic.

4.2.1 Satisfactory trait coverage

Satisfactory trait coverage analysis.

4.2.1.1 Coverage over time

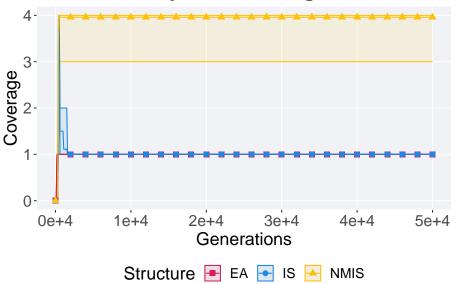
Satisfactory trait coverage over time.

```
lines = filter(base_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\ni
group_by(Structure, Generations) %>%
dplyr::summarise(
   min = min(pop_sat_cov),
   mean = mean(pop_sat_cov),
   max = max(pop_sat_cov)
)
```

`summarise()` has grouped output by 'Structure'. You can override using the
`.groups` argument.

```
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = x
 geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom_line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 1.5, stroke = 2.0,
  scale_y_continuous(
   name="Coverage"
 ) +
  scale_x_continuous(
    name="Generations",
   limits=c(0, 50000),
    breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
 ) +
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette) +
 scale_fill_manual(values = cb_palette) +
 ggtitle('Satisfactory trait coverage over time')+
 p_theme
```



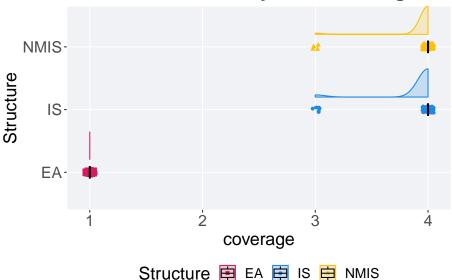


4.2.1.2 Best coverage throughout

Best satisfactory trait coverage throughout 50,000 generations.

```
### best satisfactory trait coverage throughout
filter(base_best, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` == 'TRUNCATION'
  ggplot(., aes(x = Structure, y = VAL, color = Structure, fill = Structure, shape = Structure))
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.2) +
  geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha = 1.0) +
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_y_continuous(
   name="coverage"
  scale_x_discrete(
   name="Structure"
  )+
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette, ) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Best satisfactory trait coverage')+
  p_theme + coord_flip()
```





Structure 🖹 EA 🖨 IS 🛱 NMIS

4.2.1.2.1 Stats

Summary statistics for the best satisfactory trait coverage.

```
### best
coverage = filter(base_best, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nSci
coverage %>%
  group_by(Structure) %>%
 dplyr::summarise(
    count = n(),
   na_cnt = sum(is.na(VAL)),
   min = min(VAL, na.rm = TRUE),
   median = median(VAL, na.rm = TRUE),
   mean = mean(VAL, na.rm = TRUE),
   max = max(VAL, na.rm = TRUE),
    IQR = IQR(VAL, na.rm = TRUE)
## # A tibble: 3 x 8
    Structure count na cnt
                              min median mean
##
               <int> <int> <dbl>
                                   <dbl> <dbl> <dbl> <dbl>
## 1 EA
                 100
                          0
## 2 IS
                 100
                          0
                                3
                                       4 3.93
                                                    4
                                                          0
## 3 NMIS
                 100
                          0
                                3
                                          3.96
```

Kruskal-Wallis test provides evidence of difference among satisfactory trait

```
coverage.
```

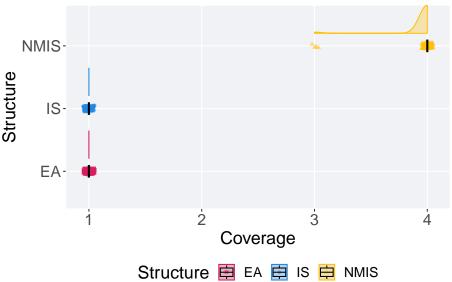
```
kruskal.test(VAL ~ Structure, data = coverage)
##
## Kruskal-Wallis rank sum test
##
## data: VAL by Structure
## Kruskal-Wallis chi-squared = 279.71, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on
satisfactory trait coverage.
pairwise.wilcox.test(x = coverage$VAL, g = coverage$Structure, p.adjust.method = "bonferroni",
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: coverage$VAL and coverage$Structure
##
##
        EΑ
               IS
      <2e-16 -
## IS
## NMIS <2e-16 0.53
## P value adjustment method: bonferroni
```

4.2.1.3 End of 50,000 generations

Satisfactory trait coverage in the population at the end of 50,000 generations.

```
### end of run
filter(base_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` == 'TRUNCAT
  ggplot(., aes(x = Structure, y = pop_sat_cov, color = Structure, fill = Structure, shape = Structure,
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.3) +
  geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha = 0.5) +
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_shape_manual(values=SHAPE)+
  scale_y_continuous(
   name="Coverage"
  scale_x_discrete(
   name="Structure"
  ) +
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Final satisfactory trait coverage')+
  p_theme + coord_flip()
```





4.2.1.3.1 Stats

Summary statistics for satisfactory trait coverage in the population at the end of 50,000 generations.

```
### end of run
coverage = filter(base_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection
coverage %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
    na_cnt = sum(is.na(pop_sat_cov)),
    min = min(pop_sat_cov, na.rm = TRUE),
    median = median(pop_sat_cov, na.rm = TRUE),
    mean = mean(pop_sat_cov, na.rm = TRUE),
    max = max(pop_sat_cov, na.rm = TRUE),
    IQR = IQR(pop_sat_cov, na.rm = TRUE)
)

## # A tibble: 3 x 8
```

```
Structure count na_cnt
                           min median mean
                                                  IQR
##
    <fct>
             <int> <int> <int> <dbl> <dbl> <int> <dbl>
## 1 EA
               100
                       0
                                   1 1
                                              1
                                                    0
                             1
                                   1 1
## 2 IS
               100
                       0
                             1
                                              1
## 3 NMIS
              100
                       0
                             3
                                   4 3.96
```

Kruskal–Wallis test provides evidence of difference among satisfactory trait coverage in the population at the end of 50,000 generations.

kruskal.test(pop_sat_cov ~ Structure, data = coverage)

```
##
## Kruskal-Wallis rank sum test
##
## data: pop_sat_cov by Structure
## Kruskal-Wallis chi-squared = 297.1, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on
satisfactory trait coverage in the population at the end of 50,000 generations.
pairwise.wilcox.test(x = coverage$pop_sat_cov, g = coverage$Structure, p.adjust.method = "bonfern
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: coverage$pop_sat_cov and coverage$Structure
##
##
        EΑ
               IS
## IS
## NMIS <2e-16 <2e-16
## P value adjustment method: bonferroni
```

4.2.2 Activation gene coverage

Activation gene coverage analysis.

4.2.2.1 Coverage over time

`.groups` argument.

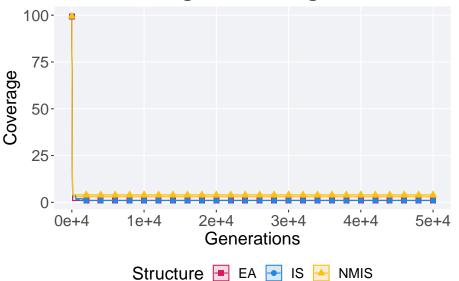
Activation gene coverage over time.

```
# data for lines and shading on plots
lines = filter(base_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` ==
group_by(Structure, Generations) %>%
dplyr::summarise(
   min = min(pop_act_cov),
   mean = mean(pop_act_cov),
   max = max(pop_act_cov)
)

## `summarise()` has grouped output by 'Structure'. You can override using the
```

```
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = 3
  geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom_line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 1.5, stroke = 2.0,
  scale_y_continuous(
    name="Coverage"
  ) +
  scale_x_continuous(
   name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
 ) +
  scale_shape_manual(values=SHAPE)+
 scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
 ggtitle('Activation gene coverage over time')+
 p_theme
```

Activation gene coverage over time

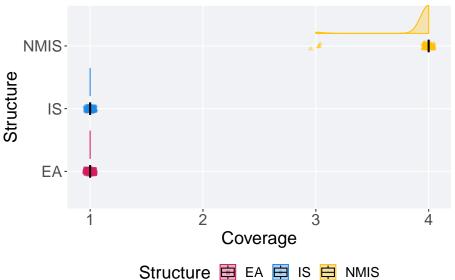


4.2.2.2 End of 50,000 generations

Activation gene coverage in the population at the end of 50,000 generations.

```
### end of run
filter(base_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` == 'TRUNCAT
  ggplot(., aes(x = Structure, y = pop_act_cov, color = Structure, fill = Structure, shape = Stru
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.3) +
  geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha = 0.5) +
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_shape_manual(values=SHAPE)+
  scale_y_continuous(
   name="Coverage"
  ) +
  scale_x_discrete(
   name="Structure"
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Final activation gene coverage')+
  p_theme + coord_flip()
```

Final activation gene coverage



4.2.2.2.1 Stats

Summary statistics for activation gene coverage.

```
coverage = filter(base_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme`
coverage %>%
  group_by(Structure) %>%
```

```
dplyr::summarise(
   count = n(),
   na_cnt = sum(is.na(pop_act_cov)),
   min = min(pop_act_cov, na.rm = TRUE),
   median = median(pop_act_cov, na.rm = TRUE),
   mean = mean(pop_act_cov, na.rm = TRUE),
   max = max(pop_act_cov, na.rm = TRUE),
   IQR = IQR(pop_act_cov, na.rm = TRUE)
## # A tibble: 3 x 8
##
    Structure count na_cnt
                           min median mean
                                             max
    <fct> <int> <int> <dbl> <dbl> <int> <dbl>
##
## 1 EA
              100
                     0 1
                                  1 1
                                               1
                                    1 1
## 2 IS
              100
                        0
                                               1
                                                     0
                             1
## 3 NMIS
               100
                        0
                             3
                                    4 3.96
                                               4
                                                     0
```

Kruskal–Wallis test provides evidence of difference among activation gene coverage.

```
kruskal.test(pop_act_cov ~ Structure, data = coverage)
```

```
##
## Kruskal-Wallis rank sum test
##
## data: pop_act_cov by Structure
## Kruskal-Wallis chi-squared = 297.1, df = 2, p-value < 2.2e-16</pre>
```

Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on activation gene coverage.

```
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: coverage$pop_act_cov and coverage$Structure
##
## EA IS
## IS 1 -
## NMIS <2e-16 <2e-16
##
## P value adjustment method: bonferroni</pre>
```

4.3 Tournament selection

Here we analyze how the different population structures affect tournament selection (size 8) on the contradictory objectives diagnostic.

4.3.1 Satisfactory trait coverage

Satisfactory trait coverage analysis.

4.3.1.1 Coverage over time

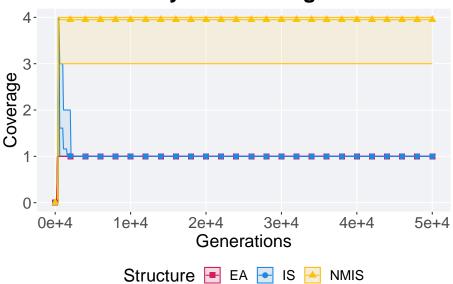
Satisfactory trait coverage over time.

```
lines = filter(base_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` ==
group_by(Structure, Generations) %>%
dplyr::summarise(
   min = min(pop_sat_cov),
   mean = mean(pop_sat_cov),
   max = max(pop_sat_cov)
)
```

`summarise()` has grouped output by 'Structure'. You can override using the
`.groups` argument.

```
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = Structure,
  geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 1.5, stroke = 2.0, alpha = 1.
  scale_y_continuous(
   name="Coverage"
  scale_x_continuous(
   name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
  ) +
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Satisfactory trait coverage over time')+
  p_theme
```



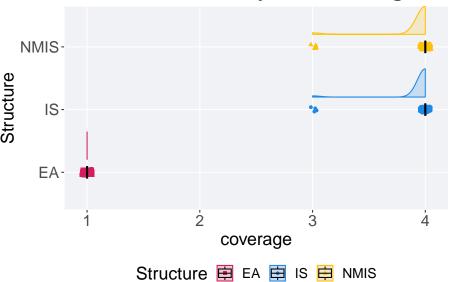


4.3.1.2 Best coverage throughout

Best satisfactory trait coverage throughout 50,000 generations.

```
### best satisfactory trait coverage throughout
filter(base_best, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` == 'Tontradiction's filter(base_best, Diagnostic == 'T
        ggplot(., aes(x = Structure, y = VAL, color = Structure, fill = Structure, shape = S
        geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = '
       geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha
        geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
       scale_y_continuous(
              name="coverage"
       ) +
        scale_x_discrete(
              name="Structure"
      )+
        scale_shape_manual(values=SHAPE)+
       scale_colour_manual(values = cb_palette, ) +
       scale_fill_manual(values = cb_palette) +
       ggtitle('Best satisfactory trait coverage')+
      p_theme + coord_flip()
```





4.3.1.2.1 Stats

Summary statistics for the best satisfactory trait coverage.

```
### best
coverage = filter(base_best, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` == 'T
coverage %>%
  group_by(Structure) %>%
  dplyr::summarise(
   count = n(),
   na_cnt = sum(is.na(VAL)),
   min = min(VAL, na.rm = TRUE),
   median = median(VAL, na.rm = TRUE),
   mean = mean(VAL, na.rm = TRUE),
   max = max(VAL, na.rm = TRUE),
   IQR = IQR(VAL, na.rm = TRUE)
## # A tibble: 3 x 8
     Structure count na cnt
                              min median mean
               <int> <int> <dbl>
                                   <dbl> <dbl> <dbl> <dbl> <
     <fct>
## 1 EA
                 100
                          0
## 2 IS
                 100
                          0
                                3
                                        4 3.96
                                                    4
                                                          0
## 3 NMIS
                 100
                          0
                                3
                                        4 3.95
```

Kruskal-Wallis test provides evidence of difference among satisfactory trait

coverage.

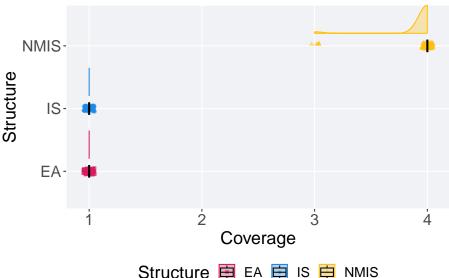
```
kruskal.test(VAL ~ Structure, data = coverage)
##
## Kruskal-Wallis rank sum test
##
## data: VAL by Structure
## Kruskal-Wallis chi-squared = 282.81, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on
satisfactory trait coverage.
pairwise.wilcox.test(x = coverage$VAL, g = coverage$Structure, p.adjust.method = "bonf")
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: coverage$VAL and coverage$Structure
##
##
        EΑ
               IS
       <2e-16 -
## IS
## NMIS <2e-16 1
## P value adjustment method: bonferroni
```

4.3.1.3 End of 50,000 generations

Satisfactory trait coverage in the population at the end of 50,000 generations.

```
### end of run
filter(base_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` :
       ggplot(., aes(x = Structure, y = pop_sat_cov, color = Structure, fill = Structure, sill = Structu
        geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = '
       geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha
        geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
       scale_shape_manual(values=SHAPE)+
       scale_y_continuous(
              name="Coverage"
       ) +
       scale_x_discrete(
              name="Structure"
       ) +
       scale_colour_manual(values = cb_palette) +
       scale_fill_manual(values = cb_palette) +
       ggtitle('Final satisfactory trait coverage')+
       p_theme + coord_flip()
```





Structure E EA E IS E NMIS

4.3.1.3.1 Stats

Summary statistics for satisfactory trait coverage in the population at the end of 50,000 generations.

```
### end of run
coverage = filter(base_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme`
coverage %>%
  group_by(Structure) %>%
  dplyr::summarise(
   count = n(),
   na_cnt = sum(is.na(pop_sat_cov)),
   min = min(pop_sat_cov, na.rm = TRUE),
   median = median(pop_sat_cov, na.rm = TRUE),
   mean = mean(pop_sat_cov, na.rm = TRUE),
   max = max(pop_sat_cov, na.rm = TRUE),
    IQR = IQR(pop_sat_cov, na.rm = TRUE)
## # A tibble: 3 x 8
     Structure count na_cnt
                              min median mean
```

```
<fct>
              <int> <int> <int> <dbl> <dbl> <int> <dbl>
## 1 EA
                100
                         0
                              1
                                     1 1
## 2 IS
                         0
                              1
                                     1 1
                                                 1
                                                       0
                100
## 3 NMIS
                100
                         0
                              3
                                     4 3.95
```

Kruskal–Wallis test provides evidence of difference among satisfactory trait coverage in the population at the end of 50,000 generations.

```
kruskal.test(pop_sat_cov ~ Structure, data = coverage)
##
##
   Kruskal-Wallis rank sum test
##
## data: pop_sat_cov by Structure
## Kruskal-Wallis chi-squared = 296.65, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on
satisfactory trait coverage in the population at the end of 50,000 generations.
pairwise.wilcox.test(x = coverage$pop_sat_cov, g = coverage$Structure, p.adjust.method
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: coverage$pop_sat_cov and coverage$Structure
##
##
        EΑ
               IS
## IS
## NMIS <2e-16 <2e-16
## P value adjustment method: bonferroni
```

4.3.2 Activation gene coverage

Activation gene coverage analysis.

4.3.2.1 Coverage over time

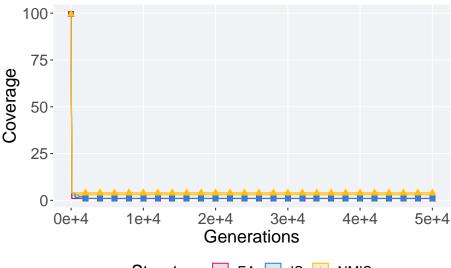
Activation gene coverage over time.

```
# data for lines and shading on plots
lines = filter(base_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\ni
group_by(Structure, Generations) %>%
dplyr::summarise(
   min = min(pop_act_cov),
   mean = mean(pop_act_cov),
   max = max(pop_act_cov)
)
```

```
## `summarise()` has grouped output by 'Structure'. You can override using the
## `.groups` argument.
```

```
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = Structure,
  geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom_line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 1.5, stroke = 2.0, alpha = 1.
  scale_y_continuous(
    name="Coverage"
  ) +
  scale_x_continuous(
   name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
  ) +
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Activation gene coverage over time')+
  p_theme
```

Activation gene coverage over time



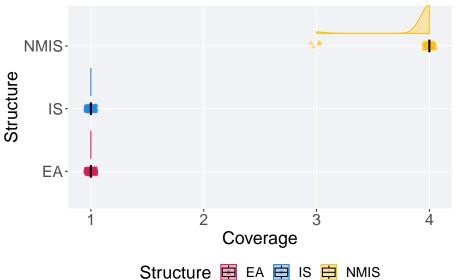
Structure 🖪 EA 💽 IS 🔼 NMIS

4.3.2.2 End of 50,000 generations

Activation gene coverage in the population at the end of 50,000 generations.

```
### end of run
filter(base_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` :
  ggplot(., aes(x = Structure, y = pop_act_cov, color = Structure, fill = Structure, si
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = '
  geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_shape_manual(values=SHAPE)+
  scale_y_continuous(
   name="Coverage"
  ) +
  scale_x_discrete(
   name="Structure"
  ) +
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Final activation gene coverage')+
 p_theme + coord_flip()
```

Final activation gene coverage



Summary statistics for activation gene coverage.

4.3.2.2.1 Stats

```
coverage = filter(base_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection
coverage %>%
  group_by(Structure) %>%
```

##

IS

EΑ

1 ## NMIS <2e-16 <2e-16

TS

P value adjustment method: bonferroni

```
dplyr::summarise(
    count = n(),
   na_cnt = sum(is.na(pop_act_cov)),
   min = min(pop_act_cov, na.rm = TRUE),
   median = median(pop_act_cov, na.rm = TRUE),
   mean = mean(pop_act_cov, na.rm = TRUE),
   max = max(pop_act_cov, na.rm = TRUE),
    IQR = IQR(pop_act_cov, na.rm = TRUE)
## # A tibble: 3 x 8
     Structure count na_cnt min median mean
                                                 max
    <fct> <int> <int> <int> <dbl> <dbl> <int> <dbl>
## 1 EA
               100
                         0
                              1
                                      1 1
                                                   1
## 2 IS
                 100
                          0
                                       1 1
                                                   1
                                                         0
                                1
                                       4 3.95
## 3 NMIS
                 100
                          0
                                3
                                                   4
                                                         0
Kruskal-Wallis test provides evidence of difference among activation gene cover-
age.
kruskal.test(pop_act_cov ~ Structure, data = coverage)
##
## Kruskal-Wallis rank sum test
##
## data: pop_act_cov by Structure
## Kruskal-Wallis chi-squared = 296.65, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on
activation gene coverage.
pairwise.wilcox.test(x = coverage$pop_act_cov, g = coverage$Structure, p.adjust.method = "bonfer")
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
## data: coverage$pop_act_cov and coverage$Structure
```

4.4 Lexicase selection

Here we analyze how the different population structures affect standard lexicase selection on the contradictory objectives diagnostic.

4.4.1 Satisfactory trait coverage

Satisfactory trait coverage analysis.

4.4.1.1 Coverage over time

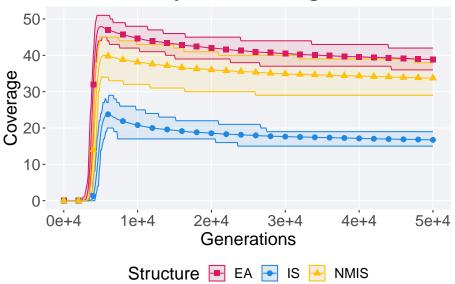
Satisfactory trait coverage over time.

```
lines = filter(base_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\ni
group_by(Structure, Generations) %>%
dplyr::summarise(
   min = min(pop_sat_cov),
   mean = mean(pop_sat_cov),
   max = max(pop_sat_cov)
)
```

`summarise()` has grouped output by 'Structure'. You can override using the
`.groups` argument.

```
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color 
        geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
        geom_line(size = 0.5) +
        geom_point(data = filter(lines, Generations %% 2000 == 0), size = 1.5, stroke = 2.0,
        scale_y_continuous(
               name="Coverage"
        ) +
        scale_x_continuous(
                name="Generations",
               limits=c(0, 50000),
                breaks=c(0, 10000, 20000, 30000, 40000, 50000),
                labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
        ) +
        scale_shape_manual(values=SHAPE)+
        scale_colour_manual(values = cb_palette) +
        scale_fill_manual(values = cb_palette) +
       ggtitle('Satisfactory trait coverage over time')+
       p_theme
```



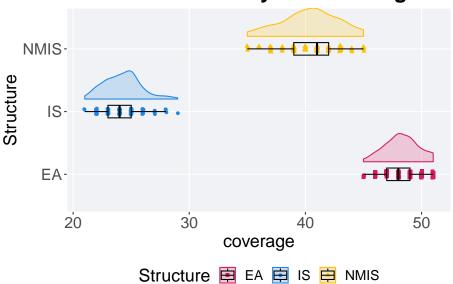


4.4.1.2 Best coverage throughout

Best satisfactory trait coverage throughout 50,000 generations.

```
### best satisfactory trait coverage throughout
filter(base_best, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` == 'LEXICASE' &
    ggplot(., aes(x = Structure, y = VAL, color = Structure, fill = Structure, shape = Structure))
    geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.2) +
    geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha = 1.0) +
    geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
    scale_y_continuous(
        name="coverage"
    ) +
    scale_x_discrete(
        name="Structure"
    )+
    scale_shape_manual(values=SHAPE)+
    scale_colour_manual(values = cb_palette, ) +
    scale_fill_manual(values = cb_palette) +
    ggtitle('Best satisfactory trait coverage')+
    p_theme + coord_flip()
```





4.4.1.2.1 Stats

3 IS

100

0

21

Summary statistics for the best satisfactory trait coverage.

```
### best
coverage = filter(base_best, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nSci
coverage$Structure = factor(coverage$Structure, levels=c('EA','NMIS','IS'))
coverage %>%
  group_by(Structure) %>%
 dplyr::summarise(
    count = n(),
   na_cnt = sum(is.na(VAL)),
   min = min(VAL, na.rm = TRUE),
   median = median(VAL, na.rm = TRUE),
   mean = mean(VAL, na.rm = TRUE),
   max = max(VAL, na.rm = TRUE),
    IQR = IQR(VAL, na.rm = TRUE)
## # A tibble: 3 x 8
     Structure count na_cnt
                              min median mean
                                                        IQR
                                                  max
##
     <fct>
               <int> <int> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <
## 1 EA
                 100
                          0
                               45
                                       48 48.3
                                                   51
                                                          2
## 2 NMIS
                 100
                          0
                               35
                                       41 40.4
                                                   45
                                                          3
```

24 24.2

29

2

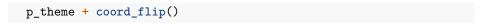
Kruskal–Wallis test provides evidence of difference among satisfactory trait coverage.

```
kruskal.test(VAL ~ Structure, data = coverage)
##
## Kruskal-Wallis rank sum test
##
## data: VAL by Structure
## Kruskal-Wallis chi-squared = 266.69, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on
satisfactory trait coverage.
pairwise.wilcox.test(x = coverage$VAL, g = coverage$Structure, p.adjust.method = "bonferroni",
                     paired = FALSE, conf.int = FALSE, alternative = '1')
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
##
## data: coverage$VAL and coverage$Structure
##
##
        EΑ
               NMIS
## NMIS <2e-16 -
## IS <2e-16 <2e-16
##
## P value adjustment method: bonferroni
```

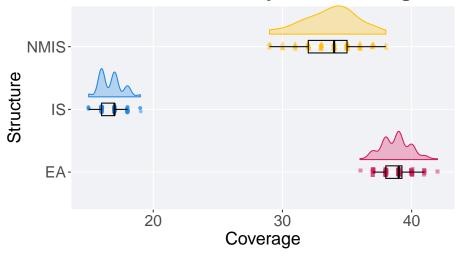
4.4.1.3 End of 50,000 generations

Satisfactory trait coverage in the population at the end of 50,000 generations.

```
### end of run
filter(base_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & Selection\nScheme` == 'LEXICAS'
ggplot(., aes(x = Structure, y = pop_sat_cov, color = Structure, fill = Structure, shape = Structure, geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.3) +
geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha = 0.5) +
geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
scale_shape_manual(values=SHAPE)+
scale_y_continuous(
    name="Coverage"
) +
scale_x_discrete(
    name="Structure"
) +
scale_colour_manual(values = cb_palette) +
scale_fill_manual(values = cb_palette) +
ggtitle('Final satisfactory trait coverage')+
```



Final satisfactory trait coverage



Structure E EA E IS NMIS

4.4.1.3.1 Stats

Summary statistics for satisfactory trait coverage in the population at the end of $50{,}000$ generations.

```
### end of run
coverage = filter(base_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection
coverage$Structure = factor(coverage$Structure, levels=c('EA','NMIS','IS'))
coverage %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
    na_cnt = sum(is.na(pop_sat_cov)),
    min = min(pop_sat_cov, na.rm = TRUE),
    median = median(pop_sat_cov, na.rm = TRUE),
    mean = mean(pop_sat_cov, na.rm = TRUE),
    max = max(pop_sat_cov, na.rm = TRUE),
    IQR = IQR(pop_sat_cov, na.rm = TRUE)
)
## # A tibble: 3 x 8
```

```
## # A tloble: 3 x 8

## Structure count na_cnt min median mean max IQR

## <fct> <int> <int> <int> <dbl> <dbl> <int> <dbl> <int> <dbl> ## 1 EA 100 0 36 39 38.8 42 1.25
```

```
## 2 NMIS 100 0 29 34 33.7 38 3 ## 3 IS 100 0 15 17 16.7 19 1
```

Kruskal–Wallis test provides evidence of difference among satisfactory trait coverage in the population at the end of 50,000 generations.

```
kruskal.test(pop_sat_cov ~ Structure, data = coverage)
##
## Kruskal-Wallis rank sum test
##
## data: pop_sat_cov by Structure
## Kruskal-Wallis chi-squared = 265.34, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on
satisfactory trait coverage in the population at the end of 50,000 generations.
pairwise.wilcox.test(x = coverage$pop_sat_cov, g = coverage$Structure, p.adjust.method = "bonfern
                      paired = FALSE, conf.int = FALSE, alternative = '1')
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: coverage$pop_sat_cov and coverage$Structure
##
##
        EΑ
               NMIS
## NMIS <2e-16 -
## IS
       <2e-16 <2e-16
##
## P value adjustment method: bonferroni
```

4.4.2 Activation gene coverage

Activation gene coverage analysis.

4.4.2.1 Coverage over time

Activation gene coverage over time.

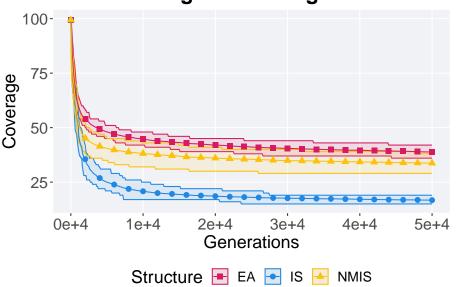
```
# data for lines and shading on plots
lines = filter(base_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` ==
group_by(Structure, Generations) %>%
dplyr::summarise(
   min = min(pop_act_cov),
   mean = mean(pop_act_cov),
   max = max(pop_act_cov)
)
```

`summarise()` has grouped output by 'Structure'. You can override using the

```
## `.groups` argument.
```

```
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = 3
  geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom_line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 1.5, stroke = 2.0,
  scale_y_continuous(
    name="Coverage"
  ) +
  scale_x_continuous(
    name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
  ) +
 scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Activation gene coverage over time')+
 p_theme
```

Activation gene coverage over time

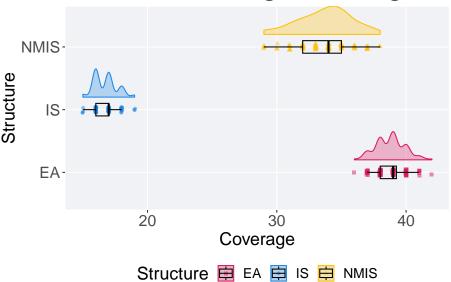


4.4.2.2 End of 50,000 generations

Activation gene coverage in the population at the end of 50,000 generations.

```
### end of run
filter(base_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` == 'LEXICAS'
  ggplot(., aes(x = Structure, y = pop_act_cov, color = Structure, fill = Structure, shape = Structure,
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.3) +
  geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha = 0.5) +
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_shape_manual(values=SHAPE)+
  scale_y_continuous(
   name="Coverage"
  ) +
  scale_x_discrete(
   name="Structure"
  ) +
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Final activation gene coverage')+
  p_theme + coord_flip()
```

Final activation gene coverage



4.4.2.2.1 Stats

Summary statistics for activation gene coverage.

```
coverage = filter(base_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme`
coverage$Structure = factor(coverage$Structure, levels=c('EA','NMIS','IS'))
coverage %>%
```

group_by(Structure) %>%

```
dplyr::summarise(
    count = n(),
    na_cnt = sum(is.na(pop_act_cov)),
   min = min(pop_act_cov, na.rm = TRUE),
    median = median(pop_act_cov, na.rm = TRUE),
   mean = mean(pop_act_cov, na.rm = TRUE),
    max = max(pop_act_cov, na.rm = TRUE),
    IQR = IQR(pop_act_cov, na.rm = TRUE)
 )
## # A tibble: 3 x 8
    Structure count na_cnt
                              min median mean
                                                 max
                                                       IQR
     <fct> <int> <int> <dbl> <dbl> <int> <dbl>
                                                  42 1.25
                                      39 38.8
## 1 EA
                100
                        0 36
## 2 NMIS
                 100
                          0
                               29
                                      34 33.7
                                                  38 3
                 100
                               15
## 3 IS
                          0
                                      17 16.7
                                                  19 1
Kruskal-Wallis test provides evidence of difference among activation gene cover-
kruskal.test(pop_act_cov ~ Structure, data = coverage)
##
##
   Kruskal-Wallis rank sum test
##
## data: pop_act_cov by Structure
## Kruskal-Wallis chi-squared = 265.34, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on
activation gene coverage.
pairwise.wilcox.test(x = coverage$pop_act_cov, g = coverage$Structure, p.adjust.method
                     paired = FALSE, conf.int = FALSE, alternative = '1')
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: coverage$pop_act_cov and coverage$Structure
##
##
        EΑ
               NMIS
## NMIS <2e-16 -
## IS
        <2e-16 <2e-16
##
## P value adjustment method: bonferroni
```

Chapter 5

BASE: Multi-path exploration results

Here we present the results for the **best performances** and **activation gene coverage** generated by each selection scheme replicate on the multi-path exploration diagnostic. Best performance found refers to the largest average trait score found in a given population. Note that activation gene coverage values are gathered at the population-level. Activation gene coverage refers to the count of unique activation genes in a given population; this gives us a range of integers between 0 and 100.

5.1 Analysis dependencies

```
library(ggplot2)
library(cowplot)
library(dplyr)
library(PupillometryR)
```

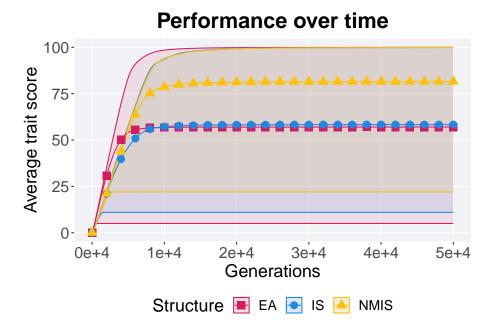
5.2 Truncation selection

Here we analyze how the different population structures affect truncation selection (size 8) on the contradictory objectives diagnostic.

