

The Evolution of Cellular Restraint in Multicellular Organisms

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Chapter 1

Introduction

This document serves as the supplemental material for the ALife 2021 conference submission “The Evolution of Cellular Restraint in Multicellular Organisms”.

1.1 Overview

The document is split into sections that are assessable via the navigation bar on the left side of the screen. Each section corresponds to an experiment (some that were discussed at length in the paper, others that were not included). As such, each section follows the same formula: setup, plots, and statistics.

1.2 Interactive web app

To build intuition on how organisms fill, we created an interactive web app, available here: <http://fergusonaj.com/webapps/primordium/>

Chapter 2

Baseline: Varying organism size

Here we show all of the data for the baseline experiment in which we vary organism size while all other parameters are set to their default values.

For this experiment, we also tested size 8x8 and 1024x1024 organisms. In the paper, however, we only included sizes 16x16 to 512x512. Size 8x8 organisms are quick to run, but these smaller organisms see the most noise in the fitness data. Conversely, size 1024x1024 organisms take so long to run that it was not computationally feasible to run them for each experiment.

Here, we show these results for the baseline experiment, including these additional sizes. The configuration script and data for the experiment can be found under 2021_02_26__org_sizes/ in the experiments directory of the git repository.

2.1 Data cleaning

Load necessary R libraries

```
library(dplyr)
library(ggplot2)
library(ggribes)
library(scales)
library(khroma)
```

Load the data and trim to only include the final generation

```
# Load the data
df = read.csv('../experiments/2021_02_26__org_sizes/evolution/data/scraped_evolution_data.csv')
# Trim off NAs (artifacts of how we scraped the data) and trim to only have gen 10,000
```

```
df2 = df[!is.na(df$MCSIZE) & df$generation == 10000,]
```

Group and summarize the data to ensure all replicates are present.

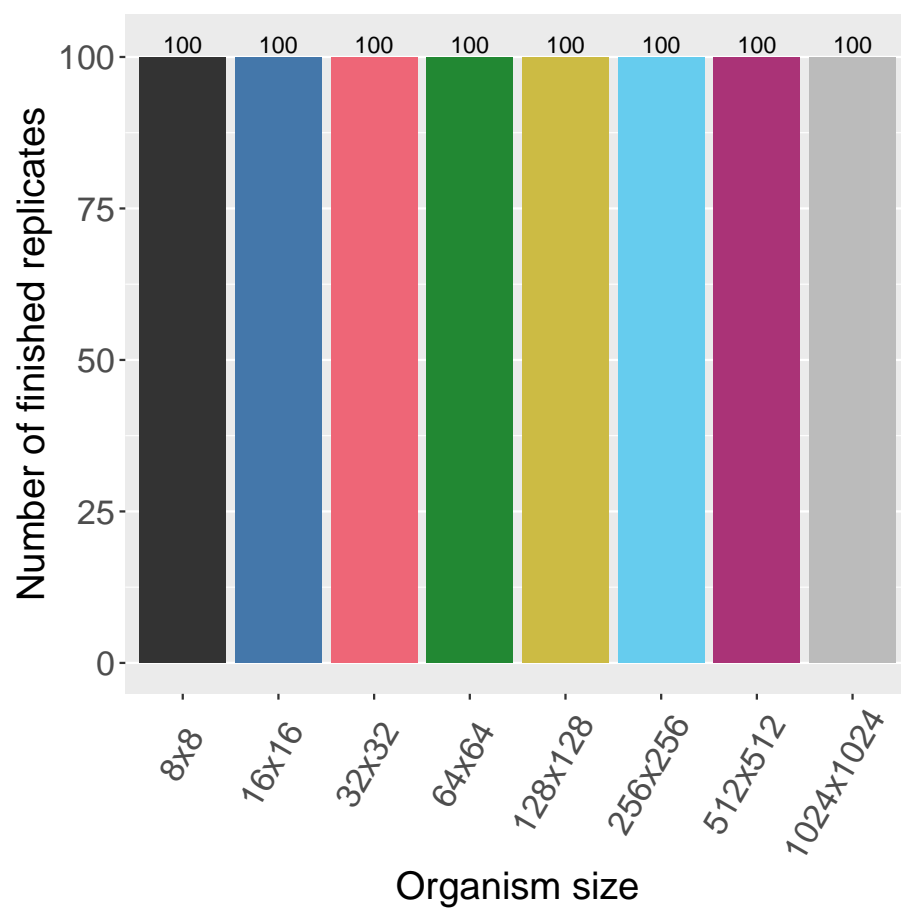
```
# Group the data by size and summarize
data_grouped = dplyr::group_by(df2, MCSIZE)
data_summary = dplyr::summarize(data_grouped, mean_ones = mean(ave_ones), n = dplyr::n
```

Clean the data and create a few helper variables to make plotting easier.

```
# Calculate restraint value (x - 60 because genome length is 100 here)
df2$restraint_value = df2$ave_ones - 60
# Make a nice, clean factor for size
df2$size_str = paste0(df2$MCSIZE, 'x', df2$MCSIZE)
df2$size_factor = factor(df2$size_str, levels = c('8x8', '16x16', '32x32', '64x64', '128x128', '256x256', '512x512', '1024x1024'))
df2$size_factor_reversed = factor(df2$size_str, levels = rev(c('8x8', '16x16', '32x32', '64x64', '128x128', '256x256', '512x512', '1024x1024')))
data_summary$size_str = paste0(data_summary$MCSIZE, 'x', data_summary$MCSIZE)
data_summary$size_factor = factor(data_summary$size_str, levels = c('8x8', '16x16', '32x32', '64x64', '128x128', '256x256', '512x512', '1024x1024'))
# Create a map of colors we'll use to plot the different organism sizes
color_vec = as.character(khroma::color('bright')(7))
color_map = c(
  '8x8' = '#333333',
  '16x16' = color_vec[1],
  '32x32' = color_vec[2],
  '64x64' = color_vec[3],
  '128x128' = color_vec[4],
  '256x256' = color_vec[5],
  '512x512' = color_vec[6],
  '1024x1024' = color_vec[7]
)
# Set the sizes for text in plots
text_major_size = 18
text_minor_size = 16
```

2.2 Data integrity check

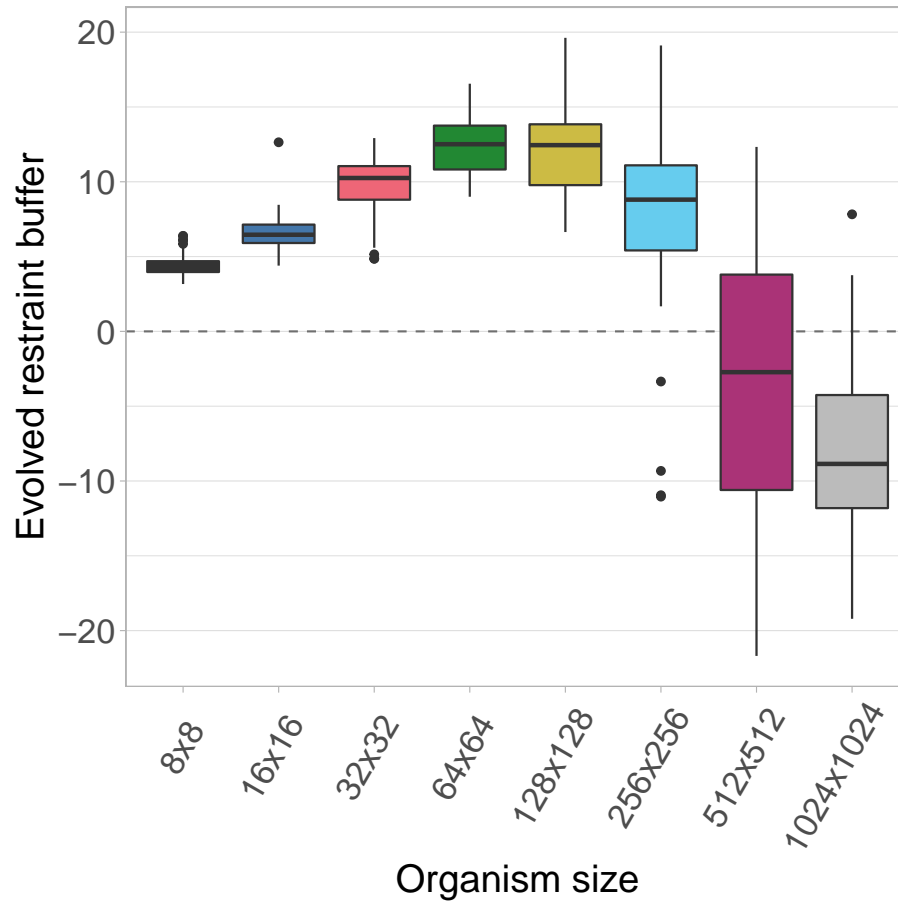
Now we plot the number of finished replicates for each treatment to make sure all data are present. Each bar/color shows a different organism size.



2.3 Aggregate plots

Here we plot all the data at once.

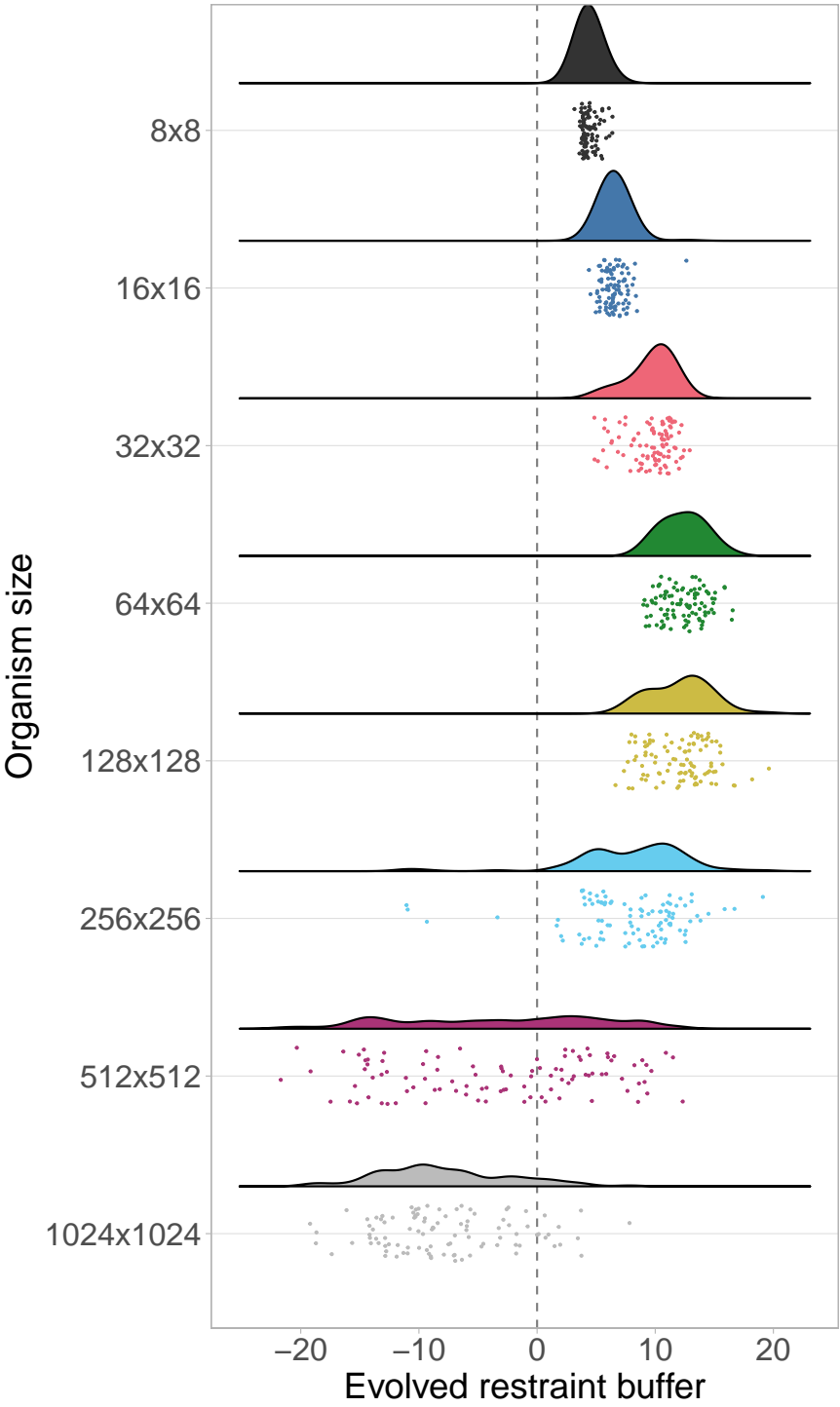
2.3.1 Boxplots



2.3.2 Raincloud plots

We can plot the same data via raincloud plots.

```
## Picking joint bandwidth of 1.16
```



2.4 Statistics

First, we perform a Kruskal-Wallis test across all organism sizes to indicate if variance exists. If variance exists, we then perform a pairwise Wilcoxon Rank-Sum test to show which pairs of organism sizes significantly differ. Finally, we perform Bonferroni-Holm corrections for multiple comparisons.

```
res = kruskal.test(df2$restraint_value ~ df2$MCSIZE, df2)
df_kruskal = data.frame(data = matrix(nrow = 0, ncol = 3))
colnames(df_kruskal) = c('p_value', 'chi_squared', 'df')
df_kruskal[nrow(df_kruskal) + 1,] = c(res$p.value, as.numeric(res$statistic)[1], as.numeric(res$df))
df_kruskal$less_0.01 = df_kruskal$p_value < 0.01
print(df_kruskal)
```

```
##           p_value chi_squared df less_0.01
## 1 1.506351e-127    610.2553  7      TRUE
```

We see that significant variation exists, so we perform pairwise Wilcoxon tests on each to see which pairs of sizes are significantly different.

```
size_vec = c(16, 32, 64, 128, 256, 512)
df_test = df2
df_wilcox = data.frame(data = matrix(nrow = 0, ncol = 5))
colnames(df_wilcox) = c('size_a', 'size_b', 'p_value_corrected', 'p_value_raw', 'W')
for(size_idx_a in 1:(length(size_vec) - 1)){
  size_a = size_vec[size_idx_a]
  for(size_idx_b in (size_idx_a + 1):length(size_vec)){
    size_b = size_vec[size_idx_b]
    res = wilcox.test(df_test[df_test$MCSIZE == size_a,]$restraint_value, df_test[df_test$MCSIZE == size_b,]$restraint_value)
    df_wilcox[nrow(df_wilcox) + 1,] = c(size_a, size_b, 0, res$p.value, as.numeric(res$statistic))
  }
}
df_wilcox$p_value_corrected = p.adjust(df_wilcox$p_value_raw, method = 'holm')
df_wilcox$less_0.01 = df_wilcox$p_value_corrected < 0.01
print(df_wilcox)
```

```
##    size_a size_b p_value_corrected p_value_raw      W less_0.01
## 1     16    32    4.406735e-21 4.406735e-22 1045.5      TRUE
## 2     16    64    1.790650e-32 1.193767e-33   51.5      TRUE
## 3     16   128    2.585339e-31 1.988723e-32  147.0      TRUE
## 4     16   256    1.864978e-03 6.216595e-04 3599.0      TRUE
## 5     16   512    3.596138e-17 4.495172e-18 8547.0      TRUE
## 6     32    64    2.103060e-15 3.004372e-16 1654.5      TRUE
## 7     32   128    1.857809e-09 4.644523e-10 2449.5      TRUE
## 8     32   256    8.472946e-03 4.236473e-03 6171.0      TRUE
## 9     32   512    1.338207e-26 1.216552e-27 9459.5      TRUE
## 10    64   128    4.429461e-01 4.429461e-01 5314.5     FALSE
## 11    64   256    2.515682e-15 4.192803e-16 8329.0      TRUE
```

##	12	64	512	1.552625e-31	1.109018e-32	9873.0	TRUE
##	13	128	256	4.763656e-12	9.527311e-13	7921.5	TRUE
##	14	128	512	3.610598e-30	3.008832e-31	9759.0	TRUE
##	15	256	512	7.155324e-19	7.950361e-20	8730.5	TRUE

Chapter 3

Somatic Mutation Rate Sweep

This was one of the preliminary experiments we conducted to find the default parameters for Primordium. Here, we vary the somatic mutation rate, which is the probability that a cell replication will result in a mutation to the offspring's genome. We settled on a somatic mutation rate of 0.5 (*i.e.*, each cell replication has a 50% chance of mutation).

The configuration script and data for the experiment can be found under 2021_02_27__soma_mut_fin/ in the experiments directory of the git repository.

3.1 Data cleaning

Load necessary libraries

```
library(dplyr)
library(ggplot2)
library(ggribes)
library(scales)
library(khroma)
```

Load the data and trim include only the final generation data for sizes 16x16 to 512x512.

```
# Load the data
df = read.csv('../experiments/2021_02_27__soma_mut_fin/evolution/data/scraped_evolution_data.csv')
# Trim off NAs (artifacts of how we scraped the data) and trim to only have gen 10,000
df2 = df[!is.na(df$MCSIZE) & df$generation == 10000,]
```

```
# Ignore data for size 8x8 and 1024x1024
df2 = df2[df2$MCSIZE != 8 & df2$MCSIZE != 1024,]
```

We group and summarize the data to ensure all replicates are present.

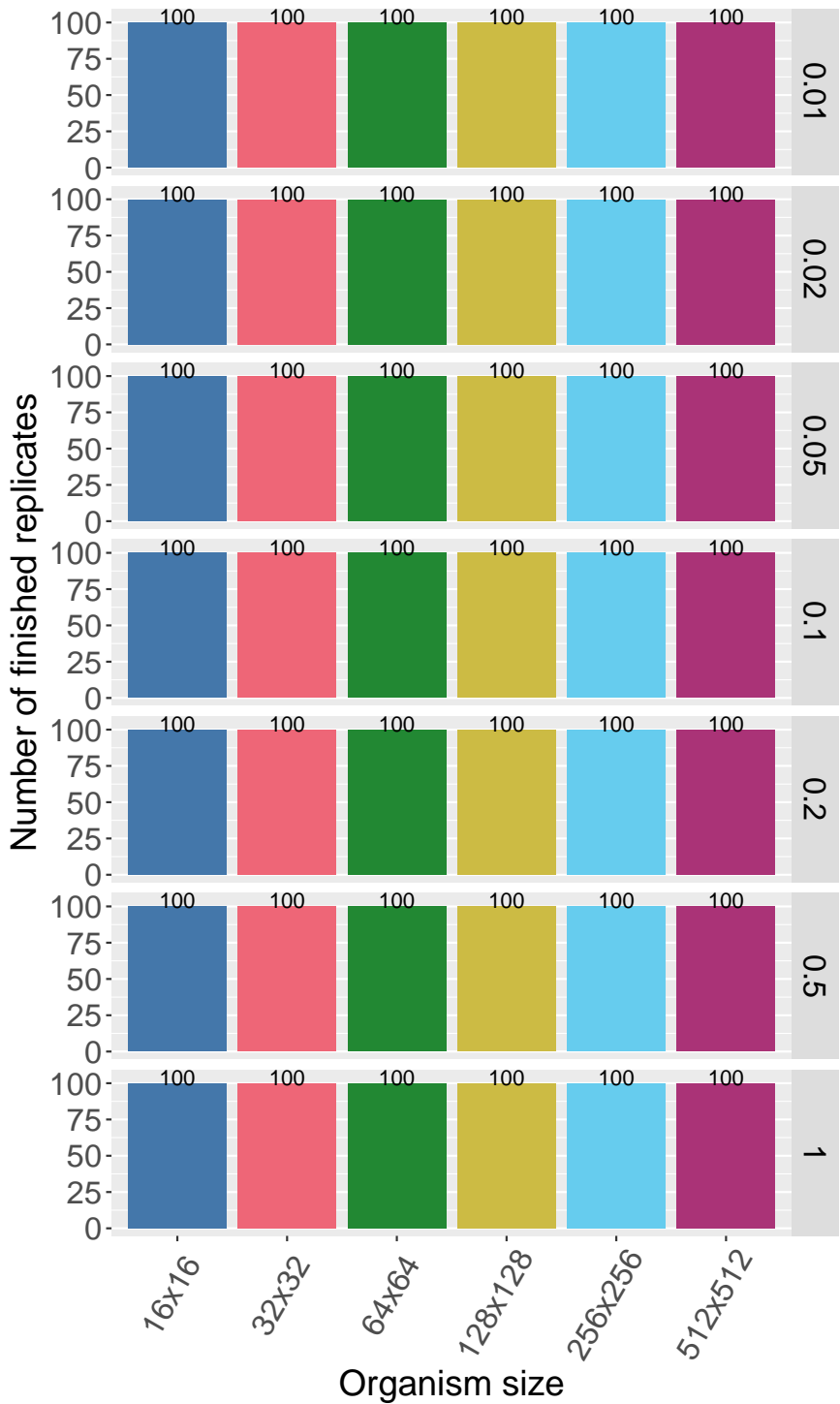
```
# Group the data by size and summarize
data_grouped = dplyr::group_by(df2, MCSIZE, CELLMUT)
data_summary = dplyr::summarize(data_grouped, mean_ones = mean(ave_ones), n = dplyr::n())
```

We clean the data and create a few helper variables to make plotting easier.

```
# Calculate restraint value (x - 60 because genome length is 100 here)
df2$restraint_value = df2$ave_ones - 60
# Make a nice, clean factor for size
df2$size_str = paste0(df2$MCSIZE, 'x', df2$MCSIZE)
df2$size_factor = factor(df2$size_str, levels = c('16x16', '32x32', '64x64', '128x128', '256x256', '512x512', '1024x1024'))
df2$size_factor_reversed = factor(df2$size_str, levels = rev(c('16x16', '32x32', '64x64', '128x128', '256x256', '512x512', '1024x1024')))
df2$soma_mut_str = paste('soma CELLMUT', df2$CELLMUT)
df2$mut_factor = factor(df2$CELLMUT, levels = c(0.01, 0.02, 0.05, 0.10, 0.20, 0.50, 1.0))
data_summary$size_str = paste0(data_summary$MCSIZE, 'x', data_summary$MCSIZE)
data_summary$size_factor = factor(data_summary$size_str, levels = c('16x16', '32x32', '64x64', '128x128', '256x256', '512x512', '1024x1024'))
data_summary$soma_mut_str = paste('soma CELLMUT', data_summary$CELLMUT)
data_summary$mut_factor = factor(data_summary$CELLMUT, levels = c(0.01, 0.02, 0.05, 0.10, 0.20, 0.50, 1.0))
# Create a map of colors we'll use to plot the different organism sizes
color_vec = as.character(khroma::color('bright')(7))
color_map = c(
  '16x16' = color_vec[1],
  '32x32' = color_vec[2],
  '64x64' = color_vec[3],
  '128x128' = color_vec[4],
  '256x256' = color_vec[5],
  '512x512' = color_vec[6],
  '1024x1024' = color_vec[7]
)
# Set the sizes for text in plots
text_major_size = 18
text_minor_size = 16
```

3.2 Data integrity check

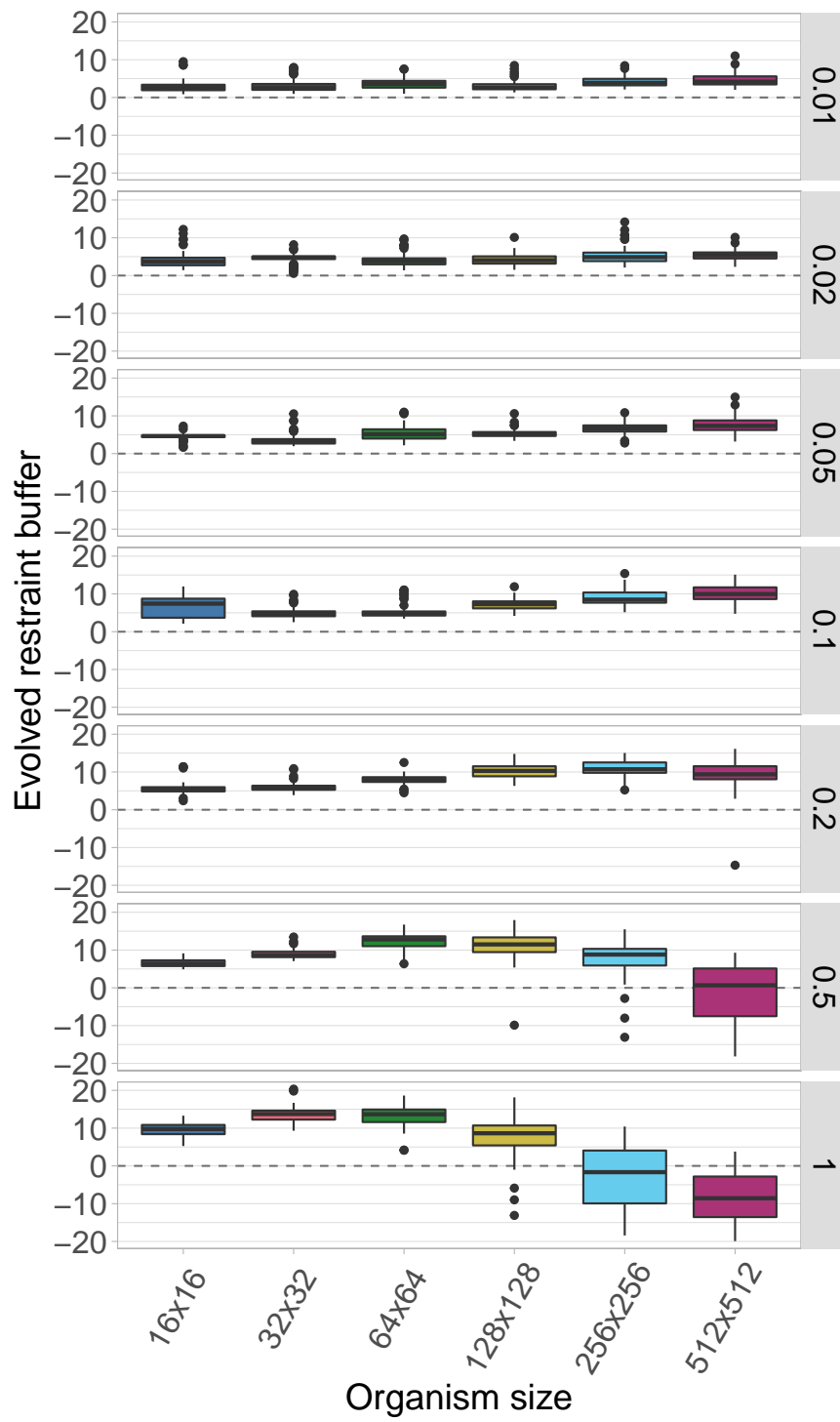
Now we plot the number of finished replicates for each treatment to make sure all data are present. Each row shows a different somatic mutation rate. Each bar/color shows a different organism size.



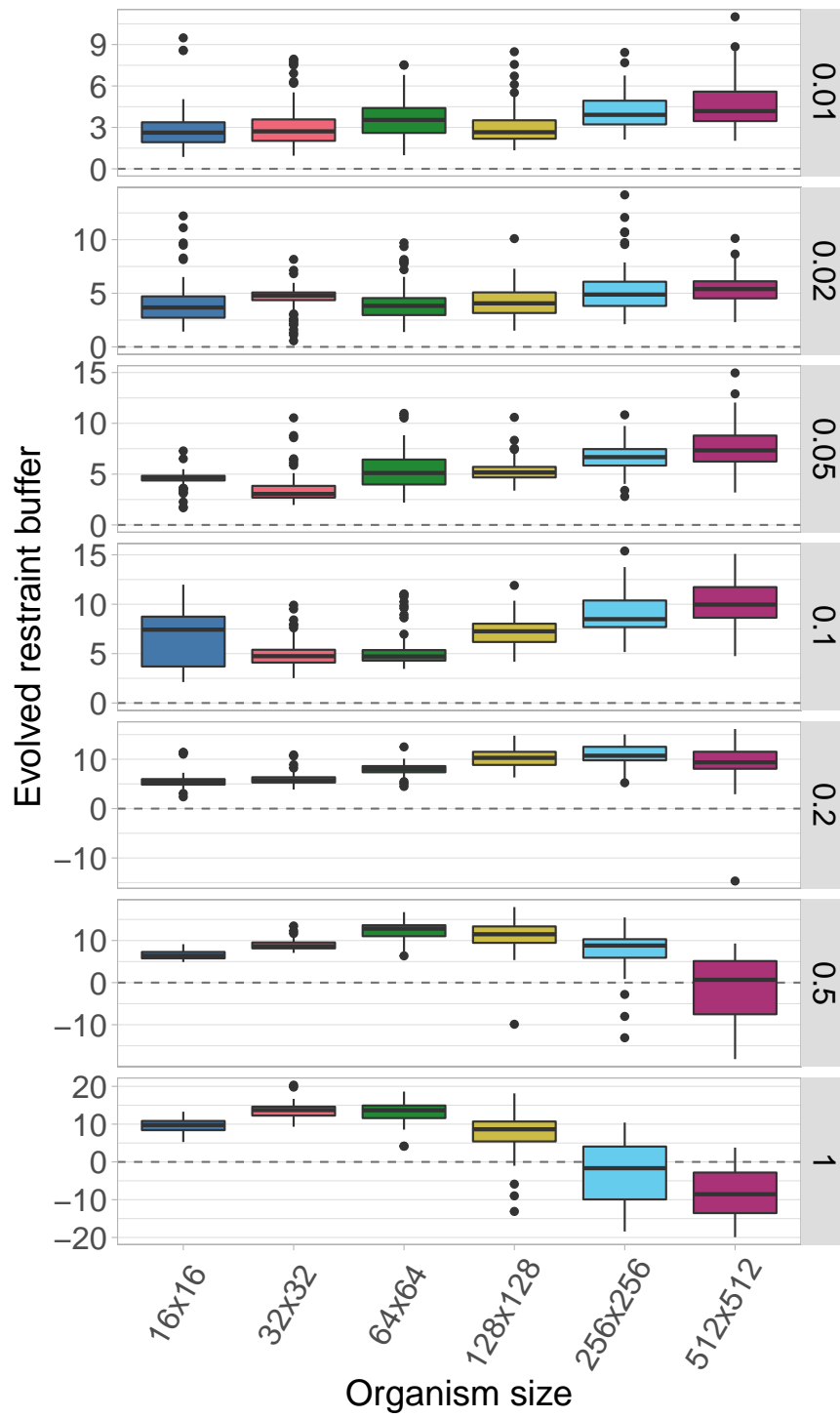
3.3 Aggregate plots

3.3.1 Facet by somatic mutation rate

Here we plot all the data at once. Each row showing a different somatic mutation rate and each boxplot shows a given organism size.