5.2.1 Performance

5.2.1.1 Performance over time

```
lines = filter(base_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScho
  group_by(Structure, Generations) %>%
  dplyr::summarise(
   min = min(pop_fit_max) / DIMENSIONALITY,
   mean = mean(pop_fit_max) / DIMENSIONALITY,
   max = max(pop_fit_max) / DIMENSIONALITY
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = 3
  geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom_line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 2.5, stroke = 2.0,
  scale_y_continuous(
   name="Average trait score"
  scale_x_continuous(
   name="Generations",
    limits=c(0, 50000),
    breaks=c(0, 10000, 20000, 30000, 40000, 50000),
    labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
  ) +
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle("Performance over time") +
  p_theme
```



5.2.1.2 Best performance

First generation a satisfactory solution is found throughout the 50,000 generations.

```
filter(base_best, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'TRUNCATION' &
    ggplot(., aes(x = Structure, y = VAL / DIMENSIONALITY, color = Structure, fill = Structure, sha
    geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.2) +
    geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
    geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
    scale_y_continuous(
        name="Average trait score"
) +
    scale_x_discrete(
        name="Structure"
)+
    scale_shape_manual(values=SHAPE)+
    scale_colour_manual(values = cb_palette, ) +
    scale_fill_manual(values = cb_palette) +
    ggtitle('Best performance')+
    p_theme + coord_flip()
```



5.2.1.2.1 Stats

3 NMIS

100

Summary statistics for the first generation a satisfactory solution is found.

```
performance = filter(base_best, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nSci
performance %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
    na_cnt = sum(is.na(VAL)),
    min = min(VAL, na.rm = TRUE) / DIMENSIONALITY,
    median = median(VAL, na.rm = TRUE) / DIMENSIONALITY,
    mean = mean(VAL, na.rm = TRUE) / DIMENSIONALITY,
    max = max(VAL, na.rm = TRUE) / DIMENSIONALITY,
    IQR = IQR(VAL, na.rm = TRUE) / DIMENSIONALITY
## # A tibble: 3 x 8
     Structure count na_cnt
                              min median mean
##
     <fct>
               <int>
                      <int> <dbl>
                                   <dbl> <dbl> <dbl> <dbl> <
## 1 EA
                 100
                                          57.0 100.
                                                       40.5
                          0
                              5
                                    58.0
## 2 IS
                 100
                          0
                                    56.0
                                         58.3 99.9
                                                       44.5
                            11
```

85.9 81.5 99.9

Kruskal–Wallis test provides evidence of difference among selection schemes.

22.0

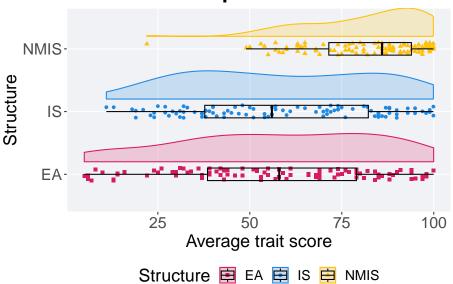
```
kruskal.test(VAL ~ Structure, data = performance)
##
## Kruskal-Wallis rank sum test
##
## data: VAL by Structure
## Kruskal-Wallis chi-squared = 57.688, df = 2, p-value = 2.973e-13
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = performance$VAL, g = performance$Structure, p.adjust.method = "bonferror
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
## data: performance$VAL and performance$Structure
##
##
        EΑ
                IS
## IS
      1
## NMIS 4.3e-11 1.3e-10
##
## P value adjustment method: bonferroni
```

5.2.1.3 Final performance

First generation a satisfactory solution is found throughout the 50,000 generations.

```
filter(base_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'TRUNCATION'
ggplot(., aes(x = Structure, y = pop_fit_max / DIMENSIONALITY, color = Structure, fill = Struct
geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.2) +
geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
scale_y_continuous(
    name="Average trait score"
) +
scale_x_discrete(
    name="Structure"
)+
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette, ) +
scale_fill_manual(values = cb_palette) +
ggtitle('Final performance')+
p_theme + coord_flip()
```





5.2.1.3.1 Stats

3 NMIS

100

Summary statistics for the first generation a satisfactory solution is found.

```
performance = filter(base_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection
performance %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
    na_cnt = sum(is.na(pop_fit_max)),
    min = min(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
    median = median(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
    mean = mean(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
    max = max(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
    IQR = IQR(pop_fit_max / DIMENSIONALITY, na.rm = TRUE)
## # A tibble: 3 x 8
     Structure count na_cnt
                              min median mean
##
     <fct>
               <int>
                      <int> <dbl>
                                   <dbl> <dbl> <dbl> <dbl> <
## 1 EA
                 100
                                          57.0 100.
                                                       40.5
                          0
                              5
                                     58.0
## 2 IS
                 100
                          0
                                     56.0
                                          58.3
                                                99.9
                                                       44.5
                             11
```

85.9 81.5 99.9

Kruskal–Wallis test provides evidence of difference among selection schemes.

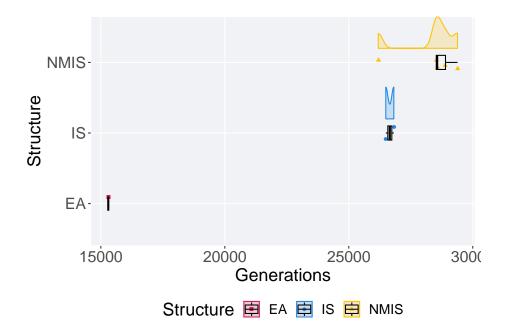
22.0

```
kruskal.test(pop_fit_max ~ Structure, data = performance)
##
   Kruskal-Wallis rank sum test
##
## data: pop_fit_max by Structure
## Kruskal-Wallis chi-squared = 57.688, df = 2, p-value = 2.973e-13
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = performance pop_fit_max, g = performance Structure, p.adjust.method = "h
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: performance$pop_fit_max and performance$Structure
##
##
        EΑ
                IS
## IS
## NMIS 4.3e-11 1.3e-10
## P value adjustment method: bonferroni
```

5.2.2 Generation satisfactory solution found

First generation a satisfactory solution is found throughout the 50,000 generations

```
filter(base_ssf, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'TRUNCATION'& Ger
ggplot(., aes(x = Structure, y = Generations, color = Structure, fill = Structure, shape = Structure, geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.2) +
geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
scale_shape_manual(values=SHAPE)+
scale_y_continuous(
   name="Generations"
) +
scale_x_discrete(
   name="Structure"
) +
scale_colour_manual(values = cb_palette) +
scale_fill_manual(values = cb_palette) +
p_theme + coord_flip()
```



5.2.2.1 Stats

Summary statistics for the first generation a satisfactory solution is found.

```
ssf = filter(base_ssf, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` ==
ssf %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
    na_cnt = sum(is.na(Generations)),
   min = min(Generations, na.rm = TRUE),
   median = median(Generations, na.rm = TRUE),
   mean = mean(Generations, na.rm = TRUE),
   max = max(Generations, na.rm = TRUE),
    IQR = IQR(Generations, na.rm = TRUE)
## # A tibble: 3 x 8
    Structure count na_cnt
                              min median
                                           mean
                                                         IQR
##
     <fct>
               <int>
                     <int> <int>
                                   <dbl>
                                           <dbl> <int> <dbl>
## 1 EA
                   1
                          0 15300
                                   15300 15300
                                                15300
## 2 IS
                   2
                          0 26492
                                   26654 26654
                                                 26816
                                                         162
## 3 NMIS
                   5
                          0 26188
                                   28563 28313. 29384
```

Kruskal–Wallis test provides evidence of no difference among selection schemes.

```
###
## Kruskal-Wallis rank sum test
##
## data: Generations by Structure
## Kruskal-Wallis chi-squared = 3.3833, df = 2, p-value = 0.1842
```

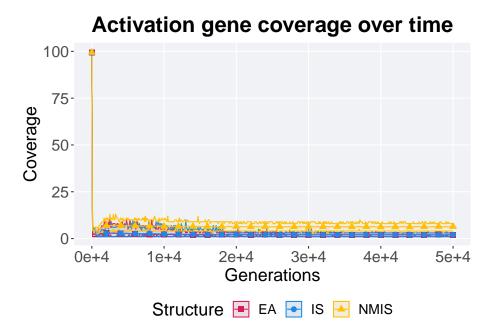
5.2.3 Activation gene coverage

Activation gene coverage analysis.

5.2.3.1 Coverage over time

Activation gene coverage over time.

```
# data for lines and shading on plots
lines = filter(base_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'THE
  group_by(Structure, Generations) %>%
  dplyr::summarise(
   min = min(pop_act_cov),
   mean = mean(pop_act_cov),
   max = max(pop_act_cov)
## `summarise()` has grouped output by 'Structure'. You can override using the
## `.groups` argument.
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = Structure,
  geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 1.5, stroke = 2.0, alpha = 1.
  scale_y_continuous(
   name="Coverage"
  ) +
  scale_x_continuous(
   name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
  ) +
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Activation gene coverage over time')+
  p_theme
```

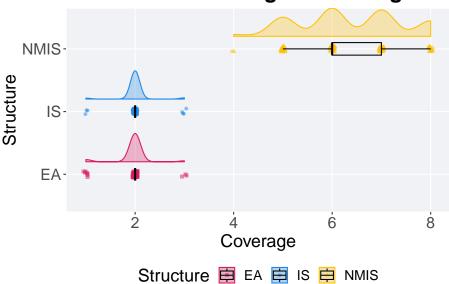


5.2.3.2 End of **50,000** generations

Activation gene coverage in the population at the end of 50,000 generations.

```
### end of run
filter(base_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` ==
  ggplot(., aes(x = Structure, y = pop_act_cov, color = Structure, fill = Structure, si
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = '
  geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_shape_manual(values=SHAPE)+
  scale_y_continuous(
   name="Coverage"
  ) +
  scale_x_discrete(
   name="Structure"
  ) +
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Final activation gene coverage')+
 p_theme + coord_flip()
```





5.2.3.2.1 Stats

Summary statistics for activation gene coverage.

```
coverage = filter(base_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` ==
coverage %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
    na_cnt = sum(is.na(pop_act_cov)),
    min = min(pop_act_cov, na.rm = TRUE),
    median = median(pop_act_cov, na.rm = TRUE),
    mean = mean(pop_act_cov, na.rm = TRUE),
    max = max(pop_act_cov, na.rm = TRUE),
    IQR = IQR(pop_act_cov, na.rm = TRUE)
)
```

```
## # A tibble: 3 x 8
     Structure count na_cnt
                                                        IQR
                              min median mean
                                                  max
               <int> <int> <int>
                                   <dbl> <dbl> <int> <dbl>
## 1 EA
                 100
                          0
                                        2 1.96
                                                          0
                                1
## 2 IS
                 100
                          0
                                        2 2.01
                                                    3
                                                          0
## 3 NMIS
                 100
                          0
                                        6 6.38
                                                          1
```

Kruskal–Wallis test provides evidence of difference among activation gene coverage.

```
kruskal.test(pop_act_cov ~ Structure, data = coverage)
##
##
   Kruskal-Wallis rank sum test
##
## data: pop_act_cov by Structure
## Kruskal-Wallis chi-squared = 258.93, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on
activation gene coverage.
pairwise.wilcox.test(x = coverage$pop_act_cov, g = coverage$Structure, p.adjust.method
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: coverage$pop_act_cov and coverage$Structure
##
##
        EΑ
               IS
## IS
        0.34
## NMIS <2e-16 <2e-16
##
## P value adjustment method: bonferroni
```

5.3 Tournament selection

Here we analyze how the different population structures affect tournament selection (size 8) on the contradictory objectives diagnostic.

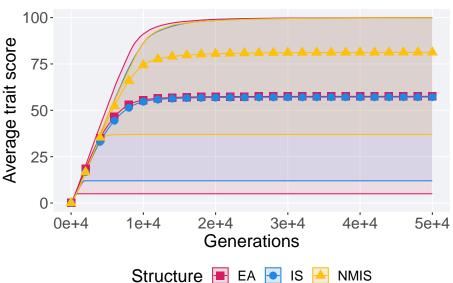
5.3.1 Performance

5.3.1.1 Performance over time

```
lines = filter(base_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nSchogroup_by(Structure, Generations) %>%
dplyr::summarise(
    min = min(pop_fit_max) / DIMENSIONALITY,
    mean = mean(pop_fit_max) / DIMENSIONALITY,
    max = max(pop_fit_max) / DIMENSIONALITY
)
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
    geom_line(size = 0.5) +
    geom_point(data = filter(lines, Generations %% 2000 == 0), size = 2.5, stroke = 2.0, scale_y_continuous(
```

```
name="Average trait score"
) +
scale_x_continuous(
  name="Generations",
  limits=c(0, 50000),
  breaks=c(0, 10000, 20000, 30000, 40000, 50000),
  labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
) +
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette) +
scale_fill_manual(values = cb_palette) +
ggtitle("Performance over time") +
p_theme
```

Performance over time



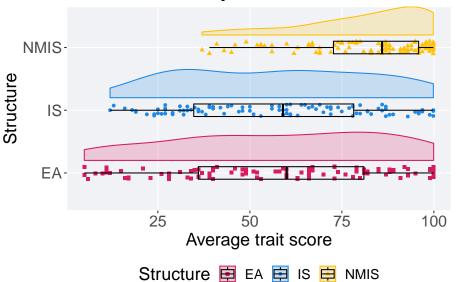
5.3.1.2 Best performance

First generation a satisfactory solution is found throughout the 50,000 generations

```
filter(base_best, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection`\nScheme` == 'TOURNAMENT' & V ggplot(., aes(x = Structure, y = VAL / DIMENSIONALITY, color = Structure, fill = Structure, sha geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.2) + geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) + geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
```

```
scale_y_continuous(
   name="Average trait score"
) +
scale_x_discrete(
   name="Structure"
)+
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette, ) +
scale_fill_manual(values = cb_palette) +
ggtitle('Best performance')+
p_theme + coord_flip()
```

Best performance



5.3.1.2.1 Stats

Summary statistics for the first generation a satisfactory solution is found.

```
performance = filter(base_best, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nSc.
performance %>%
  group_by(Structure) %>%
  dplyr::summarise(
   count = n(),
   na_cnt = sum(is.na(VAL)),
   min = min(VAL, na.rm = TRUE) / DIMENSIONALITY,
  median = median(VAL, na.rm = TRUE) / DIMENSIONALITY,
  mean = mean(VAL, na.rm = TRUE) / DIMENSIONALITY,
```

```
max = max(VAL, na.rm = TRUE) / DIMENSIONALITY,
   IQR = IQR(VAL, na.rm = TRUE) / DIMENSIONALITY
 )
## # A tibble: 3 x 8
   Structure count na_cnt
                              min median mean
                                                        IQR
##
    <fct>
               <int> <int> <dbl> <dbl> <dbl> <dbl> <dbl> <
## 1 EA
                 100
                          0
                             5
                                    60.0 57.5
                                                 99.9
## 2 IS
                 100
                          0 12
                                    59.0 57.1 99.9 43.5
## 3 NMIS
                 100
                          0 37.0
                                    85.9 81.2
                                                99.8 23.1
Kruskal–Wallis test provides evidence of difference among selection schemes.
kruskal.test(VAL ~ Structure, data = performance)
##
## Kruskal-Wallis rank sum test
##
## data: VAL by Structure
## Kruskal-Wallis chi-squared = 52.543, df = 2, p-value = 3.895e-12
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = performance$VAL, g = performance$Structure, p.adjust.method = "bonferror
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
## data: performance$VAL and performance$Structure
##
                IS
##
        ΕA
## IS
## NMIS 5.9e-09 5.3e-11
## P value adjustment method: bonferroni
```

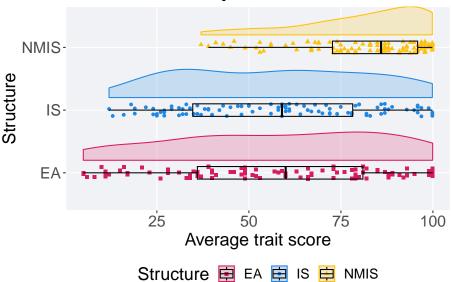
5.3.1.3 Final performance

First generation a satisfactory solution is found throughout the 50,000 generations.

```
filter(base_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'TOURNAMENT ggplot(., aes(x = Structure, y = pop_fit_max / DIMENSIONALITY, color = Structure, fill = Structure geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.2) + geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) + geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) + scale_y_continuous(
    name="Average trait score"
```

```
) +
scale_x_discrete(
   name="Structure"
)+
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette, ) +
scale_fill_manual(values = cb_palette) +
ggtitle('Final performance')+
p_theme + coord_flip()
```

Final performance



5.3.1.3.1 Stats

Summary statistics for the first generation a satisfactory solution is found.

```
performance = filter(base_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection'
performance %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
    na_cnt = sum(is.na(pop_fit_max)),
    min = min(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
    median = median(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
    mean = mean(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
    max = max(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
    IQR = IQR(pop_fit_max / DIMENSIONALITY, na.rm = TRUE)
```

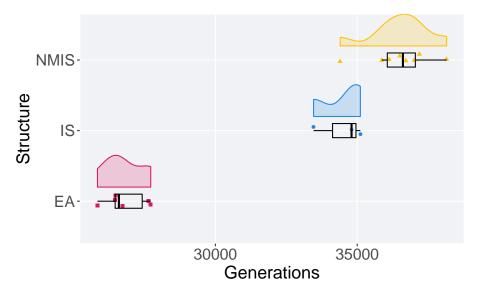
```
## # A tibble: 3 x 8
      Structure count na_cnt
                                     min median mean
                                                                    IQR
                                                            max
              <int> <int> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <</pre>
## 1 EA
                     100
                                0
                                     5
                                             60.0 57.5
                                                           99.9
                                                                   45.0
## 2 IS
                     100
                                0 12
                                            59.0 57.1
                                                           99.9
                                                                  43.5
## 3 NMTS
                     100
                                0 37.0
                                            85.9 81.2 99.8 23.1
Kruskal–Wallis test provides evidence of difference among selection schemes.
kruskal.test(pop_fit_max ~ Structure, data = performance)
##
## Kruskal-Wallis rank sum test
##
## data: pop_fit_max by Structure
## Kruskal-Wallis chi-squared = 52.543, df = 2, p-value = 3.895e-12
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = performance pop_fit_max, g = performance Structure, p.adjust.method = "landary pairwise.wilcox.test(x = performance pop_fit_max, g = performance Structure, p.adjust.method = "landary pairwise.wilcox.test(x = performance pop_fit_max, g = performance pop_fit_max)
                          paired = FALSE, conf.int = FALSE, alternative = 'g')
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
## data: performance$pop_fit_max and performance$Structure
##
##
         F.A
## IS
         1
## NMIS 5.9e-09 5.3e-11
##
## P value adjustment method: bonferroni
```

5.3.2 Generation satisfactory solution found

First generation a satisfactory solution is found throughout the 50,000 generations.

```
filter(base_ssf, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'TOURNAMENT'& Ger
ggplot(., aes(x = Structure, y = Generations, color = Structure, fill = Structure, shape = Stru
    geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.2) +
    geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
    geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
    scale_shape_manual(values=SHAPE)+
    scale_y_continuous(
    name="Generations"
```

```
) +
scale_x_discrete(
  name="Structure"
) +
scale_colour_manual(values = cb_palette) +
scale_fill_manual(values = cb_palette) +
p_theme + coord_flip()
```



Structure 🖹 EA 🛱 IS 🛱 NMIS

5.3.2.1 Stats

Summary statistics for the first generation a satisfactory solution is found.

```
ssf = filter(base_ssf, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` ==
ssf %%
group_by(Structure) %>%
dplyr::summarise(
   count = n(),
   na_cnt = sum(is.na(Generations)),
   min = min(Generations, na.rm = TRUE),
   median = median(Generations, na.rm = TRUE),
   mean = mean(Generations, na.rm = TRUE),
   max = max(Generations, na.rm = TRUE),
   IQR = IQR(Generations, na.rm = TRUE)
)
```

A tibble: 3 x 8

```
Structure count na_cnt
                              min median
                                                         IQR
                                           mean
               <int> <int> <int> <dbl> <dbl> <int> <dbl>
                          0 25843 26598. 26813 27721
## 1 EA
                   6
                                                       954
## 2 IS
                          0 33462 34801 34458. 35112
                   3
                                                       825
## 3 NMIS
                          0 34401 36612. 36496. 38154
Kruskal–Wallis test provides evidence of no difference among selection schemes.
kruskal.test(Generations ~ Structure, data = ssf)
##
## Kruskal-Wallis rank sum test
##
## data: Generations by Structure
## Kruskal-Wallis chi-squared = 12.797, df = 2, p-value = 0.001664
pairwise.wilcox.test(x = ssf$Generations, g = ssf$Structure, p.adjust.method = "bonferroni",
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
## Pairwise comparisons using Wilcoxon rank sum exact test
##
## data: ssf$Generations and ssf$Structure
##
        ΕA
##
              IS
## IS
      0.036 -
## NMIS 0.001 0.073
## P value adjustment method: bonferroni
```

5.3.3 Activation gene coverage

Activation gene coverage analysis.

5.3.3.1 Coverage over time

Activation gene coverage over time.

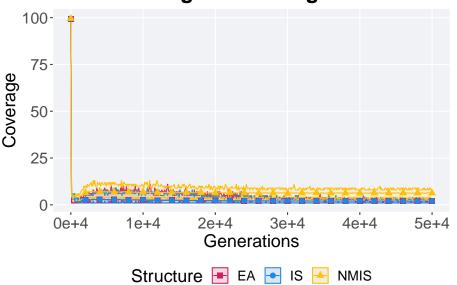
```
# data for lines and shading on plots
lines = filter(base_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'T(
    group_by(Structure, Generations) %>%
    dplyr::summarise(
    min = min(pop_act_cov),
    mean = mean(pop_act_cov),
    max = max(pop_act_cov)
)
```

`summarise()` has grouped output by 'Structure'. You can override using the

```
## `.groups` argument.
```

```
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = 3
  geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom_line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 1.5, stroke = 2.0,
  scale_y_continuous(
   name="Coverage"
  ) +
  scale_x_continuous(
    name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
  ) +
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Activation gene coverage over time')+
 p_theme
```

Activation gene coverage over time

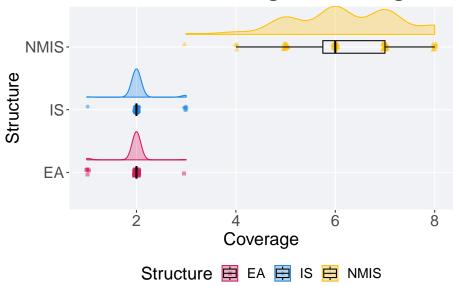


5.3.3.2 End of **50,000** generations

Activation gene coverage in the population at the end of 50,000 generations.

```
### end of run
filter(base_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'TOURNAMENT
  ggplot(., aes(x = Structure, y = pop_act_cov, color = Structure, fill = Structure, shape = Stru
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.3) +
  geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha = 0.5) +
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_shape_manual(values=SHAPE)+
  scale_y_continuous(
   name="Coverage"
  ) +
  scale_x_discrete(
   name="Structure"
  ) +
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Final activation gene coverage')+
  p_theme + coord_flip()
```

Final activation gene coverage



5.3.3.2.1 Stats

Summary statistics for activation gene coverage.

```
coverage = filter(base_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` ==
coverage %>%
  group_by(Structure) %>%
```

```
dplyr::summarise(
   count = n(),
   na_cnt = sum(is.na(pop_act_cov)),
   min = min(pop_act_cov, na.rm = TRUE),
   median = median(pop_act_cov, na.rm = TRUE),
   mean = mean(pop_act_cov, na.rm = TRUE),
   max = max(pop_act_cov, na.rm = TRUE),
   IQR = IQR(pop_act_cov, na.rm = TRUE)
## # A tibble: 3 x 8
##
    Structure count na_cnt
                           min median mean
                                             max
    <fct> <int> <int> <dbl> <dbl> <int> <dbl>
##
## 1 EA
              100
                     0 1
                                   2 1.96
                                            3 0
## 2 IS
              100
                        0
                                    2 2.05
                                               3 0
                             1
                                               8 1.25
## 3 NMIS
               100
                        0
                             3
                                    6 6.22
```

Kruskal–Wallis test provides evidence of difference among activation gene coverage.

```
kruskal.test(pop_act_cov ~ Structure, data = coverage)
```

```
##
## Kruskal-Wallis rank sum test
##
## data: pop_act_cov by Structure
## Kruskal-Wallis chi-squared = 264.53, df = 2, p-value < 2.2e-16</pre>
```

Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on activation gene coverage.

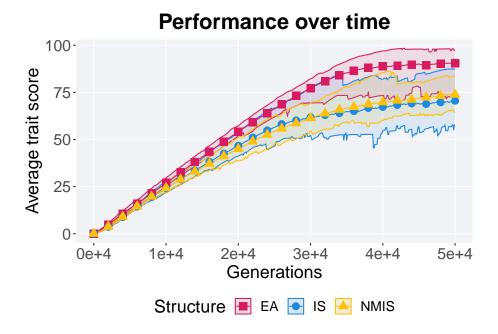
```
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: coverage$pop_act_cov and coverage$Structure
##
## EA IS
## IS 0.019 -
## NMIS <2e-16 <2e-16
##
## P value adjustment method: bonferroni</pre>
```

5.4 Lexicase selection

Here we analyze how the different population structures affect standard lexicase selection on the contradictory objectives diagnostic.

5.4.1 Performance

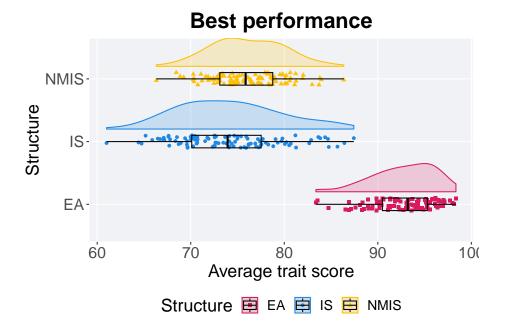
```
lines = filter(base_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'LF
  group_by(Structure, Generations) %>%
  dplyr::summarise(
   min = min(pop_fit_max) / DIMENSIONALITY,
   mean = mean(pop_fit_max) / DIMENSIONALITY,
   max = max(pop_fit_max) / DIMENSIONALITY
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = Structure,
  geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom_line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 2.5, stroke = 2.0, alpha = 1.
  scale_y_continuous(
   name="Average trait score"
  scale_x_continuous(
   name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
  ) +
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle("Performance over time") +
  p_theme
```



5.4.1.2 Best performance

First generation a satisfactory solution is found throughout the 50,000 generations.

```
filter(base_best, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'LEXI
  ggplot(., aes(x = Structure, y = VAL / DIMENSIONALITY, color = Structure, fill = Str
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = '
  geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_y_continuous(
   name="Average trait score"
  ) +
  scale_x_discrete(
   name="Structure"
  )+
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette, ) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Best performance')+
 p_theme + coord_flip()
```



5.4.1.2.1 Stats

Summary statistics for the first generation a satisfactory solution is found.

```
performance = filter(base_best, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'I
performance$Structure = factor(performance$Structure, levels=c('EA','NMIS','IS'))
performance %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
   na_cnt = sum(is.na(VAL)),
   min = min(VAL, na.rm = TRUE) / DIMENSIONALITY,
   median = median(VAL, na.rm = TRUE) / DIMENSIONALITY,
   mean = mean(VAL, na.rm = TRUE) / DIMENSIONALITY,
   max = max(VAL, na.rm = TRUE) / DIMENSIONALITY,
    IQR = IQR(VAL, na.rm = TRUE) / DIMENSIONALITY
## # A tibble: 3 x 8
     Structure count na cnt
                              min median
                                          mean
##
                                   <dbl> <dbl> <dbl> <dbl> <
     <fct>
               <int>
                      <int> <dbl>
## 1 EA
                 100
                             83.4
                                    93.2
                                          92.8
                                                98.4 4.80
## 2 NMIS
                 100
                          0
                             66.3
                                    75.9
                                          76.1
                                                86.4
                                                      5.66
## 3 IS
                 100
                             61.0
                                    73.9 74.1 87.4 7.42
```

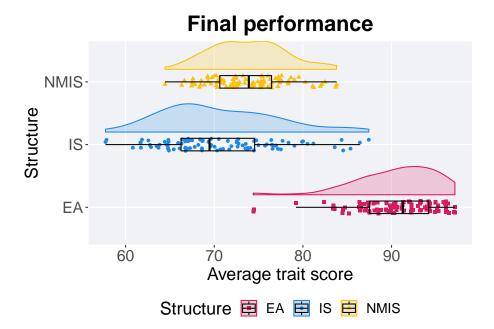
Kruskal–Wallis test provides evidence of difference among selection schemes.

```
kruskal.test(VAL ~ Structure, data = performance)
##
##
   Kruskal-Wallis rank sum test
##
## data: VAL by Structure
## Kruskal-Wallis chi-squared = 202.16, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = performance$VAL, g = performance$Structure, p.adjust.method =
                     paired = FALSE, conf.int = FALSE, alternative = '1')
##
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: performance$VAL and performance$Structure
##
##
        EΑ
               NMIS
## NMIS <2e-16 -
## IS
        <2e-16 0.0032
##
## P value adjustment method: bonferroni
```

5.4.1.3 Final performance

First generation a satisfactory solution is found throughout the 50,000 generations.

```
filter(base_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` ==
  ggplot(., aes(x = Structure, y = pop_fit_max / DIMENSIONALITY, color = Structure, fit
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = '
  geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_y_continuous(
   name="Average trait score"
  ) +
  scale_x_discrete(
   name="Structure"
  )+
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette, ) +
  scale_fill_manual(values = cb_palette) +
 ggtitle('Final performance')+
 p_theme + coord_flip()
```



5.4.1.3.1 Stats

Summary statistics for the first generation a satisfactory solution is found.

```
performance = filter(base_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme`
performance$Structure = factor(performance$Structure, levels=c('EA','NMIS','IS'))
performance %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
   na_cnt = sum(is.na(pop_fit_max)),
   min = min(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
   median = median(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
   mean = mean(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
   max = max(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
    IQR = IQR(pop_fit_max / DIMENSIONALITY, na.rm = TRUE)
## # A tibble: 3 x 8
     Structure count na cnt
                              min median
                                                        IQR
                                          mean
##
                      <int> <dbl>
                                   <dbl> <dbl> <dbl> <dbl> <
     <fct>
               <int>
## 1 EA
                 100
                             74.4
                                          90.6
                                                97.2
## 2 NMIS
                 100
                          0
                             64.4
                                    73.9
                                          73.8
                                                83.8
                                                      5.84
## 3 IS
                 100
                             57.7
                                    69.5 70.6 87.4 8.30
```

Kruskal–Wallis test provides evidence of difference among selection schemes.

```
kruskal.test(pop_fit_max ~ Structure, data = performance)
##
##
   Kruskal-Wallis rank sum test
##
## data: pop_fit_max by Structure
## Kruskal-Wallis chi-squared = 198.85, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = performance$pop_fit_max, g = performance$Structure, p.adjust.
                     paired = FALSE, conf.int = FALSE, alternative = '1')
##
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: performance$pop_fit_max and performance$Structure
##
##
                NMTS
        EΑ
## NMIS < 2e-16 -
## IS
       < 2e-16 1.6e-05
## P value adjustment method: bonferroni
```

5.4.2 Activation gene coverage

Activation gene coverage analysis.

5.4.2.1 Coverage over time

Activation gene coverage over time.

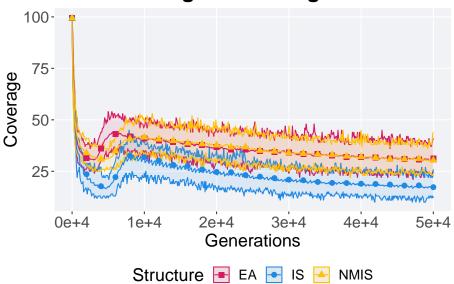
```
# data for lines and shading on plots
lines = filter(base_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nSchool
group_by(Structure, Generations) %>%
dplyr::summarise(
   min = min(pop_act_cov),
   mean = mean(pop_act_cov),
   max = max(pop_act_cov)
)
```

```
## `summarise()` has grouped output by 'Structure'. You can override using the
## `.groups` argument.

ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
    geom_line(size = 0.5) +
    geom_point(data = filter(lines, Generations %% 2000 == 0), size = 1.5, stroke = 2.0,
```

```
scale_y_continuous(
  name="Coverage"
) +
scale_x_continuous(
  name="Generations",
  limits=c(0, 50000),
  breaks=c(0, 10000, 20000, 30000, 40000, 50000),
  labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
) +
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette) +
scale_fill_manual(values = cb_palette) +
ggtitle('Activation gene coverage over time')+
p_theme
```

Activation gene coverage over time



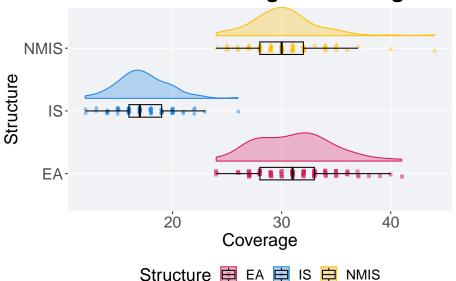
5.4.2.2 End of **50,000** generations

Activation gene coverage in the population at the end of 50,000 generations.

```
### end of run
filter(base_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'LEXICASE'
    ggplot(., aes(x = Structure, y = pop_act_cov, color = Structure, fill = Structure, shape = Structure, geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.3) +
    geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha = 0.5) +
```

```
geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
scale_shape_manual(values=SHAPE)+
scale_y_continuous(
   name="Coverage"
) +
scale_x_discrete(
   name="Structure"
) +
scale_colour_manual(values = cb_palette) +
scale_fill_manual(values = cb_palette) +
ggtitle('Final activation gene coverage')+
p_theme + coord_flip()
```

Final activation gene coverage



5.4.2.2.1 Stats

Summary statistics for activation gene coverage.

```
coverage = filter(base_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\ni
coverage$Structure = factor(coverage$Structure, levels=c('EA','NMIS','IS'))
coverage %>%
  group_by(Structure) %>%
  dplyr::summarise(
   count = n(),
   na_cnt = sum(is.na(pop_act_cov)),
   min = min(pop_act_cov, na.rm = TRUE),
```

##

P value adjustment method: bonferroni

```
median = median(pop_act_cov, na.rm = TRUE),
    mean = mean(pop_act_cov, na.rm = TRUE),
    max = max(pop_act_cov, na.rm = TRUE),
    IQR = IQR(pop_act_cov, na.rm = TRUE)
## # A tibble: 3 x 8
     Structure count na_cnt
                              min median mean
                                                  max
                                                        IQR
     <fct>
               <int> <int> <int> <dbl> <dbl> <int> <dbl>
## 1 EA
                 100
                          0
                                24
                                       31 31.2
                                                   41
## 2 NMIS
                 100
                          0
                                24
                                       30 30.3
                                                   44
                                                          4
                                                          3
## 3 IS
                 100
                          0
                                12
                                       17 17.3
                                                   26
Kruskal-Wallis test provides evidence of difference among activation gene cover-
kruskal.test(pop_act_cov ~ Structure, data = coverage)
##
## Kruskal-Wallis rank sum test
## data: pop_act_cov by Structure
## Kruskal-Wallis chi-squared = 201.31, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on
activation gene coverage.
pairwise.wilcox.test(x = coverage$pop_act_cov, g = coverage$Structure, p.adjust.method = "bonfer")
                     paired = FALSE, conf.int = FALSE, alternative = '1')
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
## data: coverage$pop_act_cov and coverage$Structure
##
##
        ΕA
               NMIS
## NMIS 0.077 -
## IS <2e-16 <2e-16
```

Chapter 6

MI50: Exploitation rate results

Here we present the results for **best performances** found by each selection scheme replicate on the exploitation rate diagnostic with configurations presented below. For our the configuration of these experiments, we execute migrations every 50 generations and there are 4 islands in a ring topology. When migrations occur, we swap two individuals (same position on each island) and guarantee that no solution can return to the same island. Best performance found refers to the largest average trait score found in a given population. Note that performance values fall between 0.0 and 100.0.