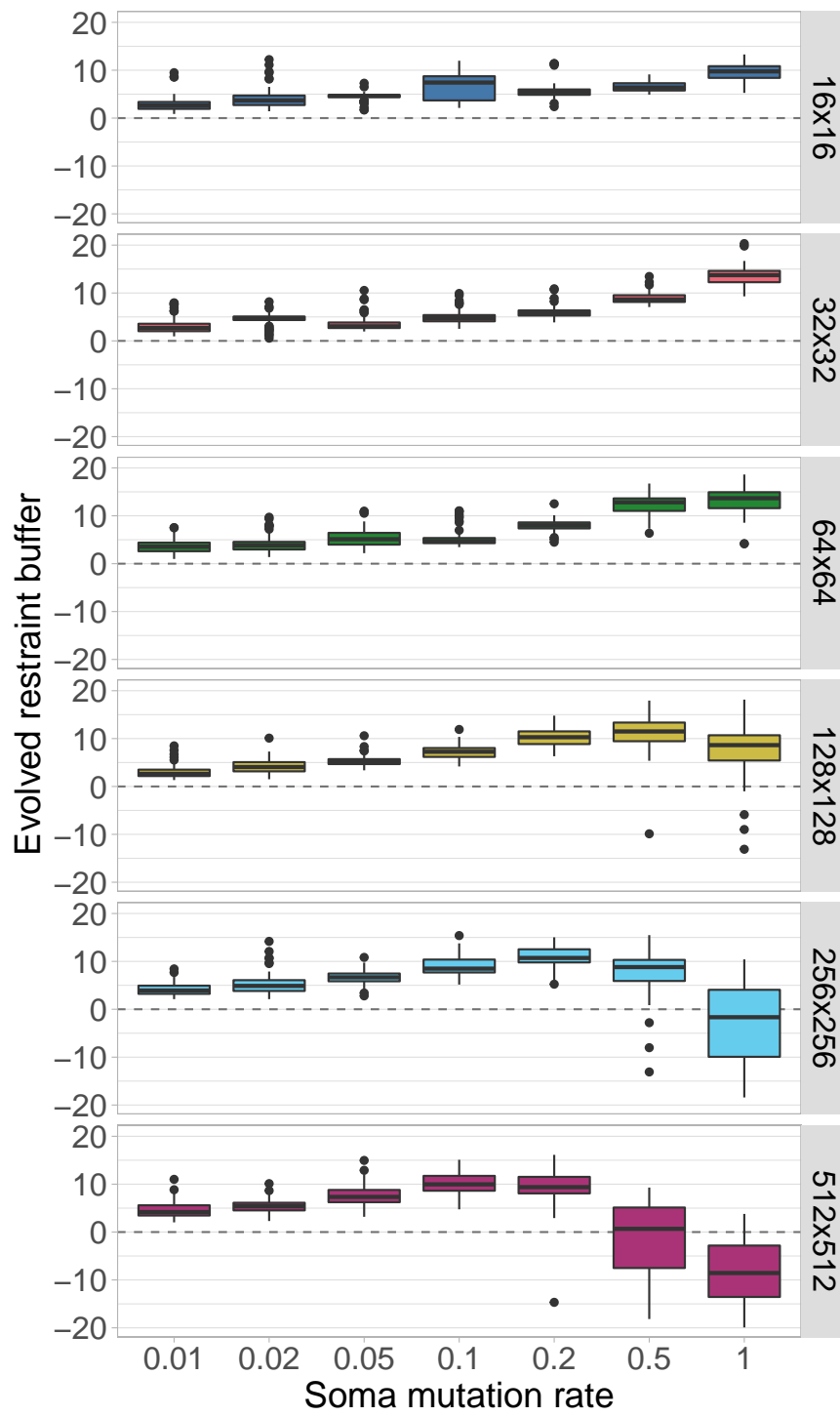


Here we plot the same data, only we allow the y-axis to vary between rows.

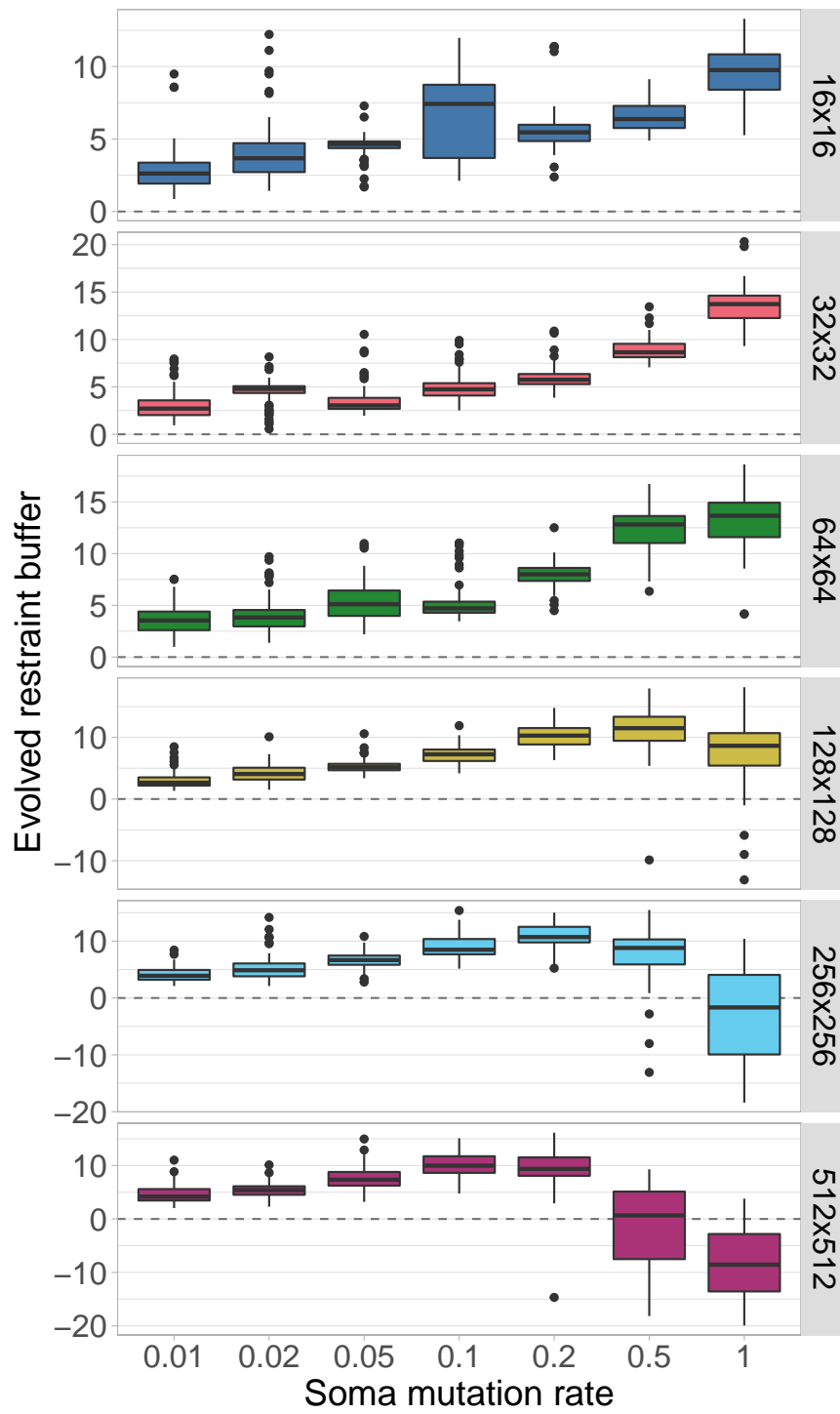


3.3.2 Facet by organism size

Next, we plot the same data, but this time each row corresponds to a certain organism size, while somatic mutation rate changes along the x-axis.



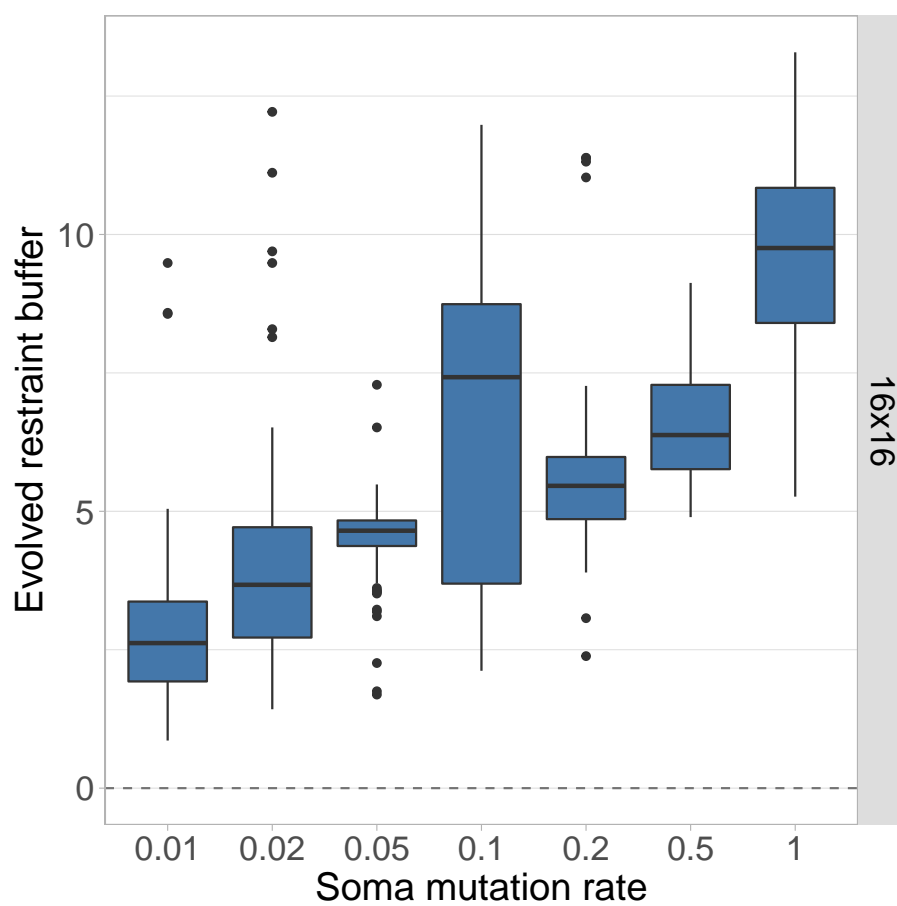
Again, we replot the same data but allow the y-axis to vary between rows.



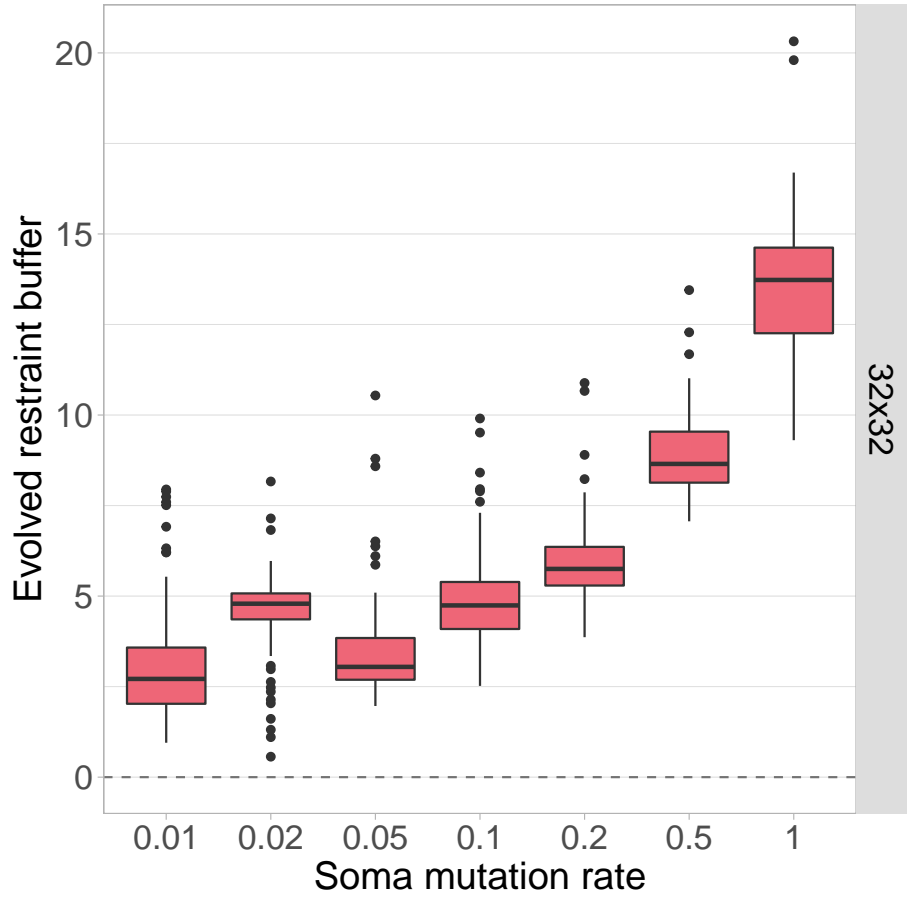
3.4 Single organism size plots

Here we plot each organism size independently, with the somatic mutation rate on the x-axis.

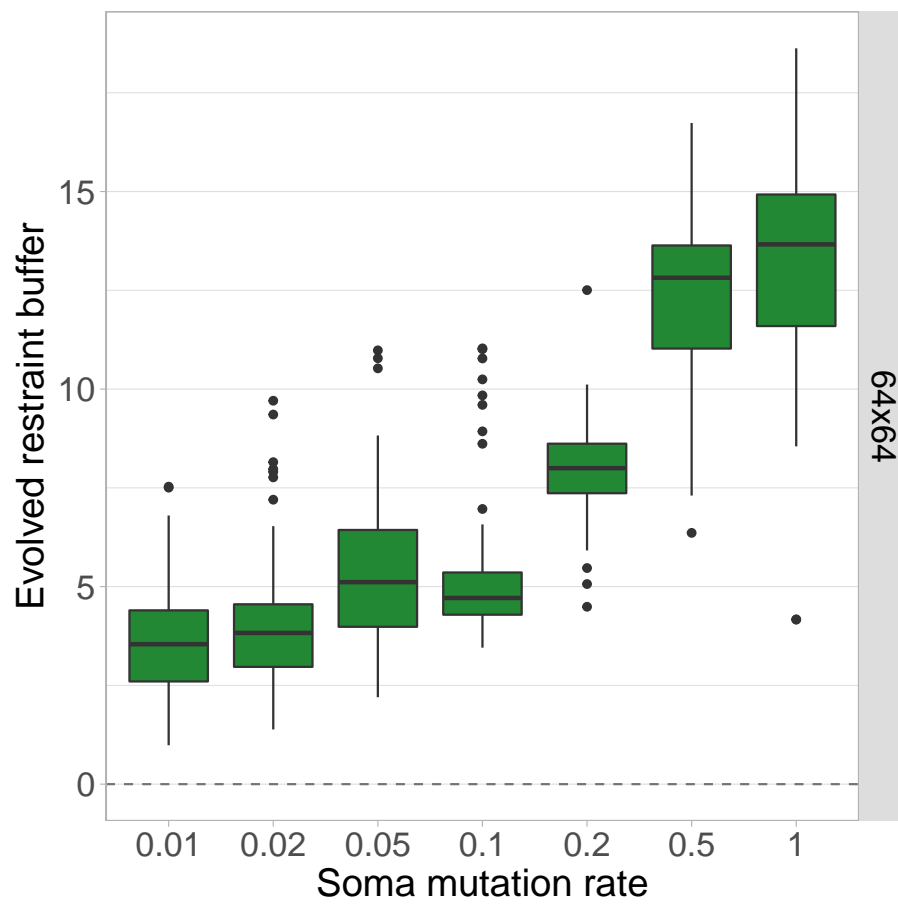
3.4.1 Organism size 16x16



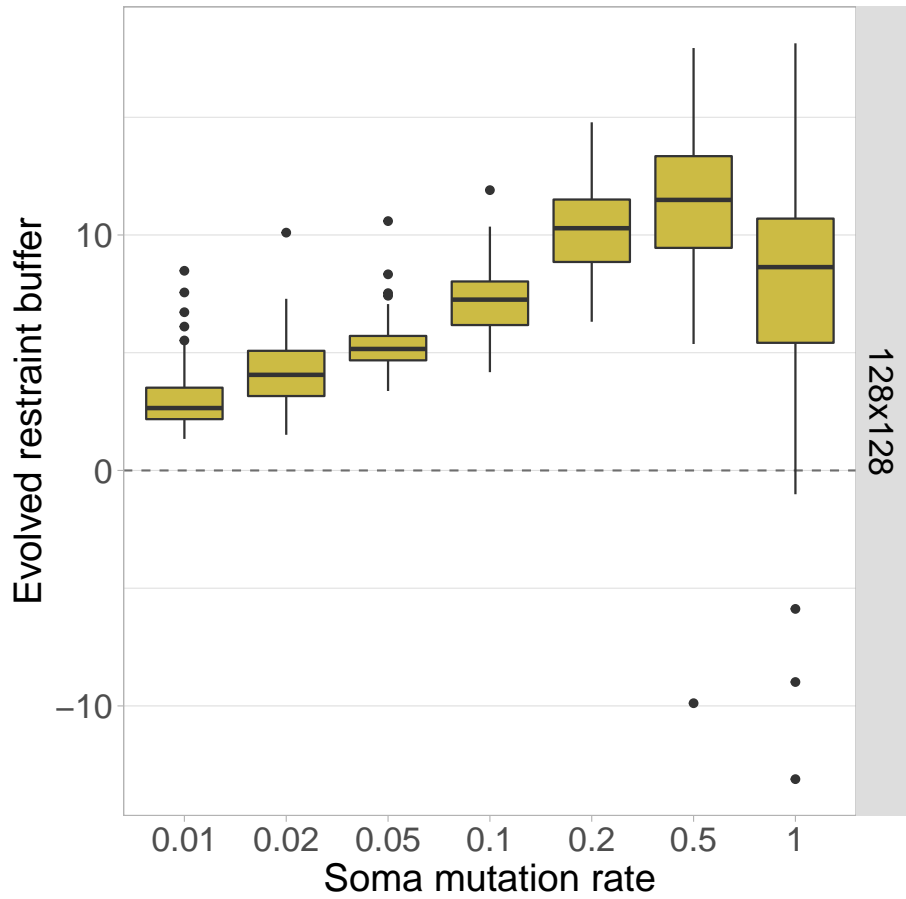
3.4.2 Organism size 32x32



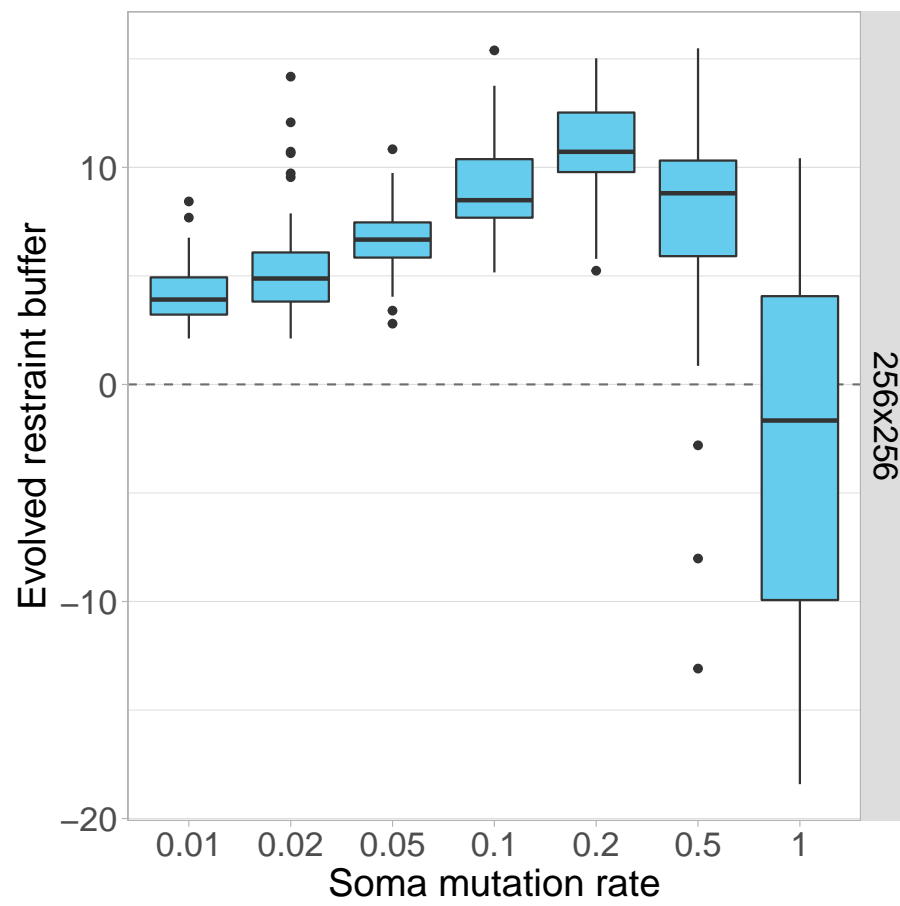
3.4.3 Organism size 64x64



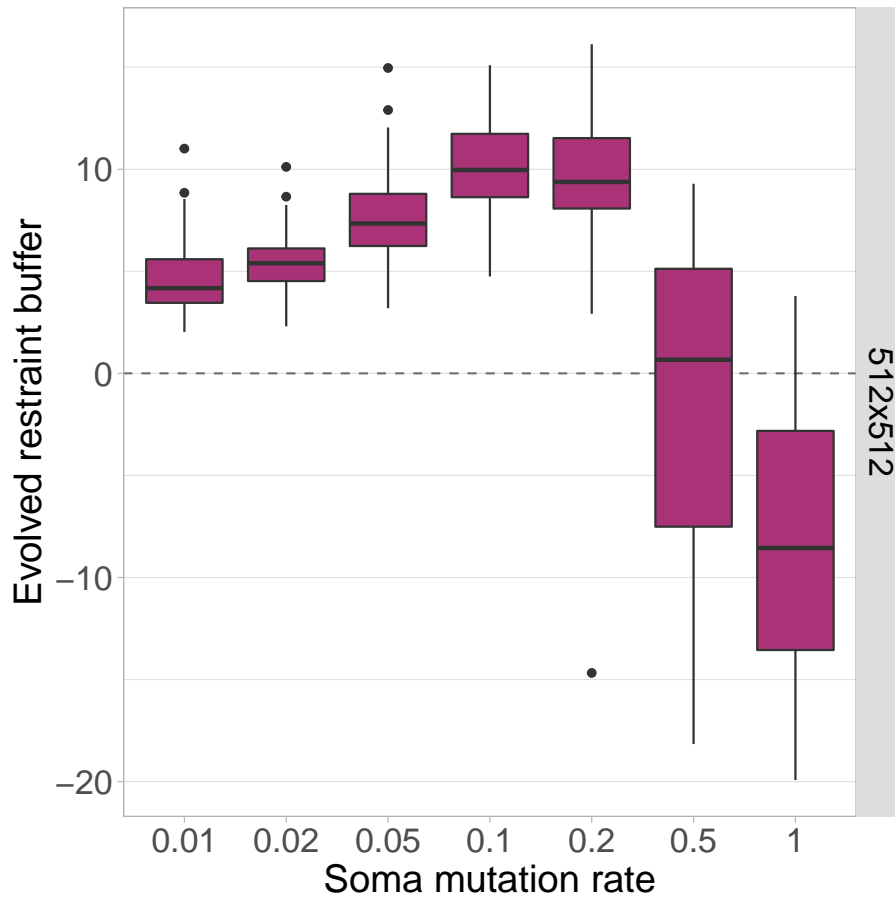
3.4.4 Organism size 128x128



3.4.5 Organism size 256x256



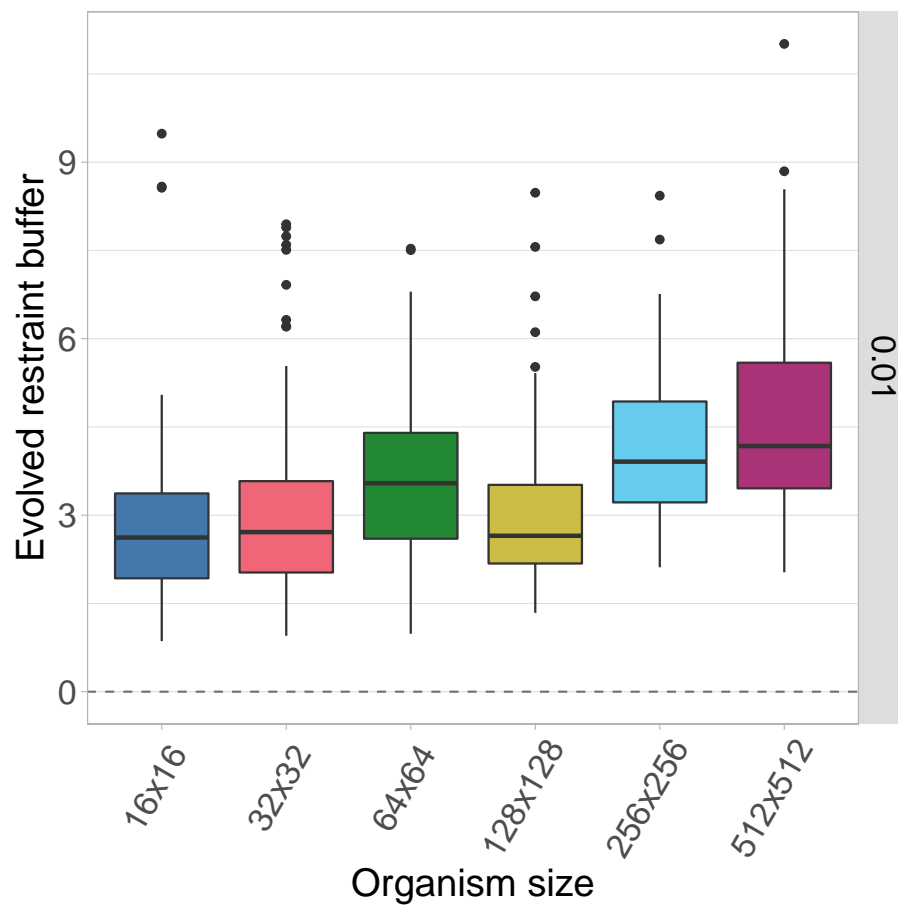
3.4.6 Organism size 512x512



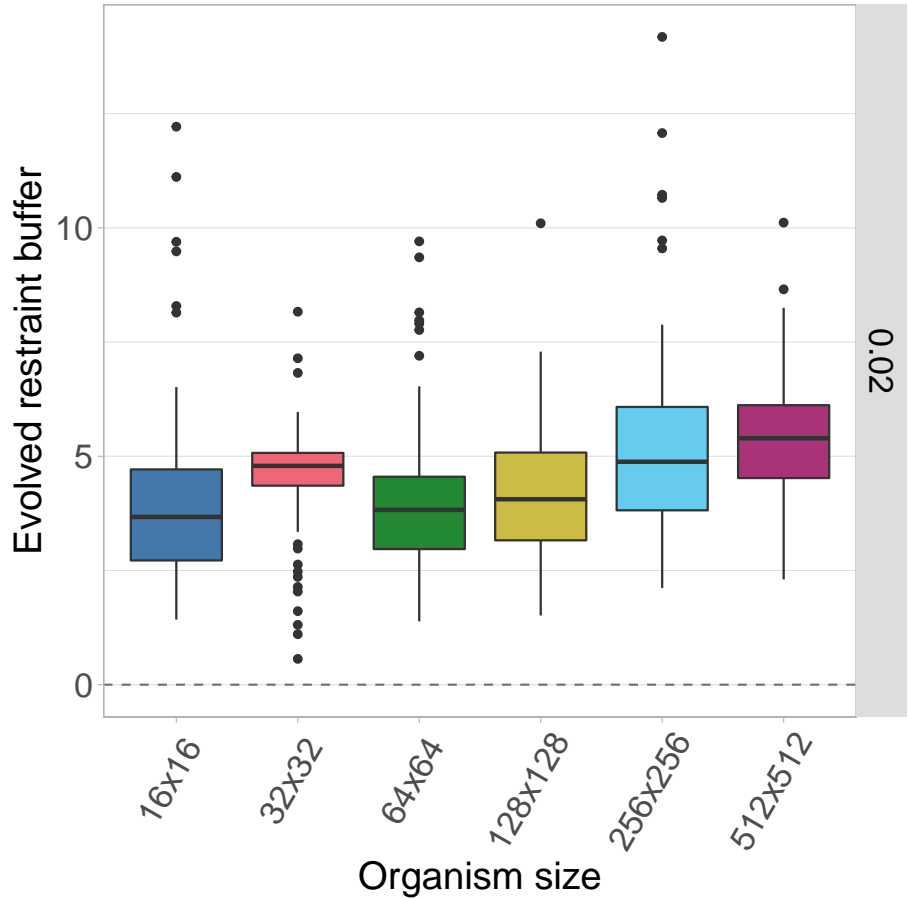
3.5 Single somatic mutation rate plots

Here we plot each somatic mutation rate independently, with organism size varying on the x-axis.