6.1 Analysis dependencies

```
library(ggplot2)
library(cowplot)
library(dplyr)
library(PupillometryR)
```

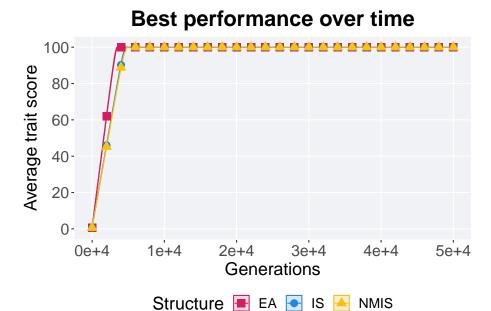
6.2 Truncation selection

Here we analyze how the different population structures affect truncation selection (size 8) on the exploitation rate diagnostic.

6.2.1 Performance over time

```
lines = filter(mi50_over_time, Diagnostic == 'EXPLOITATION_RATE' & `Selection\nScheme` == 'TRUNCA
group_by(Structure, Generations) %>%
```

```
dplyr::summarise(
   min = min(pop_fit_max) / DIMENSIONALITY,
   mean = mean(pop_fit_max) / DIMENSIONALITY,
   max = max(pop_fit_max) / DIMENSIONALITY
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = 3
 geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom_line(size = 0.5) +
 geom_point(data = filter(lines, Generations %% 2000 == 0), size = 2.5, stroke = 2.0,
 scale_y_continuous(
   name="Average trait score",
   limits=c(-1, 101),
   breaks=seq(0,100, 20),
   labels=c("0", "20", "40", "60", "80", "100")
  ) +
 scale_x_continuous(
   name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
 ) +
 scale_shape_manual(values=SHAPE)+
 scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
 ggtitle("Best performance over time") +
 p_theme
```

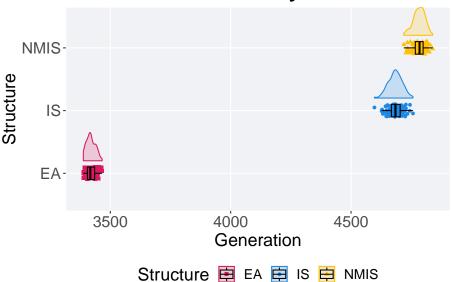


6.2.2 Generation satisfactory solution found

First generation a satisfactory solution is found throughout the 50,000 generations.

```
filter(mi50_ssf, Diagnostic == 'EXPLOITATION_RATE' & `Selection\nScheme` == 'TRUNCATION') %>%
    ggplot(., aes(x = Structure, y = Generations , color = Structure, fill = Structure, shape = Str
    geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.2) +
    geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
    geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
    scale_y_continuous(
        name="Generation"
) +
    scale_x_discrete(
        name="Structure"
)+
    scale_shape_manual(values=SHAPE)+
    scale_colour_manual(values = cb_palette, ) +
    scale_fill_manual(values = cb_palette) +
    ggtitle('Generation satisfactory solution found')+
    p_theme + coord_flip()
```

Generation satisfactory solution found



6.2.3 Stats

3 NMIS

100

Summary statistics for the first generation a satisfactory solution is found.

```
ssf = filter(mi50_ssf, Diagnostic == 'EXPLOITATION_RATE' & `Selection\nScheme` == 'TRU
ssf %>%
  group_by(Structure) %>%
 dplyr::summarise(
    count = n(),
    na_cnt = sum(is.na(Generations)),
   min = min(Generations, na.rm = TRUE),
   median = median(Generations, na.rm = TRUE),
   mean = mean(Generations, na.rm = TRUE),
   max = max(Generations, na.rm = TRUE),
    IQR = IQR(Generations, na.rm = TRUE)
## # A tibble: 3 x 8
    Structure count na_cnt
                              min median mean
##
     <fct>
               <int> <int> <int>
                                   <dbl> <dbl> <int> <dbl>
## 1 EA
                 100
                          0 3388
                                   3417
                                         3420.
                                                3466
                                                      30
## 2 IS
                 100
                             4597
                                   4684. 4684.
                                                4757
                                                      36.5
```

Kruskal–Wallis test provides evidence of difference among selection schemes.

0 4719 4784. 4783.

4839

```
kruskal.test(Generations ~ Structure, data = ssf)
##
##
   Kruskal-Wallis rank sum test
##
## data: Generations by Structure
## Kruskal-Wallis chi-squared = 264.73, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = ssf$Generations, g = ssf$Structure, p.adjust.method = "bonferroni",
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: ssf$Generations and ssf$Structure
##
##
        EΑ
               TS
## IS
       <2e-16 -
## NMIS <2e-16 <2e-16
## P value adjustment method: bonferroni
```

6.3 Tournament selection

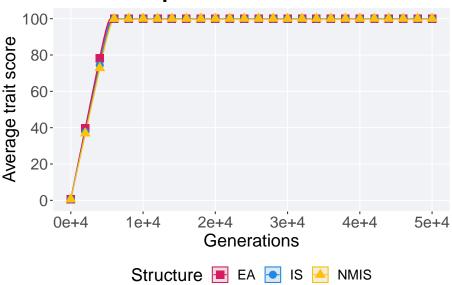
Here we analyze how the different population structures affect tournament selection (size 8) on the exploitation rate diagnostic.

6.3.1 Performance over time

```
lines = filter(mi50_over_time, Diagnostic == 'EXPLOITATION_RATE' &
group_by(Structure, Generations) %>%
dplyr::summarise(
   min = min(pop_fit_max) / DIMENSIONALITY,
   mean = mean(pop_fit_max) / DIMENSIONALITY,
   max = max(pop_fit_max) / DIMENSIONALITY
)
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = Structure,
   geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
   geom_line(size = 0.5) +
   geom_point(data = filter(lines, Generations %% 2000 == 0), size = 2.5, stroke = 2.0, alpha = 1.
   scale_y_continuous(
   name="Average trait score",
   limits=c(-1, 101),
   breaks=seq(0,100, 20),
```

```
labels=c("0", "20", "40", "60", "80", "100")
) +
scale_x_continuous(
  name="Generations",
  limits=c(0, 50000),
  breaks=c(0, 10000, 20000, 30000, 40000, 50000),
  labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
) +
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette) +
scale_fill_manual(values = cb_palette) +
ggtitle("Best performance over time") +
p_theme
```

Best performance over time



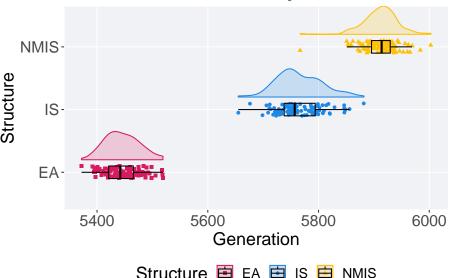
6.3.2 Generation satisfactory solution found

First generation a satisfactory solution is found throughout the $50,\!000$ generations.

```
filter(mi50_ssf, Diagnostic == 'EXPLOITATION_RATE' & `Selection\nScheme` == 'TOURNAMEN' ggplot(., aes(x = Structure, y = Generations , color = Structure, fill = Structure, geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) + geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
```

```
scale_y_continuous(
 name="Generation"
scale_x_discrete(
 name="Structure"
)+
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette, ) +
scale_fill_manual(values = cb_palette) +
ggtitle('Generation satisfactory solution found')+
p_theme + coord_flip()
```

Generation satisfactory solution found



Structure 🖹 EA 🛱 IS 🛱 NMIS

6.3.3 Stats

Summary statistics for the first generation a satisfactory solution is found.

mean = mean(Generations, na.rm = TRUE),

```
ssf = filter(mi50_ssf, Diagnostic == 'EXPLOITATION_RATE' & `Selection\nScheme` == 'TOURNAMENT' &
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
   na_cnt = sum(is.na(Generations)),
   min = min(Generations, na.rm = TRUE),
   median = median(Generations, na.rm = TRUE),
```

##

```
max = max(Generations, na.rm = TRUE),
    IQR = IQR(Generations, na.rm = TRUE)
## # A tibble: 3 x 8
    Structure count na_cnt
                              min median mean
##
              <int> <int> <int> <dbl> <dbl> <int> <dbl>
     <fct>
## 1 EA
                 100
                          0 5372
                                    5442 5446.
                                                 5519 44.5
## 2 IS
                 100
                          0 5655
                                     5757 5765. 5882 56
## 3 NMIS
                 100
                          0 5767
                                     5914 5912. 6003 33.8
Kruskal-Wallis test provides evidence of difference among selection schemes.
kruskal.test(Generations ~ Structure, data = ssf)
##
##
   Kruskal-Wallis rank sum test
##
## data: Generations by Structure
## Kruskal-Wallis chi-squared = 264.22, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = ssf$Generations, g = ssf$Structure, p.adjust.method = "bonfer.")
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: ssf$Generations and ssf$Structure
##
##
        EΑ
               IS
        <2e-16 -
## IS
## NMIS <2e-16 <2e-16
```

6.4 Lexicase selection

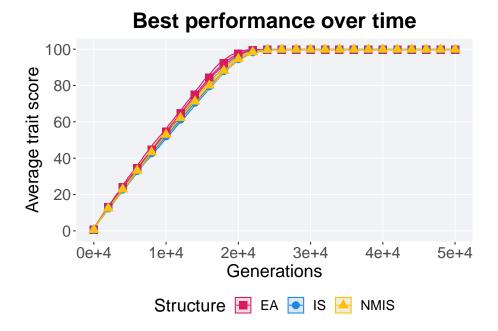
P value adjustment method: bonferroni

Here we analyze how the different population structures affect standard lexicase selection on the exploitation rate diagnostic.

6.4.1 Performance over time

```
lines = filter(mi50_over_time, Diagnostic == 'EXPLOITATION_RATE' & `Selection\nScheme`
group_by(Structure, Generations) %>%
dplyr::summarise(
```

```
min = min(pop_fit_max) / DIMENSIONALITY,
   mean = mean(pop_fit_max) / DIMENSIONALITY,
   max = max(pop_fit_max) / DIMENSIONALITY
 )
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = Structure,
  geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom_line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 2.5, stroke = 2.0, alpha = 1.
  scale_y_continuous(
   name="Average trait score",
   limits=c(-1, 101),
   breaks = seq(0, 100, 20),
   labels=c("0", "20", "40", "60", "80", "100")
  ) +
  scale_x_continuous(
   name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
  ) +
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle("Best performance over time") +
  p_theme
```

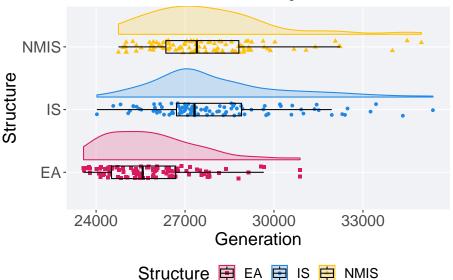


6.4.2 Generation satisfactory solution found

First generation a satisfactory solution is found throughout the 50,000 generations.

```
filter(mi50_ssf, Diagnostic == 'EXPLOITATION_RATE' & `Selection\nScheme` == 'LEXICASE'
    ggplot(., aes(x = Structure, y = Generations , color = Structure, fill = Structure, geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
    geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
    scale_y_continuous(
        name="Generation"
) +
    scale_x_discrete(
        name="Structure"
)+
    scale_shape_manual(values=SHAPE)+
    scale_colour_manual(values = cb_palette, ) +
    scale_fill_manual(values = cb_palette) +
    ggtitle('Generation satisfactory solution found')+
    p_theme + coord_flip()
```

Generation satisfactory solution found



6.4.3Stats

2 IS

3 NMIS

Summary statistics for the first generation a satisfactory solution is found.

```
ssf = filter(mi50_ssf, Diagnostic == 'EXPLOITATION_RATE' & `Selection\nScheme` == 'LEXICASE' & Ge
ssf %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
   na_cnt = sum(is.na(Generations)),
   min = min(Generations, na.rm = TRUE),
   median = median(Generations, na.rm = TRUE),
   mean = mean(Generations, na.rm = TRUE),
   max = max(Generations, na.rm = TRUE),
    IQR = IQR(Generations, na.rm = TRUE)
## # A tibble: 3 x 8
     Structure count na_cnt
                              min median
                                           mean
     <fct>
                      <int> <int>
                                   <dbl>
                                           <dbl> <int> <dbl>
               <int>
## 1 EA
                 100
                          0 23577 25572
                                         25861. 30878 2163.
```

28031. 35360 2194.

0 24755 27398. 27747. 34971 2462.

Kruskal–Wallis test provides evidence of difference among selection schemes.

0 24027 27320

100

100

```
kruskal.test(Generations ~ Structure, data = ssf)
##
##
   Kruskal-Wallis rank sum test
##
## data: Generations by Structure
## Kruskal-Wallis chi-squared = 69.626, df = 2, p-value = 7.601e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = ssf$Generations, g = ssf$Structure, p.adjust.method = "bonfer")
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: ssf$Generations and ssf$Structure
##
##
        EΑ
                IS
       1.2e-13 -
## IS
## NMIS 7.0e-12 1
## P value adjustment method: bonferroni
```

Chapter 7

MI50: Ordered exploitation results

Here we present the results for **best performances** found by each selection scheme replicate on the ordered exploitation diagnostic with configurations presented below. Best performance found refers to the largest average trait score found in a given population. Note that performance values fall between 0.0 and 100.0. For our the configuration of these experiments, we execute migrations every 50 generations and there are 4 islands in a ring topology. When migrations occur, we swap two individuals (same position on each island) and guarantee that no solution can return to the same island.

7.1 Analysis dependencies

```
library(ggplot2)
library(cowplot)
library(dplyr)
library(PupillometryR)
```

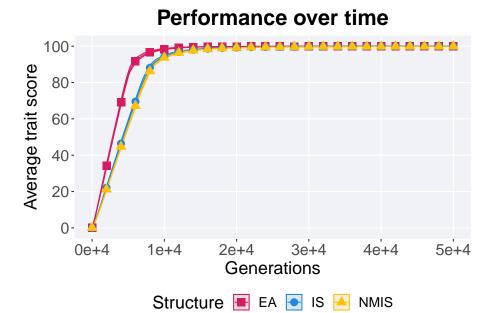
7.2 Truncation selection

Here we analyze how the different population structures affect truncation selection (size 8) on the ordered exploitation diagnostic.

7.2.1 Performance over time

```
lines = filter(mi50_over_time, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` == 'TRU
group_by(Structure, Generations) %>%
```

```
dplyr::summarise(
   min = min(pop_fit_max) / DIMENSIONALITY,
   mean = mean(pop_fit_max) / DIMENSIONALITY,
   max = max(pop_fit_max) / DIMENSIONALITY
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = 3
 geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom_line(size = 0.5) +
 geom_point(data = filter(lines, Generations %% 2000 == 0), size = 2.5, stroke = 2.0,
 scale_y_continuous(
   name="Average trait score",
   limits=c(-1, 101),
   breaks=seq(0,100, 20),
   labels=c("0", "20", "40", "60", "80", "100")
  ) +
 scale_x_continuous(
   name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
 ) +
 scale_shape_manual(values=SHAPE)+
 scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
 ggtitle("Performance over time") +
 p_theme
```

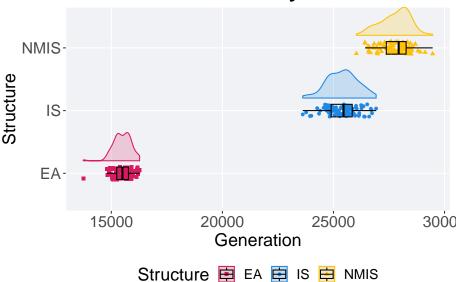


7.2.2 Generation satisfactory solution found

First generation a satisfactory solution is found throughout the 50,000 generations.

```
filter(mi50_ssf, Diagnostic == 'ORDERED_EXPLOITATION' & 'Selection\nScheme' == 'TRUNCATION') %>%
    ggplot(., aes(x = Structure, y = Generations , color = Structure, fill = Structure, shape = Str
    geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.2) +
    geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
    geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
    scale_y_continuous(
        name="Generation"
) +
    scale_x_discrete(
        name="Structure"
)+
    scale_shape_manual(values=SHAPE)+
    scale_colour_manual(values = cb_palette, ) +
    scale_fill_manual(values = cb_palette) +
    ggtitle('Generation satisfactory solution found')+
    p_theme + coord_flip()
```

Generation satisfactory solution found



7.2.2.1 Stats

Summary statistics for the first generation a satisfactory solution is found.

```
ssf = filter(mi50_ssf, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` == '
ssf %>%
  group_by(Structure) %>%
 dplyr::summarise(
    count = n(),
    na_cnt = sum(is.na(Generations)),
   min = min(Generations, na.rm = TRUE),
   median = median(Generations, na.rm = TRUE),
   mean = mean(Generations, na.rm = TRUE),
   max = max(Generations, na.rm = TRUE),
    IQR = IQR(Generations, na.rm = TRUE)
## # A tibble: 3 x 8
    Structure count na_cnt
                              min median
                                           mean
                                                         IQR
##
     <fct>
                      <int> <int>
                                   <dbl>
                                          <dbl> <int> <dbl>
               <int>
## 1 EA
                 100
                          0 13737 15500. 15493. 16273
## 2 IS
                 100
                          0 23617 25453
                                         25405. 26920
                                                       950
## 3 NMIS
                 100
                          0 26032 27935
                                        27781. 29465
```

Kruskal–Wallis test provides evidence of difference among selection schemes.

```
kruskal.test(Generations ~ Structure, data = ssf)
##
##
   Kruskal-Wallis rank sum test
##
## data: Generations by Structure
## Kruskal-Wallis chi-squared = 264.17, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = ssf$Generations, g = ssf$Structure, p.adjust.method = "bonferroni",
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: ssf$Generations and ssf$Structure
##
##
        EΑ
               TS
## IS
       <2e-16 -
## NMIS <2e-16 <2e-16
## P value adjustment method: bonferroni
```

7.3 Tournament selection

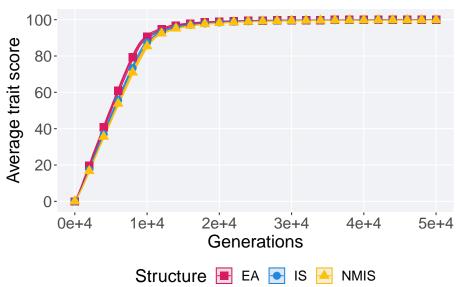
Here we analyze how the different population structures affect tournament selection (size 8) on the ordered exploitation diagnostic.

7.3.1 Performance over time

```
lines = filter(mi50_over_time, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` == 'TOO
group_by(Structure, Generations) %>%
dplyr::summarise(
   min = min(pop_fit_max) / DIMENSIONALITY,
   mean = mean(pop_fit_max) / DIMENSIONALITY,
   max = max(pop_fit_max) / DIMENSIONALITY
)
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = Structure,
   geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
   geom_line(size = 0.5) +
   geom_point(data = filter(lines, Generations %% 2000 == 0), size = 2.5, stroke = 2.0, alpha = 1.
   scale_y_continuous(
   name="Average trait score",
   limits=c(-1, 101),
   breaks=seq(0,100, 20),
```

```
labels=c("0", "20", "40", "60", "80", "100")
) +
scale_x_continuous(
  name="Generations",
  limits=c(0, 50000),
  breaks=c(0, 10000, 20000, 30000, 40000, 50000),
  labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
) +
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette) +
scale_fill_manual(values = cb_palette) +
ggtitle("Performance over time") +
p_theme
```

Performance over time



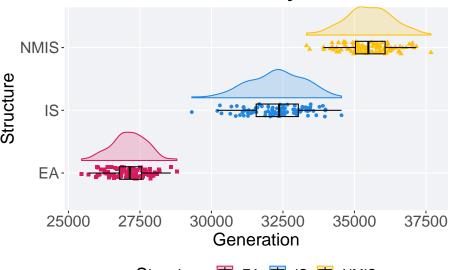
7.3.2 Generation satisfactory solution found

First generation a satisfactory solution is found throughout the 50,000 generations.

```
filter(mi50_ssf, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` == 'TOURNAL ggplot(., aes(x = Structure, y = Generations, color = Structure, fill = Structure, geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) + geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
```

```
scale_y_continuous(
   name="Generation"
) +
scale_x_discrete(
   name="Structure"
)+
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette, ) +
scale_fill_manual(values = cb_palette) +
ggtitle('Generation satisfactory solution found')+
p_theme + coord_flip()
```

Generation satisfactory solution found



Structure 🖹 EA 🛱 IS 🛱 NMIS

7.3.2.1 Stats

Summary statistics for the first generation a satisfactory solution is found.

mean = mean(Generations, na.rm = TRUE),

```
ssf = filter(mi50_ssf, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` == 'TOURNAMENT'
ssf %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
    na_cnt = sum(is.na(Generations)),
    min = min(Generations, na.rm = TRUE),
    median = median(Generations, na.rm = TRUE),
```

```
max = max(Generations, na.rm = TRUE),
    IQR = IQR(Generations, na.rm = TRUE)
## # A tibble: 3 x 8
    Structure count na_cnt
                              min median
                                            mean
                                                   max
##
               <int> <int> <int> <dbl> <dbl> <int> <dbl>
                          0 25458 27144. 27124. 28791 769.
## 1 EA
                 100
## 2 IS
                 100
                          0 29313 32368. 32281. 34547 1474
## 3 NMIS
                 100
                          0 33324 35488. 35510. 37674 1035.
Kruskal-Wallis test provides evidence of difference among selection schemes.
kruskal.test(Generations ~ Structure, data = ssf)
##
##
   Kruskal-Wallis rank sum test
##
## data: Generations by Structure
## Kruskal-Wallis chi-squared = 264.58, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = ssf$Generations, g = ssf$Structure, p.adjust.method = "bonfer.")
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: ssf$Generations and ssf$Structure
##
##
        EΑ
               TS
        <2e-16 -
## IS
## NMIS <2e-16 <2e-16
##
```

7.4 Lexicase selection

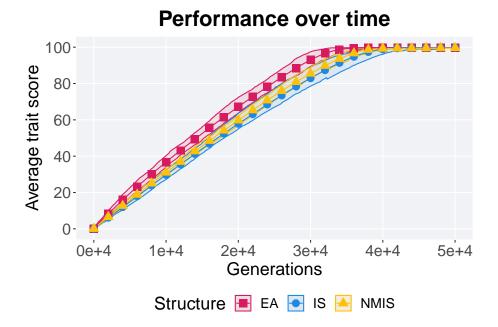
P value adjustment method: bonferroni

Here we analyze how the different population structures affect standard lexicase selection on the ordered exploitation diagnostic.

7.4.1 Performance over time

```
lines = filter(mi50_over_time, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nSchen
group_by(Structure, Generations) %>%
dplyr::summarise(
```

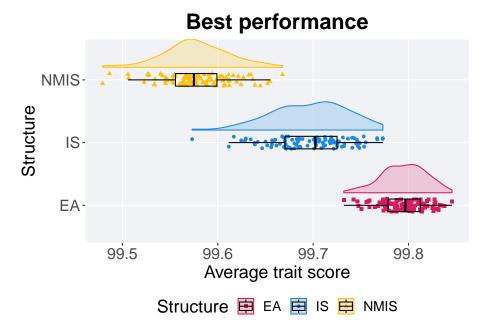
```
min = min(pop_fit_max) / DIMENSIONALITY,
   mean = mean(pop_fit_max) / DIMENSIONALITY,
   max = max(pop_fit_max) / DIMENSIONALITY
 )
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = Structure,
  geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom_line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 2.5, stroke = 2.0, alpha = 1.
  scale_y_continuous(
   name="Average trait score",
   limits=c(-1, 101),
   breaks = seq(0,100, 20),
   labels=c("0", "20", "40", "60", "80", "100")
  ) +
  scale_x_continuous(
   name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
  ) +
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle("Performance over time") +
  p_theme
```



7.4.2 Best performance

First generation a satisfactory solution is found throughout the 50,000 generations.

```
filter(mi50_best, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` == 'LEXIC.
  ggplot(., aes(x = Structure, y = VAL / DIMENSIONALITY, color = Structure, fill = Str
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = '
  geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_y_continuous(
   name="Average trait score"
  ) +
  scale_x_discrete(
   name="Structure"
  )+
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette, ) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Best performance')+
 p_theme + coord_flip()
```



7.4.2.1 Stats

3 NMIS

Summary statistics for the first generation a satisfactory solution is found.

```
performance = filter(mi50_best, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` == 'LF
performance %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
   na_cnt = sum(is.na(VAL)),
   min = min(VAL, na.rm = TRUE) / DIMENSIONALITY,
   median = median(VAL, na.rm = TRUE) / DIMENSIONALITY,
   mean = mean(VAL, na.rm = TRUE) / DIMENSIONALITY,
   max = max(VAL, na.rm = TRUE) / DIMENSIONALITY,
    IQR = IQR(VAL, na.rm = TRUE) / DIMENSIONALITY
## # A tibble: 3 x 8
     Structure count na_cnt
                              min median
                                          mean
                                                         IQR
##
     <fct>
                      <int> <dbl>
                                   <dbl> <dbl> <dbl>
                                                       <dbl>
               <int>
## 1 EA
                 100
                             99.7
                                     99.8
                                           99.8
                                                 99.8 0.0338
## 2 IS
                 100
                             99.6
                                     99.7
                                           99.7
                                                 99.8 0.0545
```

Kruskal–Wallis test provides evidence of difference among selection schemes.

99.5

99.6

99.6

99.7 0.0435

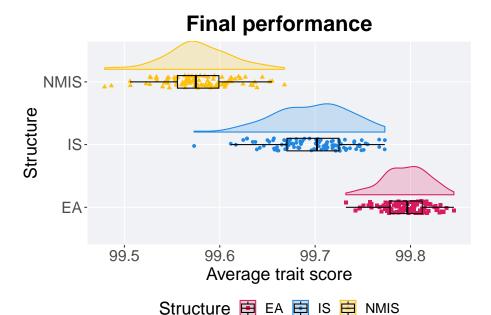
100

```
kruskal.test(VAL ~ Structure, data = performance)
##
##
   Kruskal-Wallis rank sum test
##
## data: VAL by Structure
## Kruskal-Wallis chi-squared = 259.68, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = performance$VAL, g = performance$Structure, p.adjust.method =
                     paired = FALSE, conf.int = FALSE, alternative = '1')
##
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: performance$VAL and performance$Structure
##
##
        EΑ
               TS
## IS
        <2e-16 -
## NMIS <2e-16 <2e-16
##
## P value adjustment method: bonferroni
```

7.4.3 Final performance

First generation a satisfactory solution is found throughout the 50,000 generations.

```
filter(mi50_over_time, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` == '
  ggplot(., aes(x = Structure, y = pop_fit_max / DIMENSIONALITY, color = Structure, fi
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = '
  geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_y_continuous(
   name="Average trait score"
  ) +
  scale_x_discrete(
   name="Structure"
  )+
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette, ) +
  scale_fill_manual(values = cb_palette) +
 ggtitle('Final performance')+
 p_theme + coord_flip()
```



7.4.3.1 Stats

Summary statistics for the first generation a satisfactory solution is found.

```
performance = filter(mi50_over_time, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` =
performance %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
   na_cnt = sum(is.na(pop_fit_max)),
   min = min(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
   median = median(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
   mean = mean(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
   max = max(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
    IQR = IQR(pop_fit_max / DIMENSIONALITY, na.rm = TRUE)
## # A tibble: 3 x 8
     Structure count na_cnt
                              min median
                                          mean
                                                         IQR
     <fct>
                      <int> <dbl>
                                   <dbl> <dbl> <dbl>
                                                       <dbl>
               <int>
## 1 EA
                 100
                             99.7
                                     99.8
                                           99.8
                                                 99.8 0.0338
## 2 IS
                 100
                             99.6
                                     99.7
                                           99.7
                                                 99.8 0.0545
## 3 NMIS
                 100
                             99.5
                                     99.6
                                          99.6
                                                 99.7 0.0435
```

Kruskal–Wallis test provides evidence of difference among selection schemes.

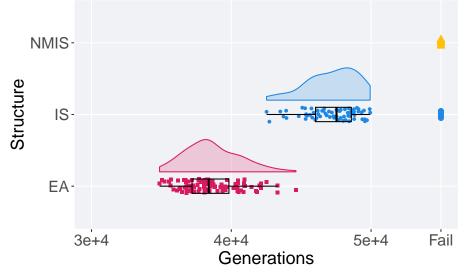
```
kruskal.test(pop_fit_max ~ Structure, data = performance)
##
##
   Kruskal-Wallis rank sum test
##
## data: pop_fit_max by Structure
## Kruskal-Wallis chi-squared = 259.68, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = performance$pop_fit_max, g = performance$Structure, p.adjust.
                     paired = FALSE, conf.int = FALSE, alternative = '1')
##
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: performance$pop_fit_max and performance$Structure
##
##
        EΑ
               TS
        <2e-16 -
## IS
## NMIS <2e-16 <2e-16
## P value adjustment method: bonferroni
```

7.4.4 Generation satisfactory solution found

First generation a satisfactory solution is found throughout the 50,000 generations.

```
lex_fail = filter(mi50_ssf, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme`
lex_fail$Generations = 55000
lex_fail$Structure <- factor(lex_fail$Structure, levels = MODEL)</pre>
filter(mi50_ssf, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` == 'LEXICA
      ggplot(., aes(x = Structure, y = Generations, color = Structure, fill = Structure, sill = Structu
             geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha =
       geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
      geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
      geom_point(data = lex_fail, aes(x = Structure, y = Generations, color = Structure, f
       scale_shape_manual(values=SHAPE)+
      scale_y_continuous(
            name="Generations",
            limits=c(30000, 55000),
            breaks=c(30000, 40000, 50000, 55000),
            labels=c("3e+4", "4e+4", "5e+4", "Fail")
      ) +
       scale_x_discrete(
```

```
name="Structure"
) +
scale_colour_manual(values = cb_palette) +
scale_fill_manual(values = cb_palette) +
p_theme + coord_flip()
```



Structure 🖹 EA 📮 IS 📴 NMIS

7.4.4.1 Stats

Summary statistics for the first generation a satisfactory solution is found.

<fct> <int> <int> <dbl> <dbl> <int> <dbl>

```
ssf = filter(mi50_ssf, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` == 'LEXICASE' &
ssf %>%
group_by(Structure) %>%
dplyr::summarise(
   count = n(),
   na_cnt = sum(is.na(Generations)),
   min = min(Generations, na.rm = TRUE),
   median = median(Generations, na.rm = TRUE),
   mean = mean(Generations, na.rm = TRUE),
   max = max(Generations, na.rm = TRUE)

## # A tibble: 2 x 8
## Structure count na_cnt min median mean max IQR
```

```
## 1 EA
                  100
                           0 34868 38382. 38649. 44624 2638.
## 2 IS
                  70
                           0 42523 47526. 47195. 49938 2560.
Kruskal-Wallis test provides evidence of difference among selection schemes.
kruskal.test(Generations ~ Structure, data = ssf)
##
##
   Kruskal-Wallis rank sum test
##
## data: Generations by Structure
## Kruskal-Wallis chi-squared = 122.11, df = 1, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = ssf$Generations, g = ssf$Structure, p.adjust.method = "bonfer.")
                      paired = FALSE, conf.int = FALSE, alternative = 'g')
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
##
## data: ssf$Generations and ssf$Structure
##
##
## IS <2e-16
##
```

P value adjustment method: bonferroni

Chapter 8

MI50: Contradictory objectives results

Here we present the results for the satisfactory trait corverage and activation gene coverage generated by each selection scheme replicate on the contradictory objectives diagnostic the configurations presented below. Note both of these values are gathered at the population-level. Activation gene coverage refers to the count of unique activation genes in a given population; this gives us a range of integers between 0 and 100. Satisfactory trait coverage refers to the count of unique satisfied traits in a given population; this gives us a range of integers between 0 and 100. For our the configuration of these experiments, we execute migrations every 50 generations and there are 4 islands in a ring topology. When migrations occur, two individuals are swapped (same position on each island) and guarantee that no solution can return to its original island.

8.1 Analysis dependencies

```
library(ggplot2)
library(cowplot)
library(dplyr)
library(PupillometryR)
```

8.2 Truncation selection

Here we analyze how the different population structures affect truncation selection (size 8) on the contradictory objectives diagnostic.

8.2.1 Satisfactory trait coverage

Satisfactory trait coverage analysis.