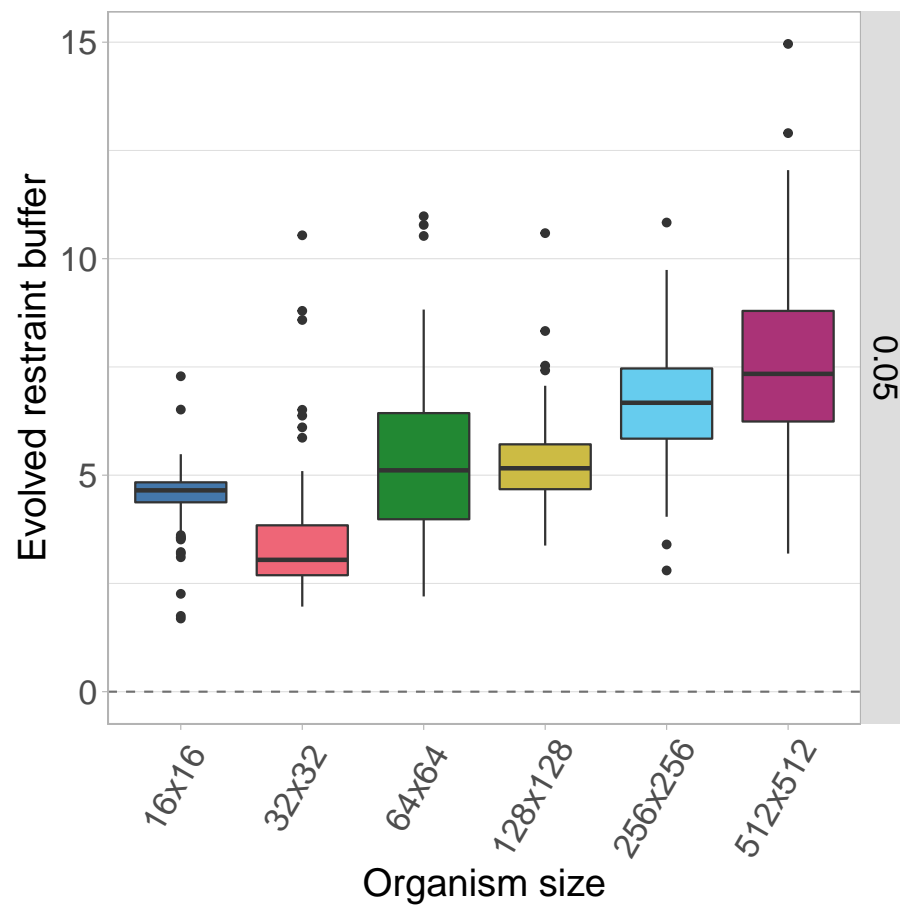
3.5.1 Somatic mut. rate 0.01



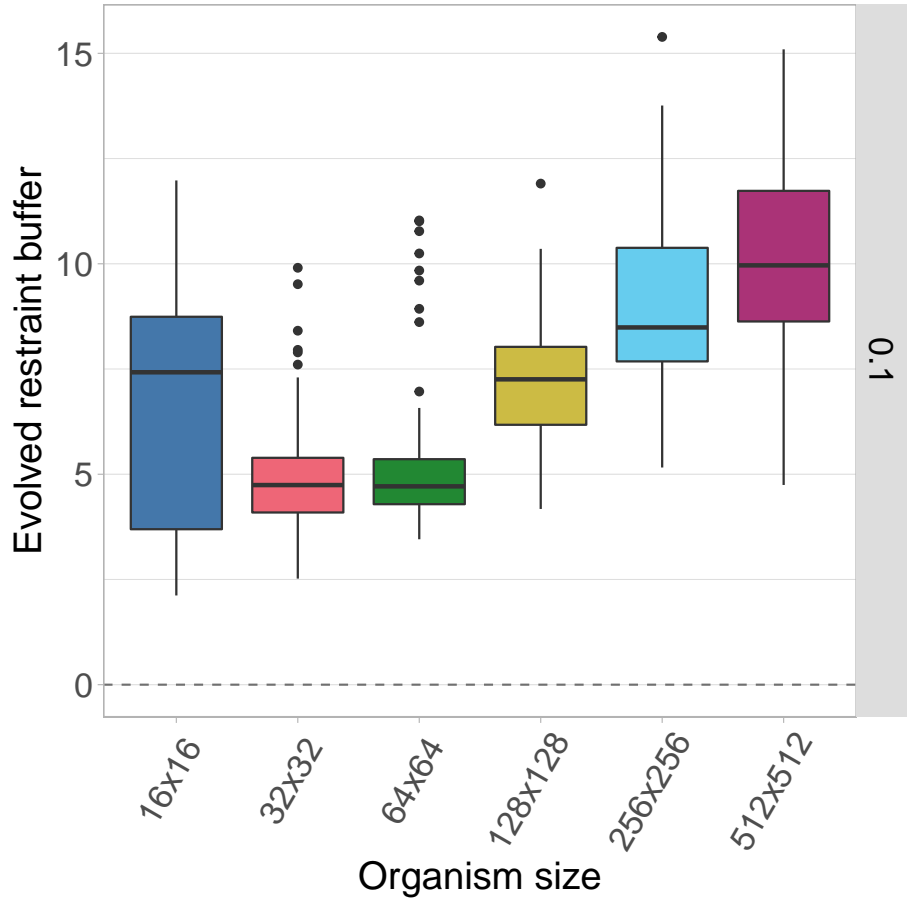
3.5.2 Somatic mut. rate 0.02



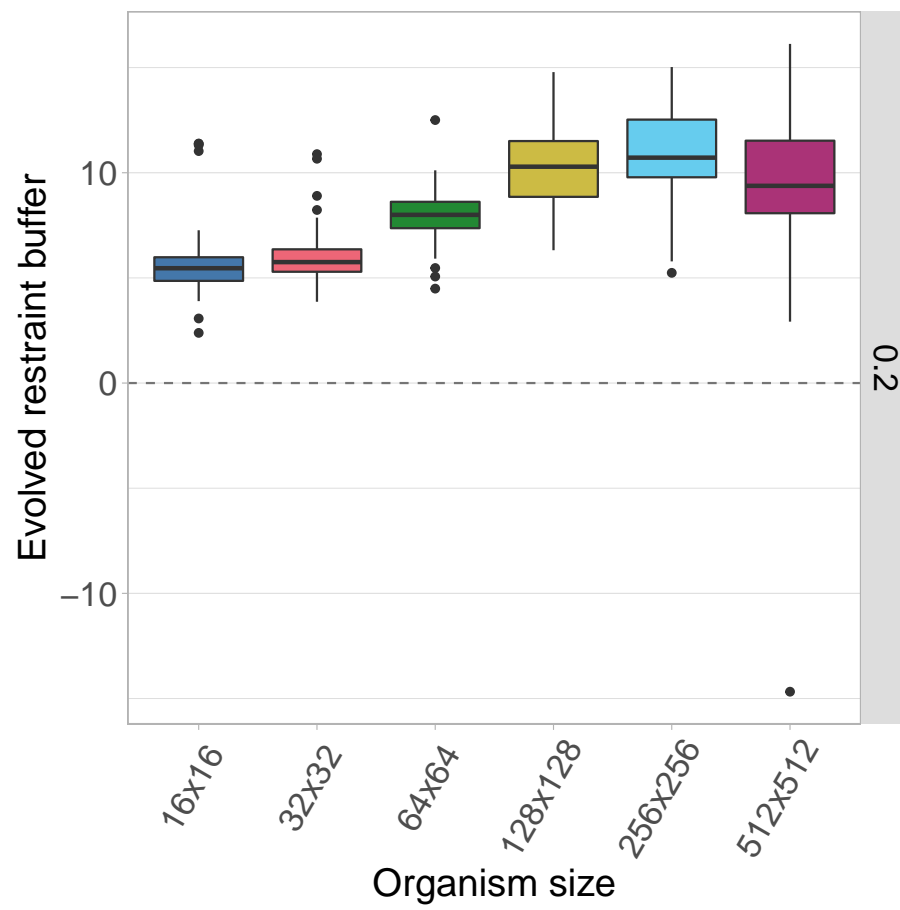
3.5.3 Somatic mut. rate 0.05



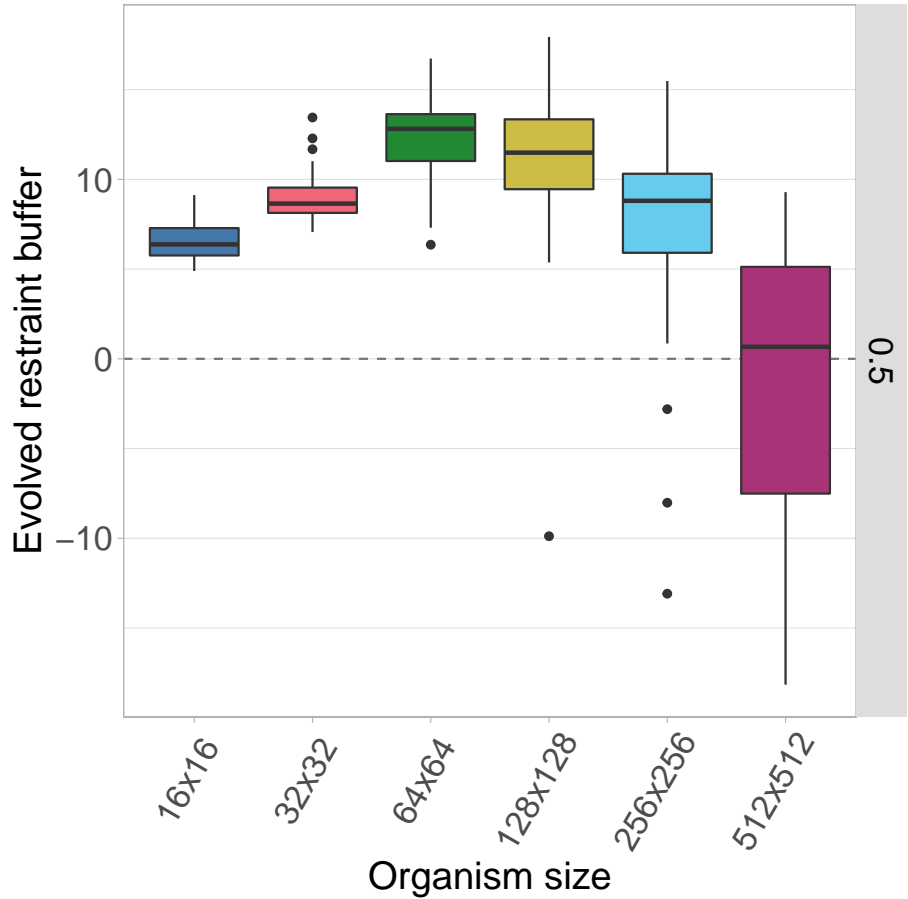
3.5.4 Somatic mut. rate 0.1



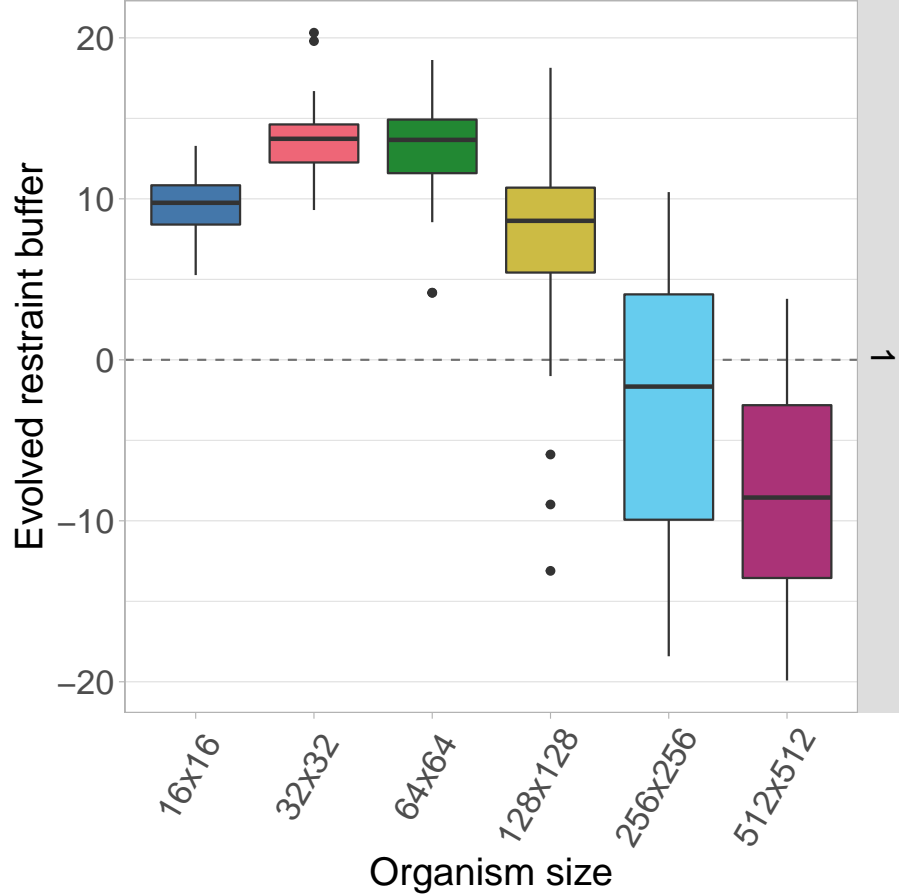
3.5.5 Somatic mut. rate 0.2



3.5.6 Somatic mut. rate 0.5



3.5.7 Somatic mut. rate 1.0



3.6 Statistics

Since organism size is our main point of comparison, we calculate statistics for each somatic mutation rate.

First, we perform a Kruskal-Wallis test across all organism sizes to indicate if variance exists at that mutation rate. If variance exists, we then perform a pairwise Wilcoxon Rank-Sum test to show which pairs of organism sizes significantly differ. Finally, we perform Bonferroni-Holm corrections for multiple comparisons.

```
mut_vec = c(0.01, 0.02, 0.05, 0.1, 0.2, 0.5, 1)
df_kruskal = data.frame(data = matrix(nrow = 0, ncol = 4))
colnames(df_kruskal) = c('soma_mut_rate', 'p_value', 'chi_squared', 'df')
for(mut_rate in mut_vec){
  df_test = df2[df2$CELLMUT == mut_rate,]
```

```

res = kruskal.test(df_test$restraint_value ~ df_test$MCSIZE, df_test)
df_kruskal[nrow(df_kruskal) + 1,] = c(mut_rate, res$p.value, as.numeric(res$statistic)[1], as
}
df_kruskal$less_0.01 = df_kruskal$p_value < 0.01
print(df_kruskal)

```

```

##   soma_mut_rate      p_value chi_squared df less_0.01
## 1          0.01 2.661659e-25    125.0566 5      TRUE
## 2          0.02 4.808020e-19     95.4471 5      TRUE
## 3          0.05 1.142677e-63    304.3847 5      TRUE
## 4          0.10 3.945761e-64    306.5323 5      TRUE
## 5          0.20 4.924029e-79    375.7743 5      TRUE
## 6          0.50 5.011460e-85    403.5832 5      TRUE
## 7          1.00 5.474947e-99    468.3229 5      TRUE

```

We see that significant variation exists within each mutation rate, so we perform pairwise Wilcoxon tests on each to see which pairs of sizes are significantly different.

```

size_vec = c(16, 32, 64, 128, 256, 512)
mut_vec = c(0.01, 0.02, 0.05, 0.1, 0.2, 0.5, 1)
for(mut_rate in mut_vec){
  df_test = df2[df2$CELLMUT == mut_rate,]
  df_wilcox = data.frame(data = matrix(nrow = 0, ncol = 6))
  colnames(df_wilcox) = c('mut_rate', 'size_a', 'size_b', 'p_value_corrected', 'p_value_raw', 'W')
  for(size_idx_a in 1:(length(size_vec) - 1)){
    size_a = size_vec[size_idx_a]
    for(size_idx_b in (size_idx_a + 1):length(size_vec)){
      size_b = size_vec[size_idx_b]
      res = wilcox.test(df_test[df_test$MCSIZE == size_a,]$restraint_value, df_test[df_test$MCSIZE == size_b,]$restraint_value)
      df_wilcox[nrow(df_wilcox) + 1,] = c(mut_rate, size_a, size_b, 0, res$p.value, as.numeric(res$statistic))
    }
  }
  df_wilcox$p_value_corrected = p.adjust(df_wilcox$p_value_raw, method = 'holm')
  df_wilcox$less_0.01 = df_wilcox$p_value_corrected < 0.01
  print(paste0('Somatic mutation rate: ', mut_rate))
  print(df_wilcox)
}

```

```

## [1] "Somatic mutation rate: 0.01"
##   mut_rate size_a size_b p_value_corrected p_value_raw      W less_0.01
## 1     0.01    16    32      9.390497e-01 4.695249e-01 4703.5    FALSE
## 2     0.01    16    64      2.988154e-04 3.735192e-05 3312.0     TRUE
## 3     0.01    16   128      7.079843e-01 2.359948e-01 4514.5    FALSE
## 4     0.01    16   256      2.034819e-12 1.453442e-13 1974.5     TRUE
## 5     0.01    16   512      4.368517e-15 2.912344e-16 1653.0     TRUE
## 6     0.01    32    64      1.074876e-02 1.535537e-03 3703.0    FALSE

```

```

## 7      0.01      32      128      9.390497e-01 7.176323e-01 4851.5      FALSE
## 8      0.01      32      256      8.111610e-09 8.111610e-10 2485.5      TRUE
## 9      0.01      32      512      1.748038e-11 1.456698e-12 2102.5      TRUE
## 10     0.01      64      128      1.074876e-02 1.601365e-03 6292.0      FALSE
## 11     0.01      64      256      1.397091e-02 2.794183e-03 3776.0      FALSE
## 12     0.01      64      512      7.748038e-05 8.608931e-06 3178.5      TRUE
## 13     0.01     128     256      3.676583e-09 3.342348e-10 2428.5      TRUE
## 14     0.01     128     512      2.110112e-12 1.623163e-13 1980.5      TRUE
## 15     0.01     256     512      2.266729e-01 5.666822e-02 4219.5      FALSE
## [1] "Somatic mutation rate: 0.02"
##      mut_rate size_a size_b p_value_corrected p_value_raw      W less_0.01
## 1      0.02      16      32      3.611494e-05 4.012771e-06 3112.5      TRUE
## 2      0.02      16      64      4.740405e-01 4.740405e-01 4706.5      FALSE
## 3      0.02      16     128      2.648393e-01 5.296786e-02 4207.5      FALSE
## 4      0.02      16     256      6.698428e-07 5.582024e-08 2776.5      TRUE
## 5      0.02      16     512      4.142268e-11 2.761512e-12 2139.0      TRUE
## 6      0.02      32      64      1.240992e-05 1.240992e-06 6985.0      TRUE
## 7      0.02      32     128      2.150816e-02 3.584693e-03 6192.5      FALSE
## 8      0.02      32     256      3.993493e-01 9.983733e-02 4326.0      FALSE
## 9      0.02      32     512      1.117168e-04 1.396459e-05 3221.5      TRUE
## 10     0.02      64     128      4.025666e-01 2.012833e-01 4476.5      FALSE
## 11     0.02      64     256      5.648464e-06 5.134967e-07 2944.5      TRUE
## 12     0.02      64     512      6.120346e-11 4.371676e-12 2165.5      TRUE
## 13     0.02     128     256      3.129242e-04 4.470345e-05 3329.0      TRUE
## 14     0.02     128     512      1.760116e-08 1.353935e-09 2519.0      TRUE
## 15     0.02     256     512      3.993493e-01 1.013587e-01 4329.0      FALSE
## [1] "Somatic mutation rate: 0.05"
##      mut_rate size_a size_b p_value_corrected p_value_raw      W less_0.01
## 1      0.05      16      32      8.163575e-15 9.070638e-16 8290.5      TRUE
## 2      0.05      16      64      1.254683e-03 4.182276e-04 3555.5      TRUE
## 3      0.05      16     128      2.819711e-09 5.639421e-10 2462.0      TRUE
## 4      0.05      16     256      1.007639e-23 8.396990e-25 791.0      TRUE
## 5      0.05      16     512      3.169326e-24 2.437943e-25 742.5      TRUE
## 6      0.05      32      64      9.865308e-14 1.409330e-14 1850.0      TRUE
## 7      0.05      32     128      9.672216e-22 8.792924e-23 978.5      TRUE
## 8      0.05      32     256      4.456762e-26 3.183402e-27 576.5      TRUE
## 9      0.05      32     512      1.225797e-27 8.171978e-29 441.0      TRUE
## 10     0.05      64     128      9.619980e-01 9.619980e-01 4980.0      FALSE
## 11     0.05      64     256      4.409184e-09 1.102296e-09 2505.5      TRUE
## 12     0.05      64     512      1.967988e-13 3.279979e-14 1894.5      TRUE
## 13     0.05     128     256      3.061979e-14 3.827473e-15 1782.5      TRUE
## 14     0.05     128     512      4.080298e-17 4.080298e-18 1448.5      TRUE
## 15     0.05     256     512      2.648877e-03 1.324439e-03 3685.5      TRUE
## [1] "Somatic mutation rate: 0.1"
##      mut_rate size_a size_b p_value_corrected p_value_raw      W less_0.01
## 1      0.1       16      32      3.903716e-03 9.759291e-04 6350.0      TRUE

```



```

## 2      0.1      16      64      9.815188e-02 3.271729e-02 5874.5      FALSE
## 3      0.1      16     128      6.061146e-01 3.140880e-01 4587.5      FALSE
## 4      0.1      16     256      3.278276e-08 5.463793e-09 2612.5      TRUE
## 5      0.1      16     512      9.506115e-18 1.188264e-18 1391.5      TRUE
## 6      0.1      32      64      6.061146e-01 3.030573e-01 4578.0      FALSE
## 7      0.1      32     128      8.673971e-21 8.673971e-22 1074.0      TRUE
## 8      0.1      32     256      6.950798e-29 4.964856e-30 340.0      TRUE
## 9      0.1      32     512      1.934395e-30 1.289597e-31 211.5      TRUE
## 10     0.1      64     128      2.239733e-18 2.488592e-19 1320.5      TRUE
## 11     0.1      64     256      1.194130e-25 9.951080e-27 619.5      TRUE
## 12     0.1      64     512      1.966283e-27 1.512525e-28 463.5      TRUE
## 13     0.1     128     256      8.038941e-11 1.148420e-11 2222.0      TRUE
## 14     0.1     128     512      1.880691e-21 1.709719e-22 1006.0      TRUE
## 15     0.1     256     512      3.931365e-04 7.862729e-05 3383.5      TRUE
## [1] "Somatic mutation rate: 0.2"
##      mut_rate size_a size_b p_value_corrected p_value_raw      W less_0.01
## 1      0.2      16      32      1.077048e-02 5.385238e-03 3860.5      FALSE
## 2      0.2      16      64      6.720281e-24 8.400351e-25 791.0      TRUE
## 3      0.2      16     128      1.215721e-28 1.013101e-29 365.5      TRUE
## 4      0.2      16     256      4.359012e-29 3.353086e-30 326.0      TRUE
## 5      0.2      16     512      3.611807e-25 3.283461e-26 665.0      TRUE
## 6      0.2      32      64      5.255254e-22 7.507505e-23 972.0      TRUE
## 7      0.2      32     128      3.542154e-29 2.530110e-30 316.0      TRUE
## 8      0.2      32     256      3.153758e-30 2.102505e-31 228.5      TRUE
## 9      0.2      32     512      1.346976e-24 1.496640e-25 723.5      TRUE
## 10     0.2      64     128      1.237545e-13 2.062574e-14 1870.0      TRUE
## 11     0.2      64     256      6.129521e-25 6.129521e-26 689.0      TRUE
## 12     0.2      64     512      1.436552e-07 2.873105e-08 2728.5      TRUE
## 13     0.2     128     256      6.935985e-03 2.311995e-03 3752.5      TRUE
## 14     0.2     128     512      1.987108e-01 1.987108e-01 5526.5      FALSE
## 15     0.2     256     512      3.309684e-04 8.274210e-05 6611.5      TRUE
## [1] "Somatic mutation rate: 0.5"
##      mut_rate size_a size_b p_value_corrected p_value_raw      W less_0.01
## 1      0.5      16      32      1.212403e-25 1.212403e-26 627.0      TRUE
## 2      0.5      16      64      1.029212e-31 7.351512e-33 113.0      TRUE
## 3      0.5      16     128      1.432034e-27 1.301849e-28 458.0      TRUE
## 4      0.5      16     256      3.887685e-06 1.295895e-06 3018.5      TRUE
## 5      0.5      16     512      1.499786e-19 2.499644e-20 8781.5      TRUE
## 6      0.5      32      64      3.854284e-24 4.282538e-25 764.5      TRUE
## 7      0.5      32     128      6.344735e-14 1.268947e-14 1844.5      TRUE
## 8      0.5      32     256      6.346151e-01 6.346151e-01 5195.0      FALSE
## 9      0.5      32     512      3.036159e-31 2.335507e-32 9847.5      TRUE
## 10     0.5      64     128      9.397051e-03 4.698526e-03 6157.5      TRUE
## 11     0.5      64     256      6.907801e-20 9.868288e-21 8822.0      TRUE
## 12     0.5      64     512      9.160009e-33 6.106673e-34 9971.0      TRUE
## 13     0.5     128     256      4.999760e-11 1.249940e-11 7773.0      TRUE

```

```

## 14      0.5    128    512      6.054856e-31 5.045714e-32 9821.0      TRUE
## 15      0.5    256    512      4.216225e-21 5.270281e-22 8947.0      TRUE
## [1] "Somatic mutation rate: 1"
##      mut_rate size_a size_b p_value_corrected p_value_raw      W less_0.01
## 1         1      16      32      2.812620e-27 3.515774e-28    494.5      TRUE
## 2         1      16      64      5.606003e-22 9.343338e-23    981.0      TRUE
## 3         1      16     128      2.202125e-02 1.101063e-02   6041.0     FALSE
## 4         1      16     256      4.073858e-28 4.526509e-29   9580.5      TRUE
## 5         1      16     512      3.841268e-33 2.561566e-34  10000.0      TRUE
## 6         1     32      64      7.619035e-01 7.619035e-01   5124.5     FALSE
## 7         1     32     128      2.931097e-22 4.187282e-23   9052.0      TRUE
## 8         1     32     256      3.841268e-33 2.976903e-34   9995.0      TRUE
## 9         1     32     512      3.841268e-33 2.561711e-34  10000.0      TRUE
## 10        1     64     128      1.456083e-19 3.640207e-20   8765.0      TRUE
## 11        1     64     256      2.413338e-32 2.193944e-33   9928.0      TRUE
## 12        1     64     512      3.841268e-33 2.560845e-34  10000.0      TRUE
## 13        1    128     256      1.180975e-20 2.361951e-21   8883.5      TRUE
## 14        1    128     512      1.253447e-30 1.253447e-31   9789.5      TRUE
## 15        1    256     512      6.072904e-07 2.024301e-07   7127.5      TRUE

```

Chapter 4

Germ Mutation Rate Sweep

This experiment was one of the preliminary experiments we conducted to find the default parameters for Primordium. We varied the mutation rate, which is the probability that an offspring experiences a mutation to its restraint buffer during organism reproduction. The final default germ mutation rate was 0.02 (*i.e.*, each organism reproduction has a 2% chance of mutation).

The configuration script and data for the experiment can be found under 2021_02_16__germ_mut_fin/ in the experiments directory of the git repository.

Load necessary R libraries

```
library(dplyr)
library(ggplot2)
library(ggthemes)
library(scales)
library(khroma)
```

Load the data and trim include only the final generation data for sizes 16x16 to 512x512.

```
# Load the data
df = read.csv('../experiments/2021_02_16__germ_mut_fin/evolution/data/scraped_evolution_data.csv')
#df = read.csv('/research/rogue_cell/Primordium/experiments/2021_02_16__germ_mut_fin/evolution/d
# Trim off NAs (artifacts of how we scraped the data) and trim to only have gen 10,000
cat(colnames(df), '\n')
```

```
## X generation ave_ones ave_repro_time min_ones max_ones var_ones rep_id MCSIZE COST GENS MUT PC
df2 = df[!is.na(df$MCSIZE) & df$generation == 10000,]
# Ignore data for size 8x8 and 1024x1024
df2 = df2[df2$MCSIZE != 8 & df2$MCSIZE != 1024,]
```

We group and summarize the data to ensure all replicates are present.

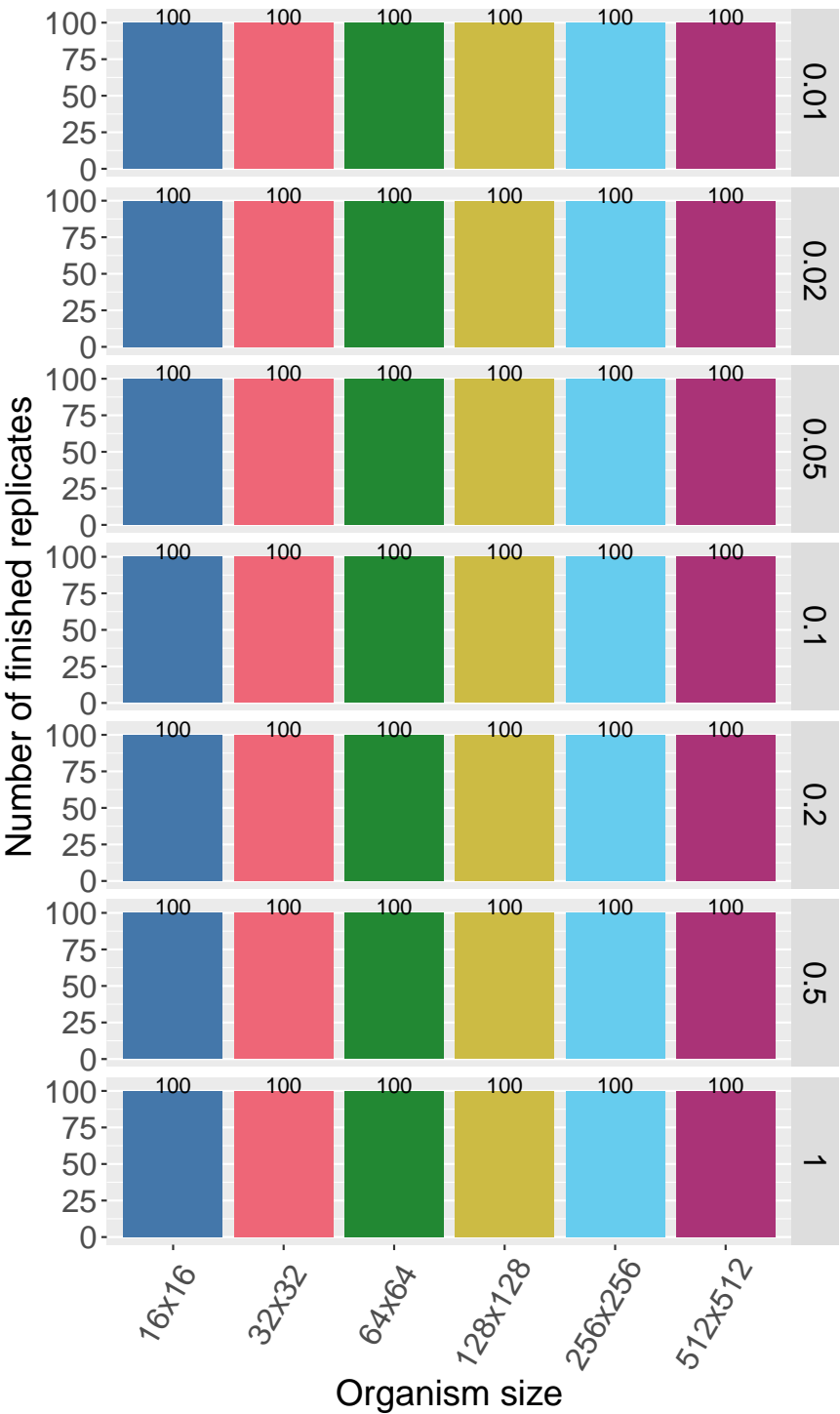
```
# Group the data by size and summarize
data_grouped = dplyr::group_by(df2, MCSIZE, MUT)
data_summary = dplyr::summarize(data_grouped, mean_ones = mean(ave_ones), n = dplyr::n
```

Further cleaning of the data plus adding some variables to make plotting easier.

```
# Calculate restraint value (x - 60 because genome length is 100 here)
df2$restraint_value = df2$ave_ones - 60
# Make a nice, clean factor for size
df2$size_str = paste0(df2$MCSIZE, 'x', df2$MCSIZE)
df2$size_factor = factor(df2$size_str, levels = c('16x16', '32x32', '64x64', '128x128', '256x256', '512x512', '1024x1024'))
df2$size_factor_reversed = factor(df2$size_str, levels = rev(c('16x16', '32x32', '64x64', '128x128', '256x256', '512x512', '1024x1024')))
df2$germ_mut_str = paste('GERM MUT', df2$MUT)
df2$mut_factor = factor(df2$MUT, levels = c(0.01, 0.02, 0.05, 0.10, 0.20, 0.50, 1.00))
data_summary$size_str = paste0(data_summary$MCSIZE, 'x', data_summary$MCSIZE)
data_summary$size_factor = factor(data_summary$size_str, levels = c('16x16', '32x32', '64x64', '128x128', '256x256', '512x512', '1024x1024'))
data_summary$germ_mut_str = paste('GERM MUT', data_summary$MUT)
data_summary$mut_factor = factor(data_summary$MUT, levels = c(0.01, 0.02, 0.05, 0.10, 0.20, 0.50, 1.00))
# Create a map of colors we'll use to plot the different organism sizes
color_vec = as.character(khroma::color('bright')(7))
color_map = c(
  '16x16' = color_vec[1],
  '32x32' = color_vec[2],
  '64x64' = color_vec[3],
  '128x128' = color_vec[4],
  '256x256' = color_vec[5],
  '512x512' = color_vec[6],
  '1024x1024' = color_vec[7]
)
# Set the sizes for text in plots
text_major_size = 18
text_minor_size = 16
boxplot_color = '#9ecae1'
```

4.1 Data integrity check

Now we plot the number of finished replicates for each treatment to make sure all data are present. Each row shows a different germ mutation rate. Each bar/color

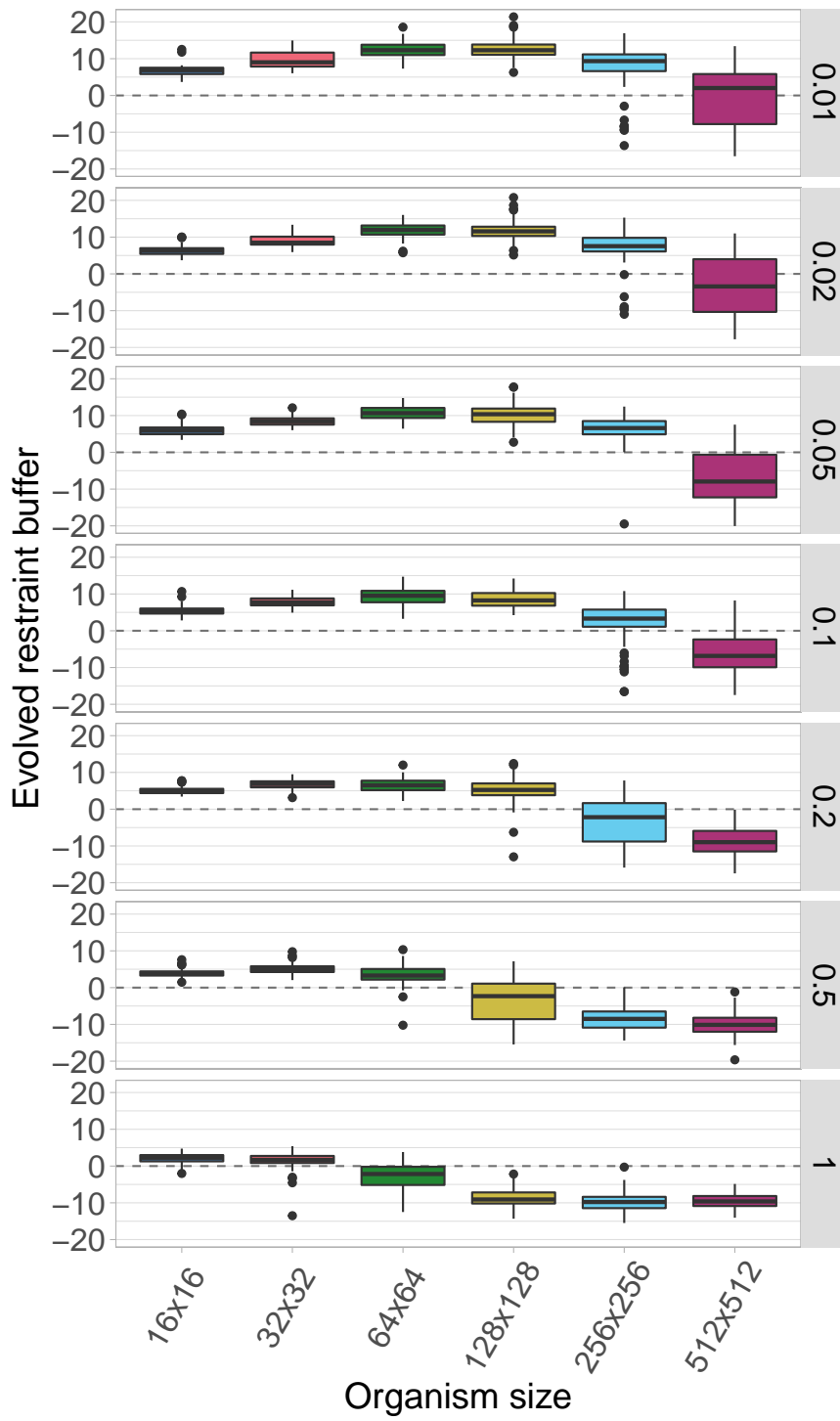


shows a different organism size.

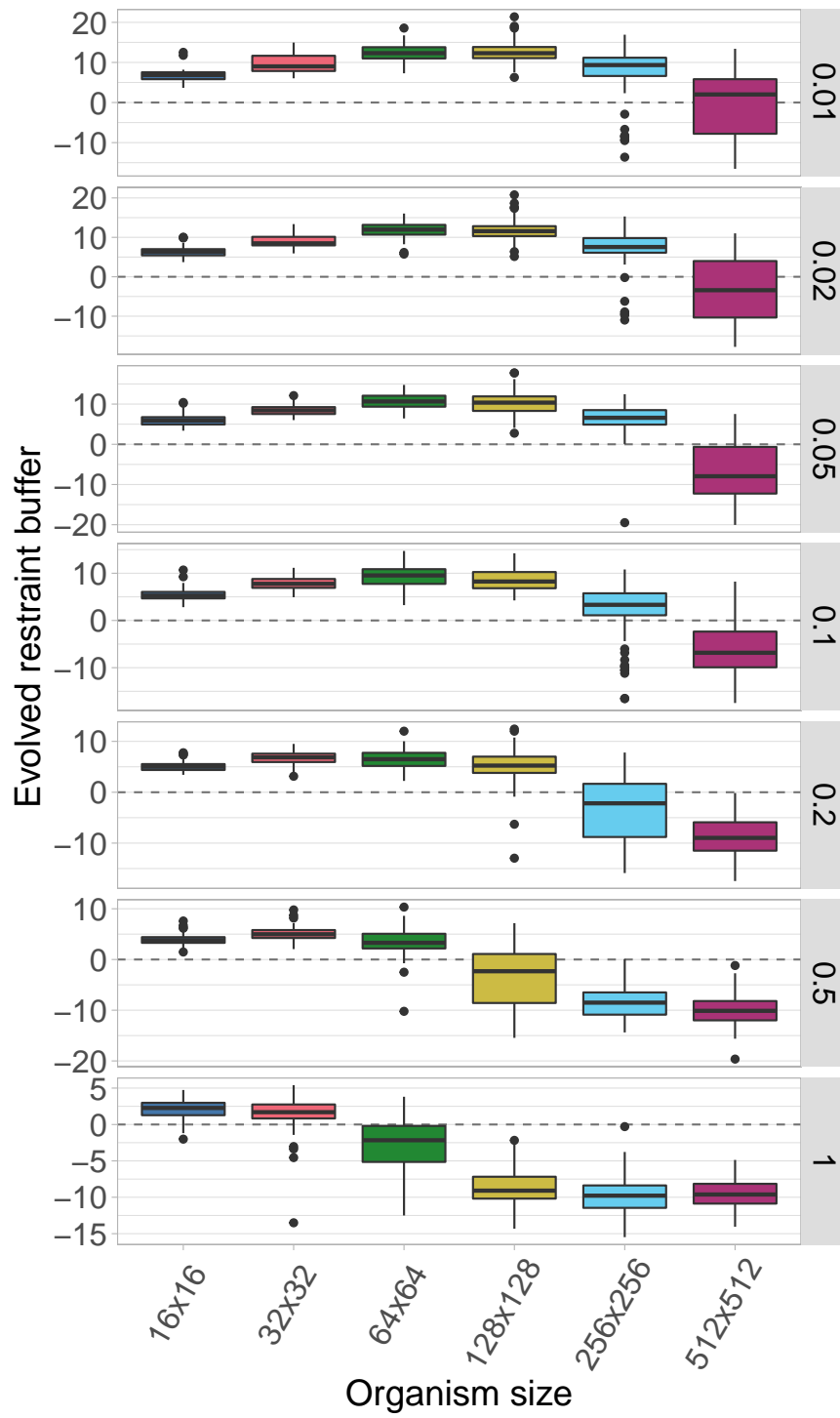
4.2 Aggregate plots

4.2.1 Facet by germ mutation rate

Here we plot all the data at once. Each row shows a different germ mutation rate and each boxplot shows a given organism size.

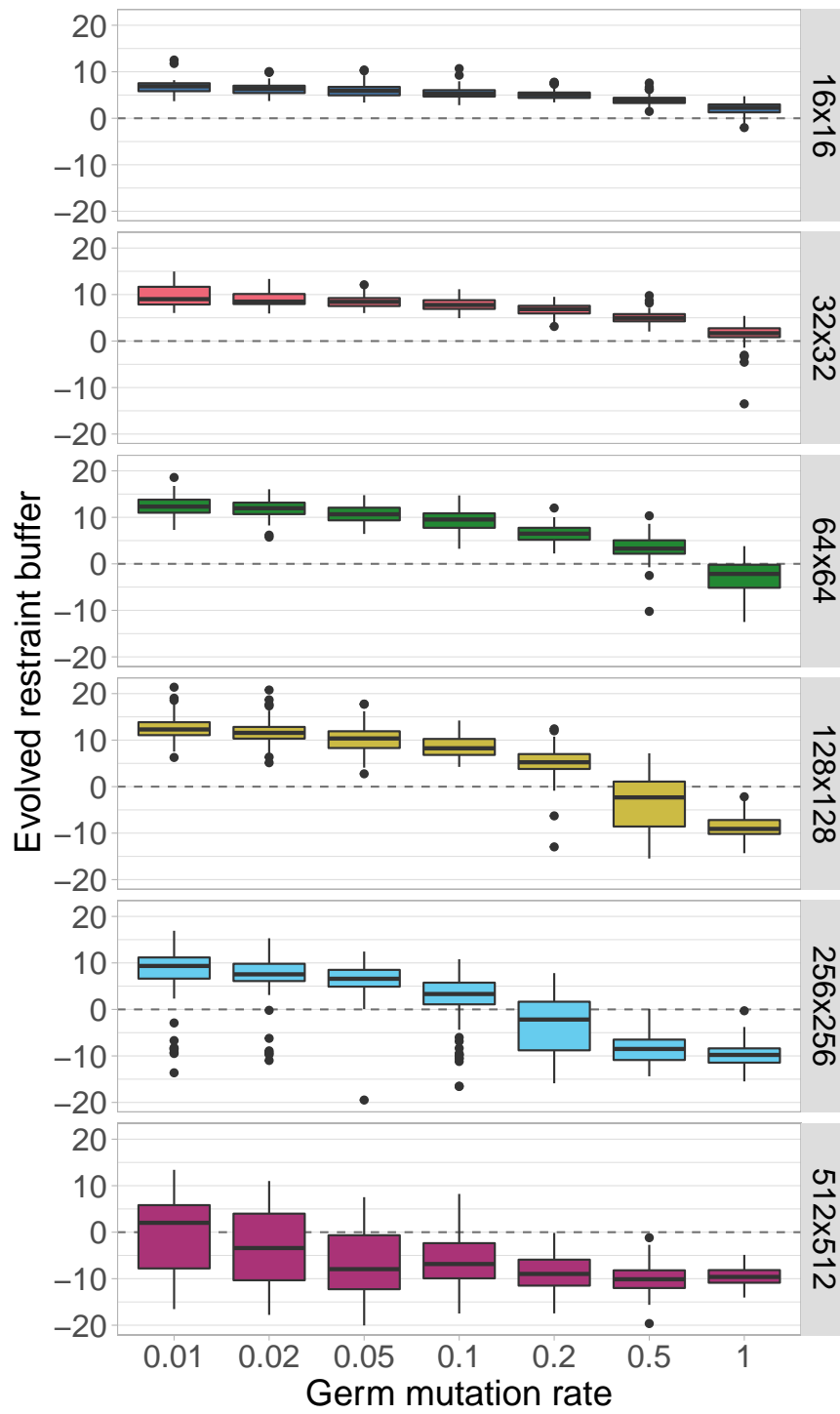


Here is the same data, plotted identically other than now each row can have a different y-axis.

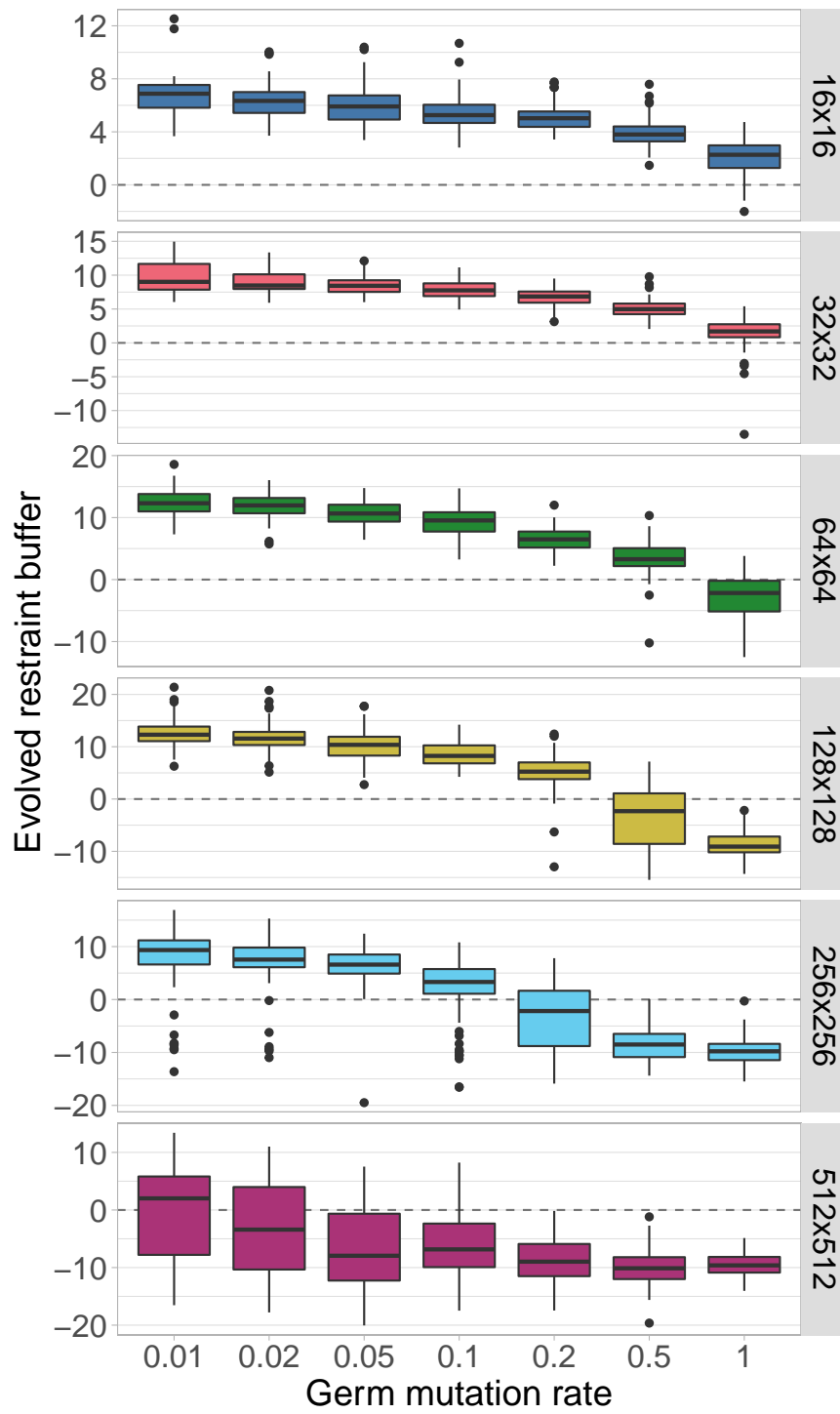


4.2.2 Facet by organism size

Next, we plot the same data, but this time each row corresponds to a certain organism size while germ mutation rate varies along the x-axis.



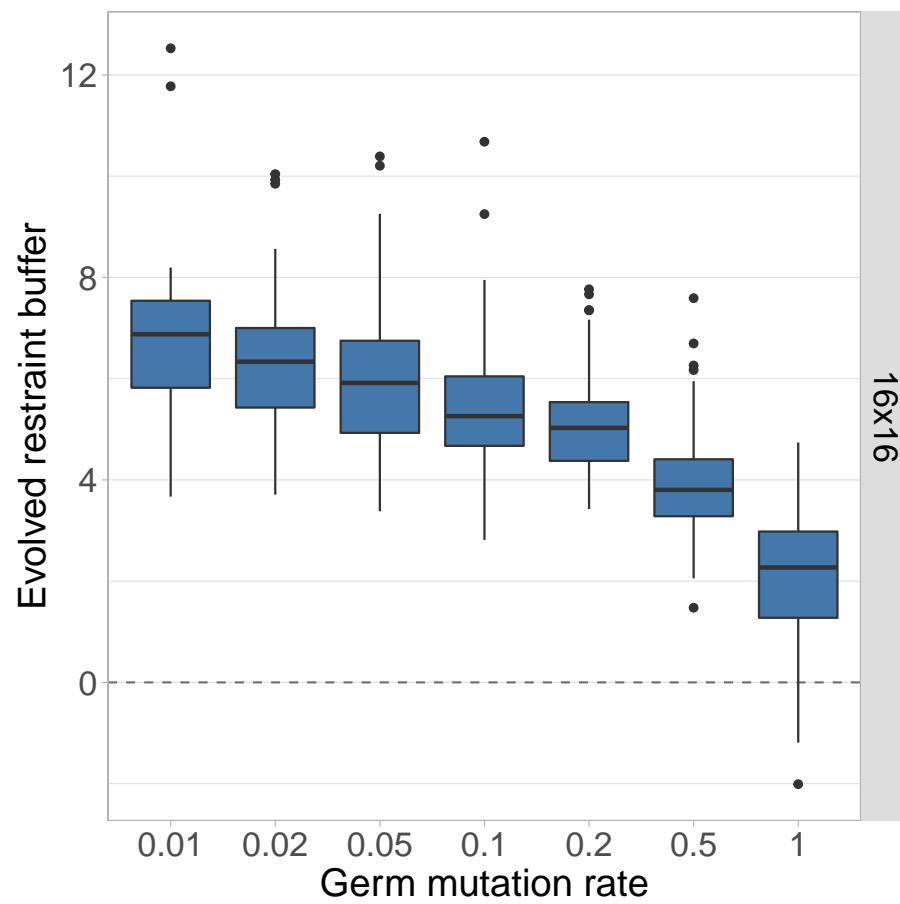
Again, we plot the same data again, but now the y-axis can change between rows.



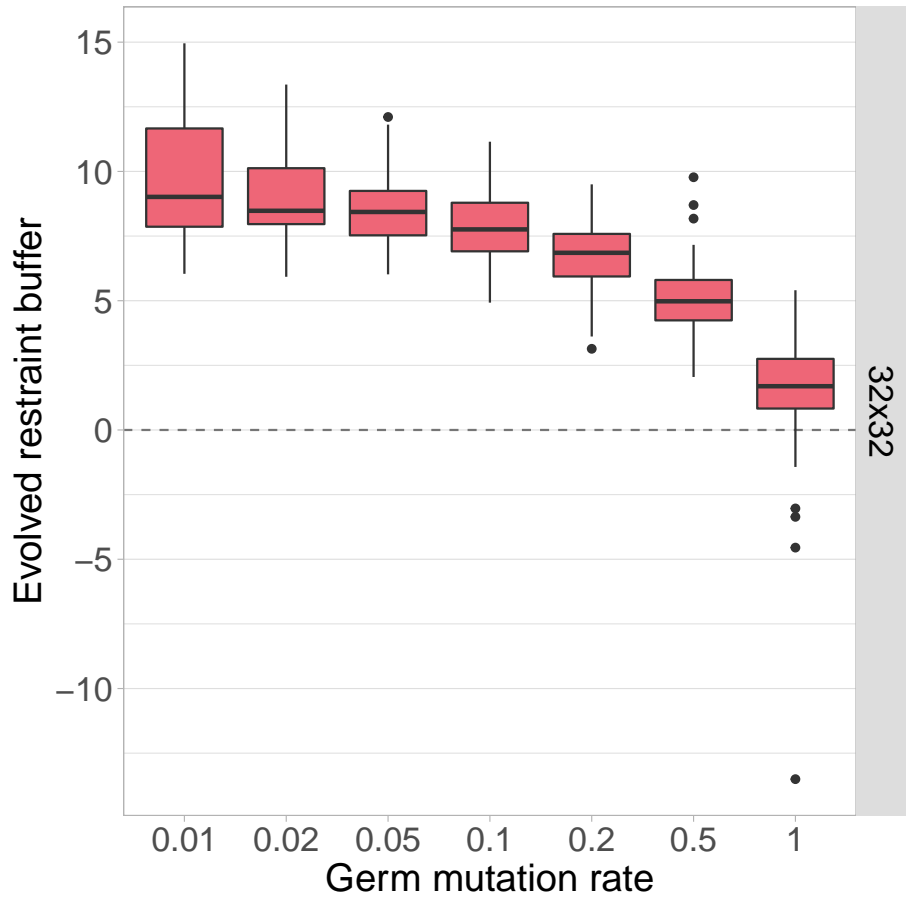
4.3 Single organism size plots

Here we plot each organism size independently, with the germ mutation rate on the x-axis.

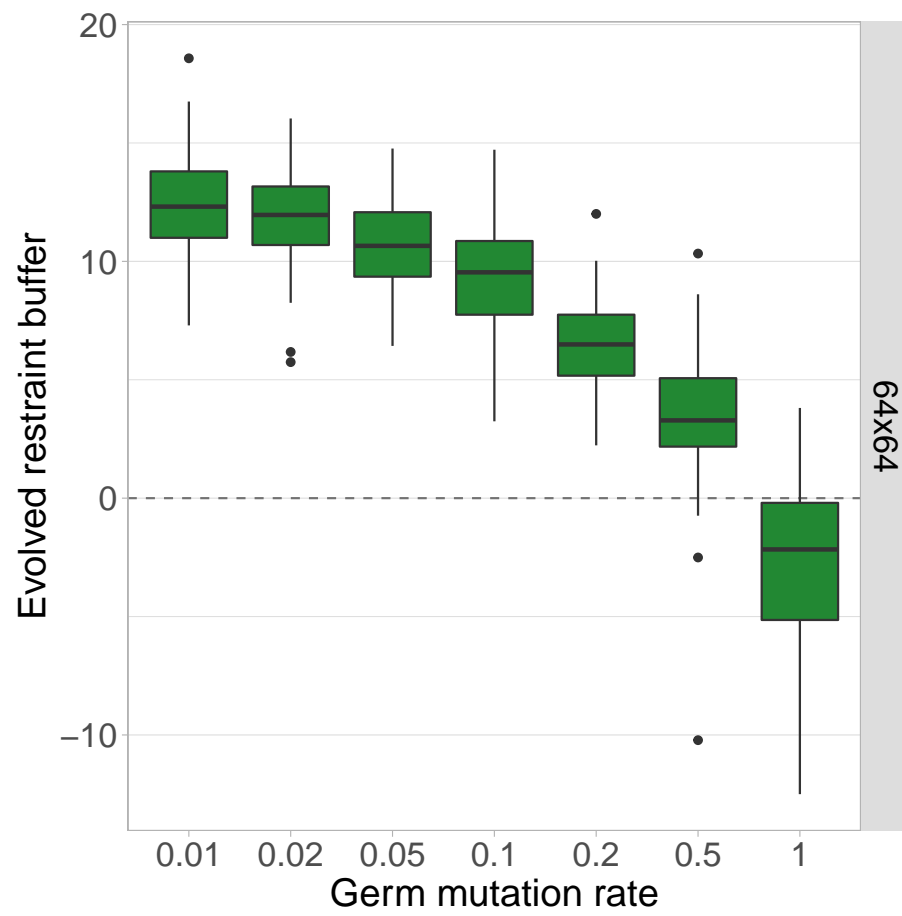
4.3.1 Organism size 16x16



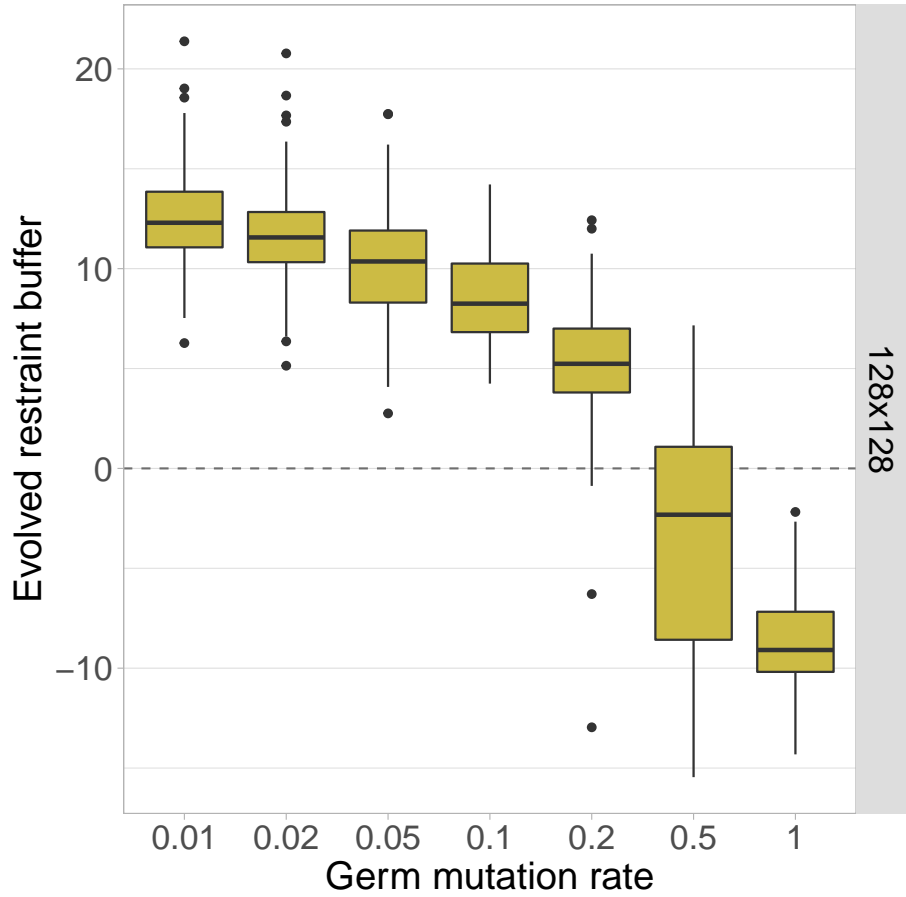
4.3.2 Organism size 32x32



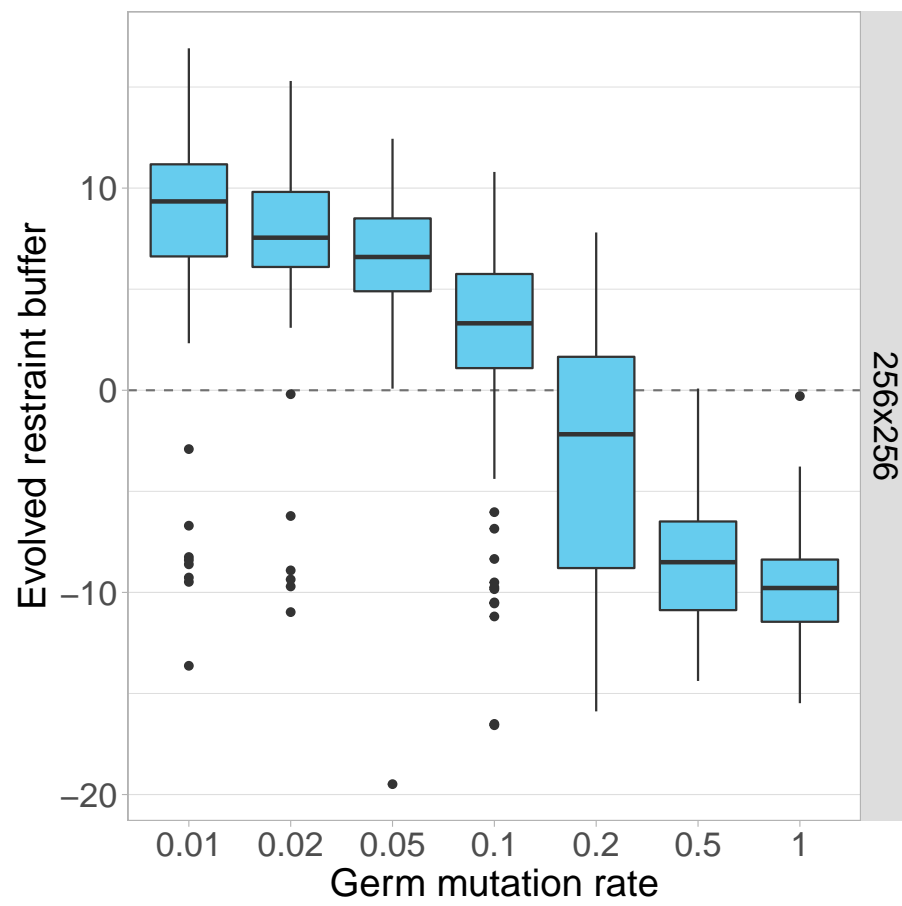
4.3.3 Organism size 64x64



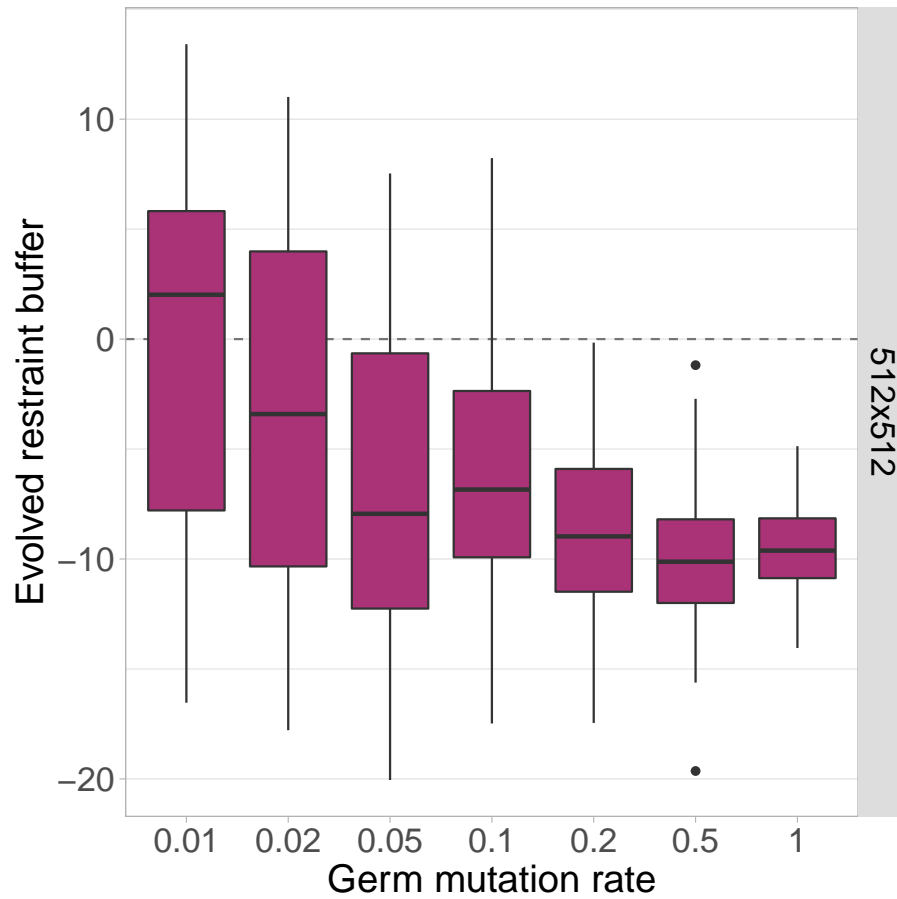
4.3.4 Organism size 128x128



4.3.5 Organism size 256x256



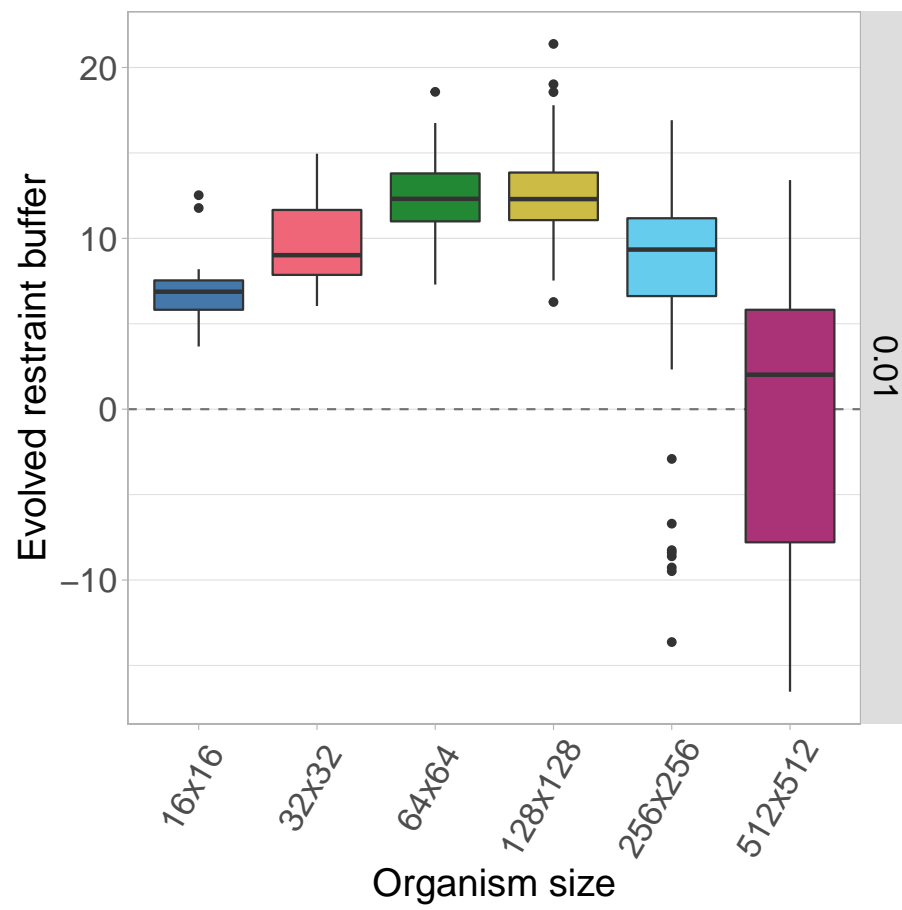
4.3.6 Organism size 512x512



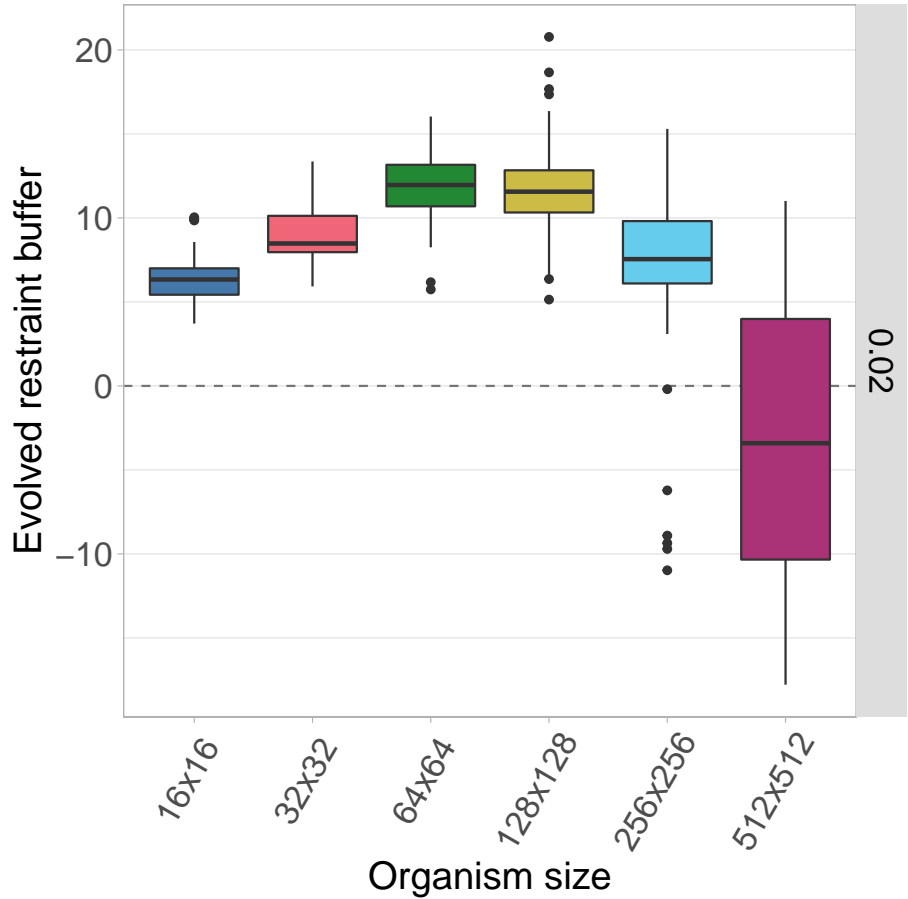
4.4 Single organism size plots

Similarly, here we plot each germ mutation rate independently, with the organism size on the x-axis.