8.2.1.1 Coverage over time

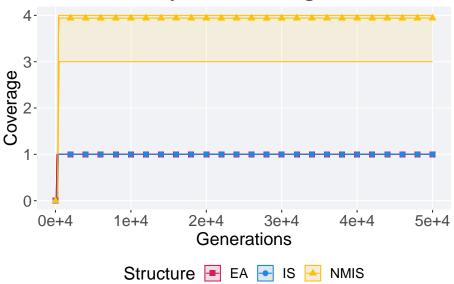
Satisfactory trait coverage over time.

```
lines = filter(mi50_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\ni
group_by(Structure, Generations) %>%
dplyr::summarise(
   min = min(pop_sat_cov),
   mean = mean(pop_sat_cov),
   max = max(pop_sat_cov)
)
```

`summarise()` has grouped output by 'Structure'. You can override using the
`.groups` argument.

```
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = x
 geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom_line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 1.5, stroke = 2.0,
  scale_y_continuous(
   name="Coverage"
 ) +
  scale_x_continuous(
    name="Generations",
   limits=c(0, 50000),
    breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
 ) +
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette) +
 scale_fill_manual(values = cb_palette) +
 ggtitle('Satisfactory trait coverage over time')+
 p_theme
```



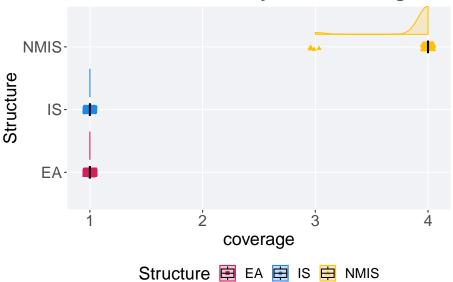


8.2.1.2 Best coverage throughout

Best satisfactory trait coverage throughout 50,000 generations.

```
### best satisfactory trait coverage throughout
filter(mi50_best, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` == 'TRUNCATION'
  ggplot(., aes(x = Structure, y = VAL, color = Structure, fill = Structure, shape = Structure))
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.2) +
  geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha = 1.0) +
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_y_continuous(
   name="coverage"
  scale_x_discrete(
   name="Structure"
  )+
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette, ) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Best satisfactory trait coverage')+
  p_theme + coord_flip()
```





8.2.1.2.1 Stats

Summary statistics for the best satisfactory trait coverage.

```
### best
coverage = filter(mi50_best, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nSci
coverage %>%
  group_by(Structure) %>%
 dplyr::summarise(
   count = n(),
   na_cnt = sum(is.na(VAL)),
   min = min(VAL, na.rm = TRUE),
   median = median(VAL, na.rm = TRUE),
   mean = mean(VAL, na.rm = TRUE),
   max = max(VAL, na.rm = TRUE),
    IQR = IQR(VAL, na.rm = TRUE)
## # A tibble: 3 x 8
    Structure count na cnt
                              min median mean
##
               <int> <int> <dbl>
                                   <dbl> <dbl> <dbl> <dbl>
## 1 EA
                 100
                          0
## 2 IS
                 100
                          0
                                       1
                                          1
                                                    1
                                                          0
                                1
## 3 NMIS
                 100
                                3
                                          3.94
                          0
```

Kruskal-Wallis test provides evidence of difference among satisfactory trait

```
coverage.
```

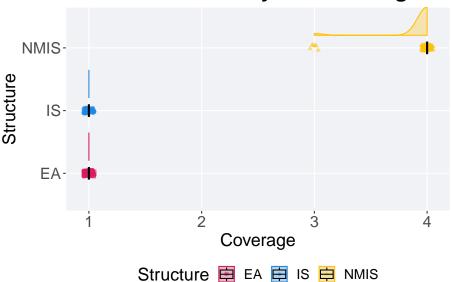
```
kruskal.test(VAL ~ Structure, data = coverage)
##
## Kruskal-Wallis rank sum test
##
## data: VAL by Structure
## Kruskal-Wallis chi-squared = 296.22, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on
satisfactory trait coverage.
pairwise.wilcox.test(x = coverage$VAL, g = coverage$Structure, p.adjust.method = "bonferroni",
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: coverage$VAL and coverage$Structure
##
##
        EΑ
               IS
## IS
      1
## NMIS <2e-16 <2e-16
## P value adjustment method: bonferroni
```

8.2.1.3 End of 50,000 generations

Satisfactory trait coverage in the population at the end of 50,000 generations.

```
### end of run
filter(mi50_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` == 'TRUNCAT
  ggplot(., aes(x = Structure, y = pop_sat_cov, color = Structure, fill = Structure, shape = Structure,
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.3) +
  geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha = 0.5) +
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_shape_manual(values=SHAPE)+
  scale_y_continuous(
   name="Coverage"
  scale_x_discrete(
   name="Structure"
  ) +
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Final satisfactory trait coverage')+
  p_theme + coord_flip()
```





8.2.1.3.1 Stats

Summary statistics for satisfactory trait coverage in the population at the end of 50,000 generations.

```
### end of run
coverage = filter(mi50_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection
coverage %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
    na_cnt = sum(is.na(pop_sat_cov)),
    min = min(pop_sat_cov, na.rm = TRUE),
    median = median(pop_sat_cov, na.rm = TRUE),
    mean = mean(pop_sat_cov, na.rm = TRUE),
    max = max(pop_sat_cov, na.rm = TRUE),
    IQR = IQR(pop_sat_cov, na.rm = TRUE)
)
```

```
## # A tibble: 3 x 8
    Structure count na_cnt
                           min median mean
                                                   IQR
##
    <fct>
             <int> <int> <int> <dbl> <dbl> <int> <dbl>
## 1 EA
               100
                        0
                                    1 1
                                               1
                                                     0
                             1
                                    1 1
## 2 IS
               100
                        0
                             1
                                               1
## 3 NMIS
              100
                        0
                             3
                                    4 3.94
```

Kruskal–Wallis test provides evidence of difference among satisfactory trait coverage in the population at the end of 50,000 generations.

kruskal.test(pop_sat_cov ~ Structure, data = coverage)

```
##
## Kruskal-Wallis rank sum test
##
## data: pop_sat_cov by Structure
## Kruskal-Wallis chi-squared = 296.22, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on
satisfactory trait coverage in the population at the end of 50,000 generations.
pairwise.wilcox.test(x = coverage$pop_sat_cov, g = coverage$Structure, p.adjust.method = "bonfern
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: coverage$pop_sat_cov and coverage$Structure
##
##
        EΑ
               IS
## IS
## NMIS <2e-16 <2e-16
## P value adjustment method: bonferroni
```

8.2.2 Activation gene coverage

Activation gene coverage analysis.

8.2.2.1 Coverage over time

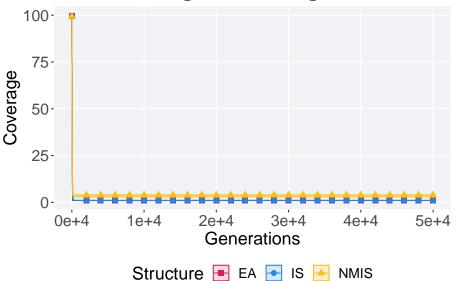
`.groups` argument.

Activation gene coverage over time.

```
# data for lines and shading on plots
lines = filter(mi50_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` ==
group_by(Structure, Generations) %>%
dplyr::summarise(
   min = min(pop_act_cov),
   mean = mean(pop_act_cov),
   max = max(pop_act_cov)
)
## `summarise()` has grouped output by 'Structure'. You can override using the
```

```
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = 3
  geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom_line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 1.5, stroke = 2.0,
  scale_y_continuous(
    name="Coverage"
  ) +
  scale_x_continuous(
   name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
 ) +
 scale_shape_manual(values=SHAPE)+
 scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
 ggtitle('Activation gene coverage over time')+
 p_theme
```

Activation gene coverage over time

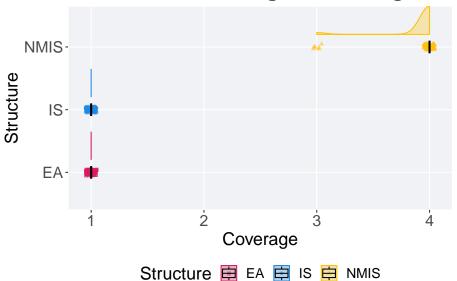


8.2.2.2 End of 50,000 generations

Activation gene coverage in the population at the end of 50,000 generations.

```
### end of run
filter(mi50_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` == 'TRUNCAT
  ggplot(., aes(x = Structure, y = pop_act_cov, color = Structure, fill = Structure, shape = Structure,
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.3) +
  geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha = 0.5) +
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_shape_manual(values=SHAPE)+
  scale_y_continuous(
   name="Coverage"
  ) +
  scale_x_discrete(
   name="Structure"
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Final activation gene coverage')+
  p_theme + coord_flip()
```

Final activation gene coverage



8.2.2.2.1 Stats

Summary statistics for activation gene coverage.

```
coverage = filter(mi50_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme`
coverage %>%
  group_by(Structure) %>%
```

```
dplyr::summarise(
   count = n(),
   na_cnt = sum(is.na(pop_act_cov)),
   min = min(pop_act_cov, na.rm = TRUE),
   median = median(pop_act_cov, na.rm = TRUE),
   mean = mean(pop_act_cov, na.rm = TRUE),
   max = max(pop_act_cov, na.rm = TRUE),
   IQR = IQR(pop_act_cov, na.rm = TRUE)
## # A tibble: 3 x 8
##
    Structure count na_cnt
                           min median mean
                                             max
    <fct> <int> <int> <dbl> <dbl> <int> <dbl>
##
## 1 EA
              100
                     0 1
                                  1 1
                                               1
## 2 IS
              100
                        0
                                    1 1
                                               1
                                                     0
                             1
## 3 NMIS
               100
                        0
                             3
                                    4 3.94
                                               4
                                                     0
```

Kruskal–Wallis test provides evidence of difference among activation gene coverage.

```
kruskal.test(pop_act_cov ~ Structure, data = coverage)
```

```
##
## Kruskal-Wallis rank sum test
##
## data: pop_act_cov by Structure
## Kruskal-Wallis chi-squared = 296.22, df = 2, p-value < 2.2e-16</pre>
```

Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on activation gene coverage.

```
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: coverage$pop_act_cov and coverage$Structure
##
## EA IS
## IS 1 -
## NMIS <2e-16 <2e-16
##
## P value adjustment method: bonferroni</pre>
```

8.3 Tournament selection

Here we analyze how the different population structures affect tournament selection (size 8) on the contradictory objectives diagnostic.

8.3.1 Satisfactory trait coverage

Satisfactory trait coverage analysis.

8.3.1.1 Coverage over time

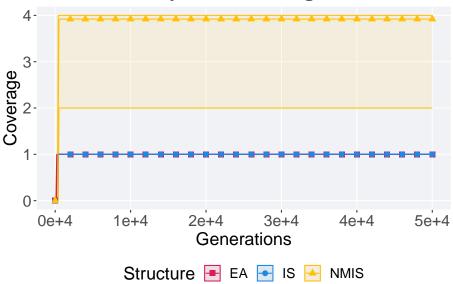
Satisfactory trait coverage over time.

```
lines = filter(mi50_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` ==
group_by(Structure, Generations) %>%
dplyr::summarise(
   min = min(pop_sat_cov),
   mean = mean(pop_sat_cov),
   max = max(pop_sat_cov)
)
```

`summarise()` has grouped output by 'Structure'. You can override using the
`.groups` argument.

```
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = Structure,
  geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 1.5, stroke = 2.0, alpha = 1.
  scale_y_continuous(
   name="Coverage"
  scale_x_continuous(
   name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
  ) +
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Satisfactory trait coverage over time')+
  p_theme
```



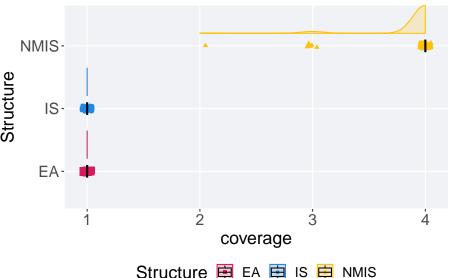


8.3.1.2 Best coverage throughout

Best satisfactory trait coverage throughout 50,000 generations.

```
### best satisfactory trait coverage throughout
ggplot(., aes(x = Structure, y = VAL, color = Structure, fill = Structure, shape = S
 geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = '
 geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha
 geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
 scale_y_continuous(
   name="coverage"
 ) +
 scale_x_discrete(
   name="Structure"
 )+
 scale_shape_manual(values=SHAPE)+
 scale_colour_manual(values = cb_palette, ) +
 scale_fill_manual(values = cb_palette) +
 ggtitle('Best satisfactory trait coverage')+
 p_theme + coord_flip()
```

Best satisfactory trait coverage



Structure 🗎 EA 🗎 IS 🛱 NMIS

8.3.1.2.1 Stats

Summary statistics for the best satisfactory trait coverage.

```
### best
coverage = filter(mi50_best, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` == 'T
coverage %>%
  group_by(Structure) %>%
  dplyr::summarise(
   count = n(),
   na_cnt = sum(is.na(VAL)),
   min = min(VAL, na.rm = TRUE),
   median = median(VAL, na.rm = TRUE),
   mean = mean(VAL, na.rm = TRUE),
   max = max(VAL, na.rm = TRUE),
   IQR = IQR(VAL, na.rm = TRUE)
## # A tibble: 3 x 8
     Structure count na cnt
                              min median mean
               <int> <int> <dbl>
                                   <dbl> <dbl> <dbl> <dbl> <
     <fct>
## 1 EA
                 100
                          0
## 2 IS
                 100
                          0
                                                          0
                                1
                                        1
                                           1
                                                    1
## 3 NMIS
                                        4 3.92
                 100
                          0
```

Kruskal-Wallis test provides evidence of difference among satisfactory trait

coverage.

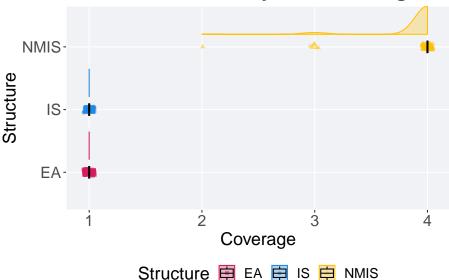
```
kruskal.test(VAL ~ Structure, data = coverage)
##
## Kruskal-Wallis rank sum test
##
## data: VAL by Structure
## Kruskal-Wallis chi-squared = 295.79, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on
satisfactory trait coverage.
pairwise.wilcox.test(x = coverage$VAL, g = coverage$Structure, p.adjust.method = "bonf")
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: coverage$VAL and coverage$Structure
##
##
        EΑ
               IS
## IS
        1
## NMIS <2e-16 <2e-16
## P value adjustment method: bonferroni
```

8.3.1.3 End of 50,000 generations

Satisfactory trait coverage in the population at the end of 50,000 generations.

```
### end of run
filter(mi50_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` :
       ggplot(., aes(x = Structure, y = pop_sat_cov, color = Structure, fill = Structure, sill = Structu
        geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = '
       geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha
        geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
       scale_shape_manual(values=SHAPE)+
       scale_y_continuous(
              name="Coverage"
       ) +
       scale_x_discrete(
              name="Structure"
       ) +
       scale_colour_manual(values = cb_palette) +
       scale_fill_manual(values = cb_palette) +
       ggtitle('Final satisfactory trait coverage')+
       p_theme + coord_flip()
```





8.3.1.3.1 Stats

Summary statistics for satisfactory trait coverage in the population at the end of 50,000 generations.

```
### end of run
coverage = filter(mi50_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme`
coverage %>%
  group_by(Structure) %>%
  dplyr::summarise(
   count = n(),
   na_cnt = sum(is.na(pop_sat_cov)),
   min = min(pop_sat_cov, na.rm = TRUE),
   median = median(pop_sat_cov, na.rm = TRUE),
   mean = mean(pop_sat_cov, na.rm = TRUE),
   max = max(pop_sat_cov, na.rm = TRUE),
    IQR = IQR(pop_sat_cov, na.rm = TRUE)
## # A tibble: 3 x 8
     Structure count na_cnt
                              min median mean
                                                 max
```

```
<fct>
              <int> <int> <int> <dbl> <dbl> <int> <dbl>
## 1 EA
                100
                         0
                               1
                                      1 1
## 2 IS
                         0
                              1
                                      1 1
                                                 1
                                                       0
                100
## 3 NMIS
                100
                         0
                               2
                                      4 3.92
```

Kruskal–Wallis test provides evidence of difference among satisfactory trait coverage in the population at the end of 50,000 generations.

```
kruskal.test(pop_sat_cov ~ Structure, data = coverage)
##
##
   Kruskal-Wallis rank sum test
##
## data: pop_sat_cov by Structure
## Kruskal-Wallis chi-squared = 295.79, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on
satisfactory trait coverage in the population at the end of 50,000 generations.
pairwise.wilcox.test(x = coverage$pop_sat_cov, g = coverage$Structure, p.adjust.method
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: coverage$pop_sat_cov and coverage$Structure
##
##
        EΑ
               IS
## IS
## NMIS <2e-16 <2e-16
## P value adjustment method: bonferroni
```

8.3.2 Activation gene coverage

Activation gene coverage analysis.

8.3.2.1 Coverage over time

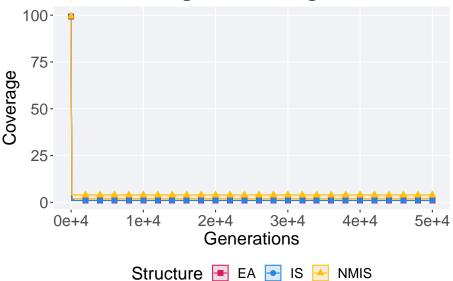
Activation gene coverage over time.

```
# data for lines and shading on plots
lines = filter(mi50_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\ni
group_by(Structure, Generations) %>%
dplyr::summarise(
   min = min(pop_act_cov),
   mean = mean(pop_act_cov),
   max = max(pop_act_cov)
)
```

```
## `summarise()` has grouped output by 'Structure'. You can override using the
## `.groups` argument.
```

```
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = Structure,
  geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom\_line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 1.5, stroke = 2.0, alpha = 1.
  scale_y_continuous(
    name="Coverage"
  ) +
  scale_x_continuous(
   name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
  ) +
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Activation gene coverage over time')+
  p_theme
```

Activation gene coverage over time

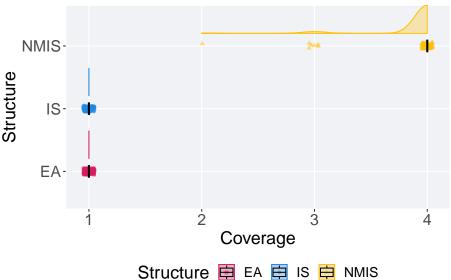


8.3.2.2 End of 50,000 generations

Activation gene coverage in the population at the end of 50,000 generations.

```
### end of run
filter(mi50_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` :
  ggplot(., aes(x = Structure, y = pop_act_cov, color = Structure, fill = Structure, si
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = '
  geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_shape_manual(values=SHAPE)+
  scale_y_continuous(
   name="Coverage"
  ) +
  scale_x_discrete(
   name="Structure"
  ) +
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Final activation gene coverage')+
 p_theme + coord_flip()
```

Final activation gene coverage



8.3.2.2.1 Stats

Summary statistics for activation gene coverage.

```
coverage = filter(mi50_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection
coverage %>%
  group_by(Structure) %>%
```

NMIS <2e-16 <2e-16

P value adjustment method: bonferroni

```
dplyr::summarise(
    count = n(),
   na_cnt = sum(is.na(pop_act_cov)),
   min = min(pop_act_cov, na.rm = TRUE),
   median = median(pop_act_cov, na.rm = TRUE),
   mean = mean(pop_act_cov, na.rm = TRUE),
   max = max(pop_act_cov, na.rm = TRUE),
   IQR = IQR(pop_act_cov, na.rm = TRUE)
## # A tibble: 3 x 8
     Structure count na_cnt min median mean
                                                 max
   <fct> <int> <int> <int> <dbl> <dbl> <int> <dbl>
## 1 EA
               100
                         0
                              1
                                     1 1
                                                   1
## 2 IS
                100
                          0
                                1
                                       1 1
                                                   1
                                                         0
                                       4 3.92
## 3 NMIS
                 100
                          0
                                2
                                                   4
                                                         0
Kruskal-Wallis test provides evidence of difference among activation gene cover-
age.
kruskal.test(pop_act_cov ~ Structure, data = coverage)
##
## Kruskal-Wallis rank sum test
##
## data: pop_act_cov by Structure
## Kruskal-Wallis chi-squared = 295.79, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on
activation gene coverage.
pairwise.wilcox.test(x = coverage$pop_act_cov, g = coverage$Structure, p.adjust.method = "bonfer")
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
## data: coverage$pop_act_cov and coverage$Structure
##
##
       EΑ
               TS
## IS
      1
```

8.4 Lexicase selection

Here we analyze how the different population structures affect standard lexicase selection on the contradictory objectives diagnostic.

8.4.1 Satisfactory trait coverage

Satisfactory trait coverage analysis.

8.4.1.1 Coverage over time

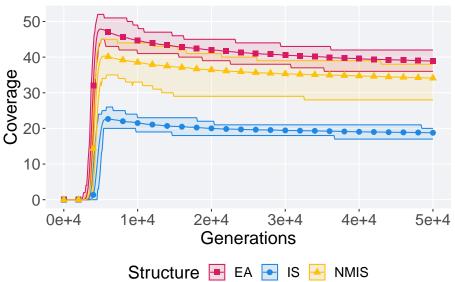
Satisfactory trait coverage over time.

```
lines = filter(mi50_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\ni
group_by(Structure, Generations) %>%
dplyr::summarise(
   min = min(pop_sat_cov),
   mean = mean(pop_sat_cov),
   max = max(pop_sat_cov)
)
```

`summarise()` has grouped output by 'Structure'. You can override using the
`.groups` argument.

```
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color 
        geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
        geom_line(size = 0.5) +
        geom_point(data = filter(lines, Generations %% 2000 == 0), size = 1.5, stroke = 2.0,
        scale_y_continuous(
               name="Coverage"
        ) +
        scale_x_continuous(
                name="Generations",
               limits=c(0, 50000),
                breaks=c(0, 10000, 20000, 30000, 40000, 50000),
                labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
        ) +
        scale_shape_manual(values=SHAPE)+
        scale_colour_manual(values = cb_palette) +
        scale_fill_manual(values = cb_palette) +
       ggtitle('Satisfactory trait coverage over time')+
       p_theme
```



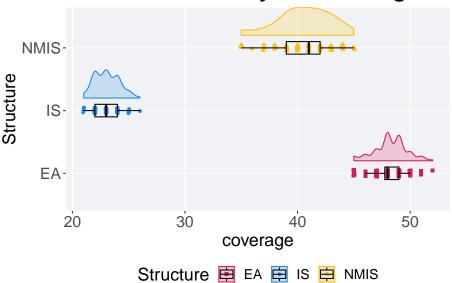


8.4.1.2 Best coverage throughout

Best satisfactory trait coverage throughout 50,000 generations.

```
### best satisfactory trait coverage throughout
filter(mi50_best, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` == 'LEXICASE' &
    ggplot(., aes(x = Structure, y = VAL, color = Structure, fill = Structure, shape = Structure))
    geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.2) +
    geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha = 1.0) +
    geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
    scale_y_continuous(
        name="coverage"
    ) +
    scale_x_discrete(
        name="Structure"
    )+
    scale_shape_manual(values=SHAPE)+
    scale_colour_manual(values = cb_palette, ) +
    scale_fill_manual(values = cb_palette) +
    ggtitle('Best satisfactory trait coverage')+
    p_theme + coord_flip()
```

Best satisfactory trait coverage



8.4.1.2.1 Stats

3 IS

100

0

21

Summary statistics for the best satisfactory trait coverage.

```
### best
coverage = filter(mi50_best, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nSci
coverage$Structure = factor(coverage$Structure, levels=c('EA','NMIS','IS'))
coverage %>%
  group_by(Structure) %>%
 dplyr::summarise(
    count = n(),
   na_cnt = sum(is.na(VAL)),
   min = min(VAL, na.rm = TRUE),
   median = median(VAL, na.rm = TRUE),
   mean = mean(VAL, na.rm = TRUE),
   max = max(VAL, na.rm = TRUE),
    IQR = IQR(VAL, na.rm = TRUE)
## # A tibble: 3 x 8
    Structure count na_cnt
                              min median mean
                                                        IQR
                                                  max
##
    <fct>
               <int> <int> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <
## 1 EA
                 100
                          0
                               45
                                      48 48.2
                                                   52 1.25
## 2 NMIS
                 100
                          0
                               35
                                      41 40.6
                                                   45 3
```

23 23.0

26 2

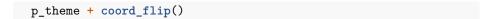
Kruskal–Wallis test provides evidence of difference among satisfactory trait coverage.

```
kruskal.test(VAL ~ Structure, data = coverage)
##
## Kruskal-Wallis rank sum test
##
## data: VAL by Structure
## Kruskal-Wallis chi-squared = 267.02, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on
satisfactory trait coverage.
pairwise.wilcox.test(x = coverage$VAL, g = coverage$Structure, p.adjust.method = "bonferroni",
                     paired = FALSE, conf.int = FALSE, alternative = '1')
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
##
## data: coverage$VAL and coverage$Structure
##
##
        EΑ
               NMIS
## NMIS <2e-16 -
## IS <2e-16 <2e-16
##
## P value adjustment method: bonferroni
```

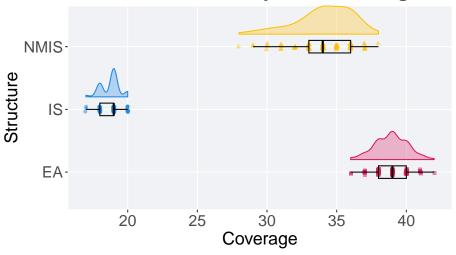
8.4.1.3 End of 50,000 generations

Satisfactory trait coverage in the population at the end of 50,000 generations.

```
### end of run
filter(mi50_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & Selection\nScheme` == 'LEXICAS'
ggplot(., aes(x = Structure, y = pop_sat_cov, color = Structure, fill = Structure, shape = Structure, geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.3) +
geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha = 0.5) +
geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
scale_shape_manual(values=SHAPE)+
scale_y_continuous(
    name="Coverage"
) +
scale_x_discrete(
    name="Structure"
) +
scale_colour_manual(values = cb_palette) +
scale_fill_manual(values = cb_palette) +
ggtitle('Final satisfactory trait coverage')+
```



Final satisfactory trait coverage



Structure 🖹 EA 📋 IS 🛱 NMIS

8.4.1.3.1 Stats

Summary statistics for satisfactory trait coverage in the population at the end of 50,000 generations.

```
### end of run
coverage = filter(mi50_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection
coverage$Structure = factor(coverage$Structure, levels=c('EA','NMIS','IS'))
coverage %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
    na_cnt = sum(is.na(pop_sat_cov)),
    min = min(pop_sat_cov, na.rm = TRUE),
    median = median(pop_sat_cov, na.rm = TRUE),
    mean = mean(pop_sat_cov, na.rm = TRUE),
    TQR = IQR(pop_sat_cov, na.rm = TRUE)
)

## # A tibble: 3 x 8
```

```
## 2 NMIS 100 0 28 34 34.1 38 3 ## 3 IS 100 0 17 19 18.8 20 1
```

Kruskal–Wallis test provides evidence of difference among satisfactory trait coverage in the population at the end of 50,000 generations.

```
kruskal.test(pop_sat_cov ~ Structure, data = coverage)
##
## Kruskal-Wallis rank sum test
##
## data: pop_sat_cov by Structure
## Kruskal-Wallis chi-squared = 266.88, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on
satisfactory trait coverage in the population at the end of 50,000 generations.
pairwise.wilcox.test(x = coverage$pop_sat_cov, g = coverage$Structure, p.adjust.method = "bonfern
                      paired = FALSE, conf.int = FALSE, alternative = '1')
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: coverage$pop_sat_cov and coverage$Structure
##
##
        EΑ
               NMIS
## NMIS <2e-16 -
## IS
       <2e-16 <2e-16
##
## P value adjustment method: bonferroni
```

8.4.2 Activation gene coverage

Activation gene coverage analysis.

8.4.2.1 Coverage over time

Activation gene coverage over time.

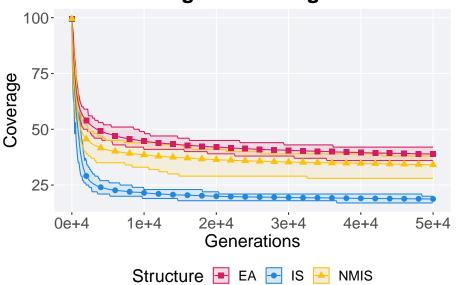
```
# data for lines and shading on plots
lines = filter(mi50_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` ==
group_by(Structure, Generations) %>%
dplyr::summarise(
   min = min(pop_act_cov),
   mean = mean(pop_act_cov),
   max = max(pop_act_cov)
)
```

`summarise()` has grouped output by 'Structure'. You can override using the

```
## `.groups` argument.
```

```
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = 3
  geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom_line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 1.5, stroke = 2.0,
  scale_y_continuous(
    name="Coverage"
  ) +
  scale_x_continuous(
    name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
  ) +
 scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Activation gene coverage over time')+
 p_theme
```

Activation gene coverage over time

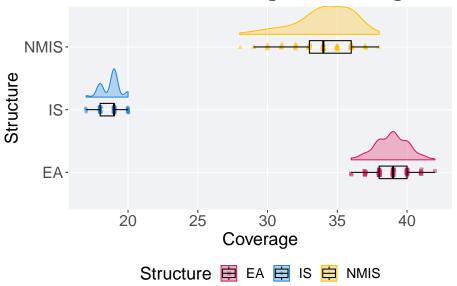


8.4.2.2 End of 50,000 generations

Activation gene coverage in the population at the end of 50,000 generations.

```
### end of run
filter(mi50_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` == 'LEXICAS'
  ggplot(., aes(x = Structure, y = pop_act_cov, color = Structure, fill = Structure, shape = Structure,
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.3) +
  geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha = 0.5) +
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_shape_manual(values=SHAPE)+
  scale_y_continuous(
   name="Coverage"
  ) +
  scale_x_discrete(
   name="Structure"
  ) +
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Final activation gene coverage')+
  p_theme + coord_flip()
```

Final activation gene coverage



8.4.2.2.1 Stats

Summary statistics for activation gene coverage.

```
coverage = filter(mi50_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme`
coverage$Structure = factor(coverage$Structure, levels=c('EA','NMIS','IS'))
coverage %>%
```

group_by(Structure) %>%

```
dplyr::summarise(
    count = n(),
    na_cnt = sum(is.na(pop_act_cov)),
   min = min(pop_act_cov, na.rm = TRUE),
   median = median(pop_act_cov, na.rm = TRUE),
   mean = mean(pop_act_cov, na.rm = TRUE),
    max = max(pop_act_cov, na.rm = TRUE),
    IQR = IQR(pop_act_cov, na.rm = TRUE)
 )
## # A tibble: 3 x 8
    Structure count na_cnt
                                                        IQR
                              min median mean
                                                 max
     <fct> <int> <int> <dbl> <dbl> <int> <dbl>
                                      39 38.9
                                                  42
                                                          2
## 1 EA
                100
                        0 36
## 2 NMIS
                 100
                          0
                               28
                                      34 34.1
                                                   38
                                                          3
                 100
                               17
## 3 IS
                          0
                                      19 18.8
                                                  20
                                                          1
Kruskal-Wallis test provides evidence of difference among activation gene cover-
kruskal.test(pop_act_cov ~ Structure, data = coverage)
##
##
   Kruskal-Wallis rank sum test
##
## data: pop_act_cov by Structure
## Kruskal-Wallis chi-squared = 266.88, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on
activation gene coverage.
pairwise.wilcox.test(x = coverage$pop_act_cov, g = coverage$Structure, p.adjust.method
                     paired = FALSE, conf.int = FALSE, alternative = '1')
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: coverage$pop_act_cov and coverage$Structure
##
##
        EΑ
               NMIS
## NMIS <2e-16 -
## IS
        <2e-16 <2e-16
##
## P value adjustment method: bonferroni
```

Chapter 9

MI50: Multi-path exploration results

Here we present the results for the **best performances** and **activation gene coverage** generated by each selection scheme replicate on the multi-path exploration diagnostic with configurations presented below. For our the configuration of these experiments, we execute migrations every 50 generations and there are 4 islands in a ring topology. Best performance found refers to the largest average trait score found in a given population. Note that activation gene coverage values are gathered at the population-level. Activation gene coverage refers to the count of unique activation genes in a given population; this gives us a range of integers between 0 and 100.

9.1 Analysis dependencies

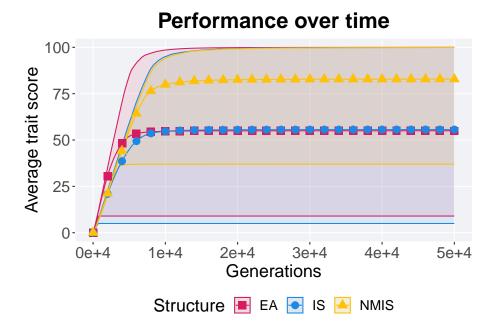
```
library(ggplot2)
library(cowplot)
library(dplyr)
library(PupillometryR)
```

9.2 Truncation selection

Here we analyze how the different population structures affect truncation selection (size 8) on the contradictory objectives diagnostic.