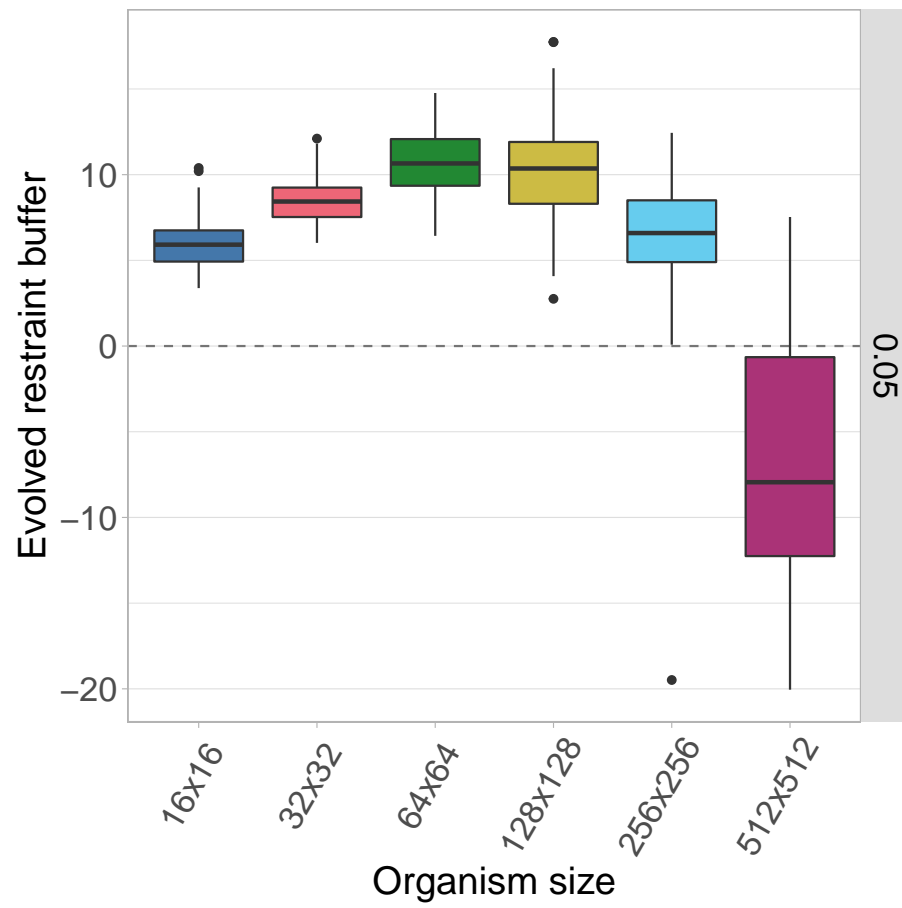
4.4.1 Germ mut. rate 0.01



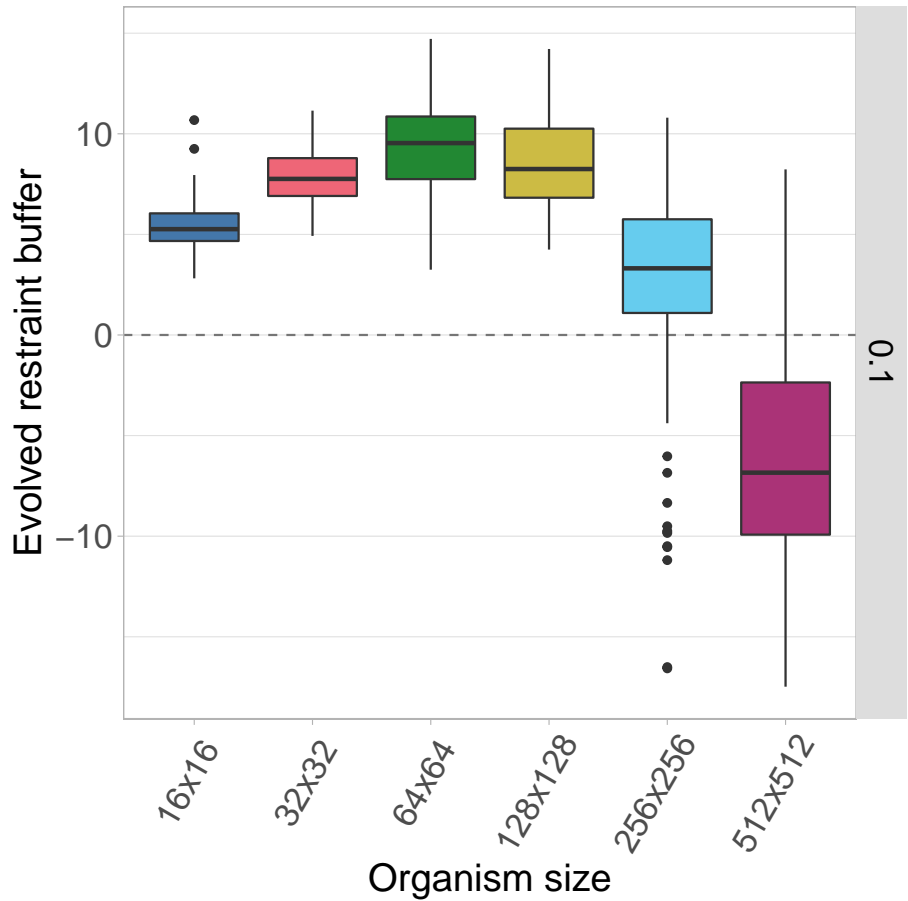
4.4.2 Germ mut. rate 0.02



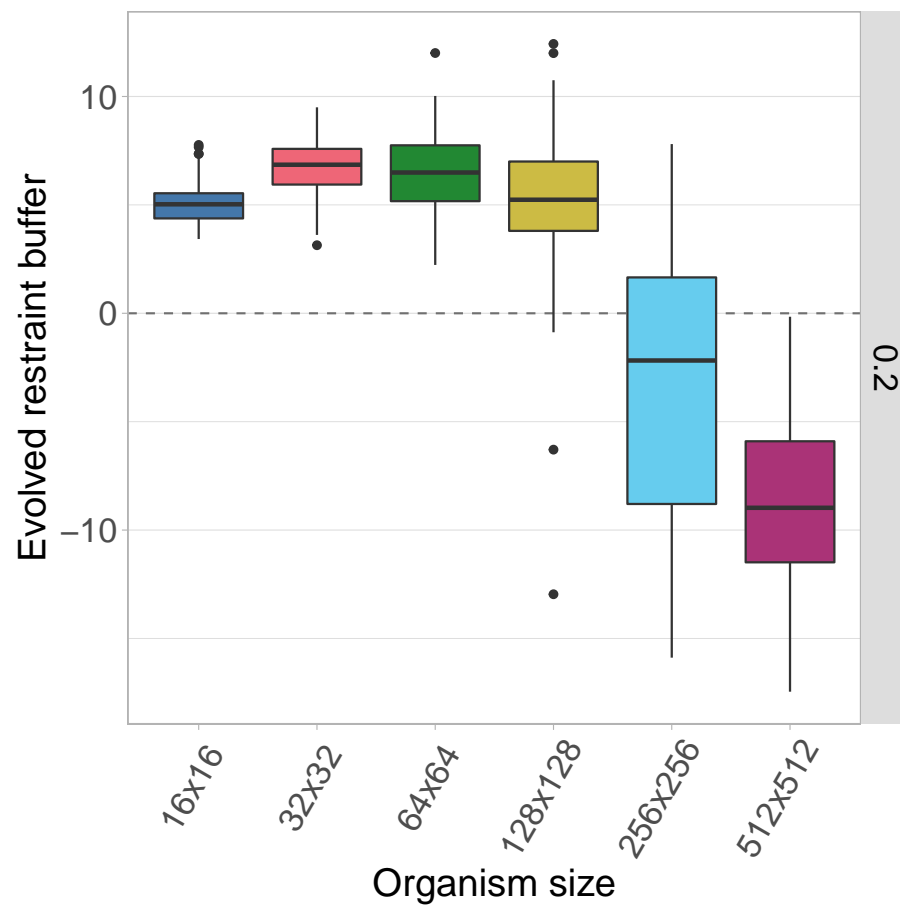
4.4.3 Germ mut. rate 0.05



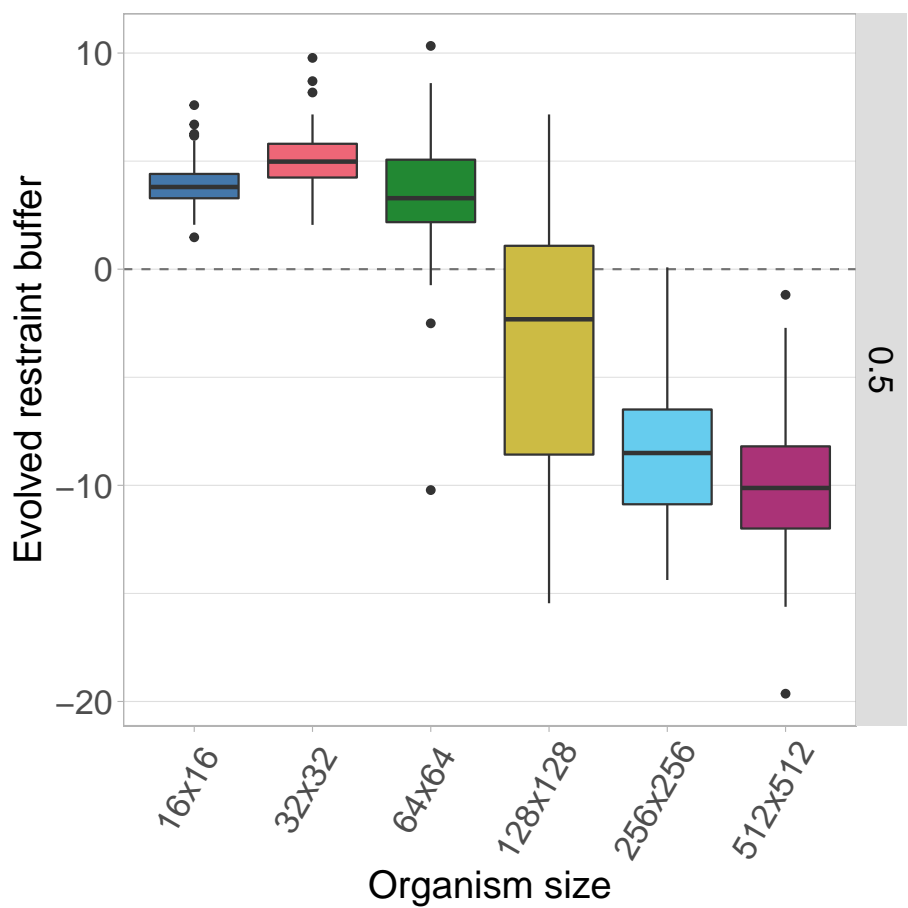
4.4.4 Germ mut. rate 0.1



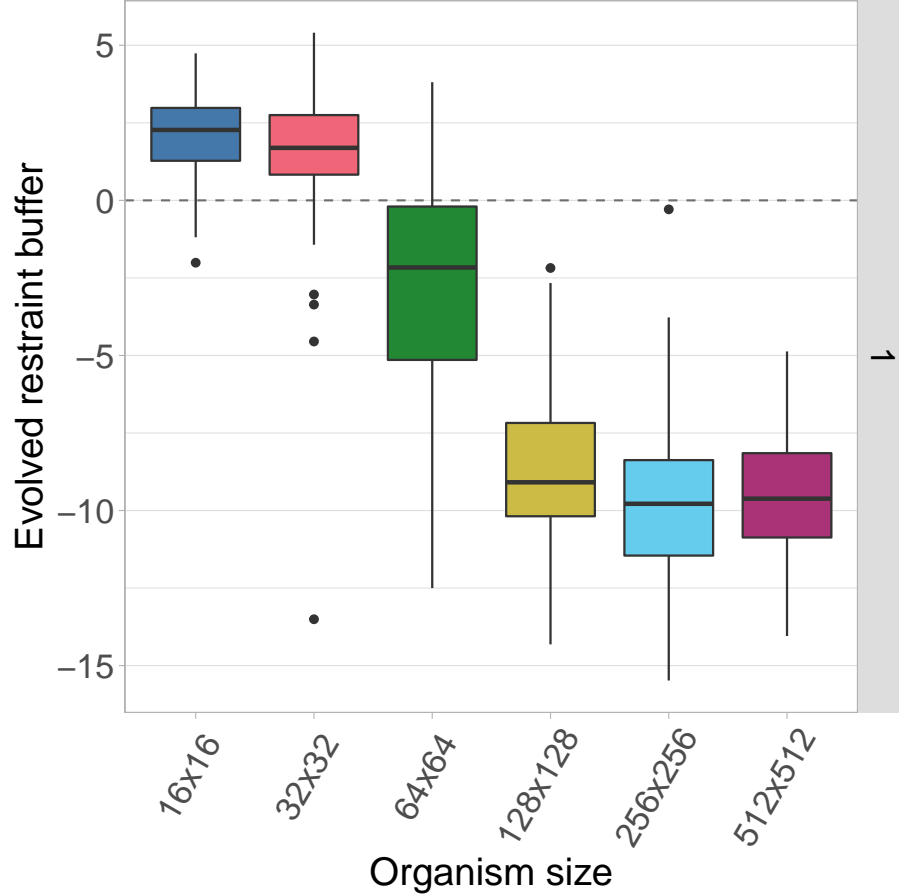
4.4.5 Germ mut. rate 0.2



4.4.6 Germ mut. rate 0.5



4.4.7 Germ mut. rate 1.0



4.5 Statistics

Since organism size is our main point of comparison, we calculate stats for each germ mutation rate.

First, we perform a Kruskal-Wallis test across all organism sizes to indicate if variance exists at that mutation rate. If variance exists, we then perform a pairwise Wilcoxon Rank-Sum test to show which pairs of organism sizes significantly differ. Finally, we perform Bonferroni-Holm corrections for multiple comparisons.

```
mut_vec = c(0.01, 0.02, 0.05, 0.1, 0.2, 0.5, 1)
df_kruskal = data.frame(data = matrix(nrow = 0, ncol = 4))
colnames(df_kruskal) = c('germ_mut_rate', 'p_value', 'chi_squared', 'df')
for(mut_rate in mut_vec){
  df_test = df2[df2$MUT == mut_rate,]
```

```

res = kruskal.test(df_test$restraint_value ~ df_test$MCSIZE, df_test)
df_kruskal[nrow(df_kruskal) + 1,] = c(mut_rate, res$p.value, as.numeric(res$statistic)[1], as
}
df_kruskal$less_0.01 = df_kruskal$p_value < 0.01
print(df_kruskal)

```

```

##   germ_mut_rate      p_value chi_squared df less_0.01
## 1          0.01 9.191452e-79    374.5160 5      TRUE
## 2          0.02 6.227269e-82    389.2251 5      TRUE
## 3          0.05 1.934895e-82    391.5809 5      TRUE
## 4          0.10 1.983976e-83    396.1708 5      TRUE
## 5          0.20 3.180895e-85    404.4991 5      TRUE
## 6          0.50 4.313881e-91    431.7152 5      TRUE
## 7          1.00 2.144229e-92    437.7600 5      TRUE

```

We see that significant variation exists within each mutation rate, so we perform pairwise Wilcoxon tests on each to see which pairs of sizes are significantly different.

```

size_vec = c(16, 32, 64, 128, 256, 512)
mut_vec = c(0.01, 0.02, 0.05, 0.1, 0.2, 0.5, 1)
for(mut_rate in mut_vec){
  df_test = df2[df2$MUT == mut_rate,]
  df_wilcox = data.frame(data = matrix(nrow = 0, ncol = 6))
  colnames(df_wilcox) = c('germ_mut_rate', 'size_a', 'size_b', 'p_value_corrected', 'p_value_raw')
  for(size_idx_a in 1:(length(size_vec) - 1)){
    size_a = size_vec[size_idx_a]
    for(size_idx_b in (size_idx_a + 1):length(size_vec)){
      size_b = size_vec[size_idx_b]
      res = wilcox.test(df_test[df_test$MCSIZE == size_a,]$restraint_value, df_test[df_test$MCSIZE == size_b,]$restraint_value)
      df_wilcox[nrow(df_wilcox) + 1,] = c(mut_rate, size_a, size_b, 0, res$p.value, as.numeric(res$statistic)[1])
    }
  }
  df_wilcox$p_value_corrected = p.adjust(df_wilcox$p_value_raw, method = 'holm')
  df_wilcox$less_0.01 = df_wilcox$p_value_corrected < 0.01
  print(paste0('Germ mutation rate: ', mut_rate))
  print(df_wilcox)
}

```

```

## [1] "Germ mutation rate: 0.01"
##   germ_mut_rate size_a size_b p_value_corrected p_value_raw      W less_0.01
## 1          0.01    16    32    1.161192e-21 1.161192e-22  990.0      TRUE
## 2          0.01    16    64    1.990837e-31 1.484433e-32  137.0      TRUE
## 3          0.01    16   128    2.032847e-30 1.694039e-31  221.0      TRUE
## 4          0.01    16   256    1.721090e-07 5.736966e-08 2778.5      TRUE
## 5          0.01    16   512    1.237738e-13 2.062896e-14 8130.0      TRUE
## 6          0.01    32    64    4.401194e-15 5.501492e-16 1684.5      TRUE

```

```

## 7      0.01      32      128      1.423615e-13 2.847230e-14 1887.0      TRUE
## 8      0.01      32      256      2.438849e-01 1.219425e-01 5633.5      FALSE
## 9      0.01      32      512      5.140604e-27 4.673276e-28 9495.0      TRUE
## 10     0.01      64      128      9.221418e-01 9.221418e-01 5040.5      FALSE
## 11     0.01      64      256      4.110744e-14 5.872491e-15 8195.5      TRUE
## 12     0.01      64      512      6.122051e-32 4.081368e-33 9907.0      TRUE
## 13     0.01     128      256      5.020912e-13 1.255228e-13 8033.5      TRUE
## 14     0.01     128      512      1.990837e-31 1.422026e-32 9864.5      TRUE
## 15     0.01     256      512      1.882508e-17 2.091675e-18 8582.5      TRUE
## [1] "Germ mutation rate: 0.02"
##      germ_mut_rate size_a size_b p_value_corrected p_value_raw      W less_0.01
## 1      0.02      16      32      5.385908e-24 5.385908e-25 773.5      TRUE
## 2      0.02      16      64      3.620092e-31 2.585780e-32 156.0      TRUE
## 3      0.02      16     128      5.876058e-29 4.896715e-30 339.5      TRUE
## 4      0.02      16     256      7.355430e-06 2.451810e-06 3071.0      TRUE
## 5      0.02      16     512      2.935849e-18 3.669812e-19 8662.0      TRUE
## 6      0.02      32      64      5.800574e-18 8.286535e-19 1375.0      TRUE
## 7      0.02      32     128      4.715120e-12 1.178780e-12 2090.5      TRUE
## 8      0.02      32     256      4.080762e-04 2.040381e-04 6520.5      TRUE
## 9      0.02      32     512      6.645814e-27 6.041649e-28 9485.5      TRUE
## 10     0.02      64     128      2.889472e-01 2.889472e-01 5434.5      FALSE
## 11     0.02      64     256      2.039804e-17 3.399674e-18 8560.0      TRUE
## 12     0.02      64     512      4.109271e-32 2.739514e-33 9920.5      TRUE
## 13     0.02     128     256      2.514342e-14 5.028683e-15 8203.5      TRUE
## 14     0.02     128     512      4.123142e-31 3.171647e-32 9837.0      TRUE
## 15     0.02     256     512      4.866893e-20 5.407659e-21 8848.0      TRUE
## [1] "Germ mutation rate: 0.05"
##      germ_mut_rate size_a size_b p_value_corrected p_value_raw      W less_0.01
## 1      0.05      16      32      1.591362e-24 1.768180e-25 730.0      TRUE
## 2      0.05      16      64      1.063762e-30 8.864684e-32 198.5      TRUE
## 3      0.05      16     128      3.321119e-21 4.151399e-22 1043.0      TRUE
## 4      0.05      16     256      2.538532e-02 1.269266e-02 3979.5      FALSE
## 5      0.05      16     512      1.050337e-26 9.548517e-28 9468.5      TRUE
## 6      0.05      32      64      3.387540e-14 5.645899e-15 1802.5      TRUE
## 7      0.05      32     128      1.306936e-05 4.356453e-06 3119.5      TRUE
## 8      0.05      32     256      1.528740e-07 3.821850e-08 7251.0      TRUE
## 9      0.05      32     512      3.162116e-32 2.258654e-33 9927.0      TRUE
## 10     0.05      64     128      1.546546e-01 1.546546e-01 5583.0      FALSE
## 11     0.05      64     256      4.390965e-19 6.272808e-20 8741.0      TRUE
## 12     0.05      64     512      6.208612e-33 4.139074e-34 9984.0      TRUE
## 13     0.05     128     256      2.838701e-12 5.677403e-13 7950.5      TRUE
## 14     0.05     128     512      9.845016e-32 7.573090e-33 9886.0      TRUE
## 15     0.05     256     512      3.142822e-26 3.142822e-27 9424.0      TRUE
## [1] "Germ mutation rate: 0.1"
##      germ_mut_rate size_a size_b p_value_corrected p_value_raw      W less_0.01
## 1      0.1      16      32      2.006447e-24 2.229385e-25 739.0      TRUE

```

```

## 2      0.1      16      64      2.197505e-25 1.997732e-26 646.0      TRUE
## 3      0.1      16     128      3.982057e-19 6.636762e-20 1261.5     TRUE
## 4      0.1      16     256      2.853915e-06 9.513050e-07 7006.5     TRUE
## 5      0.1      16     512      1.146029e-26 9.550238e-28 9468.5     TRUE
## 6      0.1      32      64      6.866683e-07 1.716671e-07 2860.0     TRUE
## 7      0.1      32     128      5.714627e-02 5.714627e-02 4221.0     FALSE
## 8      0.1      32     256      7.451552e-21 9.314440e-22 8923.0     TRUE
## 9      0.1      32     512      1.091653e-31 7.797522e-33 9885.0     TRUE
## 10     0.1      64     128      2.618271e-02 1.309135e-02 6016.0     FALSE
## 11     0.1      64     256      6.893655e-25 6.893655e-26 9306.5     TRUE
## 12     0.1      64     512      4.295636e-32 2.863757e-33 9919.0     TRUE
## 13     0.1     128     256      9.294756e-21 1.327822e-21 8908.0     TRUE
## 14     0.1     128     512      2.475810e-31 1.904469e-32 9854.5     TRUE
## 15     0.1     256     512      7.440793e-16 1.488159e-16 8380.0     TRUE
## [1] "Germ mutation rate: 0.2"
##      germ_mut_rate size_a size_b p_value_corrected p_value_raw      W less_0.01
## 1      0.2      16      32      6.711164e-17 9.587377e-18 1488.5     TRUE
## 2      0.2      16      64      2.652853e-08 5.305706e-09 2610.5     TRUE
## 3      0.2      16     128      5.723537e-01 4.033561e-01 4657.5     FALSE
## 4      0.2      16     256      9.414689e-28 1.046077e-28 9550.0     TRUE
## 5      0.2      16     512      3.841700e-33 2.561134e-34 10000.0    TRUE
## 6      0.2      32      64      5.723537e-01 2.861769e-01 5437.0     FALSE
## 7      0.2      32     128      2.713788e-06 6.784470e-07 7033.5     TRUE
## 8      0.2      32     256      2.557355e-30 2.324869e-31 9768.0     TRUE
## 9      0.2      32     512      3.841700e-33 2.561422e-34 10000.0    TRUE
## 10     0.2      64     128      8.967634e-04 2.989211e-04 6480.5     TRUE
## 11     0.2      64     256      3.597156e-29 3.597156e-30 9671.5     TRUE
## 12     0.2      64     512      3.841700e-33 2.561422e-34 10000.0    TRUE
## 13     0.2     128     256      3.256203e-24 4.070254e-25 9237.5     TRUE
## 14     0.2     128     512      1.052551e-31 8.771259e-33 9881.0     TRUE
## 15     0.2     256     512      1.558734e-09 2.597889e-10 7587.5     TRUE
## [1] "Germ mutation rate: 0.5"
##      germ_mut_rate size_a size_b p_value_corrected p_value_raw      W less_0.01
## 1      0.5      16      32      3.627488e-11 7.254975e-12 2195.0     TRUE
## 2      0.5      16      64      1.774145e-01 1.774145e-01 5552.5     FALSE
## 3      0.5      16     128      9.003159e-21 1.125395e-21 8915.0     TRUE
## 4      0.5      16     256      3.840402e-33 2.560268e-34 10000.0    TRUE
## 5      0.5      16     512      3.840402e-33 2.560412e-34 10000.0    TRUE
## 6      0.5      32      64      1.574642e-07 5.248808e-08 7228.0     TRUE
## 7      0.5      32     128      3.547680e-25 3.941867e-26 9328.0     TRUE
## 8      0.5      32     256      3.840402e-33 2.560701e-34 10000.0    TRUE
## 9      0.5      32     512      3.840402e-33 2.560845e-34 10000.0    TRUE
## 10     0.5      64     128      4.292292e-17 6.131846e-18 8532.5     TRUE
## 11     0.5      64     256      3.128938e-32 3.128938e-33 9916.0     TRUE
## 12     0.5      64     512      1.333109e-32 1.211917e-33 9948.0     TRUE
## 13     0.5     128     256      2.868826e-09 7.172065e-10 7522.5     TRUE

```

```

## 14      0.5    128    512      9.393819e-14 1.565636e-14 8144.5      TRUE
## 15      0.5    256    512      3.381624e-03 1.690812e-03 6285.5      TRUE
## [1] "Germ mutation rate: 1"
##      germ_mut_rate size_a size_b p_value_corrected p_value_raw      W less_0.01
## 1      1         16     32      1.080497e-01 5.402483e-02 5789.0      FALSE
## 2      1         16     64      2.560330e-24 2.844811e-25 9251.5      TRUE
## 3      1         16    128      3.840402e-33 2.560268e-34 10000.0     TRUE
## 4      1         16    256      3.840402e-33 2.887894e-34 9996.0      TRUE
## 5      1         16    512      3.840402e-33 2.560412e-34 10000.0     TRUE
## 6      1         32     64      1.004804e-19 1.674674e-20 8799.0      TRUE
## 7      1         32    128      8.265949e-32 8.265949e-33 9883.0      TRUE
## 8      1         32    256      7.190219e-32 6.536563e-33 9891.0      TRUE
## 9      1         32    512      5.842919e-32 4.869099e-33 9901.0      TRUE
## 10     1         64    128      1.007238e-18 2.014476e-19 8689.0      TRUE
## 11     1         64    256      7.963405e-23 1.137629e-23 9105.0      TRUE
## 12     1         64    512      5.680932e-23 7.101164e-24 9124.0      TRUE
## 13     1        128    256      1.357430e-02 3.393576e-03 6199.5     FALSE
## 14     1        128    512      3.704384e-02 1.234795e-02 6024.5     FALSE
## 15     1        256    512      4.892624e-01 4.892624e-01 4716.5     FALSE

```

Chapter 5

Timing sample count experiment

By default, we calculated 100 timing samples for each combination of organism size and restraint buffer value to use for organism fitness in Primordium (a new batch was generated for each experiment). This experiment showed that increasing from 100 samples to 10,000 samples has no qualitative difference on results. This was done by replicating the baseline experiment using 10,000 samples and comparing the results to a fresh run with 100 samples.

5.1 Data cleaning

Load necessary R libraries

```
library(dplyr)
library(ggplot2)
library(ggribes)
library(scales)
library(khroma)
```

Load the data and trim include only the final generation data for sizes 16x16 to 512x512.

```
# Load the data
df = read.csv('../experiments/2021_02_24__finite_10k_samples/evolution/data/scraped_evolution_data.csv')
df = rbind(df, read.csv('../experiments/2021_02_24__finite_10k_samples/evolution/data/scraped_evolution_data.csv'))
df = rbind(df, read.csv('../experiments/2021_02_24__finite_10k_samples/evolution/data/scraped_evolution_data.csv'))
df$LENGTH = 100
df = rbind(df, read.csv('../experiments/2021_02_24__finite_10k_samples/evolution/data/scraped_evolution_data.csv'))
df = rbind(df, read.csv('../experiments/2021_02_24__finite_10k_samples/evolution/data/scraped_evolution_data.csv'))
```

```
# Trim off NAs (artifacts of how we scraped the data) and trim to only have gen 10,000
df2 = df[!is.na(df$MCSIZE) & df$generation == 10000,]
# Ignore data for size 8x8 and 1024x1024
df2 = df2[df2$MCSIZE != 8 & df2$MCSIZE != 1024,]
```

We group and summarize the data to make to ensure all replicates are present.

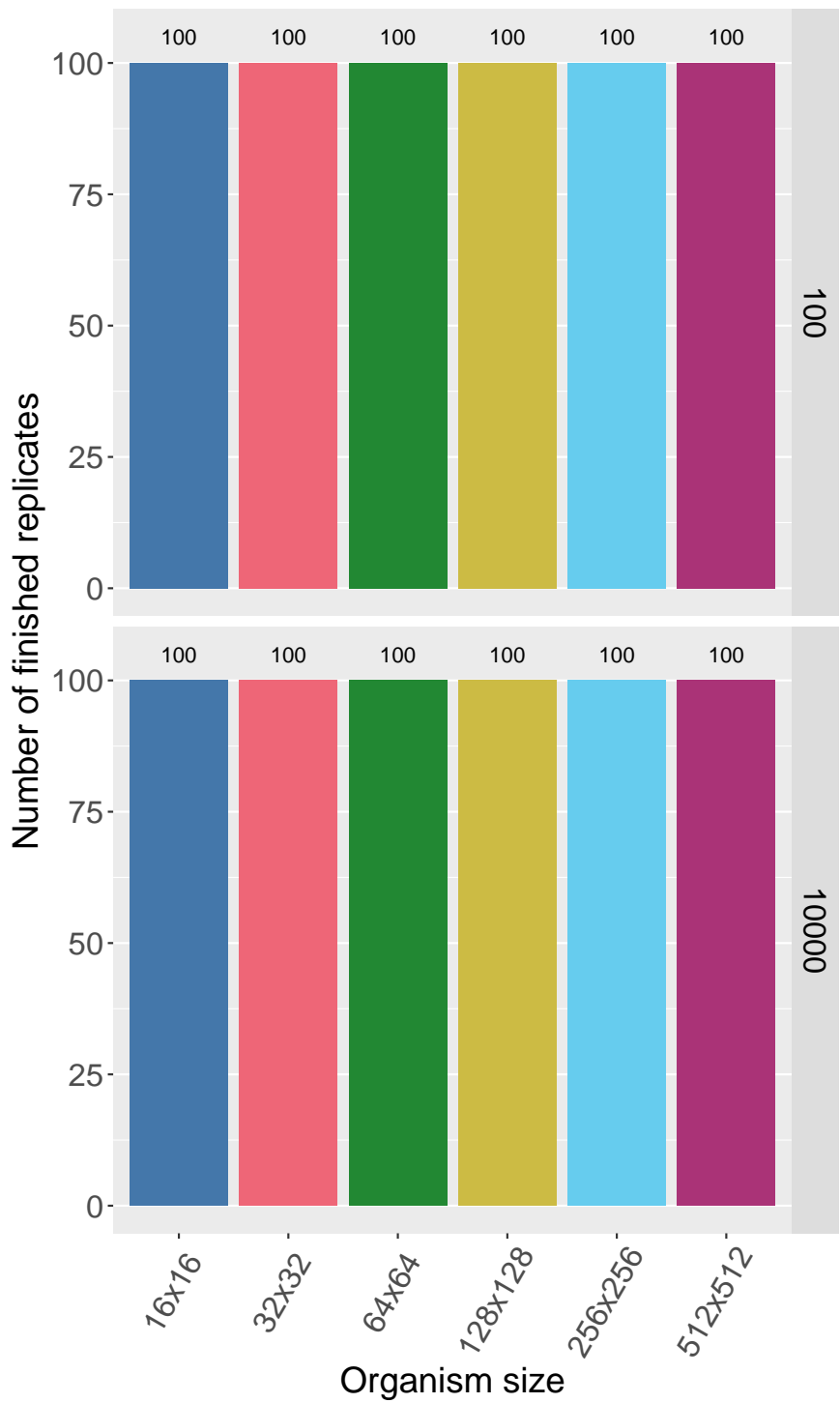
```
# Group the data by size and summarize
data_grouped = dplyr::group_by(df2, MCSIZE, SAMPLES)
data_summary = dplyr::summarize(data_grouped, mean_ones = mean(ave_ones), n = dplyr::n())
```

We clean the data and create a few helper variables to make plotting easier.

```
# Calculate restraint value (x - 60 because genome length is 100 here)
df2$restraint_value = df2$ave_ones - 60
# Make a nice, clean factor for size
df2$size_str = paste0(df2$MCSIZE, 'x', df2$MCSIZE)
df2$size_factor = factor(df2$size_str, levels = c('16x16', '32x32', '64x64', '128x128', '256x256', '512x512', '1024x1024'))
df2$size_factor_reversed = factor(df2$size_str, levels = rev(c('16x16', '32x32', '64x64', '128x128', '256x256', '512x512', '1024x1024')))
data_summary$size_str = paste0(data_summary$MCSIZE, 'x', data_summary$MCSIZE)
data_summary$size_factor = factor(data_summary$size_str, levels = c('16x16', '32x32', '64x64', '128x128', '256x256', '512x512', '1024x1024'))
# Create a map of colors we'll use to plot the different organism sizes
color_vec = as.character(khroma::color('bright')(7))
color_map = c(
  '16x16' = color_vec[1],
  '32x32' = color_vec[2],
  '64x64' = color_vec[3],
  '128x128' = color_vec[4],
  '256x256' = color_vec[5],
  '512x512' = color_vec[6],
  '1024x1024' = color_vec[7]
)
# Set the sizes for text in plots
text_major_size = 18
text_minor_size = 16
```

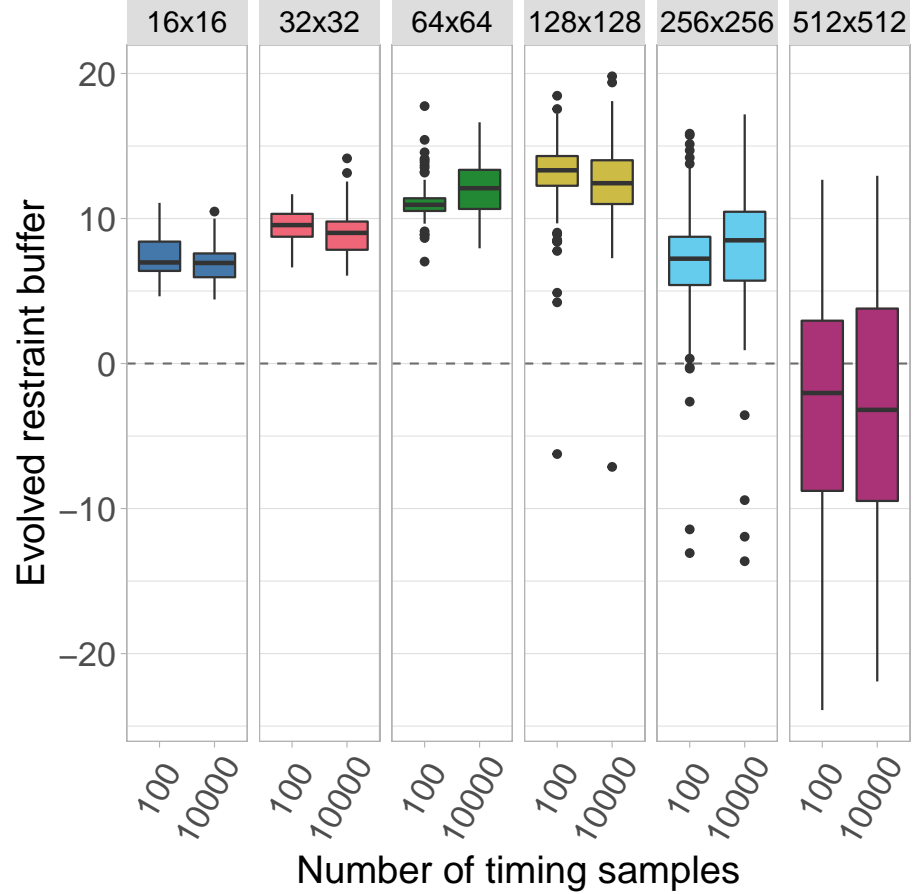
5.2 Data integrity check

Now we plot the number of finished replicates for each treatment to make sure all data are present. Rows show the number of samples used for fitness. Each bar/color shows a different organism size.



5.3 Plot

Here we plot all the data. The figure is split into 6 subplots, each showing a different organism size. Inside each subplot, the number of timing samples is shown on



the x-axis.

5.4 Statistics

The plot shows that the general trend, that the evolved restraint buffer initially increases with organism size then decreases, holds true at both sample counts. Furthermore, we see that the evolved buffer values are fairly consistent between the two sample counts.

While we concluded that this was sufficient evidence to use only 100 samples (10,000 is intractable to run for multiple experiments), we include the statistics here. Since we treat each organism size as a group, we simply conduct a Wilcoxon Rank-Sum test between 100 samples and 10,000 samples

##	org_size	p_value	W	less_0.01
## 1	16	4.243294e-02	5831.0	FALSE
## 2	32	3.489808e-04	6464.0	TRUE
## 3	64	4.913265e-05	3338.0	TRUE
## 4	128	3.021256e-02	5887.5	FALSE
## 5	256	2.561216e-02	4086.0	FALSE
## 6	512	9.066359e-01	5048.5	FALSE

Chapter 6

Population size experiment

By default, all populations contain 200 organisms. This experiment tested if increasing the population size to 2,000 organisms has any substantial effect on evolved restraint.

6.1 Data cleaning

Load necessary libraries

```
library(dplyr)
library(ggplot2)
library(ggthemes)
library(scales)
library(khroma)
```

Load the data and trim include only the final generation data for sizes 16x16 to 512x512.

```
# Load the data
df = read.csv('../experiments/2021_03_06__pop_size/evolution/data/scraped_evolution_data_200.csv')
df = rbind(df, read.csv('../experiments/2021_03_06__pop_size/evolution/data/scraped_evolution_data_2000.csv'))
# Trim off NAs (artifacts of how we scraped the data) and trim to only have gen 10,000
df2 = df[!is.na(df$MCSIZE) & df$generation == 10000,]
# Ignore data for size 8x8 and 1024x1024
df2 = df2[df2$MCSIZE != 8 & df2$MCSIZE != 1024,]
```

We group and summarize the data to ensure all replicates are present.

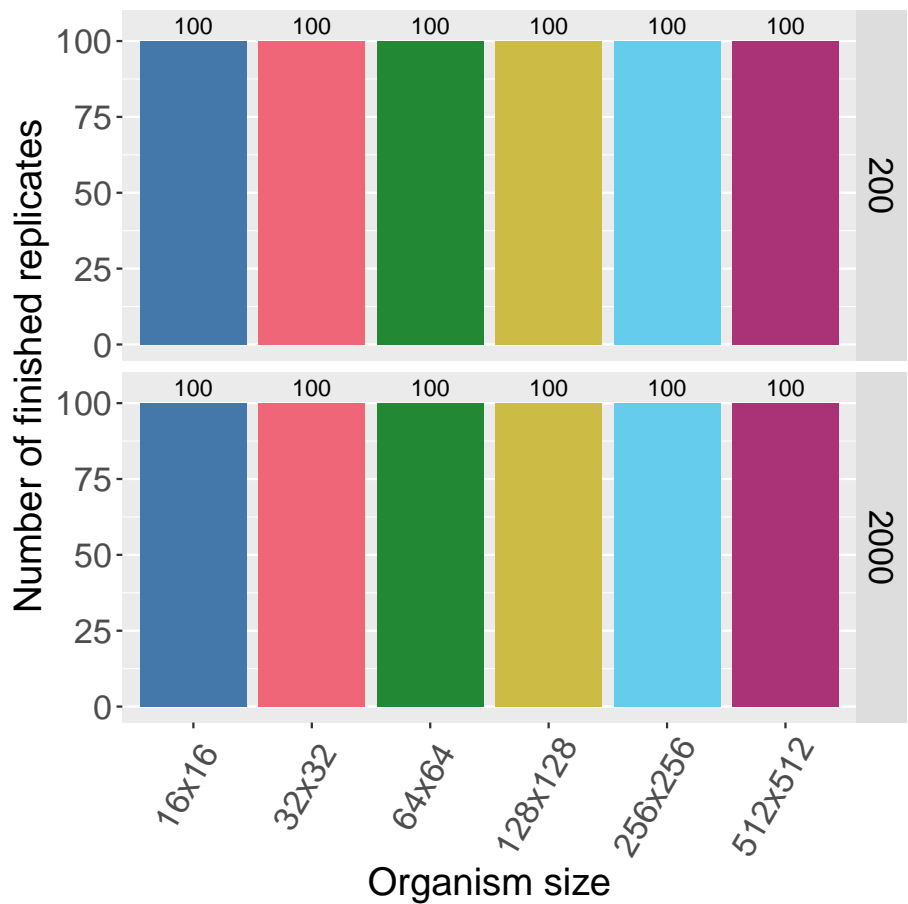
```
# Group the data by size and summarize
data_grouped = dplyr::group_by(df2, MCSIZE, POP)
data_summary = dplyr::summarize(data_grouped, mean_ones = mean(ave_ones), n = dplyr::n())
```

We clean the data and create a few helper variables to make plotting easier.

```
# Calculate restraint value (x - 60 because genome length is 100 here)
df2$restraint_value = df2$ave_ones - 60
# Make a nice, clean factor for size
df2$size_str = paste0(df2$MCSIZE, 'x', df2$MCSIZE)
df2$size_factor = factor(df2$size_str, levels = c('16x16', '32x32', '64x64', '128x128', '256x256', '512x512', '1024x1024'))
df2$size_factor_reversed = factor(df2$size_str, levels = rev(c('16x16', '32x32', '64x64', '128x128', '256x256', '512x512', '1024x1024')))
data_summary$size_str = paste0(data_summary$MCSIZE, 'x', data_summary$MCSIZE)
data_summary$size_factor = factor(data_summary$size_str, levels = c('16x16', '32x32', '64x64', '128x128', '256x256', '512x512', '1024x1024'))
# Create a map of colors we'll use to plot the different organism sizes
color_vec = as.character(khroma::color('bright')(7))
color_map = c(
  '16x16' = color_vec[1],
  '32x32' = color_vec[2],
  '64x64' = color_vec[3],
  '128x128' = color_vec[4],
  '256x256' = color_vec[5],
  '512x512' = color_vec[6],
  '1024x1024' = color_vec[7]
)
# Set the sizes for text in plots
text_major_size = 18
text_minor_size = 16
```

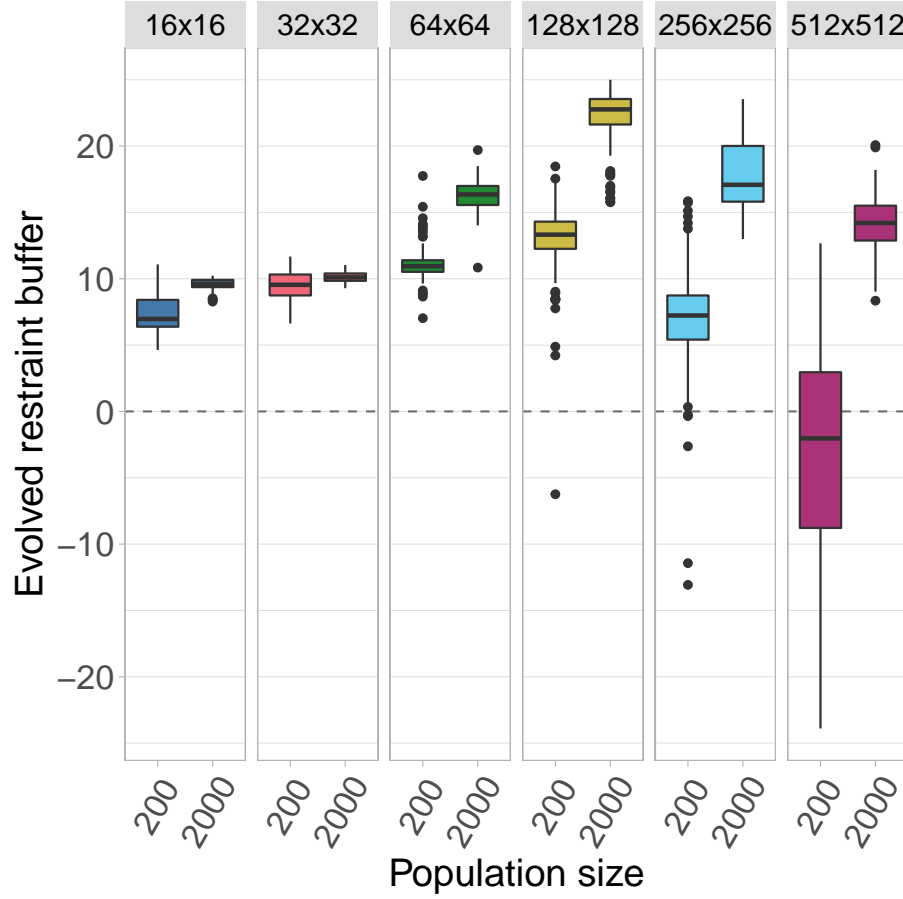
6.2 Data integrity check

Now we plot the number of finished replicates for each treatment to make sure all data are present. Rows show the number of samples used for fitness. Each bar/color shows a different organism size.



6.3 Plot

Here we plot all the data. The figure is split into 6 subplots, each showing a different organism size. Inside each subplot, population size is shown on the x-axis.



6.4 Statistics

The plot shows that increasing population size increases the evolved restraint buffer at organism sizes. Further, we see that the same general trend holds at both population sizes, that evolved restraint peaks at size 128x128.

Finally, we treat each organism size as a group and conduct a Wilcoxon Rank-Sum test between the population sizes.

##	org_size	p_value	W	less_0.01
## 1	16	3.921812e-19	1341.0	TRUE
## 2	32	8.416553e-06	3176.5	TRUE
## 3	64	4.238745e-32	173.0	TRUE
## 4	128	1.013881e-33	46.0	TRUE
## 5	256	2.781080e-33	80.0	TRUE
## 6	512	4.954199e-34	22.0	TRUE

Chapter 7

Genome Length Sweep

By default, all genomes are bitstrings with 100 bits. Here, we look into the effects of varying this genome length using lengths of 25, 50, 100, 200, and 400 bits.

The configuration script and data for the experiment can be found under 2021_02_27__genome_length/ in the experiments directory of the git repository.

7.1 Data cleaning

Load necessary libraries

```
library(dplyr)
library(ggplot2)
library(ggribes)
library(scales)
library(khroma)
```

Load the data and trim include only the final generation data for sizes 16x16 to 512x512.

```
# Load the data
df = read.csv('../experiments/2021_02_27__genome_length/evolution/data/scraped_evolution_data_len
df = rbind(df, read.csv('../experiments/2021_02_27__genome_length/evolution/data/scraped_evolutio
df = rbind(df, read.csv('../experiments/2021_02_27__genome_length/evolution/data/scraped_evolutio
df = rbind(df, read.csv('../experiments/2021_02_27__genome_length/evolution/data/scraped_evolutio
df = rbind(df, read.csv('../experiments/2021_02_27__genome_length/evolution/data/scraped_evolutio
# Trim off NAs (artifacts of how we scraped the data) and trim to only have gen 10,000
df2 = df[!is.na(df$MCSIZE) & df$generation == 10000,]
# Ignore data for size 8x8 and 1024x1024
df2 = df2[df2$MCSIZE != 8 & df2$MCSIZE != 1024,]
```

We group and summarize the data to ensure all replicates are present.

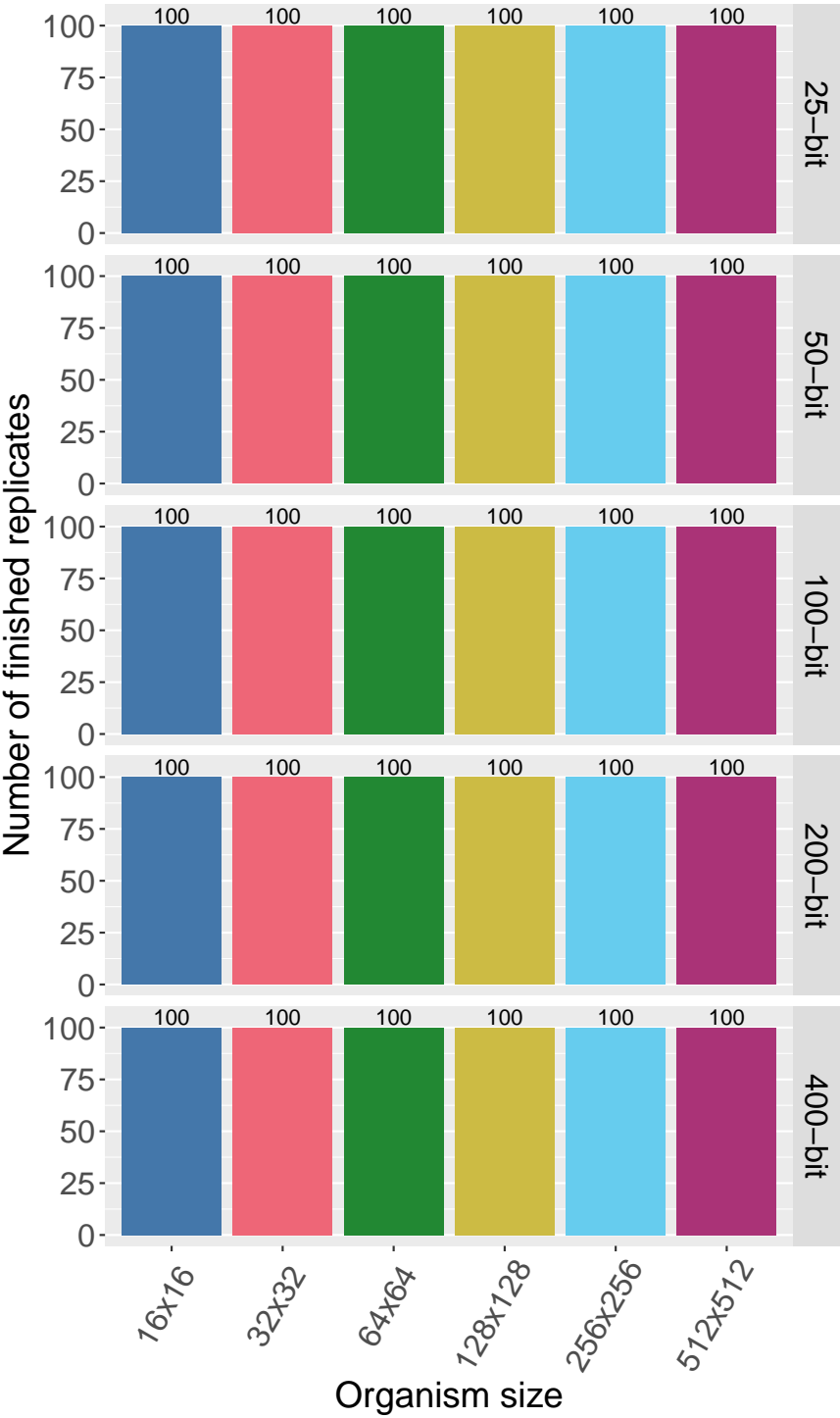
```
# Group the data by size and summarize
data_grouped = dplyr::group_by(df2, MCSIZE, LENGTH)
data_summary = dplyr::summarize(data_grouped, mean_ones = mean(ave_ones), n = dplyr::n
```

We clean the data and create a few helper variables to make plotting easier.

```
## Set variables to make plotting easier
# Calculate restraint value (x - 60% of the genome length)
df2$restraint_value = df2$ave_ones - (df2$LENGTH * 0.6)
# Make a nice, clean factor for size
df2$size_str = paste0(df2$MCSIZE, 'x', df2$MCSIZE)
df2$size_factor = factor(df2$size_str, levels = c('16x16', '32x32', '64x64', '128x128', '256x256', '512x512', '1024x1024'))
df2$size_factor_reversed = factor(df2$size_str, levels = rev(c('16x16', '32x32', '64x64', '128x128', '256x256', '512x512', '1024x1024')))
df2$length_str = paste0(df2$LENGTH, '-bit')
df2$length_factor = factor(df2$length_str, levels = c('25-bit', '50-bit', '100-bit', '200-bit', '400-bit', '800-bit', '1600-bit'))
data_summary$size_str = paste0(data_summary$MCSIZE, 'x', data_summary$MCSIZE)
data_summary$size_factor = factor(data_summary$size_str, levels = c('16x16', '32x32', '64x64', '128x128', '256x256', '512x512', '1024x1024'))
data_summary$length_str = paste0(data_summary$LENGTH, '-bit')
data_summary$length_factor = factor(data_summary$length_str, levels = c('25-bit', '50-bit', '100-bit', '200-bit', '400-bit', '800-bit', '1600-bit'))
# Create a map of colors we'll use to plot the different organism sizes
color_vec = as.character(khroma::color('bright')(7))
color_map = c(
  '16x16' = color_vec[1],
  '32x32' = color_vec[2],
  '64x64' = color_vec[3],
  '128x128' = color_vec[4],
  '256x256' = color_vec[5],
  '512x512' = color_vec[6],
  '1024x1024' = color_vec[7]
)
# Set the sizes for text in plots
text_major_size = 18
text_minor_size = 16
```

7.2 Data integrity check

Now we plot the number of finished replicates for each treatment to make sure all data are present. Each row shows a different genome length (in bits). Each

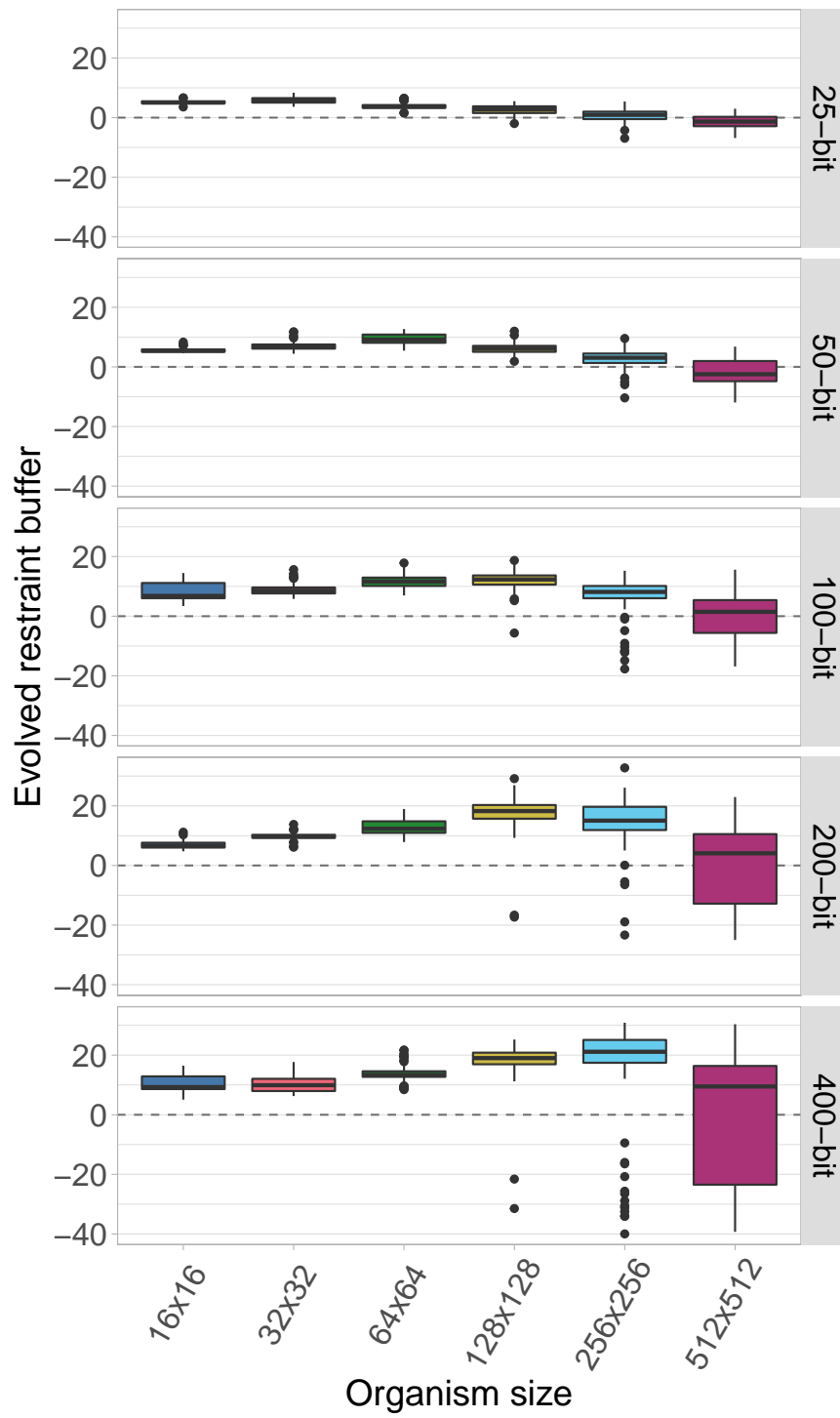


bar/color shows a different organism size.

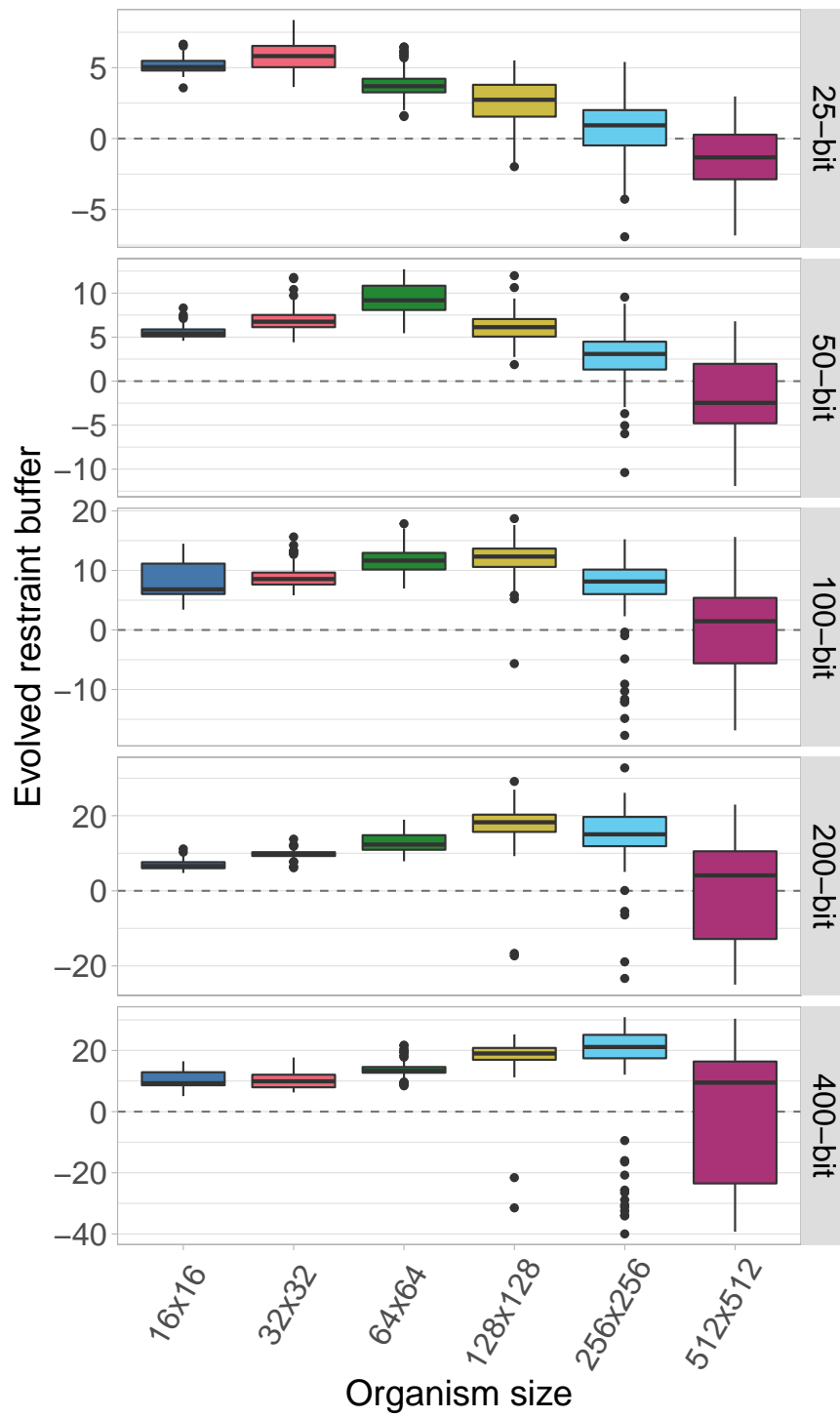
7.3 Aggregate plots

7.3.1 Facet by genome length

Here we plot all the data at once. Each row shows a different genome length and each boxplot shows a given organism size.