9.2.1 Performance

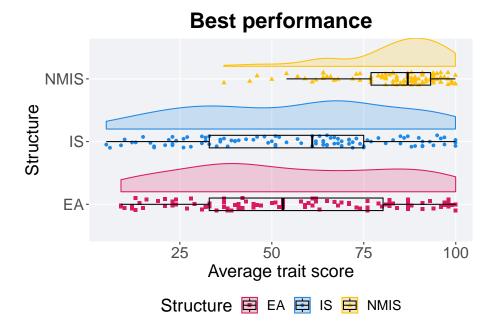
```
lines = filter(mi50_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScho
  group_by(Structure, Generations) %>%
  dplyr::summarise(
   min = min(pop_fit_max) / DIMENSIONALITY,
   mean = mean(pop_fit_max) / DIMENSIONALITY,
   max = max(pop_fit_max) / DIMENSIONALITY
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = 3
  geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom_line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 2.5, stroke = 2.0,
  scale_y_continuous(
   name="Average trait score"
  ) +
  scale_x_continuous(
    name="Generations",
   limits=c(0, 50000),
    breaks=c(0, 10000, 20000, 30000, 40000, 50000),
    labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
  ) +
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle("Performance over time") +
  p_theme
```



9.2.1.2 Best performance

First generation a satisfactory solution is found throughout the 50,000 generations.

```
filter(mi50_best, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'TRUNCATION' & `ggplot(., aes(x = Structure, y = VAL / DIMENSIONALITY, color = Structure, fill = Structure, sha geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.2) + geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) + geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) + scale_y_continuous(
    name="Average trait score"
) + scale_x_discrete(
    name="Structure"
)+
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette, ) + scale_fill_manual(values = cb_palette) + ggtitle('Best performance')+
p_theme + coord_flip()
```



9.2.1.2.1 Stats

Summary statistics for the first generation a satisfactory solution is found.

```
performance = filter(mi50_best, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nSci
performance %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
    na_cnt = sum(is.na(VAL)),
    min = min(VAL, na.rm = TRUE) / DIMENSIONALITY,
    median = median(VAL, na.rm = TRUE) / DIMENSIONALITY,
    mean = mean(VAL, na.rm = TRUE) / DIMENSIONALITY,
    max = max(VAL, na.rm = TRUE) / DIMENSIONALITY,
    IQR = IQR(VAL, na.rm = TRUE) / DIMENSIONALITY
## # A tibble: 3 x 8
     Structure count na_cnt
                              min median mean
##
     <fct>
               <int>
                      <int> <dbl>
                                   <dbl> <dbl> <dbl> <dbl> <
## 1 EA
                 100
                             9.00
                                    53.0
                                          55.0 100.
                                                       47.2
                          0
## 2 IS
                 100
                          0 5
                                    61.0 55.6 99.9
                                                       42.0
## 3 NMIS
                 100
                          0 37.0
                                    86.9 82.9 99.9
```

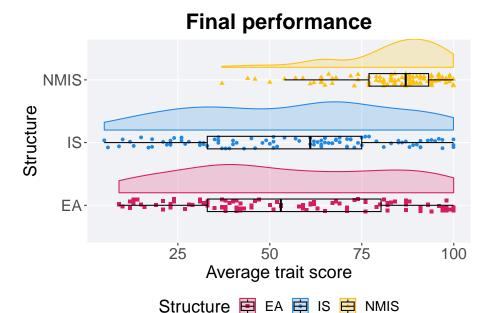
Kruskal–Wallis test provides evidence of difference among selection schemes.

```
kruskal.test(VAL ~ Structure, data = performance)
##
## Kruskal-Wallis rank sum test
##
## data: VAL by Structure
## Kruskal-Wallis chi-squared = 67.87, df = 2, p-value = 1.829e-15
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = performance$VAL, g = performance$Structure, p.adjust.method = "bonferror
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
## data: performance$VAL and performance$Structure
##
##
        EΑ
                IS
## IS
      1
## NMIS 3.0e-12 7.9e-13
##
## P value adjustment method: bonferroni
```

9.2.1.3 Final performance

First generation a satisfactory solution is found throughout the 50,000 generations.

```
filter(mi50_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'TRUNCATION'
ggplot(., aes(x = Structure, y = pop_fit_max / DIMENSIONALITY, color = Structure, fill = Struct
geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.2) +
geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
scale_y_continuous(
    name="Average trait score"
) +
scale_x_discrete(
    name="Structure"
)+
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette, ) +
scale_fill_manual(values = cb_palette) +
ggtitle('Final performance')+
p_theme + coord_flip()
```



9.2.1.3.1 Stats

3 NMIS

100

Summary statistics for the first generation a satisfactory solution is found.

```
performance = filter(mi50_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection
performance %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
    na_cnt = sum(is.na(pop_fit_max)),
    min = min(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
    median = median(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
    mean = mean(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
    max = max(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
    IQR = IQR(pop_fit_max / DIMENSIONALITY, na.rm = TRUE)
## # A tibble: 3 x 8
     Structure count na_cnt
                              min median mean
##
     <fct>
               <int>
                      <int> <dbl>
                                   <dbl> <dbl> <dbl> <dbl> <
## 1 EA
                 100
                             9.00
                                          55.0 100.
                          0
                                    53.0
## 2 IS
                 100
                          0 5
                                    61.0 55.6
                                               99.9
                                                       42.0
```

86.9 82.9 99.9

Kruskal–Wallis test provides evidence of difference among selection schemes.

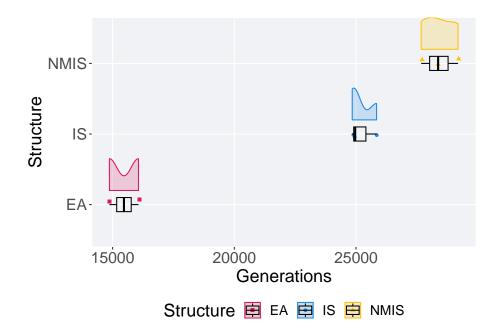
0 37.0

```
kruskal.test(pop_fit_max ~ Structure, data = performance)
##
   Kruskal-Wallis rank sum test
##
## data: pop_fit_max by Structure
## Kruskal-Wallis chi-squared = 67.87, df = 2, p-value = 1.829e-15
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = performance pop_fit_max, g = performance Structure, p.adjust.method = "h
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: performance$pop_fit_max and performance$Structure
##
##
        EΑ
                IS
## IS
## NMIS 3.0e-12 7.9e-13
## P value adjustment method: bonferroni
```

9.2.2 Generation satisfactory solution found

First generation a satisfactory solution is found throughout the 50,000 generations

```
filter(mi50_ssf, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'TRUNCATION'& Ger
    ggplot(., aes(x = Structure, y = Generations, color = Structure, fill = Structure, shape = Stru
        geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.2) +
    geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
    geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
    scale_shape_manual(values=SHAPE)+
    scale_y_continuous(
        name="Generations"
) +
    scale_x_discrete(
        name="Structure"
) +
    scale_colour_manual(values = cb_palette) +
    scale_fill_manual(values = cb_palette) +
    p_theme + coord_flip()
```



9.2.2.1 Stats

Summary statistics for the first generation a satisfactory solution is found.

```
ssf = filter(mi50_ssf, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` ==
ssf %>%
  group_by(Structure) %>%
 dplyr::summarise(
    count = n(),
    na_cnt = sum(is.na(Generations)),
   min = min(Generations, na.rm = TRUE),
   median = median(Generations, na.rm = TRUE),
   mean = mean(Generations, na.rm = TRUE),
   max = max(Generations, na.rm = TRUE),
    IQR = IQR(Generations, na.rm = TRUE)
## # A tibble: 3 x 8
    Structure count na_cnt
                              min median
                                           mean
                                                        IQR
##
     <fct>
               <int>
                      <int> <int>
                                   <dbl>
                                          <dbl> <int> <dbl>
## 1 EA
                          0 14868
                                   15465 15465 16062
## 2 IS
                   3
                                   24965 25217. 25844
                          0 24843
                                                       500.
## 3 NMIS
                   3
                          0 27675
                                  28372 28412. 29190 758.
```

Kruskal–Wallis test provides evidence of no difference among selection schemes.

```
###
## Kruskal-Wallis rank sum test
##
## data: Generations by Structure
## Kruskal-Wallis chi-squared = 6.25, df = 2, p-value = 0.04394
```

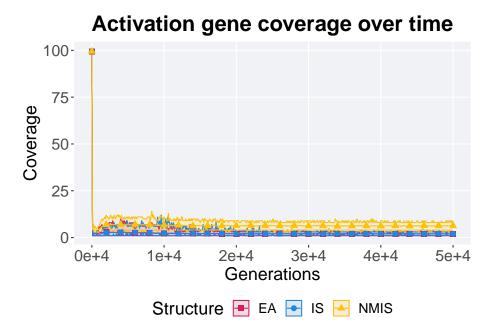
9.2.3 Activation gene coverage

Activation gene coverage analysis.

9.2.3.1 Coverage over time

Activation gene coverage over time.

```
# data for lines and shading on plots
lines = filter(mi50_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'TR
  group_by(Structure, Generations) %>%
  dplyr::summarise(
   min = min(pop_act_cov),
   mean = mean(pop_act_cov),
   max = max(pop_act_cov)
## `summarise()` has grouped output by 'Structure'. You can override using the
## `.groups` argument.
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = Structure,
  geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 1.5, stroke = 2.0, alpha = 1.
  scale_y_continuous(
   name="Coverage"
  ) +
  scale_x_continuous(
   name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
  ) +
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Activation gene coverage over time')+
  p_theme
```

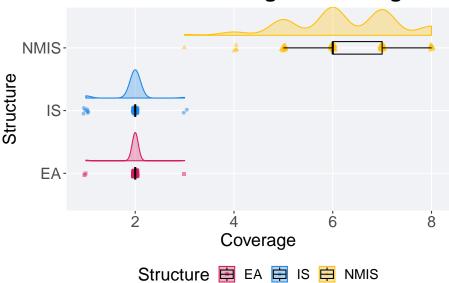


9.2.3.2 End of 50,000 generations

Activation gene coverage in the population at the end of 50,000 generations.

```
### end of run
filter(mi50_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` ==
  ggplot(., aes(x = Structure, y = pop_act_cov, color = Structure, fill = Structure, si
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = '
  geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_shape_manual(values=SHAPE)+
  scale_y_continuous(
   name="Coverage"
  ) +
  scale_x_discrete(
   name="Structure"
  ) +
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Final activation gene coverage')+
 p_theme + coord_flip()
```





9.2.3.2.1 Stats

Summary statistics for activation gene coverage.

```
coverage = filter(mi50_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` ==
coverage %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
   na_cnt = sum(is.na(pop_act_cov)),
   min = min(pop_act_cov, na.rm = TRUE),
   median = median(pop_act_cov, na.rm = TRUE),
   mean = mean(pop_act_cov, na.rm = TRUE),
   max = max(pop_act_cov, na.rm = TRUE),
    IQR = IQR(pop_act_cov, na.rm = TRUE)
 )
```

```
## # A tibble: 3 x 8
     Structure count na_cnt
                                                        IQR
                              min median mean
                                                  max
##
               <int> <int> <int>
                                    <dbl> <dbl> <int>
                                                      <dbl>
## 1 EA
                 100
                          0
                                        2 1.99
                                                          0
                                1
## 2 IS
                 100
                          0
                                        2 1.95
                                                    3
                                                          0
## 3 NMIS
                 100
                          0
                                3
                                        6 6.23
                                                          1
```

Kruskal-Wallis test provides evidence of difference among activation gene coverage.

```
kruskal.test(pop_act_cov ~ Structure, data = coverage)
##
##
   Kruskal-Wallis rank sum test
##
## data: pop_act_cov by Structure
## Kruskal-Wallis chi-squared = 265.48, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on
activation gene coverage.
pairwise.wilcox.test(x = coverage$pop_act_cov, g = coverage$Structure, p.adjust.method
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: coverage$pop_act_cov and coverage$Structure
##
##
        EΑ
               IS
## IS
## NMIS <2e-16 <2e-16
##
## P value adjustment method: bonferroni
```

9.3 Tournament selection

Here we analyze how the different population structures affect tournament selection (size 8) on the contradictory objectives diagnostic.

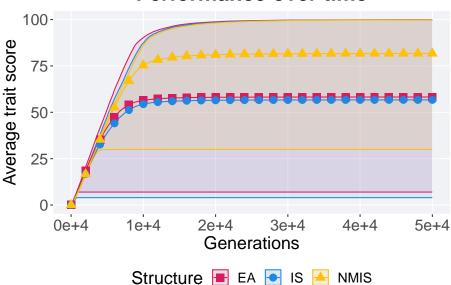
9.3.1 Performance

9.3.1.1 Performance over time

```
lines = filter(mi50_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nSchooling group_by(Structure, Generations) %>%
dplyr::summarise(
    min = min(pop_fit_max) / DIMENSIONALITY,
    mean = mean(pop_fit_max) / DIMENSIONALITY,
    max = max(pop_fit_max) / DIMENSIONALITY
)
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
    geom_line(size = 0.5) +
    geom_point(data = filter(lines, Generations %% 2000 == 0), size = 2.5, stroke = 2.0, scale_y_continuous(
```

```
name="Average trait score"
) +
scale_x_continuous(
  name="Generations",
  limits=c(0, 50000),
  breaks=c(0, 10000, 20000, 30000, 40000, 50000),
  labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
) +
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette) +
scale_fill_manual(values = cb_palette) +
ggtitle("Performance over time") +
p_theme
```

Performance over time



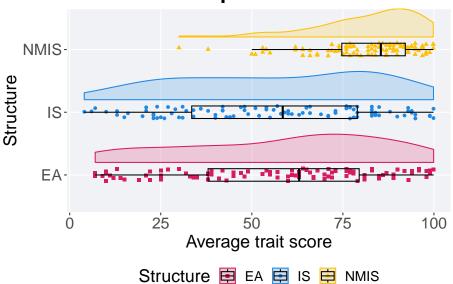
9.3.1.2 Best performance

First generation a satisfactory solution is found throughout the 50,000 generations.

```
filter(mi50_best, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection`\nScheme` == 'TOURNAMENT' & V ggplot(., aes(x = Structure, y = VAL / DIMENSIONALITY, color = Structure, fill = Structure, sha geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.2) + geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) + geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
```

```
scale_y_continuous(
   name="Average trait score"
) +
scale_x_discrete(
   name="Structure"
)+
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette, ) +
scale_fill_manual(values = cb_palette) +
ggtitle('Best performance')+
p_theme + coord_flip()
```

Best performance



9.3.1.2.1 Stats

Summary statistics for the first generation a satisfactory solution is found.

mean = mean(VAL, na.rm = TRUE) / DIMENSIONALITY,

```
performance = filter(mi50_best, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nSci
performance %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
    na_cnt = sum(is.na(VAL)),
    min = min(VAL, na.rm = TRUE) / DIMENSIONALITY,
    median = median(VAL, na.rm = TRUE) / DIMENSIONALITY,
```

```
max = max(VAL, na.rm = TRUE) / DIMENSIONALITY,
   IQR = IQR(VAL, na.rm = TRUE) / DIMENSIONALITY
 )
## # A tibble: 3 x 8
   Structure count na_cnt
                              min median mean
                                                        IQR
##
    <fct>
               <int> <int> <dbl> <dbl> <dbl> <dbl> <dbl> <
## 1 EA
                 100
                          0 7.00
                                    63.0 58.2
                                                 99.9
## 2 IS
                 100
                          0 4
                                    58.5 56.7
                                                 99.9 45.5
## 3 NMIS
                 100
                          0 30.0
                                    85.4 81.7
                                                 99.8 17.4
Kruskal–Wallis test provides evidence of difference among selection schemes.
kruskal.test(VAL ~ Structure, data = performance)
##
## Kruskal-Wallis rank sum test
##
## data: VAL by Structure
## Kruskal-Wallis chi-squared = 56.11, df = 2, p-value = 6.546e-13
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = performance$VAL, g = performance$Structure, p.adjust.method = "bonferror
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
## data: performance$VAL and performance$Structure
##
                IS
##
        ΕA
## IS
## NMIS 4.2e-10 5.1e-11
## P value adjustment method: bonferroni
```

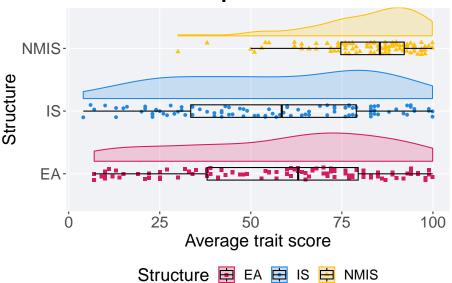
9.3.1.3 Final performance

First generation a satisfactory solution is found throughout the 50,000 generations.

```
filter(mi50_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'TOURNAMENT ggplot(., aes(x = Structure, y = pop_fit_max / DIMENSIONALITY, color = Structure, fill = Structure geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.2) + geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) + geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) + scale_y_continuous(
    name="Average trait score"
```

```
) +
scale_x_discrete(
  name="Structure"
)+
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette, ) +
scale_fill_manual(values = cb_palette) +
ggtitle('Final performance')+
p_theme + coord_flip()
```

Final performance



9.3.1.3.1 Stats

Summary statistics for the first generation a satisfactory solution is found.

```
performance = filter(mi50_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection
performance %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
    na_cnt = sum(is.na(pop_fit_max)),
    min = min(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
    median = median(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
    mean = mean(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
    max = max(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
    IQR = IQR(pop_fit_max / DIMENSIONALITY, na.rm = TRUE)
```

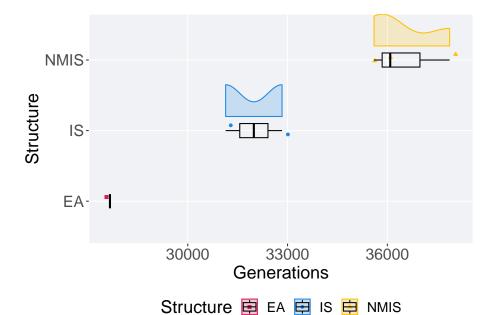
```
## # A tibble: 3 x 8
     Structure count na_cnt
                               min median mean
                                                         IQR
                                                   max
            <int> <int> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <</pre>
## 1 EA
                          0 7.00
                 100
                                     63.0 58.2
                                                  99.9 41.5
## 2 IS
                 100
                           0 4
                                     58.5
                                           56.7
                                                  99.9 45.5
## 3 NMTS
                 100
                           0.30.0
                                     85.4 81.7
                                                 99.8 17.4
Kruskal–Wallis test provides evidence of difference among selection schemes.
kruskal.test(pop_fit_max ~ Structure, data = performance)
##
## Kruskal-Wallis rank sum test
##
## data: pop_fit_max by Structure
## Kruskal-Wallis chi-squared = 56.11, df = 2, p-value = 6.546e-13
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = performance pop_fit_max, g = performance Structure, p.adjust.method = "land")
                      paired = FALSE, conf.int = FALSE, alternative = 'g')
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
## data: performance$pop_fit_max and performance$Structure
##
##
        F.A
                IS
## IS
        1
## NMIS 4.2e-10 5.1e-11
##
## P value adjustment method: bonferroni
```

9.3.2 Generation satisfactory solution found

First generation a satisfactory solution is found throughout the 50,000 generations.

```
filter(mi50_ssf, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'TOURNAMENT'& Ger
ggplot(., aes(x = Structure, y = Generations, color = Structure, fill = Structure, shape = Stru
geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.2) +
geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
scale_shape_manual(values=SHAPE)+
scale_y_continuous(
    name="Generations"
```

```
) +
scale_x_discrete(
  name="Structure"
) +
scale_colour_manual(values = cb_palette) +
scale_fill_manual(values = cb_palette) +
p_theme + coord_flip()
```



9.3.2.1 Stats

Summary statistics for the first generation a satisfactory solution is found.

```
ssf = filter(mi50_ssf, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` ==
ssf %%
group_by(Structure) %>%
dplyr::summarise(
   count = n(),
   na_cnt = sum(is.na(Generations)),
   min = min(Generations, na.rm = TRUE),
   median = median(Generations, na.rm = TRUE),
   mean = mean(Generations, na.rm = TRUE),
   max = max(Generations, na.rm = TRUE),
   IQR = IQR(Generations, na.rm = TRUE)
)
```

```
## # A tibble: 3 x 8
     Structure count na_cnt
                              min median
                                                        IQR
                                           mean
              <int> <int> <int> <dbl> <dbl> <int> <dbl>
## 1 EA
                          0 27661 27661 27661 27661
                                                          0
                   1
## 2 IS
                          0 31139 31987 31987
                   2
                                                32835
                                                        848
## 3 NMIS
                   3
                          0 35601 36087 36520. 37873 1136
Kruskal–Wallis test provides evidence of no difference among selection schemes.
kruskal.test(Generations ~ Structure, data = ssf)
##
## Kruskal-Wallis rank sum test
##
## data: Generations by Structure
## Kruskal-Wallis chi-squared = 4.2857, df = 2, p-value = 0.1173
pairwise.wilcox.test(x = ssf$Generations, g = ssf$Structure, p.adjust.method = "bonferroni",
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
## Pairwise comparisons using Wilcoxon rank sum exact test
##
## data: ssf$Generations and ssf$Structure
##
        EΑ
            IS
##
      1.00 -
## IS
## NMIS 0.75 0.30
## P value adjustment method: bonferroni
```

9.3.3 Activation gene coverage

Activation gene coverage analysis.

9.3.3.1 Coverage over time

Activation gene coverage over time.

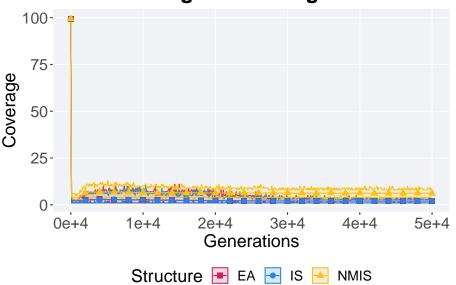
```
# data for lines and shading on plots
lines = filter(mi50_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'TO
group_by(Structure, Generations) %>%
dplyr::summarise(
   min = min(pop_act_cov),
   mean = mean(pop_act_cov),
   max = max(pop_act_cov)
)
```

`summarise()` has grouped output by 'Structure'. You can override using the

```
## `.groups` argument.
```

```
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = 3
  geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom_line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 1.5, stroke = 2.0,
  scale_y_continuous(
   name="Coverage"
  ) +
  scale_x_continuous(
    name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
  ) +
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Activation gene coverage over time')+
 p_theme
```

Activation gene coverage over time

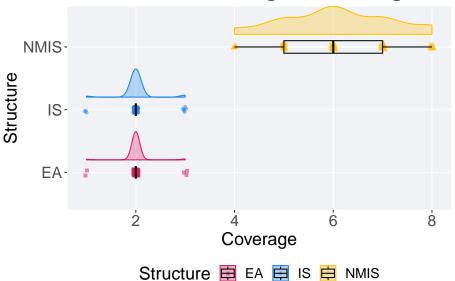


9.3.3.2 End of 50,000 generations

Activation gene coverage in the population at the end of 50,000 generations.

```
### end of run
filter(mi50_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'TOURNAMENT
  ggplot(., aes(x = Structure, y = pop_act_cov, color = Structure, fill = Structure, shape = Stru
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.3) +
  geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha = 0.5) +
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_shape_manual(values=SHAPE)+
  scale_y_continuous(
   name="Coverage"
  ) +
  scale_x_discrete(
   name="Structure"
  ) +
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Final activation gene coverage')+
  p_theme + coord_flip()
```

Final activation gene coverage



9.3.3.2.1 Stats

Summary statistics for activation gene coverage.

```
coverage = filter(mi50_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` ==
coverage %>%
  group_by(Structure) %>%
```

```
dplyr::summarise(
   count = n(),
   na_cnt = sum(is.na(pop_act_cov)),
   min = min(pop_act_cov, na.rm = TRUE),
   median = median(pop_act_cov, na.rm = TRUE),
   mean = mean(pop_act_cov, na.rm = TRUE),
   max = max(pop_act_cov, na.rm = TRUE),
   IQR = IQR(pop_act_cov, na.rm = TRUE)
## # A tibble: 3 x 8
##
    Structure count na_cnt
                            min median mean
                                                     IQR
                                               max
##
    <fct> <int> <int> <int> <dbl> <dbl> <int> <dbl>
## 1 EA
                                     2 2.01
              100
                      0
                             1
                                                 3
## 2 IS
                100
                         0
                                     2 2.03
                                                 3
                                                       0
                              1
## 3 NMIS
                100
                         0
                               4
                                     6 6.09
                                                 8
                                                       2
```

Kruskal–Wallis test provides evidence of difference among activation gene coverage.

```
kruskal.test(pop_act_cov ~ Structure, data = coverage)
```

```
##
## Kruskal-Wallis rank sum test
##
## data: pop_act_cov by Structure
## Kruskal-Wallis chi-squared = 262.68, df = 2, p-value < 2.2e-16</pre>
```

Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on activation gene coverage.

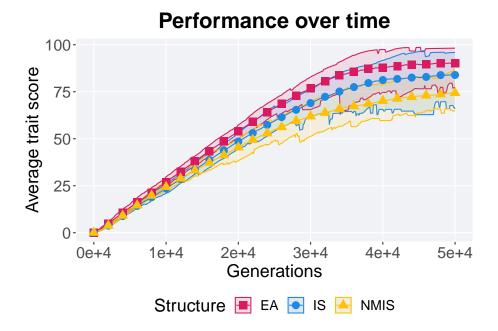
```
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: coverage$pop_act_cov and coverage$Structure
##
## EA IS
## IS 0.88 -
## NMIS <2e-16 <2e-16
##
## P value adjustment method: bonferroni</pre>
```

9.4 Lexicase selection

Here we analyze how the different population structures affect standard lexicase selection on the contradictory objectives diagnostic.

9.4.1 Performance

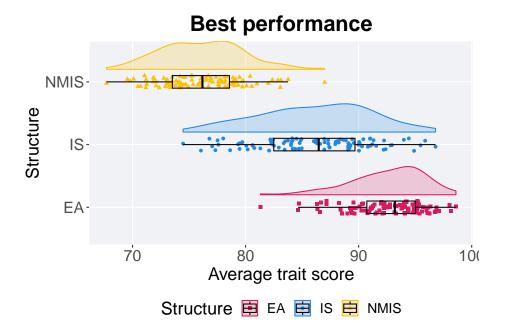
```
lines = filter(mi50_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'LF
  group_by(Structure, Generations) %>%
  dplyr::summarise(
   min = min(pop_fit_max) / DIMENSIONALITY,
   mean = mean(pop_fit_max) / DIMENSIONALITY,
   max = max(pop fit max) / DIMENSIONALITY
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = Structure,
  geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom_line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 2.5, stroke = 2.0, alpha = 1.
  scale_y_continuous(
   name="Average trait score"
  scale_x_continuous(
   name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
  ) +
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle("Performance over time") +
  p_theme
```



9.4.1.2 Best performance

First generation a satisfactory solution is found throughout the 50,000 generations.

```
filter(mi50_best, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'LEXI
  ggplot(., aes(x = Structure, y = VAL / DIMENSIONALITY, color = Structure, fill = Str
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = '
  geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_y_continuous(
   name="Average trait score"
  ) +
  scale_x_discrete(
   name="Structure"
  )+
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette, ) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Best performance')+
 p_theme + coord_flip()
```



9.4.1.2.1 Stats

Summary statistics for the first generation a satisfactory solution is found.

```
performance = filter(mi50_best, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'I
performance$Structure = factor(performance$Structure, levels=c('EA','NMIS','IS'))
performance %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
   na_cnt = sum(is.na(VAL)),
   min = min(VAL, na.rm = TRUE) / DIMENSIONALITY,
   median = median(VAL, na.rm = TRUE) / DIMENSIONALITY,
   mean = mean(VAL, na.rm = TRUE) / DIMENSIONALITY,
   max = max(VAL, na.rm = TRUE) / DIMENSIONALITY,
    IQR = IQR(VAL, na.rm = TRUE) / DIMENSIONALITY
## # A tibble: 3 x 8
     Structure count na cnt
                              min median
                                                        IQR
                                          mean
##
                                   <dbl> <dbl> <dbl> <dbl> <
     <fct>
               <int>
                      <int> <dbl>
## 1 EA
                 100
                             81.3
                                    93.2
                                          92.6
                                                98.6
## 2 NMIS
                 100
                          0
                             67.7
                                    76.2
                                          76.1
                                                87.0
                                                      5.05
## 3 IS
                 100
                             74.5
                                    86.5
                                         86.1
                                                96.8 7.18
```

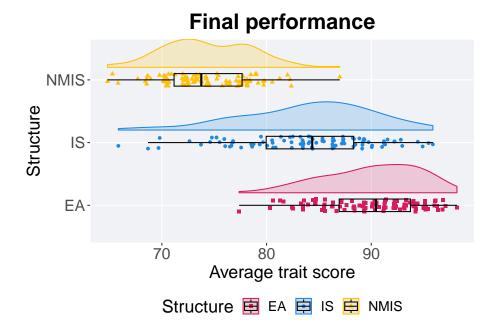
Kruskal–Wallis test provides evidence of difference among selection schemes.

```
kruskal.test(VAL ~ Structure, data = performance)
##
##
   Kruskal-Wallis rank sum test
##
## data: VAL by Structure
## Kruskal-Wallis chi-squared = 217.42, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = performance$VAL, g = performance$Structure, p.adjust.method =
                     paired = FALSE, conf.int = FALSE, alternative = '1')
##
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: performance$VAL and performance$Structure
##
##
        EΑ
               NMIS
## NMIS <2e-16 -
## IS
        <2e-16 1
##
## P value adjustment method: bonferroni
```

9.4.1.3 Final performance

First generation a satisfactory solution is found throughout the 50,000 generations.

```
filter(mi50_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` ==
  ggplot(., aes(x = Structure, y = pop_fit_max / DIMENSIONALITY, color = Structure, fit
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = '
  geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_y_continuous(
   name="Average trait score"
  ) +
  scale_x_discrete(
   name="Structure"
  )+
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette, ) +
  scale_fill_manual(values = cb_palette) +
 ggtitle('Final performance')+
 p_theme + coord_flip()
```



9.4.1.3.1 Stats

Summary statistics for the first generation a satisfactory solution is found.

```
performance = filter(mi50_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme`
performance$Structure = factor(performance$Structure, levels=c('EA','NMIS','IS'))
performance %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
   na_cnt = sum(is.na(pop_fit_max)),
   min = min(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
   median = median(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
   mean = mean(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
   max = max(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
    IQR = IQR(pop_fit_max / DIMENSIONALITY, na.rm = TRUE)
## # A tibble: 3 x 8
     Structure count na cnt
                              min median
                                                        IQR
                                          mean
##
                                   <dbl> <dbl> <dbl> <dbl> <
     <fct>
               <int>
                      <int> <dbl>
## 1 EA
                 100
                             77.4
                                    90.4
                                          90.1
                                                 98.2
## 2 NMIS
                 100
                          0
                             64.8
                                    73.8
                                          74.4
                                                87.0
                                                      6.49
## 3 IS
                 100
                             65.8
                                    84.4 83.9
                                                95.9 8.35
```

Kruskal–Wallis test provides evidence of difference among selection schemes.

```
kruskal.test(pop_fit_max ~ Structure, data = performance)
##
##
   Kruskal-Wallis rank sum test
##
## data: pop_fit_max by Structure
## Kruskal-Wallis chi-squared = 186.92, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = performance$pop_fit_max, g = performance$Structure, p.adjust.
                     paired = FALSE, conf.int = FALSE, alternative = '1')
##
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: performance$pop_fit_max and performance$Structure
##
##
                NMTS
        EΑ
## NMIS < 2e-16 -
       2.5e-12 1
## IS
## P value adjustment method: bonferroni
```

9.4.2 Activation gene coverage

Activation gene coverage analysis.

9.4.2.1 Coverage over time

Activation gene coverage over time.

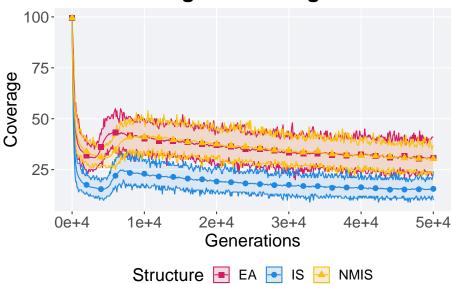
```
# data for lines and shading on plots
lines = filter(mi50_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nSchool
group_by(Structure, Generations) %>%
dplyr::summarise(
   min = min(pop_act_cov),
   mean = mean(pop_act_cov),
   max = max(pop_act_cov)
)
```

```
## `summarise()` has grouped output by 'Structure'. You can override using the
## `.groups` argument.

ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
    geom_line(size = 0.5) +
    geom_point(data = filter(lines, Generations %% 2000 == 0), size = 1.5, stroke = 2.0,
```

```
scale_y_continuous(
  name="Coverage"
) +
scale_x_continuous(
  name="Generations",
  limits=c(0, 50000),
  breaks=c(0, 10000, 20000, 30000, 40000, 50000),
  labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
) +
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette) +
scale_fill_manual(values = cb_palette) +
ggtitle('Activation gene coverage over time')+
p_theme
```

Activation gene coverage over time



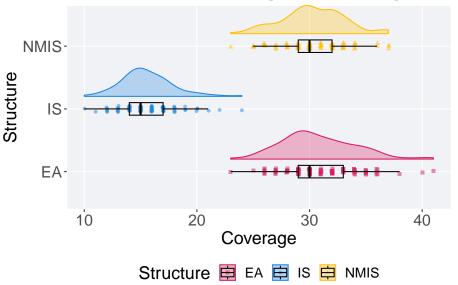
9.4.2.2 End of 50,000 generations

Activation gene coverage in the population at the end of 50,000 generations.

```
### end of run
filter(mi50_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'LEXICASE'
ggplot(., aes(x = Structure, y = pop_act_cov, color = Structure, fill = Structure, shape = Structure, geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.3) +
geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha = 0.5) +
```

```
geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
scale_shape_manual(values=SHAPE)+
scale_y_continuous(
   name="Coverage"
) +
scale_x_discrete(
   name="Structure"
) +
scale_colour_manual(values = cb_palette) +
scale_fill_manual(values = cb_palette) +
ggtitle('Final activation gene coverage')+
p_theme + coord_flip()
```

Final activation gene coverage



9.4.2.2.1 Stats

Summary statistics for activation gene coverage.

```
coverage = filter(mi50_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\ni
coverage$Structure = factor(coverage$Structure, levels=c('EA','NMIS','IS'))
coverage %>%
  group_by(Structure) %>%
  dplyr::summarise(
   count = n(),
   na_cnt = sum(is.na(pop_act_cov)),
   min = min(pop_act_cov, na.rm = TRUE),
```

##

P value adjustment method: bonferroni

```
median = median(pop_act_cov, na.rm = TRUE),
    mean = mean(pop_act_cov, na.rm = TRUE),
    max = max(pop_act_cov, na.rm = TRUE),
    IQR = IQR(pop_act_cov, na.rm = TRUE)
## # A tibble: 3 x 8
     Structure count na_cnt
                              min median mean
                                                  max
                                                        IQR
     <fct>
               <int> <int> <int> <dbl> <dbl> <int> <dbl>
## 1 EA
                 100
                          0
                                23
                                       30
                                           30.8
                                                   41
## 2 NMIS
                 100
                           0
                                23
                                       30 30.3
                                                   37
                                                          3
                                                          3
## 3 IS
                 100
                           0
                                10
                                       15 15.6
                                                   24
Kruskal-Wallis test provides evidence of difference among activation gene cover-
kruskal.test(pop_act_cov ~ Structure, data = coverage)
##
## Kruskal-Wallis rank sum test
## data: pop_act_cov by Structure
## Kruskal-Wallis chi-squared = 200.36, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on
activation gene coverage.
pairwise.wilcox.test(x = coverage$pop_act_cov, g = coverage$Structure, p.adjust.method = "bonfer")
                     paired = FALSE, conf.int = FALSE, alternative = '1')
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
## data: coverage$pop_act_cov and coverage$Structure
##
##
        ΕA
               NMIS
## NMIS 0.81
## IS <2e-16 <2e-16
```

Chapter 10

MI5000: Exploitation rate results

Here we present the results for **best performances** found by each selection scheme replicate on the exploitation rate diagnostic with configurations presented below. For our the configuration of these experiments, we execute migrations every 50 generations and there are 4 islands in a ring topology. When migrations occur, we swap two individuals (same position on each island) and guarantee that no solution can return to the same island. Best performance found refers to the largest average trait score found in a given population. Note that performance values fall between 0.0 and 100.0.

10.1 Analysis dependencies

```
library(ggplot2)
library(cowplot)
library(dplyr)
library(PupillometryR)
```

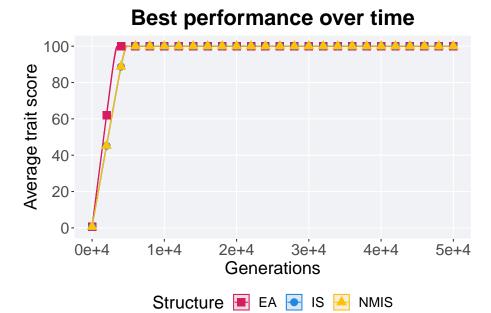
10.2 Truncation selection

Here we analyze how the different population structures affect truncation selection (size 8) on the exploitation rate diagnostic.

10.2.1 Performance over time

```
lines = filter(mi5000_over_time, Diagnostic == 'EXPLOITATION_RATE' & `Selection\nScheme` == 'TRUN
group_by(Structure, Generations) %>%
```

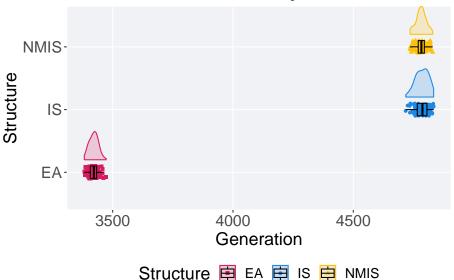
```
dplyr::summarise(
   min = min(pop_fit_max) / DIMENSIONALITY,
   mean = mean(pop_fit_max) / DIMENSIONALITY,
   max = max(pop_fit_max) / DIMENSIONALITY
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = 3
 geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom_line(size = 0.5) +
 geom_point(data = filter(lines, Generations %% 2000 == 0), size = 2.5, stroke = 2.0,
 scale_y_continuous(
   name="Average trait score",
   limits=c(-1, 101),
   breaks=seq(0,100, 20),
   labels=c("0", "20", "40", "60", "80", "100")
  ) +
 scale_x_continuous(
   name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
 ) +
 scale_shape_manual(values=SHAPE)+
 scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
 ggtitle("Best performance over time") +
 p_theme
```



10.2.2 Generation satisfactory solution found

```
filter(mi5000_ssf, Diagnostic == 'EXPLOITATION_RATE' & `Selection\nScheme` == 'TRUNCATION') %>%
    ggplot(., aes(x = Structure, y = Generations , color = Structure, fill = Structure, shape = Str
    geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.2) +
    geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
    geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
    scale_y_continuous(
        name="Generation"
) +
    scale_x_discrete(
        name="Structure"
)+
    scale_shape_manual(values=SHAPE)+
    scale_colour_manual(values = cb_palette, ) +
    scale_fill_manual(values = cb_palette) +
    ggtitle('Generation satisfactory solution found')+
    p_theme + coord_flip()
```

Generation satisfactory solution found



10.2.3 Stats

3 NMIS

100

Summary statistics for the first generation a satisfactory solution is found.

```
ssf = filter(mi5000_ssf, Diagnostic == 'EXPLOITATION_RATE' & `Selection\nScheme` == 'T.
ssf %>%
  group_by(Structure) %>%
 dplyr::summarise(
    count = n(),
    na_cnt = sum(is.na(Generations)),
   min = min(Generations, na.rm = TRUE),
   median = median(Generations, na.rm = TRUE),
   mean = mean(Generations, na.rm = TRUE),
   max = max(Generations, na.rm = TRUE),
    IQR = IQR(Generations, na.rm = TRUE)
## # A tibble: 3 x 8
    Structure count na_cnt
                              min median mean
##
     <fct>
               <int> <int> <int>
                                   <dbl> <dbl> <int> <dbl>
## 1 EA
                 100
                          0 3382
                                   3422
                                         3421.
                                                3473
## 2 IS
                 100
                             4718
                                   4788. 4786.
                                                4834
                                                      40
```

Kruskal-Wallis test provides evidence of difference among selection schemes.

0 4736 4783 4782.

4830

```
kruskal.test(Generations ~ Structure, data = ssf)
##
##
   Kruskal-Wallis rank sum test
##
## data: Generations by Structure
## Kruskal-Wallis chi-squared = 200.03, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = ssf$Generations, g = ssf$Structure, p.adjust.method = "bonferroni",
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: ssf$Generations and ssf$Structure
##
##
        EΑ
               TS
## IS
       <2e-16 -
## NMIS <2e-16 1
## P value adjustment method: bonferroni
```

10.3 Tournament selection

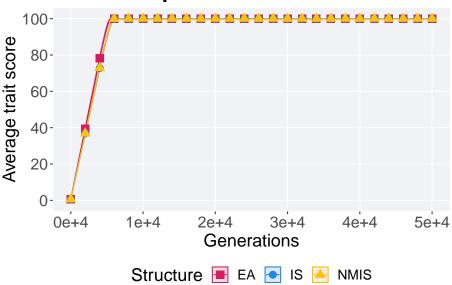
Here we analyze how the different population structures affect tournament selection (size 8) on the exploitation rate diagnostic.

10.3.1 Performance over time

```
lines = filter(mi5000_over_time, Diagnostic == 'EXPLOITATION_RATE'
group_by(Structure, Generations) %>%
dplyr::summarise(
   min = min(pop_fit_max) / DIMENSIONALITY,
   mean = mean(pop_fit_max) / DIMENSIONALITY,
   max = max(pop_fit_max) / DIMENSIONALITY
)
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = Structure,
   geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
   geom_line(size = 0.5) +
   geom_point(data = filter(lines, Generations %% 2000 == 0), size = 2.5, stroke = 2.0, alpha = 1.
   scale_y_continuous(
   name="Average trait score",
   limits=c(-1, 101),
   breaks=seq(0,100, 20),
```

```
labels=c("0", "20", "40", "60", "80", "100")
) +
scale_x_continuous(
  name="Generations",
  limits=c(0, 50000),
  breaks=c(0, 10000, 20000, 30000, 40000, 50000),
  labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
) +
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette) +
scale_fill_manual(values = cb_palette) +
ggtitle("Best performance over time") +
p_theme
```

Best performance over time

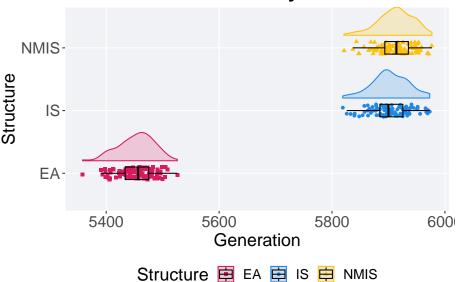


10.3.2 Generation satisfactory solution found

```
filter(mi5000_ssf, Diagnostic == 'EXPLOITATION_RATE' & `Selection\nScheme` == 'TOURNAM ggplot(., aes(x = Structure, y = Generations , color = Structure, fill = Structure, geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) + geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
```

```
scale_y_continuous(
   name="Generation"
) +
scale_x_discrete(
   name="Structure"
)+
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette, ) +
scale_fill_manual(values = cb_palette) +
ggtitle('Generation satisfactory solution found')+
p_theme + coord_flip()
```

Generation satisfactory solution found



10.3.3 Stats

Summary statistics for the first generation a satisfactory solution is found.

```
ssf = filter(mi5000_ssf, Diagnostic == 'EXPLOITATION_RATE' & `Selection\nScheme` == 'TOURNAMENT'
ssf %>%
  group_by(Structure) %>%
  dplyr::summarise(
   count = n(),
   na_cnt = sum(is.na(Generations)),
   min = min(Generations, na.rm = TRUE),
   median = median(Generations, na.rm = TRUE),
   mean = mean(Generations, na.rm = TRUE),
```

```
max = max(Generations, na.rm = TRUE),
    IQR = IQR(Generations, na.rm = TRUE)
## # A tibble: 3 x 8
    Structure count na_cnt
                              min median mean
##
              <int> <int> <int> <dbl> <dbl> <int> <dbl>
    <fct>
## 1 EA
                 100
                          0 5358 5456. 5453.
                                                5526 41.8
## 2 IS
                 100
                          0 5819 5900 5903. 5973 40.8
## 3 NMIS
                 100
                          0 5821
                                   5914 5912. 5977 41.8
Kruskal-Wallis test provides evidence of difference among selection schemes.
kruskal.test(Generations ~ Structure, data = ssf)
##
##
   Kruskal-Wallis rank sum test
##
## data: Generations by Structure
## Kruskal-Wallis chi-squared = 201.55, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = ssf$Generations, g = ssf$Structure, p.adjust.method = "bonfer.")
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: ssf$Generations and ssf$Structure
##
##
        EΑ
               IS
        <2e-16 -
## IS
## NMIS <2e-16 0.04
##
```

10.4 Lexicase selection

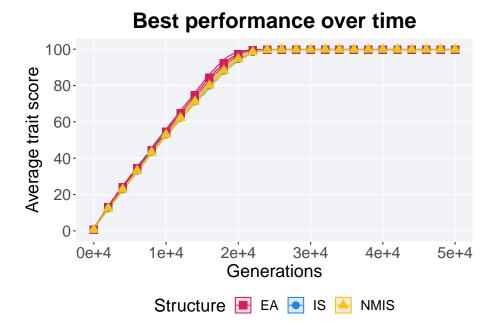
P value adjustment method: bonferroni

Here we analyze how the different population structures affect standard lexicase selection on the exploitation rate diagnostic.

10.4.1 Performance over time

```
lines = filter(mi5000_over_time, Diagnostic == 'EXPLOITATION_RATE' & `Selection\nScheme
group_by(Structure, Generations) %>%
dplyr::summarise(
```

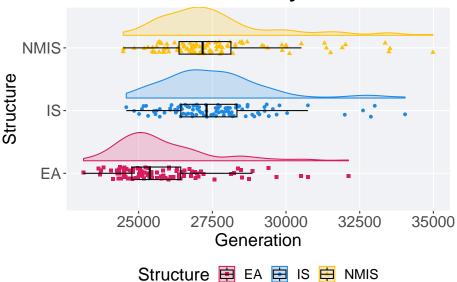
```
min = min(pop_fit_max) / DIMENSIONALITY,
   mean = mean(pop_fit_max) / DIMENSIONALITY,
   max = max(pop_fit_max) / DIMENSIONALITY
 )
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = Structure,
  geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom_line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 2.5, stroke = 2.0, alpha = 1.
  scale_y_continuous(
   name="Average trait score",
   limits=c(-1, 101),
   breaks = seq(0,100, 20),
   labels=c("0", "20", "40", "60", "80", "100")
  ) +
  scale_x_continuous(
   name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
  ) +
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle("Best performance over time") +
  p_theme
```



10.4.2 Generation satisfactory solution found

```
filter(mi5000_ssf, Diagnostic == 'EXPLOITATION_RATE' & `Selection\nScheme` == 'LEXICAS'
ggplot(., aes(x = Structure, y = Generations , color = Structure, fill = Structure, geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
scale_y_continuous(
   name="Generation"
) +
scale_x_discrete(
   name="Structure"
)+
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette, ) +
scale_fill_manual(values = cb_palette) +
ggtitle('Generation satisfactory solution found')+
p_theme + coord_flip()
```

Generation satisfactory solution found



10.4.3 Stats

1 EA

2 IS

3 NMIS

Summary statistics for the first generation a satisfactory solution is found.

```
ssf = filter(mi5000_ssf, Diagnostic == 'EXPLOITATION_RATE' & `Selection\nScheme` == 'LEXICASE' &
ssf %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
   na_cnt = sum(is.na(Generations)),
   min = min(Generations, na.rm = TRUE),
   median = median(Generations, na.rm = TRUE),
   mean = mean(Generations, na.rm = TRUE),
   max = max(Generations, na.rm = TRUE),
    IQR = IQR(Generations, na.rm = TRUE)
## # A tibble: 3 x 8
     Structure count na_cnt
                              min median
                                           mean
     <fct>
               <int>
                     <int> <int>
                                   <dbl>
                                          <dbl> <int> <dbl>
```

25814. 32119 1658.

0 24579 27304. 27591. 34039 1903.

0 24476 27170. 27601. 34985 1759.

Kruskal–Wallis test provides evidence of difference among selection schemes.

0 23129 25376

100

100

100

```
kruskal.test(Generations ~ Structure, data = ssf)
##
##
   Kruskal-Wallis rank sum test
##
## data: Generations by Structure
## Kruskal-Wallis chi-squared = 72.912, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = ssf$Generations, g = ssf$Structure, p.adjust.method = "bonfer")
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: ssf$Generations and ssf$Structure
##
##
        EΑ
                IS
       1.1e-13 -
## IS
## NMIS 5.6e-13 1
## P value adjustment method: bonferroni
```

Chapter 11

MI5000: Ordered exploitation results

Here we present the results for **best performances** found by each selection scheme replicate on the ordered exploitation diagnostic with configurations presented below. Best performance found refers to the largest average trait score found in a given population. Note that performance values fall between 0.0 and 100.0. For our the configuration of these experiments, we execute migrations every 50 generations and there are 4 islands in a ring topology. When migrations occur, we swap two individuals (same position on each island) and guarantee that no solution can return to the same island.

11.1 Analysis dependencies

```
library(ggplot2)
library(cowplot)
library(dplyr)
library(PupillometryR)
```

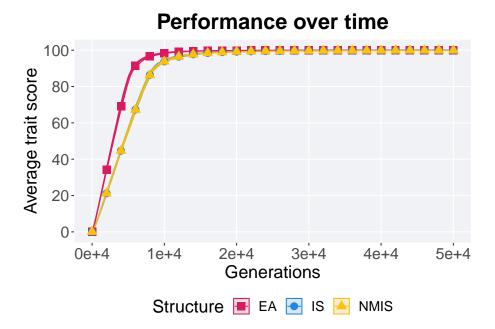
11.2 Truncation selection

Here we analyze how the different population structures affect truncation selection (size 8) on the ordered exploitation diagnostic.

11.2.1 Performance over time

```
lines = filter(mi5000_over_time, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` == 'Terror of the selection of th
```

```
dplyr::summarise(
   min = min(pop_fit_max) / DIMENSIONALITY,
   mean = mean(pop_fit_max) / DIMENSIONALITY,
   max = max(pop_fit_max) / DIMENSIONALITY
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = 3
 geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom_line(size = 0.5) +
 geom_point(data = filter(lines, Generations %% 2000 == 0), size = 2.5, stroke = 2.0,
 scale_y_continuous(
   name="Average trait score",
   limits=c(-1, 101),
   breaks=seq(0,100, 20),
   labels=c("0", "20", "40", "60", "80", "100")
  ) +
 scale_x_continuous(
   name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
 ) +
 scale_shape_manual(values=SHAPE)+
 scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
 ggtitle("Performance over time") +
 p_theme
```

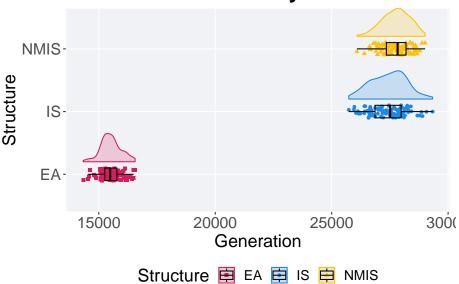


11.2.2 Generation satisfactory solution found

p_theme + coord_flip()

```
filter(mi5000_ssf, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` == 'TRUNCATION') %;
ggplot(., aes(x = Structure, y = Generations , color = Structure, fill = Structure, shape = Structure, fill = Structure, shape = Structure, geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.2) +
geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
scale_y_continuous(
    name="Generation"
) +
scale_x_discrete(
    name="Structure"
)+
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette, ) +
scale_fill_manual(values = cb_palette) +
ggtitle('Generation satisfactory solution found')+
```

Generation satisfactory solution found



11.2.2.1 Stats

Summary statistics for the first generation a satisfactory solution is found.

```
ssf = filter(mi5000_ssf, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` ==
ssf %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
    na_cnt = sum(is.na(Generations)),
   min = min(Generations, na.rm = TRUE),
   median = median(Generations, na.rm = TRUE),
   mean = mean(Generations, na.rm = TRUE),
   max = max(Generations, na.rm = TRUE),
    IQR = IQR(Generations, na.rm = TRUE)
## # A tibble: 3 x 8
    Structure count na_cnt
                              min median
                                           mean
                                                        IQR
##
     <fct>
               <int>
                     <int> <int> <dbl>
                                          <dbl> <int> <dbl>
## 1 EA
                 100
                          0 14333 15487
                                         15522. 16559 521.
## 2 IS
                 100
                          0 25736 27512. 27446. 29337 1121.
## 3 NMIS
                 100
                          0 26084 27832 27762. 29013 844.
```

Kruskal–Wallis test provides evidence of difference among selection schemes.

```
kruskal.test(Generations ~ Structure, data = ssf)
##
##
   Kruskal-Wallis rank sum test
##
## data: Generations by Structure
## Kruskal-Wallis chi-squared = 203.38, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = ssf$Generations, g = ssf$Structure, p.adjust.method = "bonferroni",
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: ssf$Generations and ssf$Structure
##
##
        EΑ
               TS
## IS
       <2e-16 -
## NMIS <2e-16 0.0039
## P value adjustment method: bonferroni
```

11.3 Tournament selection

Here we analyze how the different population structures affect tournament selection (size 8) on the ordered exploitation diagnostic.

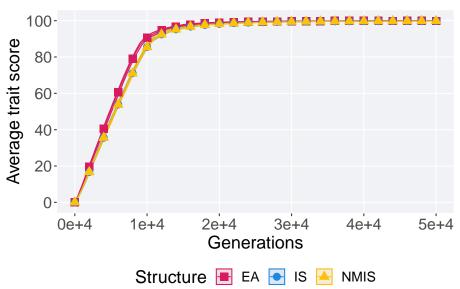
11.3.1 Performance over time

```
lines = filter(mi5000_over_time, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` == 'Temporary group_by(Structure, Generations) %>%
dplyr::summarise(
   min = min(pop_fit_max) / DIMENSIONALITY,
   mean = mean(pop_fit_max) / DIMENSIONALITY,
   max = max(pop_fit_max) / DIMENSIONALITY
)
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = Structure, geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
   geom_line(size = 0.5) +
   geom_point(data = filter(lines, Generations %% 2000 == 0), size = 2.5, stroke = 2.0, alpha = 1.
   scale_y_continuous(
   name="Average trait score",
   limits=c(-1, 101),
   breaks=seq(0,100, 20),
```

```
labels=c("0", "20", "40", "60", "80", "100")
) +
scale_x_continuous(
   name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")

) +
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette) +
scale_fill_manual(values = cb_palette) +
ggtitle("Performance over time") +
p_theme
```

Performance over time

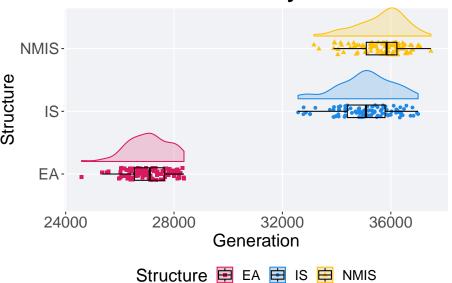


11.3.2 Generation satisfactory solution found

```
filter(mi5000_ssf, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` == 'TOUR' ggplot(., aes(x = Structure, y = Generations , color = Structure, fill = Structure, geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) + geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
```

```
scale_y_continuous(
   name="Generation"
) +
scale_x_discrete(
   name="Structure"
)+
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette, ) +
scale_fill_manual(values = cb_palette) +
ggtitle('Generation satisfactory solution found')+
p_theme + coord_flip()
```

Generation satisfactory solution found



11.3.2.1 Stats

Summary statistics for the first generation a satisfactory solution is found.

```
ssf = filter(mi5000_ssf, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` == 'TOURNAMEN'
ssf %>%
group_by(Structure) %>%
dplyr::summarise(
   count = n(),
   na_cnt = sum(is.na(Generations)),
   min = min(Generations, na.rm = TRUE),
   median = median(Generations, na.rm = TRUE),
   mean = mean(Generations, na.rm = TRUE),
```

```
max = max(Generations, na.rm = TRUE),
    IQR = IQR(Generations, na.rm = TRUE)
## # A tibble: 3 x 8
    Structure count na_cnt
                              min median
                                            mean
                                                   max
##
              <int> <int> <int> <dbl> <dbl> <int> <dbl>
                          0 24586 27104. 27057. 28367 1101.
## 1 EA
                 100
## 2 IS
                 100
                          0 32578 35082 35088. 37009 1392
## 3 NMIS
                 100
                          0 33162 35845 35659. 37481 1130.
Kruskal-Wallis test provides evidence of difference among selection schemes.
kruskal.test(Generations ~ Structure, data = ssf)
##
##
   Kruskal-Wallis rank sum test
##
## data: Generations by Structure
## Kruskal-Wallis chi-squared = 206.91, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = ssf$Generations, g = ssf$Structure, p.adjust.method = "bonfer.")
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: ssf$Generations and ssf$Structure
##
##
        EΑ
                TS
        < 2e-16 -
## IS
## NMIS < 2e-16 5.6e-05
##
```

11.4 Lexicase selection

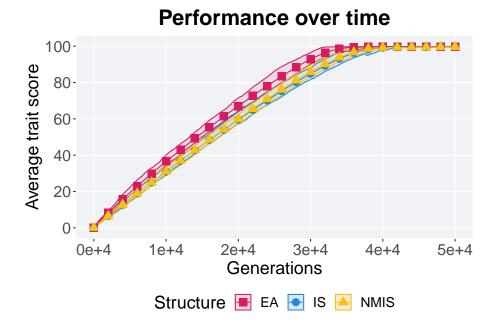
P value adjustment method: bonferroni

Here we analyze how the different population structures affect standard lexicase selection on the ordered exploitation diagnostic.

11.4.1 Performance over time

```
lines = filter(mi5000_over_time, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nSci
group_by(Structure, Generations) %>%
dplyr::summarise(
```

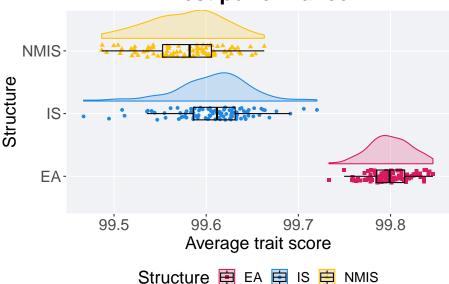
```
min = min(pop_fit_max) / DIMENSIONALITY,
   mean = mean(pop_fit_max) / DIMENSIONALITY,
   max = max(pop_fit_max) / DIMENSIONALITY
 )
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = Structure,
  geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom_line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 2.5, stroke = 2.0, alpha = 1.
  scale_y_continuous(
   name="Average trait score",
   limits=c(-1, 101),
   breaks = seq(0,100, 20),
   labels=c("0", "20", "40", "60", "80", "100")
  ) +
  scale_x_continuous(
   name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
  ) +
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle("Performance over time") +
  p_theme
```



11.4.2 Best performance

```
filter(mi5000_best, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` == 'LEX
  ggplot(., aes(x = Structure, y = VAL / DIMENSIONALITY, color = Structure, fill = Str
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = '
  geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_y_continuous(
   name="Average trait score"
  ) +
  scale_x_discrete(
   name="Structure"
  )+
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette, ) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Best performance')+
 p_theme + coord_flip()
```





11.4.2.1 Stats

2 IS

3 NMIS

Summary statistics for the first generation a satisfactory solution is found.

```
performance = filter(mi5000_best, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` ==
performance %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
   na_cnt = sum(is.na(VAL)),
   min = min(VAL, na.rm = TRUE) / DIMENSIONALITY,
   median = median(VAL, na.rm = TRUE) / DIMENSIONALITY,
   mean = mean(VAL, na.rm = TRUE) / DIMENSIONALITY,
   max = max(VAL, na.rm = TRUE) / DIMENSIONALITY,
    IQR = IQR(VAL, na.rm = TRUE) / DIMENSIONALITY
## # A tibble: 3 x 8
     Structure count na_cnt
                              min median
                                          mean
                                                         IQR
##
     <fct>
                      <int> <dbl>
                                   <dbl> <dbl> <dbl>
                                                       <dbl>
               <int>
## 1 EA
                 100
                             99.7
                                    99.8
                                          99.8
                                                 99.8 0.0303
```

99.5 Kruskal–Wallis test provides evidence of difference among selection schemes.

99.5

99.6

99.6

99.6

99.6

99.7 0.0454

99.7 0.0529

100

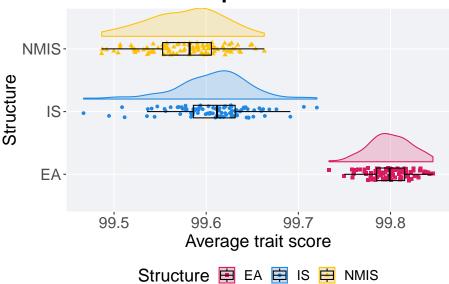
100

```
kruskal.test(VAL ~ Structure, data = performance)
##
##
   Kruskal-Wallis rank sum test
##
## data: VAL by Structure
## Kruskal-Wallis chi-squared = 211.11, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = performance$VAL, g = performance$Structure, p.adjust.method =
                     paired = FALSE, conf.int = FALSE, alternative = '1')
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: performance$VAL and performance$Structure
##
##
        F.A
                TS
## IS
        < 2e-16 -
## NMIS < 2e-16 4.1e-07
##
## P value adjustment method: bonferroni
```

11.4.3 Final performance

```
filter(mi5000_over_time, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` ==
  ggplot(., aes(x = Structure, y = pop_fit_max / DIMENSIONALITY, color = Structure, fit
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = '
  geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_y_continuous(
   name="Average trait score"
  ) +
  scale_x_discrete(
   name="Structure"
  )+
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette, ) +
  scale_fill_manual(values = cb_palette) +
 ggtitle('Final performance')+
 p_theme + coord_flip()
```





11.4.3.1 Stats

3 NMIS

Summary statistics for the first generation a satisfactory solution is found.

```
performance = filter(mi5000_over_time, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme`
performance %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
   na_cnt = sum(is.na(pop_fit_max)),
   min = min(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
   median = median(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
   mean = mean(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
   max = max(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
    IQR = IQR(pop_fit_max / DIMENSIONALITY, na.rm = TRUE)
## # A tibble: 3 x 8
     Structure count na_cnt
                              min median
                                          mean
                                                         IQR
##
     <fct>
                      <int> <dbl>
                                   <dbl> <dbl> <dbl>
                                                       <dbl>
               <int>
## 1 EA
                 100
                             99.7
                                     99.8
                                           99.8
                                                 99.8 0.0303
## 2 IS
                 100
                          0
                             99.5
                                     99.6
                                           99.6
                                                 99.7 0.0454
```

99.6

99.7 0.0529

Kruskal–Wallis test provides evidence of difference among selection schemes.

99.5

99.6

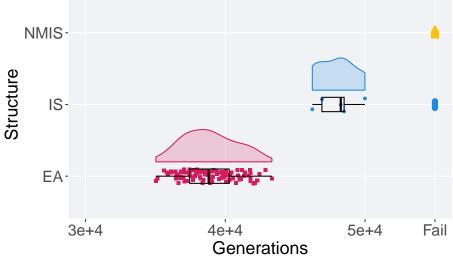
100

```
kruskal.test(pop_fit_max ~ Structure, data = performance)
##
##
   Kruskal-Wallis rank sum test
##
## data: pop_fit_max by Structure
## Kruskal-Wallis chi-squared = 211.12, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = performance$pop_fit_max, g = performance$Structure, p.adjust.
                     paired = FALSE, conf.int = FALSE, alternative = '1')
##
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: performance$pop_fit_max and performance$Structure
##
##
        EΑ
               TS
        <2e-16 -
## IS
## NMIS <2e-16 4e-07
## P value adjustment method: bonferroni
```

11.4.4 Generation satisfactory solution found

```
lex_fail = filter(mi5000_ssf, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nSchem.
lex_fail$Generations = 55000
lex_fail$Structure <- factor(lex_fail$Structure, levels = MODEL)</pre>
filter(mi5000_ssf, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` == 'LEXI
      ggplot(., aes(x = Structure, y = Generations, color = Structure, fill = Structure, sill = Structu
             geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha =
       geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
      geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
      geom_point(data = lex_fail, aes(x = Structure, y = Generations, color = Structure, f
       scale_shape_manual(values=SHAPE)+
      scale_y_continuous(
            name="Generations",
            limits=c(30000, 55000),
            breaks=c(30000, 40000, 50000, 55000),
            labels=c("3e+4", "4e+4", "5e+4", "Fail")
      ) +
       scale_x_discrete(
```

```
name="Structure"
) +
scale_colour_manual(values = cb_palette) +
scale_fill_manual(values = cb_palette) +
p_theme + coord_flip()
```



Structure 🖹 EA 📮 IS 📴 NMIS

11.4.4.1 Stats

Summary statistics for the first generation a satisfactory solution is found.

<fct> <int> <int> <dbl> <dbl> <int> <dbl>

```
ssf = filter(mi5000_ssf, Diagnostic == 'ORDERED_EXPLOITATION' & `Selection\nScheme` == 'LEXICASE'
ssf %>%
group_by(Structure) %>%
dplyr::summarise(
   count = n(),
   na_cnt = sum(is.na(Generations)),
   min = min(Generations, na.rm = TRUE),
   median = median(Generations, na.rm = TRUE),
   mean = mean(Generations, na.rm = TRUE),
   max = max(Generations, na.rm = TRUE),
   IQR = IQR(Generations, na.rm = TRUE)
)

## # A tibble: 2 x 8
## Structure count na_cnt min median mean max IQR
```

```
## 1 EA
                  100
                           0 35033 38809 38906. 43331 2822.
## 2 IS
                           0 46227 48262 47980. 49992 1587
Kruskal-Wallis test provides evidence of difference among selection schemes.
kruskal.test(Generations ~ Structure, data = ssf)
##
##
   Kruskal-Wallis rank sum test
##
## data: Generations by Structure
## Kruskal-Wallis chi-squared = 14.151, df = 1, p-value = 0.0001687
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = ssf$Generations, g = ssf$Structure, p.adjust.method = "bonfer.")
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: ssf$Generations and ssf$Structure
##
      ΕA
##
## IS 8.7e-05
##
```

P value adjustment method: bonferroni

Chapter 12

MI5000: Contradictory objectives results

Here we present the results for the **satisfactory trait corverage** and **activation gene coverage** generated by each selection scheme replicate on the contradictory objectives diagnostic the configurations presented below. Note both of these values are gathered at the population-level. Activation gene coverage refers to the count of unique activation genes in a given population; this gives us a range of integers between 0 and 100. Satisfactory trait coverage refers to the count of unique satisfied traits in a given population; this gives us a range of integers between 0 and 100. For our the configuration of these experiments, we execute migrations every 50 generations and there are 4 islands in a ring topology. When migrations occur, two individuals are swapped (same position on each island) and guarantee that no solution can return to its original island.

12.1 Analysis dependencies

```
library(ggplot2)
library(cowplot)
library(dplyr)
library(PupillometryR)
```

12.2 Truncation selection

Here we analyze how the different population structures affect truncation selection (size 8) on the contradictory objectives diagnostic.

12.2.1 Satisfactory trait coverage

Satisfactory trait coverage analysis.