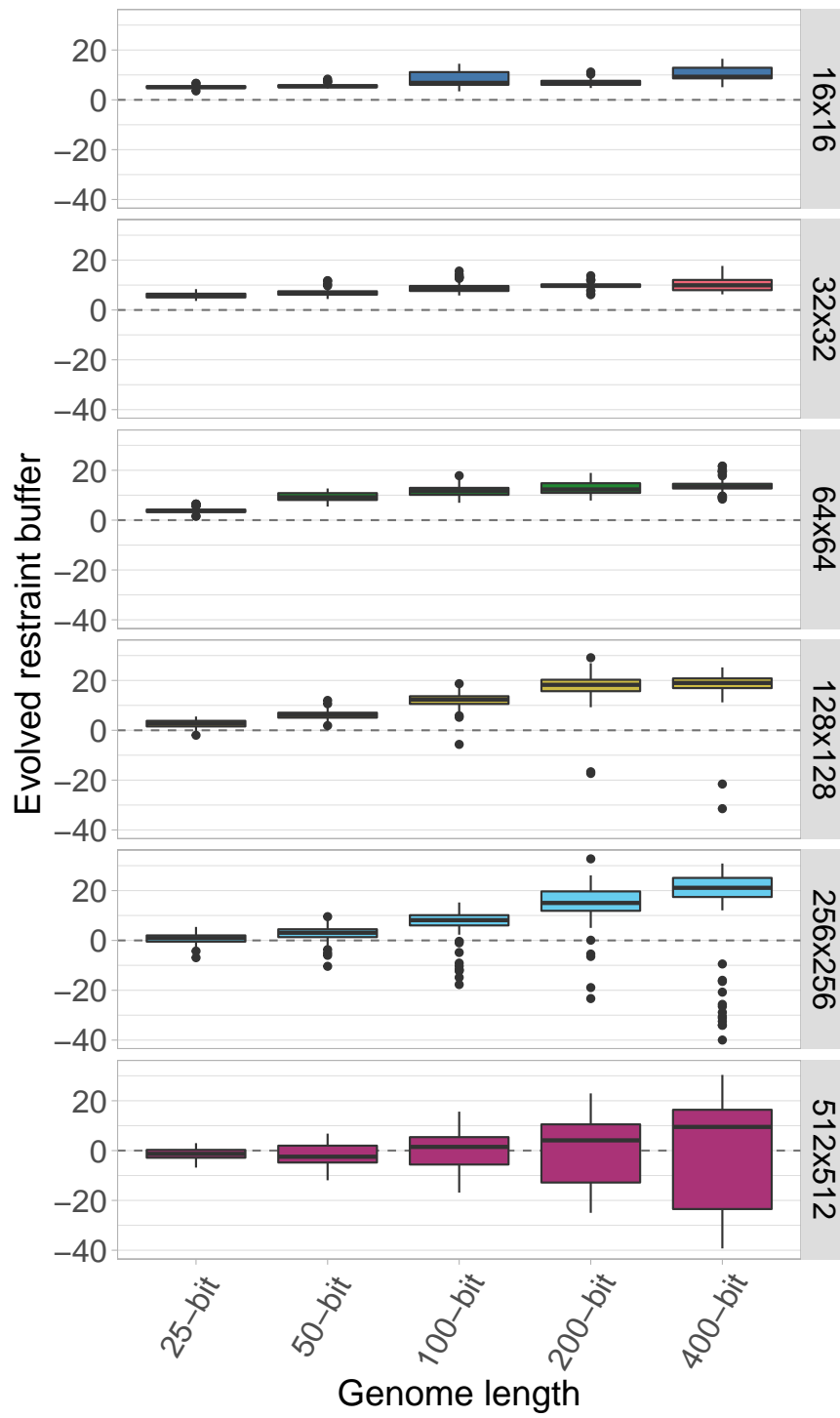


Here we plot the same data, only we allow the y-axis to vary between rows.

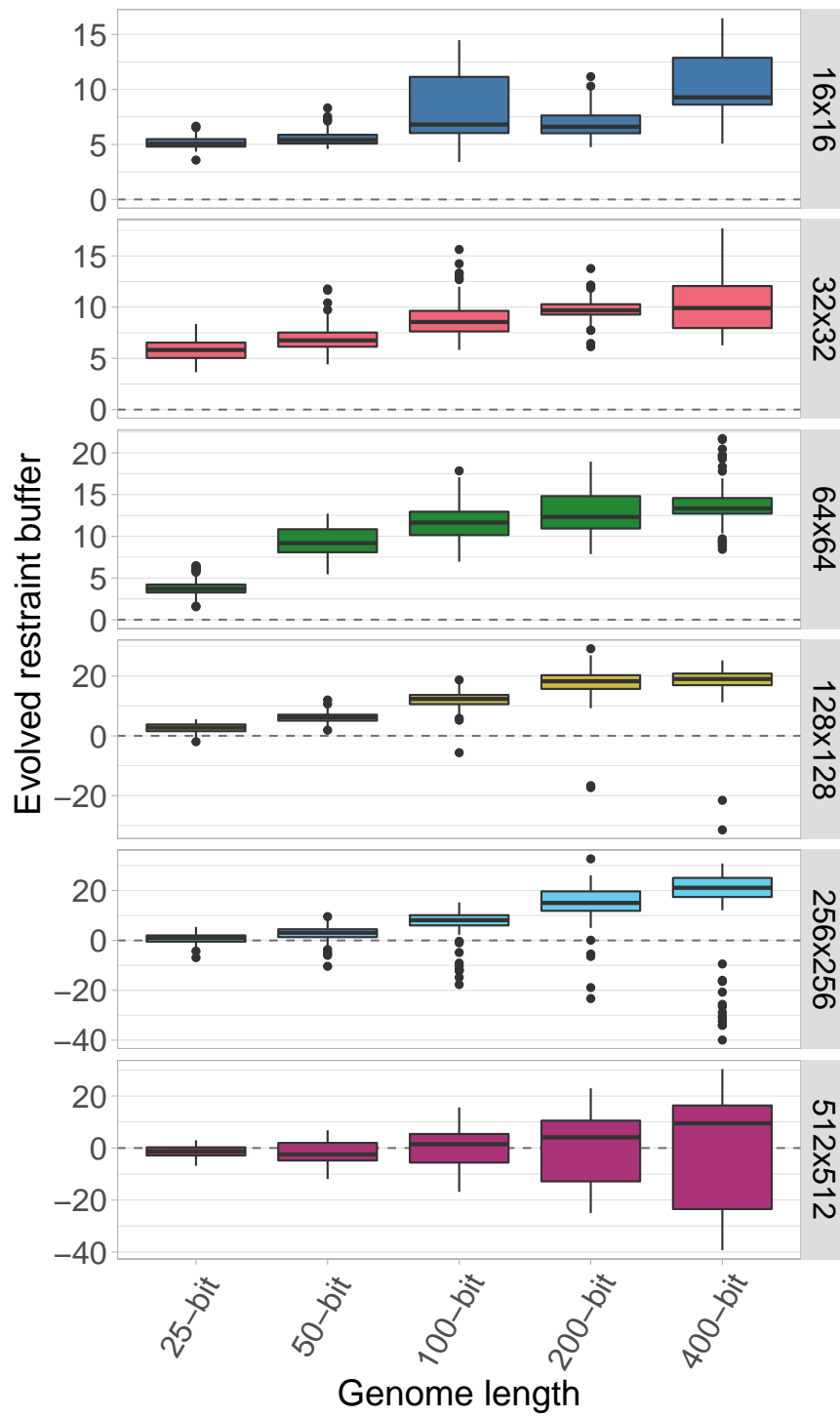


7.3.2 Facet by organism size

Here we plot the same data again, only now each row shows an organisms size while genome length varies on the x-axis.



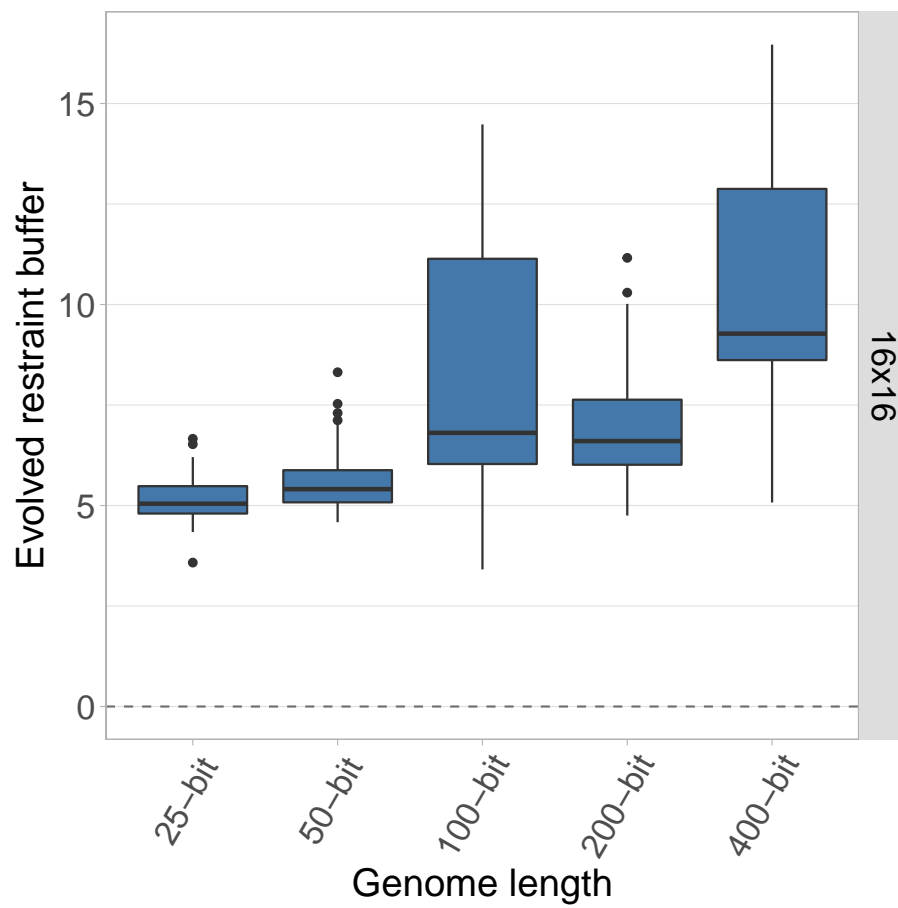
Here is the identical plot, but now we allow the y-axis to vary between the rows.



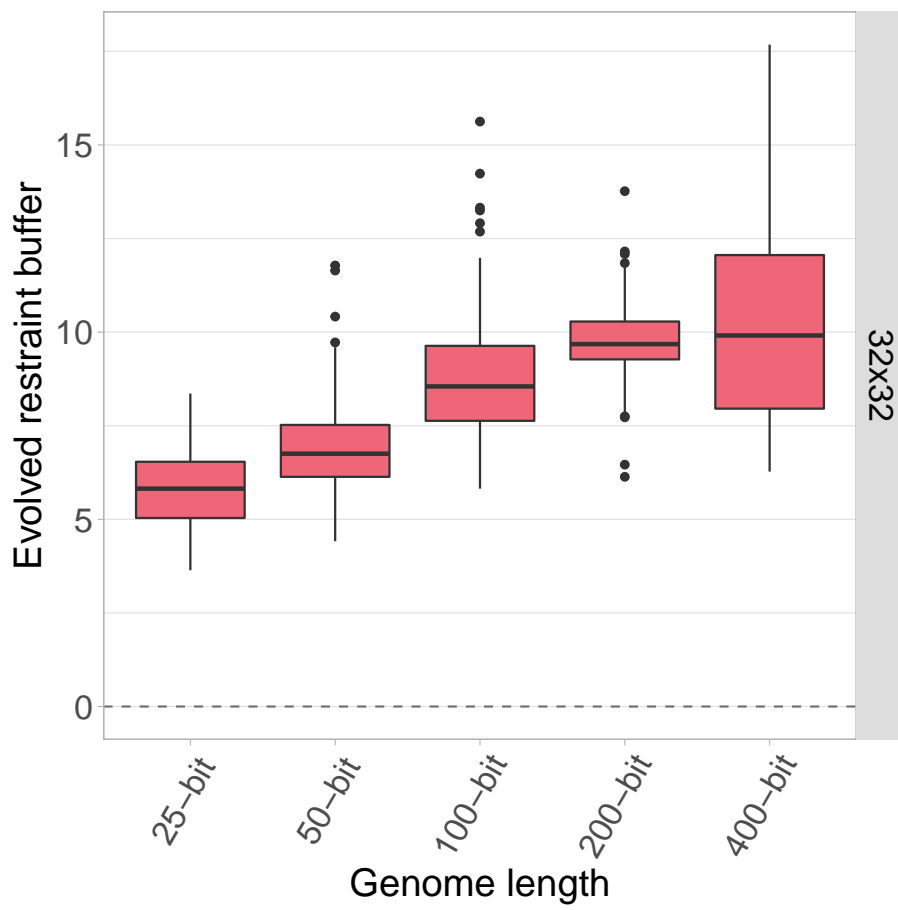
7.4 Single organism size plots

Here we plot each organism size independently, with the genome length on the x-axis.

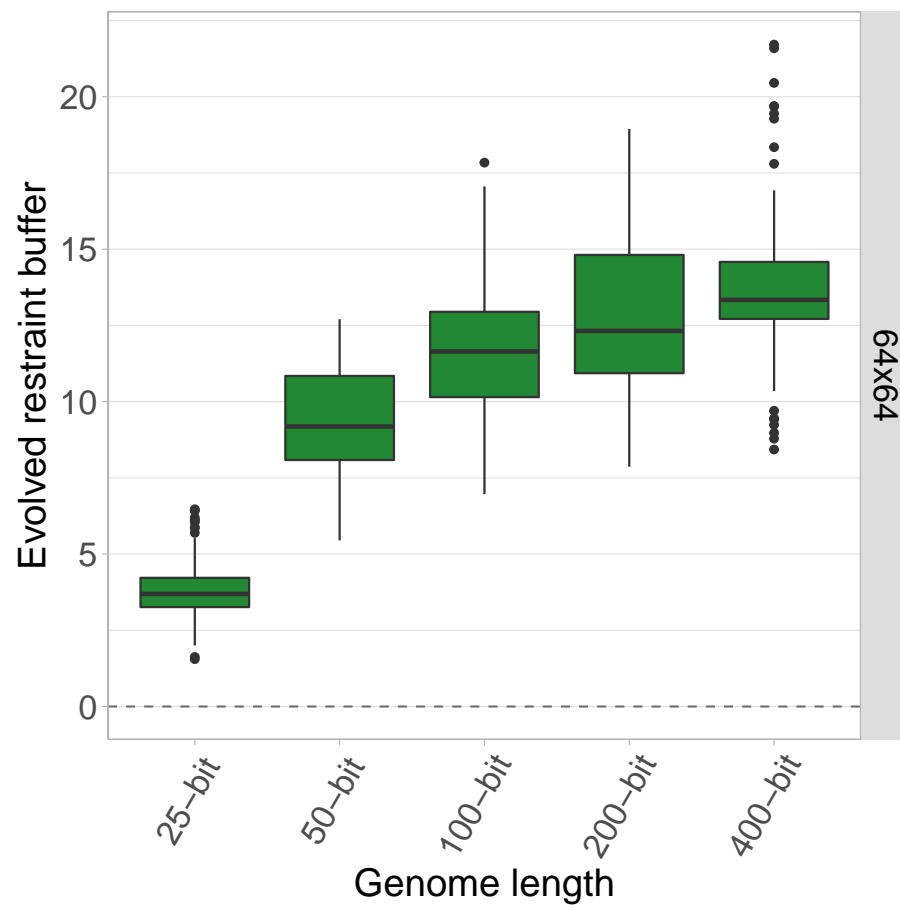
7.4.1 Organism size 16x16



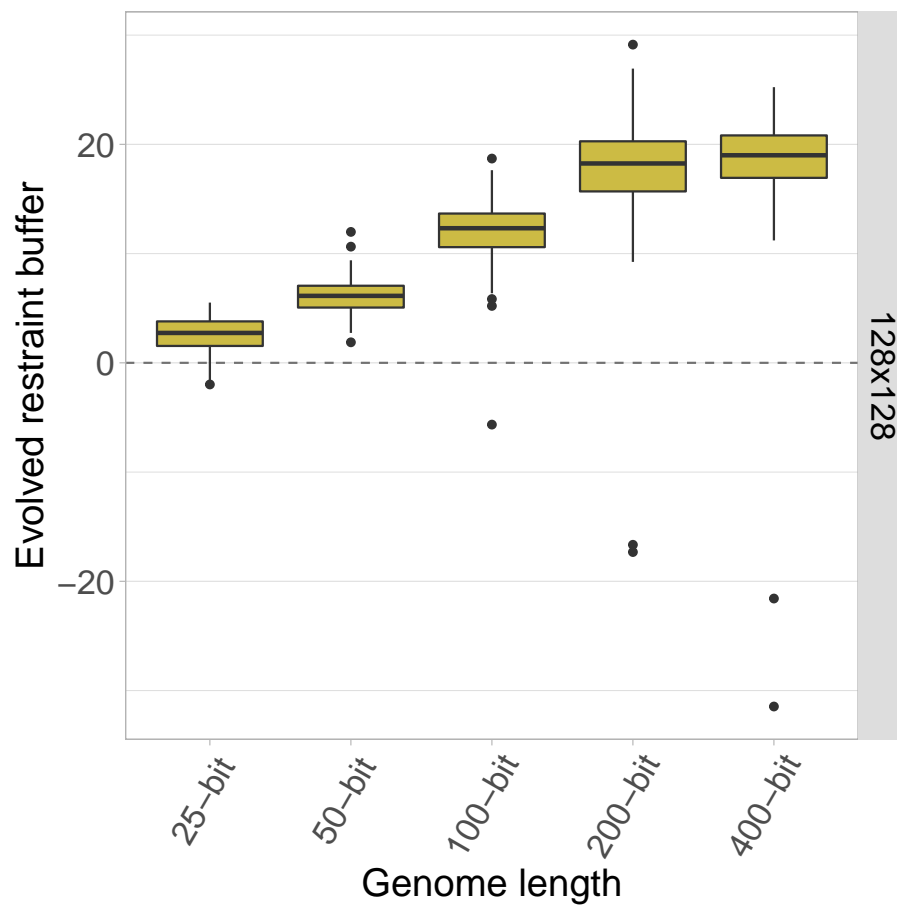
7.4.2 Organism size 32x32



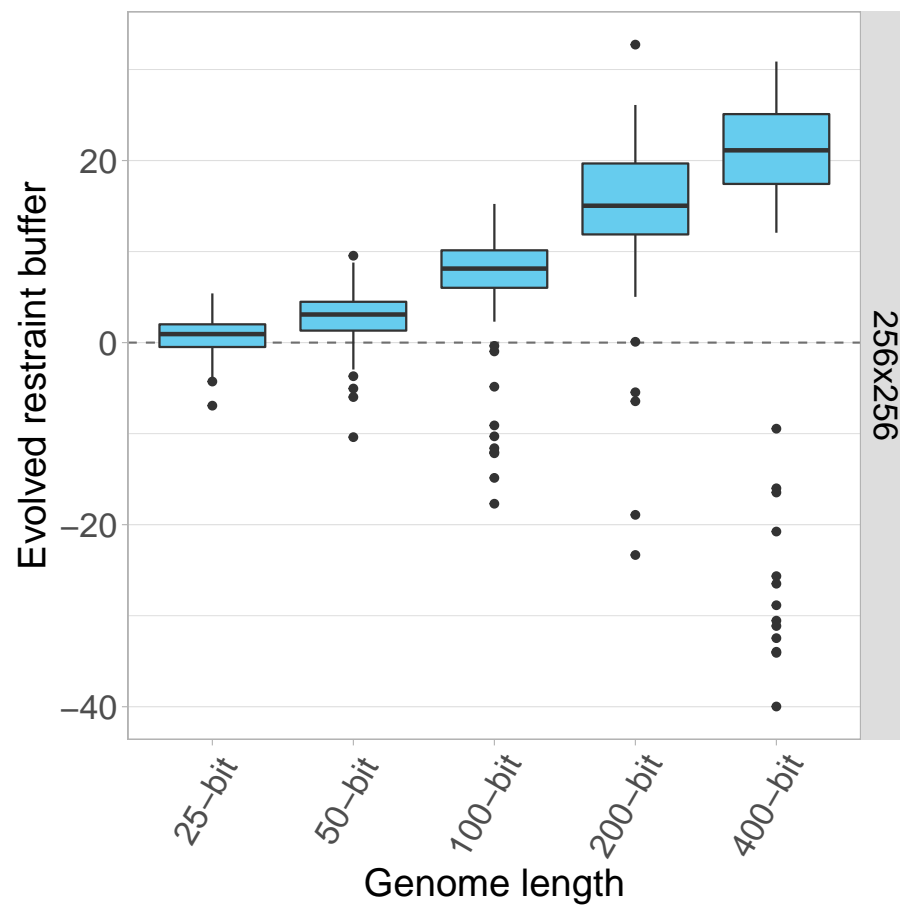
7.4.3 Organism size 64x64



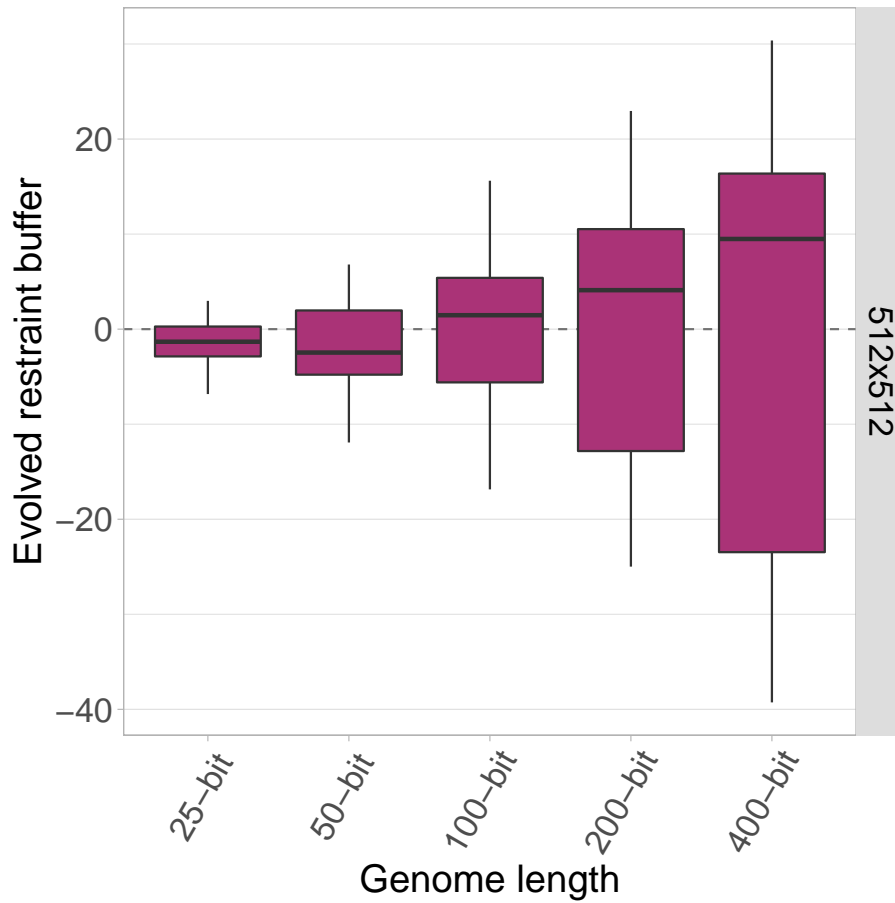
7.4.4 Organism size 128x128



7.4.5 Organism size 256x256



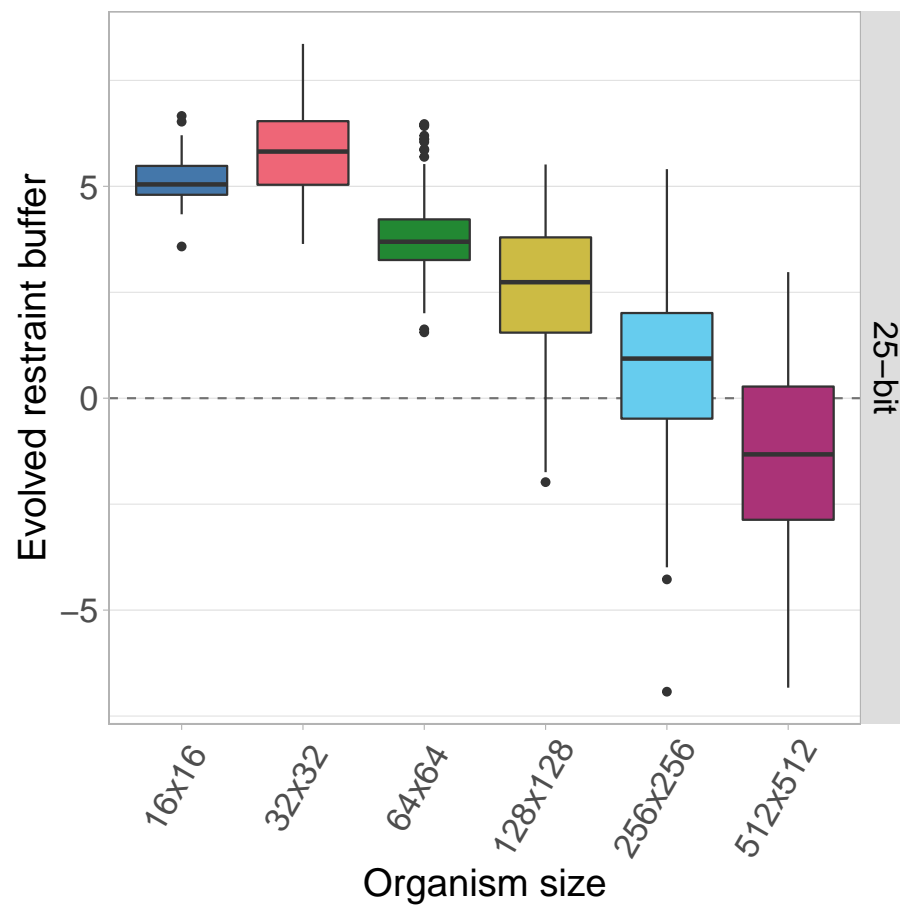
7.4.6 Organism size 512x512



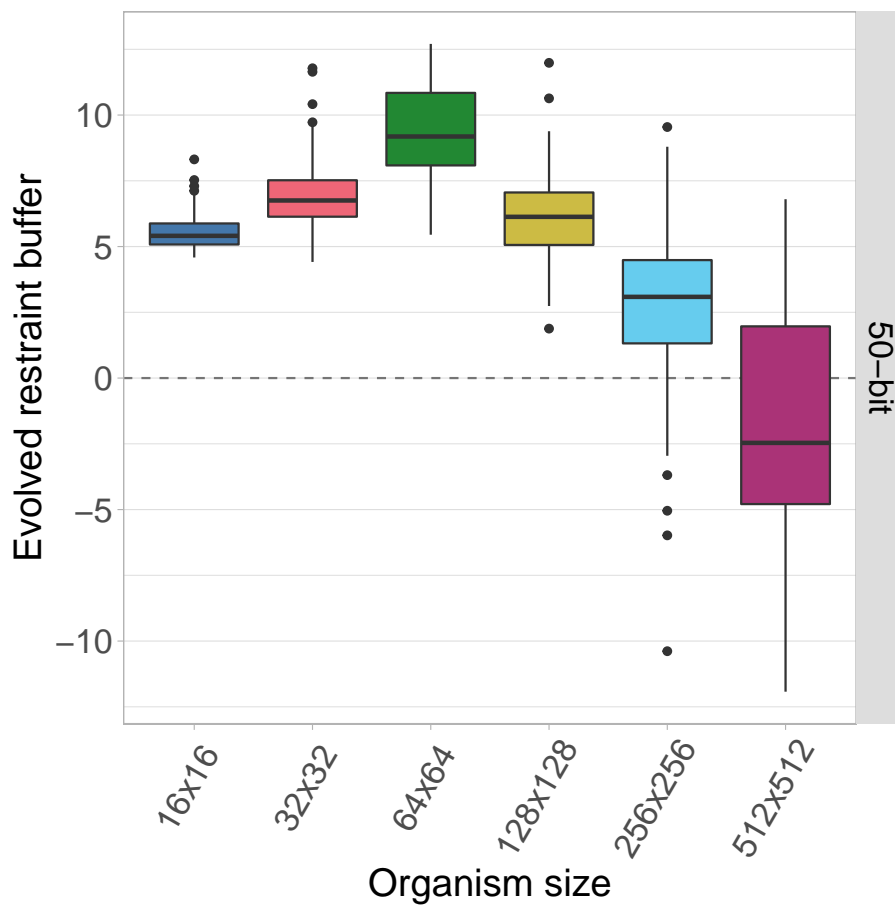
7.5 Single genome length plots

Here we plot each genome length independently, with the organism size on the x-axis.