12.2.1.1 Coverage over time

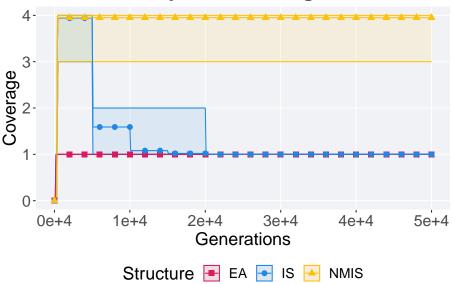
Satisfactory trait coverage over time.

```
lines = filter(mi5000_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection'
group_by(Structure, Generations) %>%
dplyr::summarise(
   min = min(pop_sat_cov),
   mean = mean(pop_sat_cov),
   max = max(pop_sat_cov)
)
```

`summarise()` has grouped output by 'Structure'. You can override using the
`.groups` argument.

```
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = x
 geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom_line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 1.5, stroke = 2.0,
 scale_y_continuous(
   name="Coverage"
 ) +
  scale_x_continuous(
    name="Generations",
   limits=c(0, 50000),
    breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
 ) +
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette) +
 scale_fill_manual(values = cb_palette) +
 ggtitle('Satisfactory trait coverage over time')+
 p_theme
```



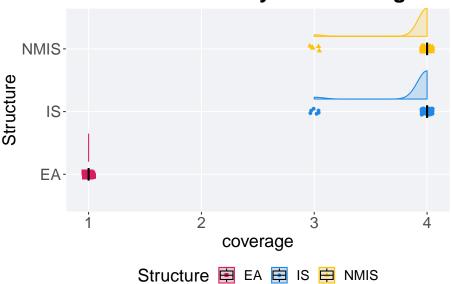


12.2.1.2 Best coverage throughout

Best satisfactory trait coverage throughout 50,000 generations.

```
### best satisfactory trait coverage throughout
filter(mi5000_best, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` == 'TRUNCATION'
ggplot(., aes(x = Structure, y = VAL, color = Structure, fill = Structure, shape = Structure))
geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.2) +
geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha = 1.0) +
geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
scale_y_continuous(
    name="coverage"
) +
scale_x_discrete(
    name="Structure"
)+
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette, ) +
scale_fill_manual(values = cb_palette) +
ggtitle('Best satisfactory trait coverage')+
p_theme + coord_flip()
```

Best satisfactory trait coverage



12.2.1.2.1 Stats

Summary statistics for the best satisfactory trait coverage.

```
### best
coverage = filter(mi5000_best, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\ni
coverage %>%
  group_by(Structure) %>%
 dplyr::summarise(
    count = n(),
   na_cnt = sum(is.na(VAL)),
   min = min(VAL, na.rm = TRUE),
   median = median(VAL, na.rm = TRUE),
   mean = mean(VAL, na.rm = TRUE),
   max = max(VAL, na.rm = TRUE),
    IQR = IQR(VAL, na.rm = TRUE)
## # A tibble: 3 x 8
    Structure count na cnt
                              min median mean
##
               <int> <int> <dbl>
                                   <dbl> <dbl> <dbl> <dbl>
## 1 EA
                 100
                          0
## 2 IS
                 100
                          0
                                3
                                       4 3.94
                                                    4
                                                          0
## 3 NMIS
                 100
                          0
                                3
                                          3.95
```

Kruskal-Wallis test provides evidence of difference among satisfactory trait

```
coverage.
```

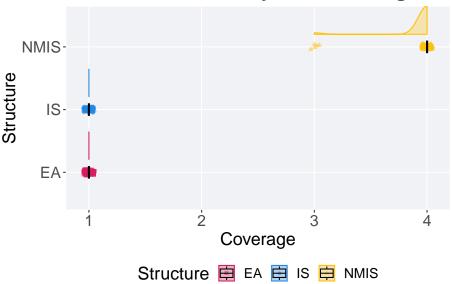
```
kruskal.test(VAL ~ Structure, data = coverage)
##
## Kruskal-Wallis rank sum test
##
## data: VAL by Structure
## Kruskal-Wallis chi-squared = 279.63, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on
satisfactory trait coverage.
pairwise.wilcox.test(x = coverage$VAL, g = coverage$Structure, p.adjust.method = "bonferroni",
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: coverage$VAL and coverage$Structure
##
##
        EΑ
               IS
      <2e-16 -
## IS
## NMIS <2e-16 1
##
## P value adjustment method: bonferroni
```

12.2.1.3 End of 50,000 generations

Satisfactory trait coverage in the population at the end of 50,000 generations.

```
### end of run
filter(mi5000_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` == 'TRUNC
  ggplot(., aes(x = Structure, y = pop_sat_cov, color = Structure, fill = Structure, shape = Structure,
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.3) +
  geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha = 0.5) +
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_shape_manual(values=SHAPE)+
  scale_y_continuous(
   name="Coverage"
  scale_x_discrete(
   name="Structure"
  ) +
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Final satisfactory trait coverage')+
  p_theme + coord_flip()
```

Final satisfactory trait coverage



12.2.1.3.1 Stats

Summary statistics for satisfactory trait coverage in the population at the end of 50,000 generations.

```
### end of run
coverage = filter(mi5000_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Select
coverage %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
    na_cnt = sum(is.na(pop_sat_cov)),
    min = min(pop_sat_cov, na.rm = TRUE),
    median = median(pop_sat_cov, na.rm = TRUE),
    mean = mean(pop_sat_cov, na.rm = TRUE),
    max = max(pop_sat_cov, na.rm = TRUE),
    IQR = IQR(pop_sat_cov, na.rm = TRUE)
)
```

```
## # A tibble: 3 x 8
    Structure count na_cnt
                           min median mean
                                                  IQR
##
    <fct>
             <int> <int> <int> <dbl> <dbl> <int> <dbl>
## 1 EA
               100
                       0
                                   1 1
                                              1
                                                    0
                             1
## 2 IS
                                   1 1
              100
                       0
                             1
                                              1
## 3 NMIS
              100
                       0
                             3
                                   4 3.95
```

Kruskal–Wallis test provides evidence of difference among satisfactory trait coverage in the population at the end of 50,000 generations.

kruskal.test(pop_sat_cov ~ Structure, data = coverage)

```
##
## Kruskal-Wallis rank sum test
##
## data: pop_sat_cov by Structure
## Kruskal-Wallis chi-squared = 296.65, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on
satisfactory trait coverage in the population at the end of 50,000 generations.
pairwise.wilcox.test(x = coverage$pop_sat_cov, g = coverage$Structure, p.adjust.method = "bonfern
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: coverage$pop_sat_cov and coverage$Structure
##
##
        EΑ
               IS
## IS
## NMIS <2e-16 <2e-16
## P value adjustment method: bonferroni
```

12.2.2 Activation gene coverage

Activation gene coverage analysis.

12.2.2.1 Coverage over time

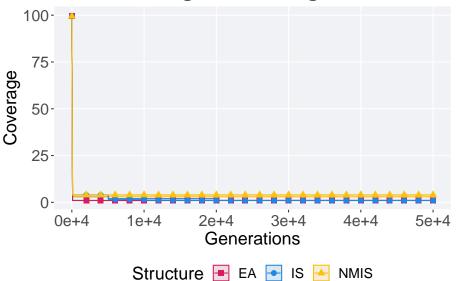
Activation gene coverage over time.

`.groups` argument.

```
# data for lines and shading on plots
lines = filter(mi5000_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` =
group_by(Structure, Generations) %>%
dplyr::summarise(
   min = min(pop_act_cov),
   mean = mean(pop_act_cov),
   max = max(pop_act_cov)
)
## `summarise()` has grouped output by 'Structure'. You can override using the
```

```
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = 3
  geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom_line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 1.5, stroke = 2.0,
  scale_y_continuous(
    name="Coverage"
  ) +
  scale_x_continuous(
   name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
 ) +
  scale_shape_manual(values=SHAPE)+
 scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Activation gene coverage over time')+
 p_theme
```

Activation gene coverage over time

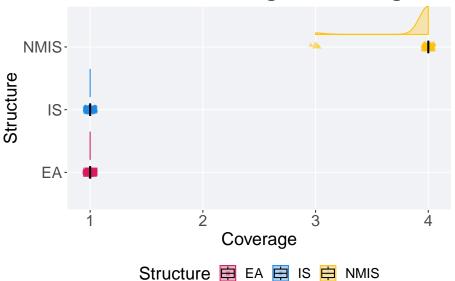


12.2.2.2 End of 50,000 generations

Activation gene coverage in the population at the end of 50,000 generations.

```
### end of run
filter(mi5000_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` == 'TRUNG
  ggplot(., aes(x = Structure, y = pop_act_cov, color = Structure, fill = Structure, shape = Stru
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.3) +
  geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha = 0.5) +
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_shape_manual(values=SHAPE)+
  scale_y_continuous(
   name="Coverage"
  ) +
  scale_x_discrete(
   name="Structure"
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Final activation gene coverage')+
  p_theme + coord_flip()
```

Final activation gene coverage



12.2.2.2.1 Stats

Summary statistics for activation gene coverage.

```
coverage = filter(mi5000_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme
coverage %>%
  group_by(Structure) %>%
```

dplyr::summarise(

P value adjustment method: bonferroni

```
count = n(),
    na_cnt = sum(is.na(pop_act_cov)),
   min = min(pop_act_cov, na.rm = TRUE),
   median = median(pop_act_cov, na.rm = TRUE),
   mean = mean(pop_act_cov, na.rm = TRUE),
   max = max(pop_act_cov, na.rm = TRUE),
    IQR = IQR(pop_act_cov, na.rm = TRUE)
## # A tibble: 3 x 8
     Structure count na_cnt min median mean
                                                 max
     <fct> <int> <int> <dbl> <dbl> <int> <dbl>
##
## 1 EA
               100
                       0 1
                                     1 1
                                                  1
## 2 IS
               100
                          0
                                       1 1
                                                   1
                                                         0
                                1
## 3 NMIS
                 100
                          0
                                3
                                       4 3.95
                                                   4
                                                         0
Kruskal-Wallis test provides evidence of difference among activation gene cover-
age.
kruskal.test(pop_act_cov ~ Structure, data = coverage)
##
##
   Kruskal-Wallis rank sum test
##
## data: pop_act_cov by Structure
## Kruskal-Wallis chi-squared = 296.65, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on
activation gene coverage.
pairwise.wilcox.test(x = coverage pop_act_cov, g = coverage Structure, p.adjust.method
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: coverage$pop_act_cov and coverage$Structure
##
##
       F.A
               TS
## IS
       1
## NMIS <2e-16 <2e-16
```

12.3 Tournament selection

Here we analyze how the different population structures affect tournament selection (size 8) on the contradictory objectives diagnostic.

12.3.1 Satisfactory trait coverage

Satisfactory trait coverage analysis.

12.3.1.1 Coverage over time

p_theme

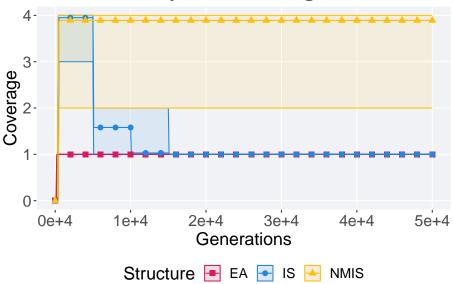
Satisfactory trait coverage over time.

```
lines = filter(mi5000_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` =
    group_by(Structure, Generations) %>%
    dplyr::summarise(
        min = min(pop_sat_cov),
        mean = mean(pop_sat_cov),
        max = max(pop_sat_cov)
)

## `summarise()` has grouped output by 'Structure'. You can override using the
## `.groups` argument.
```

ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = Structure, geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) + geom line(size = 0.5) + geom_point(data = filter(lines, Generations %% 2000 == 0), size = 1.5, stroke = 2.0, alpha = 1. scale_y_continuous(name="Coverage" scale_x_continuous(name="Generations", limits=c(0, 50000),breaks=c(0, 10000, 20000, 30000, 40000, 50000), labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")) + scale_shape_manual(values=SHAPE)+ scale_colour_manual(values = cb_palette) + scale_fill_manual(values = cb_palette) + ggtitle('Satisfactory trait coverage over time')+



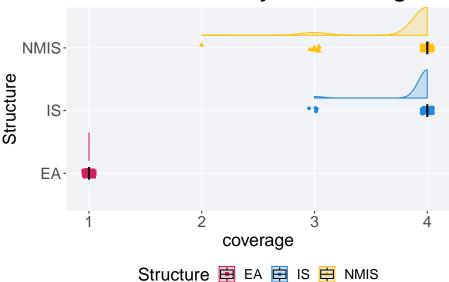


12.3.1.2 Best coverage throughout

Best satisfactory trait coverage throughout 50,000 generations.

```
### best satisfactory trait coverage throughout
filter(mi5000_best, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` ==
  ggplot(., aes(x = Structure, y = VAL, color = Structure, fill = Structure, shape = S
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = '
  geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_y_continuous(
   name="coverage"
  ) +
  scale_x_discrete(
   name="Structure"
  )+
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette, ) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Best satisfactory trait coverage')+
 p_theme + coord_flip()
```





12.3.1.2.1 Stats

3 NMIS

100

Summary statistics for the best satisfactory trait coverage.

```
### best
coverage = filter(mi5000_best, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` ==
coverage %>%
  group_by(Structure) %>%
  dplyr::summarise(
   count = n(),
   na_cnt = sum(is.na(VAL)),
   min = min(VAL, na.rm = TRUE),
   median = median(VAL, na.rm = TRUE),
   mean = mean(VAL, na.rm = TRUE),
   max = max(VAL, na.rm = TRUE),
   IQR = IQR(VAL, na.rm = TRUE)
## # A tibble: 3 x 8
     Structure count na cnt
                              min median mean
               <int> <int> <dbl>
                                   <dbl> <dbl> <dbl> <dbl> <
     <fct>
## 1 EA
                 100
                          0
## 2 IS
                 100
                          0
                                3
                                       4 3.95
                                                    4
                                                          0
```

4 3.89

Kruskal-Wallis test provides evidence of difference among satisfactory trait

0

coverage.

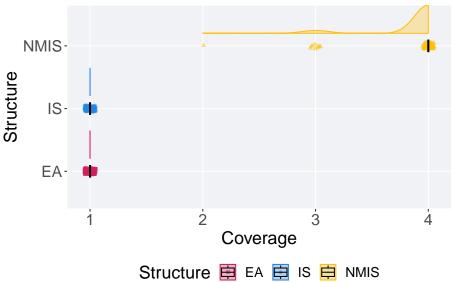
```
kruskal.test(VAL ~ Structure, data = coverage)
##
## Kruskal-Wallis rank sum test
##
## data: VAL by Structure
## Kruskal-Wallis chi-squared = 273.91, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on
satisfactory trait coverage.
pairwise.wilcox.test(x = coverage$VAL, g = coverage$Structure, p.adjust.method = "bonf")
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: coverage$VAL and coverage$Structure
##
##
        EΑ
               IS
       <2e-16 -
## IS
## NMIS <2e-16 1
## P value adjustment method: bonferroni
```

12.3.1.3 End of 50,000 generations

Satisfactory trait coverage in the population at the end of 50,000 generations.

```
### end of run
filter(mi5000_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme
       ggplot(., aes(x = Structure, y = pop_sat_cov, color = Structure, fill = Structure, sill = Structu
        geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = '
       geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha
        geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
       scale_shape_manual(values=SHAPE)+
       scale_y_continuous(
              name="Coverage"
       ) +
       scale_x_discrete(
              name="Structure"
       ) +
       scale_colour_manual(values = cb_palette) +
       scale_fill_manual(values = cb_palette) +
       ggtitle('Final satisfactory trait coverage')+
       p_theme + coord_flip()
```





12.3.1.3.1 Stats

Summary statistics for satisfactory trait coverage in the population at the end of $50,\!000$ generations.

```
### end of run
coverage = filter(mi5000_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme
coverage %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
    na_cnt = sum(is.na(pop_sat_cov)),
    min = min(pop_sat_cov, na.rm = TRUE),
    median = median(pop_sat_cov, na.rm = TRUE),
    mean = mean(pop_sat_cov, na.rm = TRUE),
    max = max(pop_sat_cov, na.rm = TRUE),
    IQR = IQR(pop_sat_cov, na.rm = TRUE)
)
```

```
## # A tibble: 3 x 8
    Structure count na_cnt
                             min median mean
                                                      IQR
    <fct>
              <int> <int> <int> <dbl> <dbl> <int> <dbl>
## 1 EA
                100
                         0
                               1
                                      1 1
## 2 IS
                         0
                               1
                                      1 1
                                                  1
                                                        0
                100
## 3 NMIS
                100
                         0
                               2
                                      4 3.89
```

Kruskal–Wallis test provides evidence of difference among satisfactory trait coverage in the population at the end of 50,000 generations.

```
kruskal.test(pop_sat_cov ~ Structure, data = coverage)
##
##
   Kruskal-Wallis rank sum test
##
## data: pop_sat_cov by Structure
## Kruskal-Wallis chi-squared = 294.58, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on
satisfactory trait coverage in the population at the end of 50,000 generations.
pairwise.wilcox.test(x = coverage$pop_sat_cov, g = coverage$Structure, p.adjust.method
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: coverage$pop_sat_cov and coverage$Structure
##
##
        EΑ
               IS
## IS
## NMIS <2e-16 <2e-16
## P value adjustment method: bonferroni
```

12.3.2 Activation gene coverage

Activation gene coverage analysis.

12.3.2.1 Coverage over time

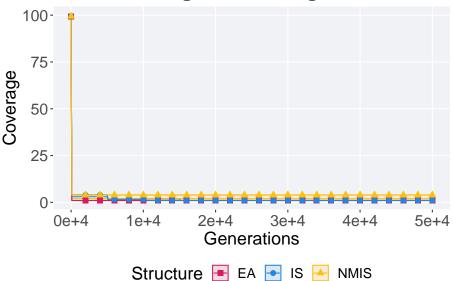
Activation gene coverage over time.

```
# data for lines and shading on plots
lines = filter(mi5000_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection'
group_by(Structure, Generations) %>%
dplyr::summarise(
   min = min(pop_act_cov),
   mean = mean(pop_act_cov),
   max = max(pop_act_cov)
)
```

```
## `summarise()` has grouped output by 'Structure'. You can override using the
## `.groups` argument.
```

```
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = Structure,
  geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom_line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 1.5, stroke = 2.0, alpha = 1.
  scale_y_continuous(
    name="Coverage"
  ) +
  scale_x_continuous(
   name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
  ) +
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Activation gene coverage over time')+
  p_theme
```

Activation gene coverage over time

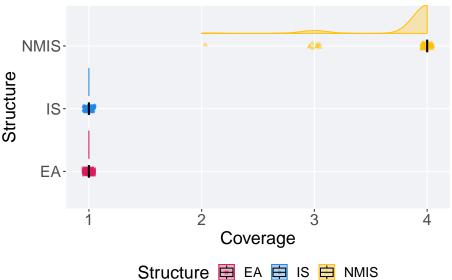


12.3.2.2 End of 50,000 generations

Activation gene coverage in the population at the end of 50,000 generations.

```
### end of run
filter(mi5000_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme
  ggplot(., aes(x = Structure, y = pop_act_cov, color = Structure, fill = Structure, si
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = '
  geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_shape_manual(values=SHAPE)+
  scale_y_continuous(
   name="Coverage"
  ) +
  scale_x_discrete(
   name="Structure"
  ) +
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Final activation gene coverage')+
 p_theme + coord_flip()
```

Final activation gene coverage



12.3.2.2.1 Stats

Summary statistics for activation gene coverage.

```
coverage = filter(mi5000_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Select
coverage %>%
  group_by(Structure) %>%
```

NMIS <2e-16 <2e-16

P value adjustment method: bonferroni

```
dplyr::summarise(
    count = n(),
   na_cnt = sum(is.na(pop_act_cov)),
   min = min(pop_act_cov, na.rm = TRUE),
   median = median(pop_act_cov, na.rm = TRUE),
   mean = mean(pop_act_cov, na.rm = TRUE),
   max = max(pop_act_cov, na.rm = TRUE),
   IQR = IQR(pop_act_cov, na.rm = TRUE)
## # A tibble: 3 x 8
     Structure count na_cnt min median mean
                                                 max
   <fct> <int> <int> <int> <dbl> <dbl> <int> <dbl>
## 1 EA
               100
                         0
                              1
                                     1 1
                                                   1
## 2 IS
                 100
                          0
                                1
                                       1 1
                                                   1
                                                         0
                                       4 3.89
## 3 NMIS
                 100
                          0
                                2
                                                   4
                                                         0
Kruskal-Wallis test provides evidence of difference among activation gene cover-
age.
kruskal.test(pop_act_cov ~ Structure, data = coverage)
##
## Kruskal-Wallis rank sum test
##
## data: pop_act_cov by Structure
## Kruskal-Wallis chi-squared = 294.58, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on
activation gene coverage.
pairwise.wilcox.test(x = coverage$pop_act_cov, g = coverage$Structure, p.adjust.method = "bonfer")
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
## data: coverage$pop_act_cov and coverage$Structure
##
##
       EΑ
               TS
## IS
      1
```

12.4 Lexicase selection

Here we analyze how the different population structures affect standard lexicase selection on the contradictory objectives diagnostic.

12.4.1 Satisfactory trait coverage

Satisfactory trait coverage analysis.

12.4.1.1 Coverage over time

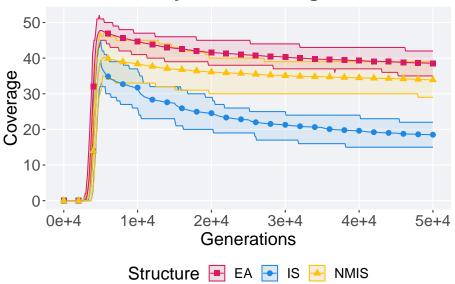
Satisfactory trait coverage over time.

```
lines = filter(mi5000_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection'
group_by(Structure, Generations) %>%
dplyr::summarise(
   min = min(pop_sat_cov),
   mean = mean(pop_sat_cov),
   max = max(pop_sat_cov)
)
```

`summarise()` has grouped output by 'Structure'. You can override using the
`.groups` argument.

```
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color 
        geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
        geom line(size = 0.5) +
        geom_point(data = filter(lines, Generations %% 2000 == 0), size = 1.5, stroke = 2.0,
        scale_y_continuous(
               name="Coverage"
        ) +
        scale_x_continuous(
                name="Generations",
               limits=c(0, 50000),
                breaks=c(0, 10000, 20000, 30000, 40000, 50000),
                labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
        ) +
        scale_shape_manual(values=SHAPE)+
        scale_colour_manual(values = cb_palette) +
        scale_fill_manual(values = cb_palette) +
       ggtitle('Satisfactory trait coverage over time')+
       p_theme
```



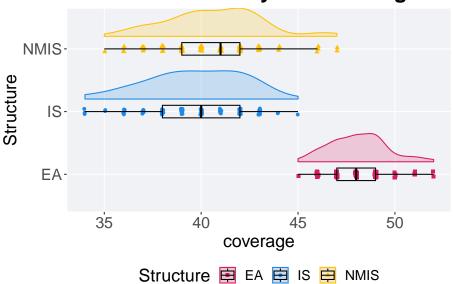


12.4.1.2 Best coverage throughout

Best satisfactory trait coverage throughout 50,000 generations.

```
### best satisfactory trait coverage throughout
filter(mi5000_best, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` == 'LEXICASE'
    ggplot(., aes(x = Structure, y = VAL, color = Structure, fill = Structure, shape = Structure))
    geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.2) +
    geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha = 1.0) +
    geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
    scale_y_continuous(
        name="coverage"
    ) +
    scale_x_discrete(
        name="Structure"
    )+
    scale_shape_manual(values=SHAPE)+
    scale_colour_manual(values = cb_palette, ) +
    scale_fill_manual(values = cb_palette) +
    ggtitle('Best satisfactory trait coverage')+
    p_theme + coord_flip()
```

Best satisfactory trait coverage



12.4.1.2.1 Stats

3 IS

100

0 34

Summary statistics for the best satisfactory trait coverage.

```
### best
coverage = filter(mi5000_best, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\n:
coverage$Structure = factor(coverage$Structure, levels=c('EA','NMIS','IS'))
coverage %>%
  group_by(Structure) %>%
 dplyr::summarise(
    count = n(),
   na_cnt = sum(is.na(VAL)),
   min = min(VAL, na.rm = TRUE),
   median = median(VAL, na.rm = TRUE),
   mean = mean(VAL, na.rm = TRUE),
   max = max(VAL, na.rm = TRUE),
    IQR = IQR(VAL, na.rm = TRUE)
## # A tibble: 3 x 8
     Structure count na_cnt
                              min median mean
                                                        IQR
                                                  max
##
     <fct>
               <int> <int> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <
## 1 EA
                 100
                          0
                               45
                                       48 48.1
                                                   52
                                                          2
## 2 NMIS
                 100
                          0
                               35
                                       41 40.6
                                                   47
                                                          3
```

40 39.7

45

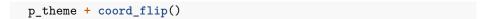
Kruskal–Wallis test provides evidence of difference among satisfactory trait coverage.

```
kruskal.test(VAL ~ Structure, data = coverage)
##
## Kruskal-Wallis rank sum test
##
## data: VAL by Structure
## Kruskal-Wallis chi-squared = 200.46, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on
satisfactory trait coverage.
pairwise.wilcox.test(x = coverage$VAL, g = coverage$Structure, p.adjust.method = "bonferroni",
                     paired = FALSE, conf.int = FALSE, alternative = '1')
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
##
## data: coverage$VAL and coverage$Structure
##
##
        EΑ
               NMIS
## NMIS <2e-16 -
## IS <2e-16 0.025
##
## P value adjustment method: bonferroni
```

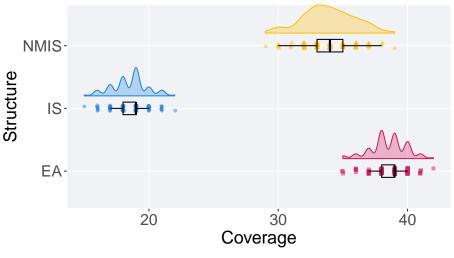
12.4.1.3 End of 50,000 generations

Satisfactory trait coverage in the population at the end of 50,000 generations.

```
### end of run
filter(mi5000_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` == 'LEXIC
ggplot(., aes(x = Structure, y = pop_sat_cov, color = Structure, fill = Structure, shape = Stru
geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.3) +
geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha = 0.5) +
geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
scale_shape_manual(values=SHAPE)+
scale_y_continuous(
    name="Coverage"
) +
scale_x_discrete(
    name="Structure"
) +
scale_colour_manual(values = cb_palette) +
scale_fill_manual(values = cb_palette) +
ggtitle('Final satisfactory trait coverage')+
```



Final satisfactory trait coverage



Structure 🖹 EA 📋 IS 🛱 NMIS

12.4.1.3.1 Stats

1 EA

Summary statistics for satisfactory trait coverage in the population at the end of $50,\!000$ generations.

<fct> <int> <int> <int> <dbl> <dbl> <int> <dbl>

35

0

100

```
### end of run
coverage = filter(mi5000_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Select
coverage$Structure = factor(coverage$Structure, levels=c('EA','NMIS','IS'))
coverage %>%
  group_by(Structure) %>%
 dplyr::summarise(
    count = n(),
   na_cnt = sum(is.na(pop_sat_cov)),
   min = min(pop_sat_cov, na.rm = TRUE),
   median = median(pop_sat_cov, na.rm = TRUE),
   mean = mean(pop_sat_cov, na.rm = TRUE),
   max = max(pop_sat_cov, na.rm = TRUE),
    IQR = IQR(pop_sat_cov, na.rm = TRUE)
  )
## # A tibble: 3 x 8
    Structure count na_cnt
                                                       IQR
                              min median mean
```

39 38.5

42

```
## 2 NMIS 100 0 29 34 33.9 39 2
## 3 IS 100 0 15 19 18.5 22 1
```

Kruskal–Wallis test provides evidence of difference among satisfactory trait coverage in the population at the end of 50,000 generations.

```
kruskal.test(pop_sat_cov ~ Structure, data = coverage)
##
## Kruskal-Wallis rank sum test
##
## data: pop_sat_cov by Structure
## Kruskal-Wallis chi-squared = 259.02, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on
satisfactory trait coverage in the population at the end of 50,000 generations.
pairwise.wilcox.test(x = coverage$pop_sat_cov, g = coverage$Structure, p.adjust.method = "bonfern
                      paired = FALSE, conf.int = FALSE, alternative = '1')
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: coverage$pop_sat_cov and coverage$Structure
##
##
        EΑ
               NMIS
## NMIS <2e-16 -
## IS
       <2e-16 <2e-16
##
## P value adjustment method: bonferroni
```

12.4.2 Activation gene coverage

Activation gene coverage analysis.

12.4.2.1 Coverage over time

Activation gene coverage over time.

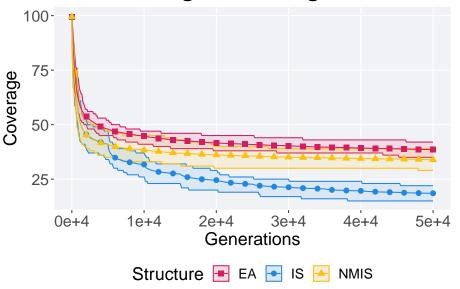
```
# data for lines and shading on plots
lines = filter(mi5000_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` =
group_by(Structure, Generations) %>%
dplyr::summarise(
   min = min(pop_act_cov),
   mean = mean(pop_act_cov),
   max = max(pop_act_cov)
)
```

`summarise()` has grouped output by 'Structure'. You can override using the

```
## `.groups` argument.
```

```
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = 3
  geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom_line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 1.5, stroke = 2.0,
  scale_y_continuous(
    name="Coverage"
  ) +
  scale_x_continuous(
    name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
  ) +
 scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Activation gene coverage over time')+
 p_theme
```

Activation gene coverage over time

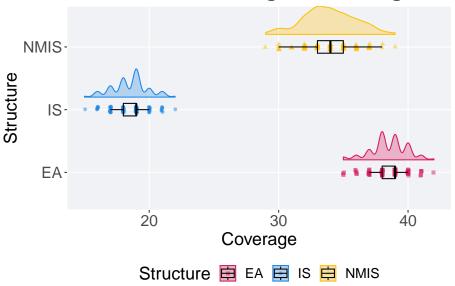


12.4.2.2 End of 50,000 generations

Activation gene coverage in the population at the end of 50,000 generations.

```
### end of run
filter(mi5000_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme` == 'LEXIC
  ggplot(., aes(x = Structure, y = pop_act_cov, color = Structure, fill = Structure, shape = Stru
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.3) +
  geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha = 0.5) +
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_shape_manual(values=SHAPE)+
  scale_y_continuous(
   name="Coverage"
  ) +
  scale_x_discrete(
   name="Structure"
  ) +
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Final activation gene coverage')+
  p_theme + coord_flip()
```

Final activation gene coverage



12.4.2.2.1 Stats

Summary statistics for activation gene coverage.

```
coverage = filter(mi5000_over_time, Diagnostic == 'CONTRADICTORY_OBJECTIVES' & `Selection\nScheme
coverage$Structure = factor(coverage$Structure, levels=c('EA','NMIS','IS'))
coverage %>%
```

```
group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
    na_cnt = sum(is.na(pop_act_cov)),
   min = min(pop_act_cov, na.rm = TRUE),
   median = median(pop_act_cov, na.rm = TRUE),
   mean = mean(pop_act_cov, na.rm = TRUE),
    max = max(pop_act_cov, na.rm = TRUE),
    IQR = IQR(pop_act_cov, na.rm = TRUE)
 )
## # A tibble: 3 x 8
    Structure count na_cnt
                                                        IQR
                              min median mean
                                                 max
     <fct> <int> <int> <dbl> <dbl> <int> <dbl>
                                      39 38.5
                                                  42
## 1 EA
                100
                        0 35
                                                          1
## 2 NMIS
                 100
                          0
                               29
                                      34 33.9
                                                   39
                                                          2
                 100
                               15
                                                  22
## 3 IS
                          0
                                      19 18.5
                                                          1
Kruskal-Wallis test provides evidence of difference among activation gene cover-
kruskal.test(pop_act_cov ~ Structure, data = coverage)
##
##
   Kruskal-Wallis rank sum test
##
## data: pop_act_cov by Structure
## Kruskal-Wallis chi-squared = 259.02, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on
activation gene coverage.
pairwise.wilcox.test(x = coverage$pop_act_cov, g = coverage$Structure, p.adjust.method
                     paired = FALSE, conf.int = FALSE, alternative = '1')
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: coverage$pop_act_cov and coverage$Structure
##
##
        EΑ
               NMIS
## NMIS <2e-16 -
## IS
        <2e-16 <2e-16
##
## P value adjustment method: bonferroni
```

Chapter 13

MI5000: Multi-path exploration results

Here we present the results for the **best performances** and **activation gene coverage** generated by each selection scheme replicate on the multi-path exploration diagnostic with configurations presented below. For our the configuration of these experiments, we execute migrations every 50 generations and there are 4 islands in a ring topology. Best performance found refers to the largest average trait score found in a given population. Note that activation gene coverage values are gathered at the population-level. Activation gene coverage refers to the count of unique activation genes in a given population; this gives us a range of integers between 0 and 100.

13.1 Analysis dependencies

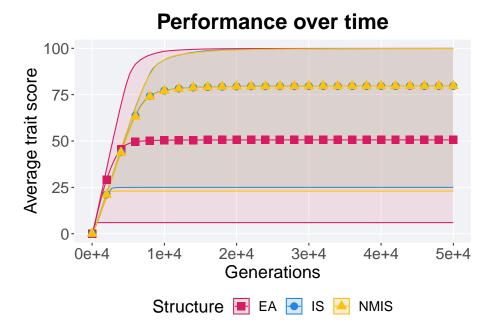
```
library(ggplot2)
library(cowplot)
library(dplyr)
library(PupillometryR)
```

13.2 Truncation selection

Here we analyze how the different population structures affect truncation selection (size 8) on the contradictory objectives diagnostic.

13.2.1 Performance

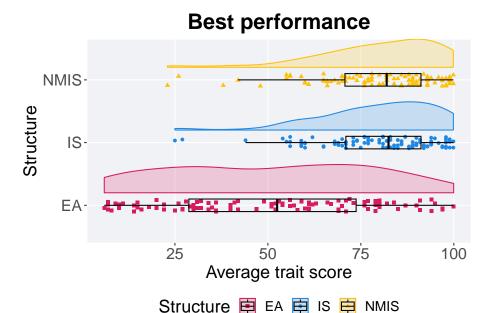
```
lines = filter(mi5000_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nS
  group_by(Structure, Generations) %>%
  dplyr::summarise(
   min = min(pop_fit_max) / DIMENSIONALITY,
   mean = mean(pop_fit_max) / DIMENSIONALITY,
   max = max(pop_fit_max) / DIMENSIONALITY
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = 3
  geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom_line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 2.5, stroke = 2.0,
  scale_y_continuous(
   name="Average trait score"
  ) +
  scale_x_continuous(
    name="Generations",
   limits=c(0, 50000),
    breaks=c(0, 10000, 20000, 30000, 40000, 50000),
    labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
  ) +
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle("Performance over time") +
  p_theme
```



13.2.1.2 Best performance

First generation a satisfactory solution is found throughout the 50,000 generations.

```
filter(mi5000_best, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'TRUNCATION' &
ggplot(., aes(x = Structure, y = VAL / DIMENSIONALITY, color = Structure, fill = Structure, sha
geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.2) +
geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
scale_y_continuous(
    name="Average trait score"
) +
scale_x_discrete(
    name="Structure"
)+
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette, ) +
scale_fill_manual(values = cb_palette) +
ggtitle('Best performance')+
p_theme + coord_flip()
```



13.2.1.2.1 Stats

3 NMIS

100

Summary statistics for the first generation a satisfactory solution is found.

```
performance = filter(mi5000_best, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\ns
performance %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
    na_cnt = sum(is.na(VAL)),
    min = min(VAL, na.rm = TRUE) / DIMENSIONALITY,
    median = median(VAL, na.rm = TRUE) / DIMENSIONALITY,
    mean = mean(VAL, na.rm = TRUE) / DIMENSIONALITY,
    max = max(VAL, na.rm = TRUE) / DIMENSIONALITY,
    IQR = IQR(VAL, na.rm = TRUE) / DIMENSIONALITY
## # A tibble: 3 x 8
     Structure count na_cnt
                              min median mean
##
     <fct>
               <int>
                      <int> <dbl>
                                   <dbl> <dbl> <dbl> <dbl> <
## 1 EA
                 100
                                     52.5
                                           50.6 100.
                                                       45.0
                          0
                              6
## 2 IS
                 100
                          0
                             25.0
                                     82.5
                                          79.7
                                                 99.9
                                                       20.2
```

82.0 79.7

99.9 20.5

Kruskal–Wallis test provides evidence of difference among selection schemes.

23.0

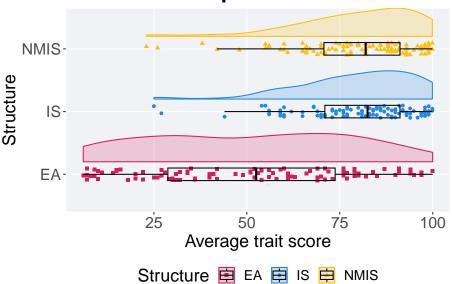
```
kruskal.test(VAL ~ Structure, data = performance)
##
## Kruskal-Wallis rank sum test
##
## data: VAL by Structure
## Kruskal-Wallis chi-squared = 75.468, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = performance$VAL, g = performance$Structure, p.adjust.method = "bonferror
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
## data: performance$VAL and performance$Structure
##
##
        EΑ
                IS
## IS 8.2e-14 -
## NMIS 8.7e-14 1
##
## P value adjustment method: bonferroni
```

13.2.1.3 Final performance

First generation a satisfactory solution is found throughout the 50,000 generations.

```
filter(mi5000_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & Selection\nScheme` == 'TRUNCATI
ggplot(., aes(x = Structure, y = pop_fit_max / DIMENSIONALITY, color = Structure, fill = Struct
geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.2) +
geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
scale_y_continuous(
    name="Average trait score"
) +
scale_x_discrete(
    name="Structure"
)+
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette, ) +
scale_fill_manual(values = cb_palette) +
ggtitle('Final performance')+
p_theme + coord_flip()
```





13.2.1.3.1 Stats

3 NMIS

100

Summary statistics for the first generation a satisfactory solution is found.

```
performance = filter(mi5000_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Select
performance %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
    na_cnt = sum(is.na(pop_fit_max)),
    min = min(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
    median = median(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
    mean = mean(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
    max = max(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
    IQR = IQR(pop_fit_max / DIMENSIONALITY, na.rm = TRUE)
## # A tibble: 3 x 8
     Structure count na_cnt
                              min median mean
##
     <fct>
               <int>
                      <int> <dbl>
                                    <dbl> <dbl> <dbl> <dbl> <
## 1 EA
                 100
                                          50.6 100.
                                                       45.0
                          0
                              6
                                     52.5
## 2 IS
                 100
                          0
                             25.0
                                     82.5
                                          79.7
                                                 99.9
                                                       20.2
```

82.0 79.7

99.9

Kruskal–Wallis test provides evidence of difference among selection schemes.

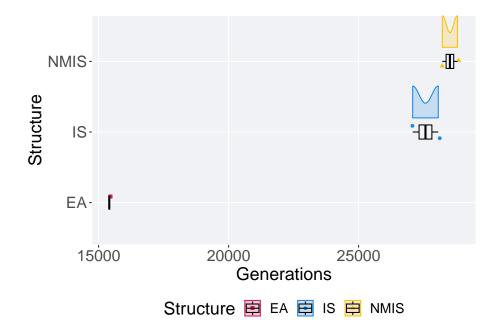
23.0

```
kruskal.test(pop_fit_max ~ Structure, data = performance)
##
   Kruskal-Wallis rank sum test
##
## data: pop_fit_max by Structure
## Kruskal-Wallis chi-squared = 75.468, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = performance pop_fit_max, g = performance Structure, p.adjust.method = "h
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: performance$pop_fit_max and performance$Structure
##
##
        EΑ
                IS
## IS
       8.2e-14 -
## NMIS 8.7e-14 1
## P value adjustment method: bonferroni
```

13.2.2 Generation satisfactory solution found

First generation a satisfactory solution is found throughout the 50,000 generations

```
filter(mi5000_ssf, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'TRUNCATION'& (
    ggplot(., aes(x = Structure, y = Generations, color = Structure, fill = Structure, shape = Structure, geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.2) +
    geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
    geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
    scale_shape_manual(values=SHAPE)+
    scale_y_continuous(
        name="Generations") +
    scale_x_discrete(
        name="Structure") +
    scale_colour_manual(values = cb_palette) +
    scale_fill_manual(values = cb_palette) +
    p_theme + coord_flip()
```



13.2.2.1 Stats

Summary statistics for the first generation a satisfactory solution is found.

```
ssf = filter(mi5000_ssf, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` ==
ssf %>%
  group_by(Structure) %>%
 dplyr::summarise(
    count = n(),
    na_cnt = sum(is.na(Generations)),
   min = min(Generations, na.rm = TRUE),
   median = median(Generations, na.rm = TRUE),
   mean = mean(Generations, na.rm = TRUE),
   max = max(Generations, na.rm = TRUE),
    IQR = IQR(Generations, na.rm = TRUE)
## # A tibble: 3 x 8
    Structure count na_cnt
                              min median mean
                                                        IQR
##
     <fct>
               <int>
                     <int> <int>
                                   <dbl> <dbl> <int> <dbl>
## 1 EA
                   1
                          0 15409
                                   15409 15409 15409
## 2 IS
                   2
                                   27572 27572 28064
                          0 27080
                                                        492
## 3 NMIS
                          0 28220
                                   28512 28512 28804
```

Kruskal–Wallis test provides evidence of no difference among selection schemes.

```
###
## Kruskal-Wallis rank sum test
##
## data: Generations by Structure
## Kruskal-Wallis chi-squared = 3.6, df = 2, p-value = 0.1653
```

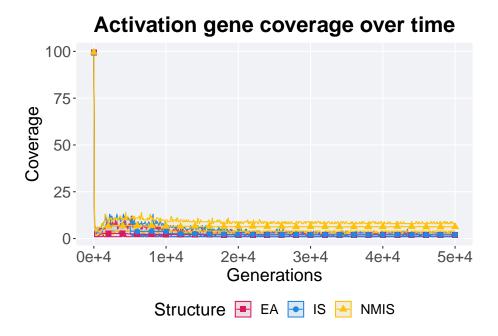
13.2.3 Activation gene coverage

Activation gene coverage analysis.

13.2.3.1 Coverage over time

Activation gene coverage over time.

```
# data for lines and shading on plots
lines = filter(mi5000_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == '
  group_by(Structure, Generations) %>%
  dplyr::summarise(
   min = min(pop_act_cov),
   mean = mean(pop_act_cov),
   max = max(pop_act_cov)
## `summarise()` has grouped output by 'Structure'. You can override using the
## `.groups` argument.
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = Structure,
  geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 1.5, stroke = 2.0, alpha = 1.
  scale_y_continuous(
   name="Coverage"
  ) +
  scale_x_continuous(
   name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
  ) +
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Activation gene coverage over time')+
  p_theme
```

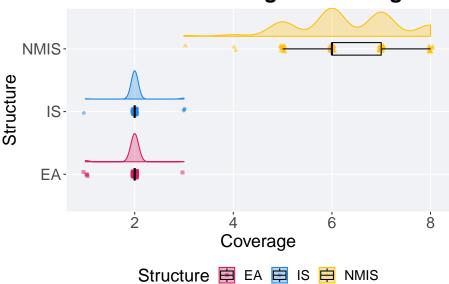


13.2.3.2 End of 50,000 generations

Activation gene coverage in the population at the end of 50,000 generations.

```
### end of run
filter(mi5000_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` ==
  ggplot(., aes(x = Structure, y = pop_act_cov, color = Structure, fill = Structure, si
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = '
  geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_shape_manual(values=SHAPE)+
  scale_y_continuous(
   name="Coverage"
  ) +
  scale_x_discrete(
   name="Structure"
  ) +
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Final activation gene coverage')+
 p_theme + coord_flip()
```





13.2.3.2.1 Stats

Summary statistics for activation gene coverage.

```
coverage = filter(mi5000_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` =
coverage %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
    na_cnt = sum(is.na(pop_act_cov)),
    min = min(pop_act_cov, na.rm = TRUE),
    median = median(pop_act_cov, na.rm = TRUE),
    mean = mean(pop_act_cov, na.rm = TRUE),
    max = max(pop_act_cov, na.rm = TRUE),
    IQR = IQR(pop_act_cov, na.rm = TRUE)
)
```

```
## # A tibble: 3 x 8
                                                         IQR
     Structure count na_cnt
                               min median mean
                                                  max
##
               <int>
                     <int> <int>
                                    <dbl> <dbl> <int> <dbl>
## 1 EA
                 100
                          0
                                        2 1.97
                                                           0
                                 1
## 2 IS
                 100
                           0
                                           2.02
                                                    3
                                                           0
## 3 NMIS
                 100
                           0
                                 3
                                        6 6.33
                                                           1
```

Kruskal–Wallis test provides evidence of difference among activation gene coverage.

```
kruskal.test(pop_act_cov ~ Structure, data = coverage)
##
##
   Kruskal-Wallis rank sum test
##
## data: pop_act_cov by Structure
## Kruskal-Wallis chi-squared = 269.84, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on
activation gene coverage.
pairwise.wilcox.test(x = coverage$pop_act_cov, g = coverage$Structure, p.adjust.method
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: coverage$pop_act_cov and coverage$Structure
##
##
        EΑ
               IS
## IS
        0.15
## NMIS <2e-16 <2e-16
##
## P value adjustment method: bonferroni
```

13.3 Tournament selection

Here we analyze how the different population structures affect tournament selection (size 8) on the contradictory objectives diagnostic.

13.3.1 Performance

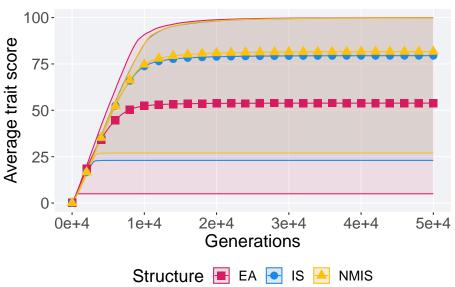
13.3.1.1 Performance over time

```
lines = filter(mi5000_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nS
group_by(Structure, Generations) %>%
dplyr::summarise(
    min = min(pop_fit_max) / DIMENSIONALITY,
    mean = mean(pop_fit_max) / DIMENSIONALITY,
    max = max(pop_fit_max) / DIMENSIONALITY
)
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
    geom_line(size = 0.5) +
    geom_point(data = filter(lines, Generations %% 2000 == 0), size = 2.5, stroke = 2.0, scale_y_continuous(
```

```
name="Average trait score"
) +
scale_x_continuous(
  name="Generations",
  limits=c(0, 50000),
  breaks=c(0, 10000, 20000, 30000, 40000, 50000),
  labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")

) +
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette) +
scale_fill_manual(values = cb_palette) +
ggtitle("Performance over time") +
p_theme
```

Performance over time

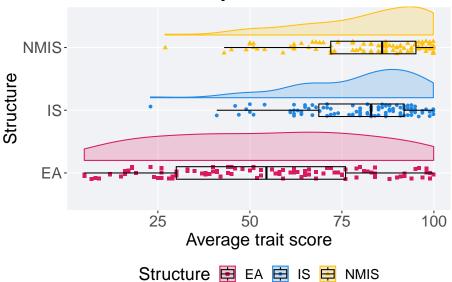


13.3.1.2 Best performance

```
filter(mi5000_best, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'TOURNAMENT' & ggplot(., aes(x = Structure, y = VAL / DIMENSIONALITY, color = Structure, fill = Structure, sha geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.2) + geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) + geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
```

```
scale_y_continuous(
   name="Average trait score"
) +
scale_x_discrete(
   name="Structure"
)+
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette, ) +
scale_fill_manual(values = cb_palette) +
ggtitle('Best performance')+
p_theme + coord_flip()
```

Best performance



13.3.1.2.1 Stats

Summary statistics for the first generation a satisfactory solution is found.

```
performance = filter(mi5000_best, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\ni
performance %>%
  group_by(Structure) %>%
  dplyr::summarise(
   count = n(),
   na_cnt = sum(is.na(VAL)),
   min = min(VAL, na.rm = TRUE) / DIMENSIONALITY,
   median = median(VAL, na.rm = TRUE) / DIMENSIONALITY,
  mean = mean(VAL, na.rm = TRUE) / DIMENSIONALITY,
```

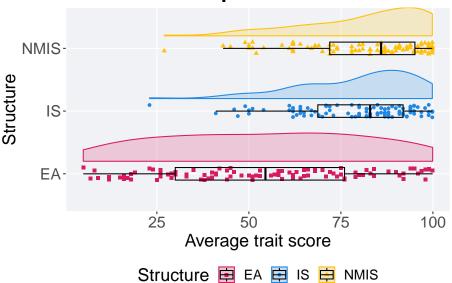
```
max = max(VAL, na.rm = TRUE) / DIMENSIONALITY,
   IQR = IQR(VAL, na.rm = TRUE) / DIMENSIONALITY
 )
## # A tibble: 3 x 8
   Structure count na_cnt
                              min median mean
                                                        IQR
##
   <fct>
               <int> <int> <dbl> <dbl> <dbl> <dbl> <dbl> <
## 1 EA
                 100
                          0 5
                                    54.5 53.9
                                                99.9
## 2 IS
                 100
                          0 23.0
                                    82.9 79.5
                                                99.8 23.2
## 3 NMIS
                 100
                          0 27.0
                                    85.9 81.6
                                                99.8 23.1
Kruskal–Wallis test provides evidence of difference among selection schemes.
kruskal.test(VAL ~ Structure, data = performance)
##
## Kruskal-Wallis rank sum test
##
## data: VAL by Structure
## Kruskal-Wallis chi-squared = 63.856, df = 2, p-value = 1.361e-14
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = performance$VAL, g = performance$Structure, p.adjust.method = "bonferror
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
## data: performance$VAL and performance$Structure
##
##
        EΑ
                IS
## IS
       6.2e-11 -
## NMIS 1.5e-12 0.37
## P value adjustment method: bonferroni
```

13.3.1.3 Final performance

```
filter(mi5000_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'TOURNAME
ggplot(., aes(x = Structure, y = pop_fit_max / DIMENSIONALITY, color = Structure, fill = Struct
geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.2) +
geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
scale_y_continuous(
    name="Average trait score"
```

```
) +
scale_x_discrete(
  name="Structure"
)+
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette, ) +
scale_fill_manual(values = cb_palette) +
ggtitle('Final performance')+
p_theme + coord_flip()
```

Final performance



13.3.1.3.1 Stats

Summary statistics for the first generation a satisfactory solution is found.

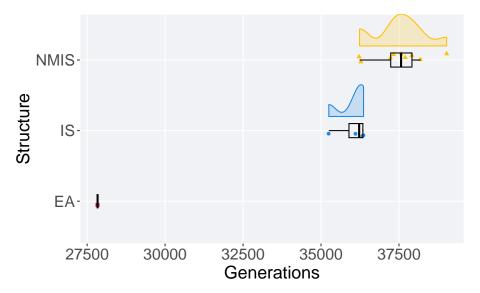
```
performance = filter(mi5000_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Select
performance %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
    na_cnt = sum(is.na(pop_fit_max)),
    min = min(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
    median = median(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
    mean = mean(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
    max = max(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
    IQR = IQR(pop_fit_max / DIMENSIONALITY, na.rm = TRUE)
```

```
## # A tibble: 3 x 8
     Structure count na_cnt
                              min median mean
                                                        IQR
                                                  max
            <int> <int> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <
## 1 EA
                 100
                          0
                              5
                                     54.5 53.9
                                                 99.9 46.0
## 2 IS
                 100
                          0 23.0
                                     82.9
                                           79.5
                                                 99.8
                                                       23.2
## 3 NMTS
                 100
                          0 27.0
                                     85.9 81.6 99.8 23.1
Kruskal–Wallis test provides evidence of difference among selection schemes.
kruskal.test(pop_fit_max ~ Structure, data = performance)
##
## Kruskal-Wallis rank sum test
##
## data: pop_fit_max by Structure
## Kruskal-Wallis chi-squared = 63.856, df = 2, p-value = 1.361e-14
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = performance pop_fit_max, g = performance Structure, p.adjust.method = "land")
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
## data: performance$pop_fit_max and performance$Structure
##
##
        EA
## IS 6.2e-11 -
## NMIS 1.5e-12 0.37
##
## P value adjustment method: bonferroni
```

13.3.2 Generation satisfactory solution found

```
filter(mi5000_ssf, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'TOURNAMENT'& (
    ggplot(., aes(x = Structure, y = Generations, color = Structure, fill = Structure, shape = Stru
        geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.2) +
    geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
    geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
    scale_shape_manual(values=SHAPE)+
    scale_y_continuous(
        name="Generations"
```

```
) +
scale_x_discrete(
  name="Structure"
) +
scale_colour_manual(values = cb_palette) +
scale_fill_manual(values = cb_palette) +
p_theme + coord_flip()
```



Structure 🖹 EA 🗎 IS 🛱 NMIS

13.3.2.1 Stats

Summary statistics for the first generation a satisfactory solution is found.

```
ssf = filter(mi5000_ssf, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` ==
ssf %>%
group_by(Structure) %>%
dplyr::summarise(
   count = n(),
   na_cnt = sum(is.na(Generations)),
   min = min(Generations, na.rm = TRUE),
   median = median(Generations, na.rm = TRUE),
   mean = mean(Generations, na.rm = TRUE),
   max = max(Generations, na.rm = TRUE),
   IQR = IQR(Generations, na.rm = TRUE)
)
```

A tibble: 3 x 8

```
Structure count na_cnt
                              min median
                                                         IQR
                                           mean
              <int> <int> <int> <dbl> <dbl> <int> <dbl>
## 1 EA
                          0 27835 27835 27835 27835
                                                         0
                   1
## 2 IS
                   4
                          0 35249 36223 36015. 36364
                                                       445.
## 3 NMIS
                   9
                          0 36235 37567 37498. 39029
Kruskal–Wallis test provides evidence of no difference among selection schemes.
kruskal.test(Generations ~ Structure, data = ssf)
##
## Kruskal-Wallis rank sum test
##
## data: Generations by Structure
## Kruskal-Wallis chi-squared = 6.6444, df = 2, p-value = 0.03607
pairwise.wilcox.test(x = ssf$Generations, g = ssf$Structure, p.adjust.method = "bonferroni",
                     paired = FALSE, conf.int = FALSE, alternative = 'g')
##
## Pairwise comparisons using Wilcoxon rank sum exact test
##
## data: ssf$Generations and ssf$Structure
##
        EΑ
##
             IS
      0.60 -
## IS
## NMIS 0.30 0.05
## P value adjustment method: bonferroni
```

13.3.3 Activation gene coverage

Activation gene coverage analysis.

13.3.3.1 Coverage over time

Activation gene coverage over time.

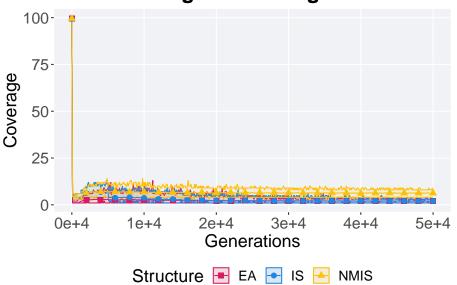
```
# data for lines and shading on plots
lines = filter(mi5000_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == group_by(Structure, Generations) %>%
dplyr::summarise(
   min = min(pop_act_cov),
   mean = mean(pop_act_cov),
   max = max(pop_act_cov)
)
```

`summarise()` has grouped output by 'Structure'. You can override using the

```
## `.groups` argument.
```

```
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = 3
  geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom_line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 1.5, stroke = 2.0,
  scale_y_continuous(
    name="Coverage"
  ) +
  scale_x_continuous(
    name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
  ) +
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Activation gene coverage over time')+
 p_theme
```

Activation gene coverage over time

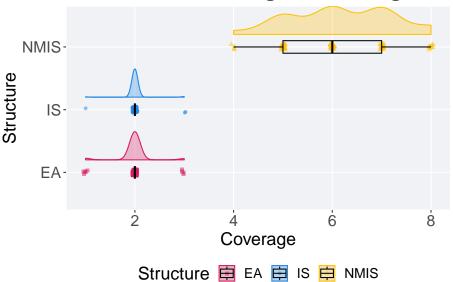


13.3.3.2 End of 50,000 generations

Activation gene coverage in the population at the end of 50,000 generations.

```
### end of run
filter(mi5000_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'TOURNAME
  ggplot(., aes(x = Structure, y = pop_act_cov, color = Structure, fill = Structure, shape = Stru
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.3) +
  geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha = 0.5) +
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_shape_manual(values=SHAPE)+
  scale_y_continuous(
   name="Coverage"
  ) +
  scale_x_discrete(
   name="Structure"
  ) +
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Final activation gene coverage')+
  p_theme + coord_flip()
```

Final activation gene coverage



13.3.3.2.1 Stats

Summary statistics for activation gene coverage.

```
coverage = filter(mi5000_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` =
coverage %>%
  group_by(Structure) %>%
```

```
dplyr::summarise(
   count = n(),
   na_cnt = sum(is.na(pop_act_cov)),
   min = min(pop_act_cov, na.rm = TRUE),
   median = median(pop_act_cov, na.rm = TRUE),
   mean = mean(pop_act_cov, na.rm = TRUE),
   max = max(pop_act_cov, na.rm = TRUE),
   IQR = IQR(pop_act_cov, na.rm = TRUE)
## # A tibble: 3 x 8
##
    Structure count na_cnt
                            min median mean
                                                    IQR
                                              max
    <fct> <int> <int> <dbl> <dbl> <int> <dbl>
##
## 1 EA
              100
                     0 1
                                    2 1.99
                                             3
## 2 IS
              100
                        0
                                    2 2.01
                                                3
                                                     0
                             1
## 3 NMIS
               100
                        0
                              4
                                    6 6.2
                                                8
                                                     2
```

Kruskal–Wallis test provides evidence of difference among activation gene coverage.

```
kruskal.test(pop_act_cov ~ Structure, data = coverage)
```

```
##
## Kruskal-Wallis rank sum test
##
## data: pop_act_cov by Structure
## Kruskal-Wallis chi-squared = 265.43, df = 2, p-value < 2.2e-16</pre>
```

Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on activation gene coverage.

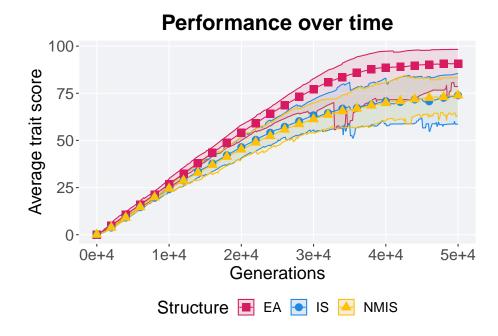
```
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: coverage$pop_act_cov and coverage$Structure
##
## EA IS
## IS 0.85 -
## NMIS <2e-16 <2e-16
##
## P value adjustment method: bonferroni</pre>
```

13.4 Lexicase selection

Here we analyze how the different population structures affect standard lexicase selection on the contradictory objectives diagnostic.

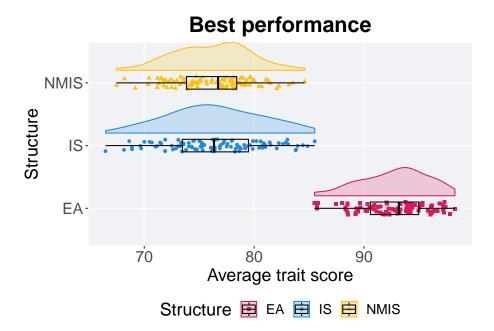
13.4.1 Performance

```
lines = filter(mi5000_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == '
  group_by(Structure, Generations) %>%
  dplyr::summarise(
   min = min(pop_fit_max) / DIMENSIONALITY,
   mean = mean(pop_fit_max) / DIMENSIONALITY,
   max = max(pop_fit_max) / DIMENSIONALITY
ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = Structure,
  geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
  geom_line(size = 0.5) +
  geom_point(data = filter(lines, Generations %% 2000 == 0), size = 2.5, stroke = 2.0, alpha = 1.
  scale_y_continuous(
   name="Average trait score"
  scale_x_continuous(
   name="Generations",
   limits=c(0, 50000),
   breaks=c(0, 10000, 20000, 30000, 40000, 50000),
   labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
  ) +
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette) +
  scale_fill_manual(values = cb_palette) +
  ggtitle("Performance over time") +
  p_theme
```



13.4.1.2 Best performance

```
filter(mi5000_best, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'LE
  ggplot(., aes(x = Structure, y = VAL / DIMENSIONALITY, color = Structure, fill = Str
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = '
  geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_y_continuous(
   name="Average trait score"
  ) +
  scale_x_discrete(
   name="Structure"
  )+
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette, ) +
  scale_fill_manual(values = cb_palette) +
  ggtitle('Best performance')+
 p_theme + coord_flip()
```



13.4.1.2.1 Stats

3 IS

Summary statistics for the first generation a satisfactory solution is found.

```
performance = filter(mi5000_best, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` ==
performance$Structure = factor(performance$Structure, levels=c('EA','NMIS','IS'))
performance %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
   na_cnt = sum(is.na(VAL)),
   min = min(VAL, na.rm = TRUE) / DIMENSIONALITY,
   median = median(VAL, na.rm = TRUE) / DIMENSIONALITY,
   mean = mean(VAL, na.rm = TRUE) / DIMENSIONALITY,
   max = max(VAL, na.rm = TRUE) / DIMENSIONALITY,
    IQR = IQR(VAL, na.rm = TRUE) / DIMENSIONALITY
## # A tibble: 3 x 8
     Structure count na cnt
                              min median
                                                        IQR
                                          mean
##
                                   <dbl> <dbl> <dbl> <dbl> <
     <fct>
               <int>
                      <int> <dbl>
## 1 EA
                 100
                             85.5
                                    93.2
                                          92.8
                                                98.3
## 2 NMIS
                 100
                          0
                             67.5
                                    76.7
                                          76.2
                                                84.6
                                                      4.57
```

76.3 76.4 85.5 6.01

Kruskal–Wallis test provides evidence of difference among selection schemes.

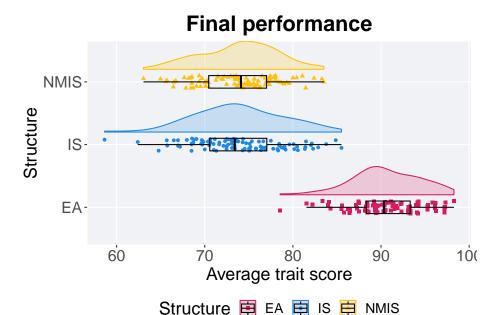
66.5

100

```
kruskal.test(VAL ~ Structure, data = performance)
##
##
   Kruskal-Wallis rank sum test
##
## data: VAL by Structure
## Kruskal-Wallis chi-squared = 199.33, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = performance$VAL, g = performance$Structure, p.adjust.method =
                     paired = FALSE, conf.int = FALSE, alternative = '1')
##
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: performance$VAL and performance$Structure
##
##
        EΑ
               NMIS
## NMIS <2e-16 -
## IS
        <2e-16 1
##
## P value adjustment method: bonferroni
```

13.4.1.3 Final performance

```
filter(mi5000_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` ==
  ggplot(., aes(x = Structure, y = pop_fit_max / DIMENSIONALITY, color = Structure, fi
  geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = '
  geom_point(position = position_jitter(width = .1), size = 1.5, alpha = 1.0) +
  geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
  scale_y_continuous(
   name="Average trait score"
  ) +
  scale_x_discrete(
   name="Structure"
  )+
  scale_shape_manual(values=SHAPE)+
  scale_colour_manual(values = cb_palette, ) +
  scale_fill_manual(values = cb_palette) +
 ggtitle('Final performance')+
 p_theme + coord_flip()
```



13.4.1.3.1 Stats

Summary statistics for the first generation a satisfactory solution is found.

```
performance = filter(mi5000_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme
performance$Structure = factor(performance$Structure, levels=c('EA','NMIS','IS'))
performance %>%
  group_by(Structure) %>%
  dplyr::summarise(
    count = n(),
   na_cnt = sum(is.na(pop_fit_max)),
   min = min(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
   median = median(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
   mean = mean(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
   max = max(pop_fit_max / DIMENSIONALITY, na.rm = TRUE),
    IQR = IQR(pop_fit_max / DIMENSIONALITY, na.rm = TRUE)
## # A tibble: 3 x 8
     Structure count na cnt
                              min median
                                                        IQR
                                          mean
##
                                   <dbl> <dbl> <dbl> <dbl> <
     <fct>
               <int>
                      <int> <dbl>
## 1 EA
                 100
                             78.5
                                    90.3
                                          90.5
                                                 98.3
## 2 NMIS
                 100
                          0
                             63.0
                                    74.1
                                          73.9
                                                 83.5
                                                      6.57
## 3 IS
                 100
                             58.6
                                    73.4 73.9
                                                85.5
```

Kruskal–Wallis test provides evidence of difference among selection schemes.

```
kruskal.test(pop_fit_max ~ Structure, data = performance)
##
##
   Kruskal-Wallis rank sum test
##
## data: pop_fit_max by Structure
## Kruskal-Wallis chi-squared = 196.97, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction.
pairwise.wilcox.test(x = performance$pop_fit_max, g = performance$Structure, p.adjust.
                     paired = FALSE, conf.int = FALSE, alternative = '1')
##
##
   Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data: performance$pop_fit_max and performance$Structure
##
##
               NMTS
        EΑ
## NMIS <2e-16 -
## IS
        <2e-16 1
## P value adjustment method: bonferroni
```

13.4.2 Activation gene coverage

Activation gene coverage analysis.

13.4.2.1 Coverage over time

Activation gene coverage over time.

```
# data for lines and shading on plots
lines = filter(mi5000_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nSet
group_by(Structure, Generations) %>%
dplyr::summarise(
   min = min(pop_act_cov),
   mean = mean(pop_act_cov),
   max = max(pop_act_cov)
)
```

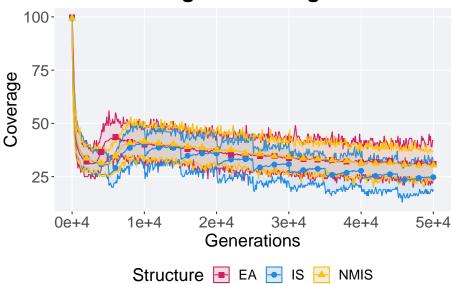
```
## `summarise()` has grouped output by 'Structure'. You can override using the
## `.groups` argument.

ggplot(lines, aes(x=Generations, y=mean, group = Structure, fill = Structure, color = geom_ribbon(aes(ymin = min, ymax = max), alpha = 0.1) +
    geom_line(size = 0.5) +
```

geom_point(data = filter(lines, Generations %% 2000 == 0), size = 1.5, stroke = 2.0,

```
scale_y_continuous(
  name="Coverage"
) +
scale_x_continuous(
  name="Generations",
  limits=c(0, 50000),
  breaks=c(0, 10000, 20000, 30000, 40000, 50000),
  labels=c("0e+4", "1e+4", "2e+4", "3e+4", "4e+4", "5e+4")
) +
scale_shape_manual(values=SHAPE)+
scale_colour_manual(values = cb_palette) +
scale_fill_manual(values = cb_palette) +
ggtitle('Activation gene coverage over time')+
p_theme
```

Activation gene coverage over time



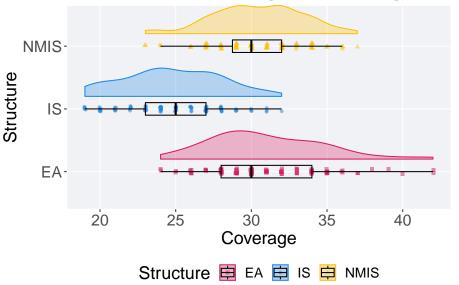
13.4.2.2 End of 50,000 generations

Activation gene coverage in the population at the end of 50,000 generations.

```
### end of run
filter(mi5000_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection\nScheme` == 'LEXICASE
    ggplot(., aes(x = Structure, y = pop_act_cov, color = Structure, fill = Structure, shape = Structure, geom_flat_violin(position = position_nudge(x = .2, y = 0), scale = 'width', alpha = 0.3) +
    geom_point(position = position_jitter(height = .05, width = .05), size = 1.5, alpha = 0.5) +
```

```
geom_boxplot(color = 'black', width = .2, outlier.shape = NA, alpha = 0.0) +
scale_shape_manual(values=SHAPE)+
scale_y_continuous(
   name="Coverage"
) +
scale_x_discrete(
   name="Structure"
) +
scale_colour_manual(values = cb_palette) +
scale_fill_manual(values = cb_palette) +
ggtitle('Final activation gene coverage')+
p_theme + coord_flip()
```

Final activation gene coverage



13.4.2.2.1 Stats

Summary statistics for activation gene coverage. $\,$

```
coverage = filter(mi5000_over_time, Diagnostic == 'MULTIPATH_EXPLORATION' & `Selection'
coverage$Structure = factor(coverage$Structure, levels=c('EA','NMIS','IS'))
coverage %>%
  group_by(Structure) %>%
  dplyr::summarise(
   count = n(),
   na_cnt = sum(is.na(pop_act_cov)),
   min = min(pop_act_cov, na.rm = TRUE),
```

P value adjustment method: bonferroni

```
median = median(pop_act_cov, na.rm = TRUE),
   mean = mean(pop_act_cov, na.rm = TRUE),
   max = max(pop_act_cov, na.rm = TRUE),
    IQR = IQR(pop_act_cov, na.rm = TRUE)
## # A tibble: 3 x 8
     Structure count na_cnt
                              min median mean
                                                  max
                                                        IQR
     <fct>
               <int> <int> <int> <dbl> <dbl> <int> <dbl>
## 1 EA
                 100
                          0
                               24
                                       30
                                          31
                                                   42 6
                                                   37 3.25
## 2 NMIS
                 100
                          0
                               23
                                       30 30.4
## 3 IS
                 100
                          0
                               19
                                       25 24.8
                                                   32 4
Kruskal-Wallis test provides evidence of difference among activation gene cover-
kruskal.test(pop_act_cov ~ Structure, data = coverage)
##
## Kruskal-Wallis rank sum test
## data: pop_act_cov by Structure
## Kruskal-Wallis chi-squared = 130.57, df = 2, p-value < 2.2e-16
Results for post-hoc Wilcoxon rank-sum test with a Bonferroni correction on
activation gene coverage.
pairwise.wilcox.test(x = coverage$pop_act_cov, g = coverage$Structure, p.adjust.method = "bonfer")
                     paired = FALSE, conf.int = FALSE, alternative = '1')
##
## Pairwise comparisons using Wilcoxon rank sum test with continuity correction
## data: coverage$pop_act_cov and coverage$Structure
##
##
        EΑ
               NMIS
## NMIS 0.81
## IS <2e-16 <2e-16
##
```