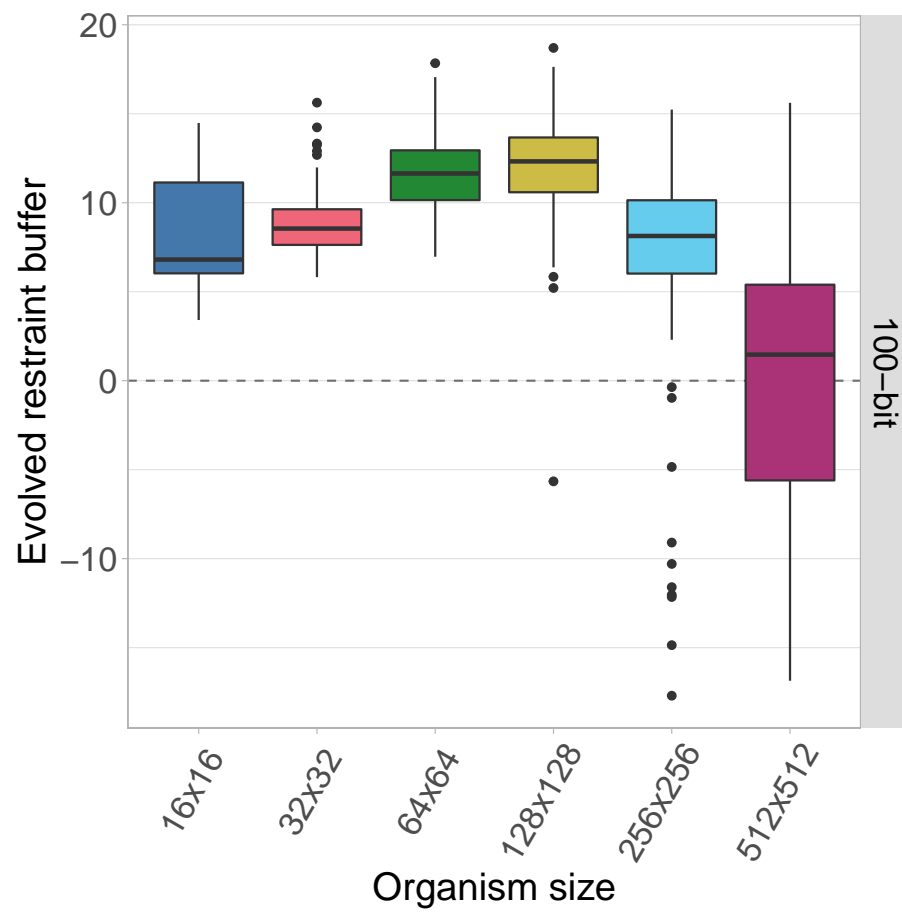
7.5.1 25-bit genomes



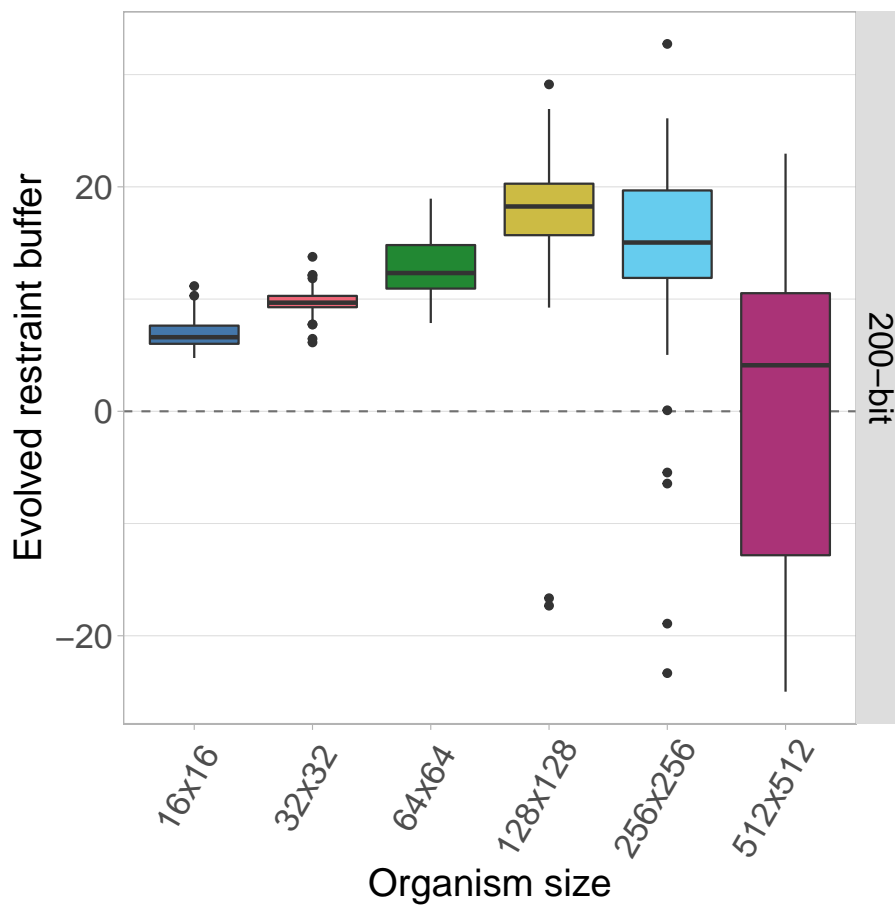
7.5.2 50-bit genomes



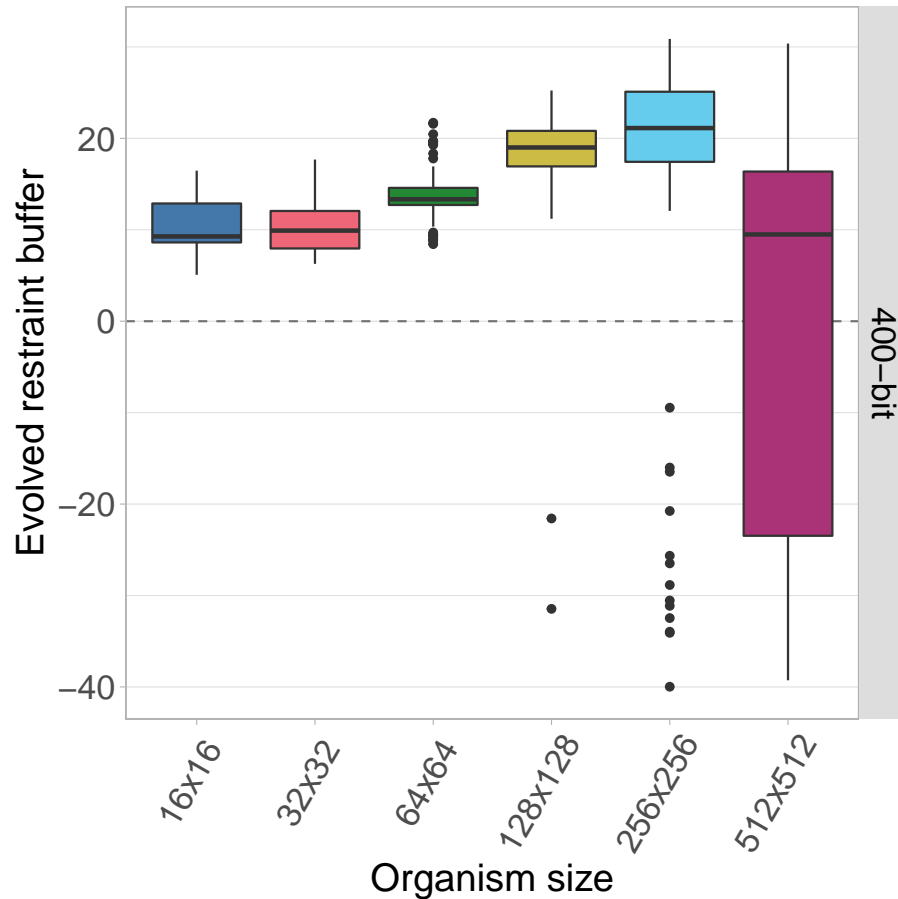
7.5.3 100-bit genomes



7.5.4 200-bit genomes



7.5.5 400-bit genomes



7.6 Statistics

Since organism size is our main point of comparison, we calculate statistics for each genome length.

First, we perform a Kruskal-Wallis test across all organism sizes to indicate if variance exists at that mutation rate. If variance exists, we then perform a pairwise Wilcoxon Rank-Sum test to show which pairs of organism sizes significantly differ. Finally, we perform Bonferroni-Holm corrections for multiple comparisons.

```
length_vec = c(25, 50, 100, 200, 400)
df_kruskal = data.frame(data = matrix(nrow = 0, ncol = 4))
colnames(df_kruskal) = c('genome_length', 'p_value', 'chi_squared', 'df')
for(genome_length in length_vec){
```

```

df_test = df2[df2$LENGTH == genome_length,]
res = kruskal.test(df_test$restraint_value ~ df_test$MCSIZE, df_test)
df_kruskal[nrow(df_kruskal) + 1,] = c(genome_length, res$p.value, as.numeric(res$statistic)[1])
}
df_kruskal$less_0.01 = df_kruskal$p_value < 0.01
print(df_kruskal)

```

```

##  genome_length      p_value chi_squared df less_0.01
## 1             25 1.508889e-97    461.6473  5      TRUE
## 2             50 9.772852e-87    411.5159  5      TRUE
## 3            100 7.491319e-60    286.6294  5      TRUE
## 4            200 1.626963e-75    359.4358  5      TRUE
## 5            400 2.857912e-49    237.3380  5      TRUE

```

We see that significant variation exists within each genome length, so we perform pairwise Wilcoxon tests on each to see which pairs of sizes are significantly different.

```

size_vec = c(16, 32, 64, 128, 256, 512)
length_vec = c(25, 50, 100, 200, 400)
for(genome_length in length_vec){
  df_test = df2[df2$LENGTH == genome_length,]
  df_wilcox = data.frame(data = matrix(nrow = 0, ncol = 6))
  colnames(df_wilcox) = c('genome_length', 'size_a', 'size_b', 'p_value_corrected', 'p_value_raw')
  for(size_idx_a in 1:(length(size_vec) - 1)){
    size_a = size_vec[size_idx_a]
    for(size_idx_b in (size_idx_a + 1):length(size_vec)){
      size_b = size_vec[size_idx_b]
      res = wilcox.test(df_test[df_test$MCSIZE == size_a,]$restraint_value, df_test[df_test$MCSIZE == size_b,]$restraint_value)
      df_wilcox[nrow(df_wilcox) + 1,] = c(genome_length, size_a, size_b, 0, res$p.value, as.numeric(res$statistic)[1])
    }
  }
  df_wilcox$p_value_corrected = p.adjust(df_wilcox$p_value_raw, method = 'holm')
  df_wilcox$less_0.01 = df_wilcox$p_value_corrected < 0.01
  print(paste0('Genome length: ', genome_length))
  print(df_wilcox)
}

```

```

## [1] "Genome length: 25"
##  genome_length size_a size_b p_value_corrected p_value_raw      W less_0.01
## 1             25    16    32    2.337475e-07 2.337475e-07 2883.5      TRUE
## 2             25    16    64    6.069986e-18 1.213997e-18 8607.5      TRUE
## 3             25    16   128    1.663209e-24 2.376012e-25 9258.5      TRUE
## 4             25    16   256    6.203828e-32 5.639844e-33 9896.0      TRUE
## 5             25    16   512    3.838888e-33 2.559259e-34 10000.0     TRUE
## 6             25    32    64    1.447210e-22 2.412016e-23 9074.5      TRUE
## 7             25    32   128    1.283820e-27 1.283820e-28 9542.5      TRUE

```

```

## 8      25      32      256      2.711275e-32 2.259396e-33 9927.0      TRUE
## 9      25      32      512      3.838888e-33 2.560557e-34 10000.0     TRUE
## 10     25      64      128      1.187343e-07 5.936715e-08 7219.0      TRUE
## 11     25      64      256      2.378014e-26 2.642238e-27 9430.5      TRUE
## 12     25      64      512      1.298354e-32 9.987336e-34 9954.5      TRUE
## 13     25     128      256      1.433015e-10 3.582536e-11 7710.0      TRUE
## 14     25     128      512      7.524923e-25 9.406154e-26 9294.5      TRUE
## 15     25     256      512      4.120336e-10 1.373445e-10 7627.5      TRUE
## [1] "Genome length: 50"
##      genome_length size_a size_b p_value_corrected p_value_raw      W less_0.01
## 1      50      16      32      2.588989e-15 5.177978e-16 1681.5      TRUE
## 2      50      16      64      2.694326e-30 2.072558e-31 228.0      TRUE
## 3      50      16     128      3.224011e-03 3.224011e-03 3794.0      TRUE
## 4      50      16     256      4.089878e-15 1.022470e-15 8284.5      TRUE
## 5      50      16     512      1.182991e-27 1.182991e-28 9545.5      TRUE
## 6      50      32      64      1.797027e-17 2.567181e-18 1427.0      TRUE
## 7      50      32     128      7.415731e-04 3.707866e-04 6457.5      TRUE
## 8      50      32     256      1.165570e-21 1.295078e-22 9005.5      TRUE
## 9      50      32     512      4.567933e-31 3.262810e-32 9836.0      TRUE
## 10     50      64     128      2.265727e-21 2.832159e-22 8973.0      TRUE
## 11     50      64     256      8.866606e-30 7.388839e-31 9727.5      TRUE
## 12     50      64     512      7.213069e-33 4.808713e-34 9979.0      TRUE
## 13     50     128     256      4.869262e-16 8.115436e-17 8409.5      TRUE
## 14     50     128     512      4.777498e-28 4.343180e-29 9582.0      TRUE
## 15     50     256     512      3.236734e-12 1.078911e-12 7914.5      TRUE
## [1] "Genome length: 100"
##      genome_length size_a size_b p_value_corrected p_value_raw      W less_0.01
## 1     100      16      32      7.697389e-02 1.924347e-02 4041.5     FALSE
## 2     100      16      64      3.952168e-13 7.904337e-14 1941.5      TRUE
## 3     100      16     128      2.398968e-14 2.998710e-15 1770.0      TRUE
## 4     100      16     256      4.158441e-01 4.158441e-01 5333.5     FALSE
## 5     100      16     512      5.614119e-18 4.678432e-19 8651.0      TRUE
## 6     100      32      64      1.034976e-13 1.478537e-14 1852.5      TRUE
## 7     100      32     128      3.085548e-17 3.085548e-18 1435.5      TRUE
## 8     100      32     256      1.117541e-01 3.725137e-02 5853.0     FALSE
## 9     100      32     512      2.483010e-22 1.910008e-23 9084.0      TRUE
## 10    100      64     128      1.117541e-01 4.890986e-02 4193.5     FALSE
## 11    100      64     256      5.002561e-15 5.558401e-16 8315.0      TRUE
## 12    100      64     512      5.082595e-28 3.388396e-29 9591.0      TRUE
## 13    100     128     256      1.590814e-17 1.446195e-18 8599.5      TRUE
## 14    100     128     512      9.444159e-28 6.745828e-29 9566.0      TRUE
## 15    100     256     512      2.634367e-13 4.390611e-14 8090.0      TRUE
## [1] "Genome length: 200"
##      genome_length size_a size_b p_value_corrected p_value_raw      W less_0.01
## 1     200      16      32      4.663546e-26 3.886289e-27 584.0      TRUE
## 2     200      16      64      7.523609e-32 5.015739e-33 100.0      TRUE

```



```

## 3      200      16      128      2.146093e-30 1.532923e-31 217.5      TRUE
## 4      200      16      256      1.997886e-24 1.911300e-25 733.0      TRUE
## 5      200      16      512      9.462181e-03 9.462181e-03 6062.5     TRUE
## 6      200      32      64       1.344008e-20 1.493343e-21 1097.0     TRUE
## 7      200      32      128      5.645064e-28 4.342357e-29 418.0      TRUE
## 8      200      32      256      1.309572e-19 1.636965e-20 1200.0     TRUE
## 9      200      32      512      2.440723e-07 6.101808e-08 7217.0     TRUE
## 10     200      64      128      1.166719e-18 1.666742e-19 1302.5     TRUE
## 11     200      64      256      9.151807e-05 3.050602e-05 3293.0     TRUE
## 12     200      64      512      6.237644e-15 1.247529e-15 8274.5     TRUE
## 13     200     128      256      9.982635e-05 4.991318e-05 6660.5     TRUE
## 14     200     128      512      1.997886e-24 1.816260e-25 9269.0     TRUE
## 15     200     256      512      1.717006e-17 2.861676e-18 8568.0     TRUE
## [1] "Genome length: 400"
##      genome_length size_a size_b p_value_corrected p_value_raw      W less_0.01
## 1      400      16      32      5.405382e-01 5.348472e-01 5254.5     FALSE
## 2      400      16      64      3.472338e-14 3.472338e-15 1777.5     TRUE
## 3      400      16     128      4.072814e-28 2.715209e-29 401.0      TRUE
## 4      400      16     256      1.163125e-16 9.692706e-18 1489.0     TRUE
## 5      400      16     512      5.405382e-01 1.801794e-01 5549.0     FALSE
## 6      400      32      64      5.784416e-12 8.263451e-13 2070.5     TRUE
## 7      400      32     128      1.489024e-26 1.063588e-27 535.5      TRUE
## 8      400      32     256      2.187697e-16 1.988815e-17 1523.0     TRUE
## 9      400      32     512      5.405382e-01 1.825748e-01 5546.0     FALSE
## 10     400      64     128      2.993077e-18 2.302367e-19 1317.0     TRUE
## 11     400      64     256      3.197608e-12 3.997010e-13 2030.0     TRUE
## 12     400      64     512      8.293488e-05 1.658698e-05 6763.0     TRUE
## 13     400     128     256      1.019174e-02 2.547935e-03 3764.5     FALSE
## 14     400     128     512      9.137039e-13 1.015227e-13 8045.0     TRUE
## 15     400     256     512      6.084030e-12 1.014005e-12 7918.0     TRUE

```


Chapter 8

Genome Length Control Experiment

In the genome length experiment, we observed that varying the genome length affects the evolution of organisms in two ways: 1) mutational pressure is reduced at the population level as genome length increases, and 2) longer genomes have a higher organism fitness at the same restraint buffer value. We wanted to test the effect of reduced mutational pressure by itself.

To accomplish this, we generated fitness data for organisms with 400-bit genomes. For smaller genome lengths, we reuse the 400-bit data by lining up restraint buffer values. Thus the difference in genome lengths simply changes the range of restraint buffer values available in the genome. The fitness data for 64x64 organisms is shown below, showing the range of each genome length.

The configuration script and data for the experiment can be found under `2021_03_04__genome_length_control/` in the experiments directory of the git repository.

8.1 Data cleaning

Load necessary R libraries

```
library(dplyr)
library(ggplot2)
library(ggribes)
library(scales)
library(khroma)
```

Load the data and trim include only the final generation data for sizes 16x16 to 512x512.

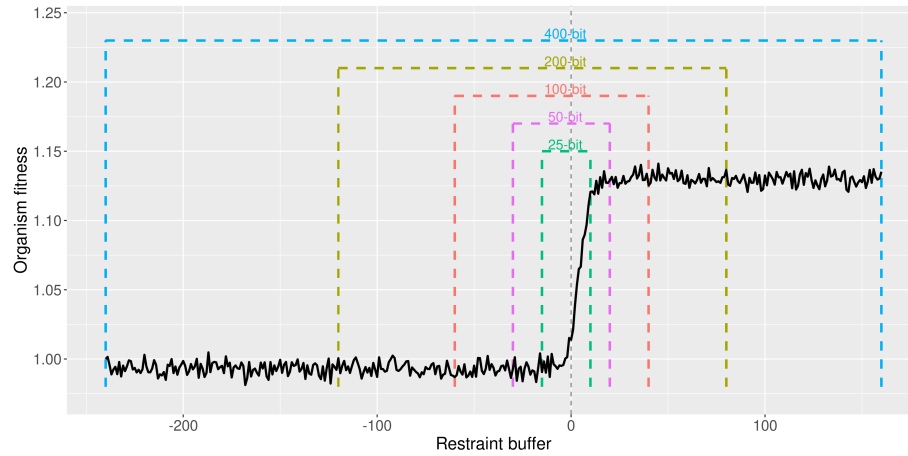


Figure 8.1: Genome length control explainer

```
# Load the data
df = read.csv('.../experiments/2021_03_04__genome_length_control/evolution/data.csv')
df = rbind(df, read.csv('.../experiments/2021_03_04__genome_length_control/evolution/data.csv'))
df = rbind(df, read.csv('.../experiments/2021_03_04__genome_length_control/evolution/data.csv'))
df = rbind(df, read.csv('.../experiments/2021_03_04__genome_length_control/evolution/data.csv'))
df = rbind(df, read.csv('.../experiments/2021_03_04__genome_length_control/evolution/data.csv'))
# Trim off NAs (artifacts of how we scraped the data) and trim to only have gen 10,000
df2 = df[!is.na(df$MCSIZE) & df$generation == 10000,]
# Ignore data for size 8x8 and 1024x1024
df2 = df2[df2$MCSIZE != 8 & df2$MCSIZE != 1024,]
```

We group and summarize the data to make to ensure all replicates are present.

```
# Group the data by size and summarize
data_grouped = dplyr::group_by(df2, MCSIZE, LENGTH)
data_summary = dplyr::summarize(data_grouped, mean_ones = mean(ave_ones), n = dplyr::n())
```

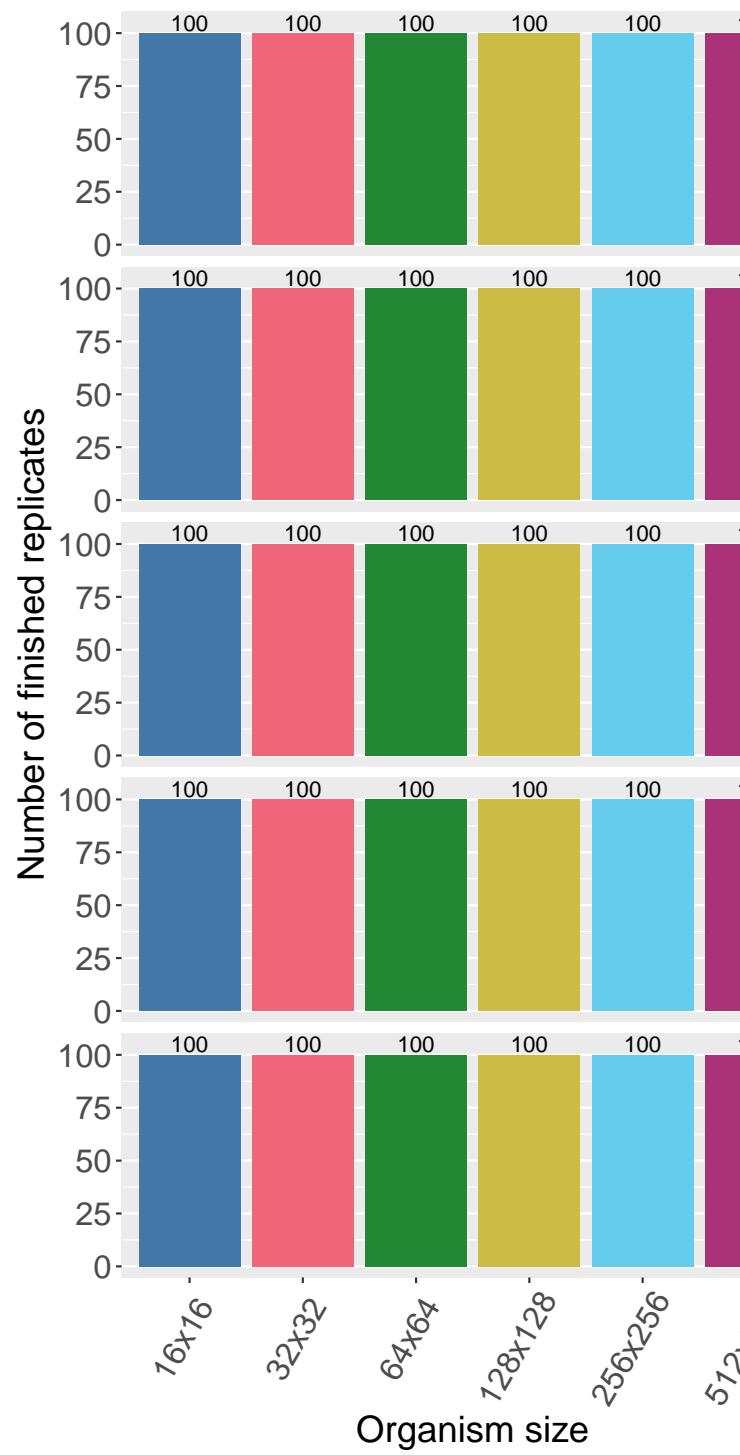
We clean the data and create a few helper variables to make plotting easier.

```
# Calculate restraint value (x - 60% of the genome length)
df2$restraint_value = df2$ave_ones - (df2$LENGTH * 0.6)
# Make a nice, clean factor for size
df2$size_str = paste0(df2$MCSIZE, 'x', df2$MCSIZE)
df2$size_factor = factor(df2$size_str, levels = c('16x16', '32x32', '64x64', '128x128', '256x256'))
df2$size_factor_reversed = factor(df2$size_str, levels = rev(c('16x16', '32x32', '64x64', '128x128', '256x256')))
df2$length_str = paste0(df2$LENGTH, '-bit')
df2$length_factor = factor(df2$length_str, levels = c('25-bit', '50-bit', '100-bit', '200-bit', '400-bit'))
data_summary$size_str = paste0(data_summary$MCSIZE, 'x', data_summary$MCSIZE)
data_summary$size_factor = factor(data_summary$size_str, levels = c('16x16', '32x32', '64x64', '128x128', '256x256'))
```

```
data_summary$length_str = paste0(data_summary$LENGTH, '-bit')
data_summary$length_factor = factor(data_summary$length_str, levels = c('25-bit', '50-bit', '100-bit'))
# Create a map of colors we'll use to plot the different organism sizes
color_vec = as.character(khroma::color('bright')(7))
color_map = c(
  '16x16' = color_vec[1],
  '32x32' = color_vec[2],
  '64x64' = color_vec[3],
  '128x128' = color_vec[4],
  '256x256' = color_vec[5],
  '512x512' = color_vec[6],
  '1024x1024' = color_vec[7]
)
# Set the sizes for text in plots
text_major_size = 18
text_minor_size = 16
```

8.2 Data integrity check

Now we plot the number of finished replicates for each treatment to make sure all data are present. Each row shows a different genome length (in bits). Each

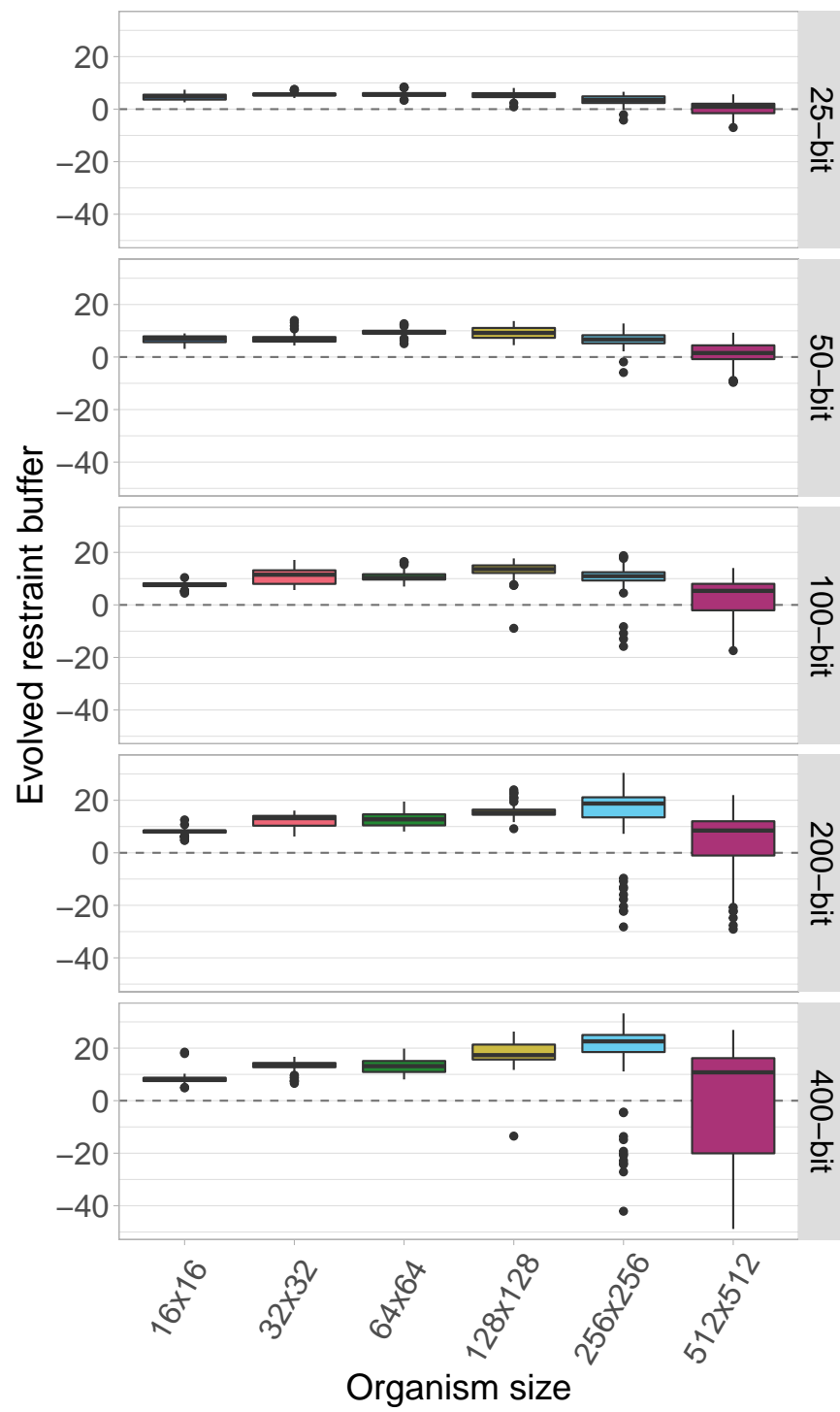


bar/color shows a different organism size.

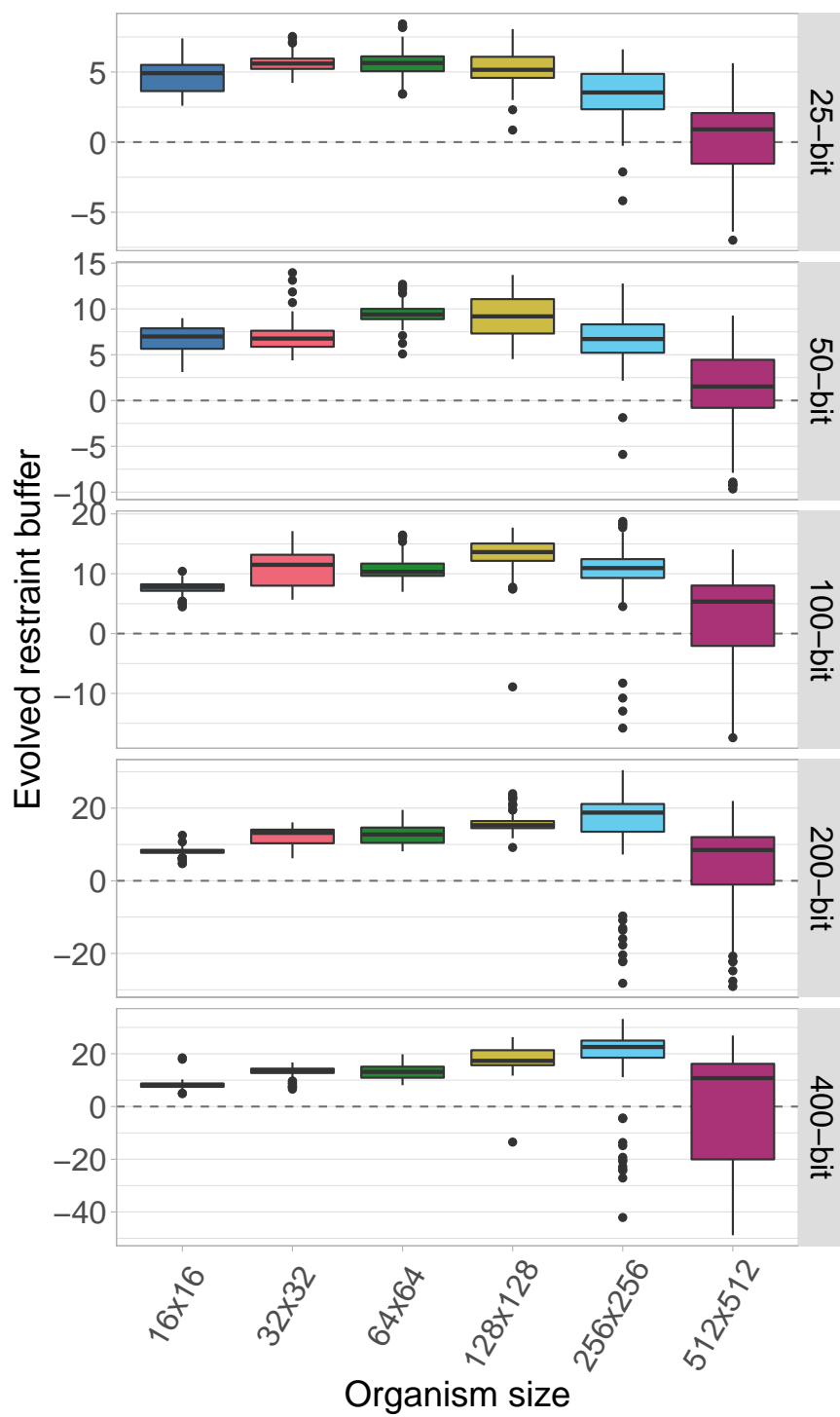
8.3 Aggregate plots

8.3.1 Facet by genome length

Here we plot all the data at once. Each row shows a different genome length and each boxplot shows a given organism size.

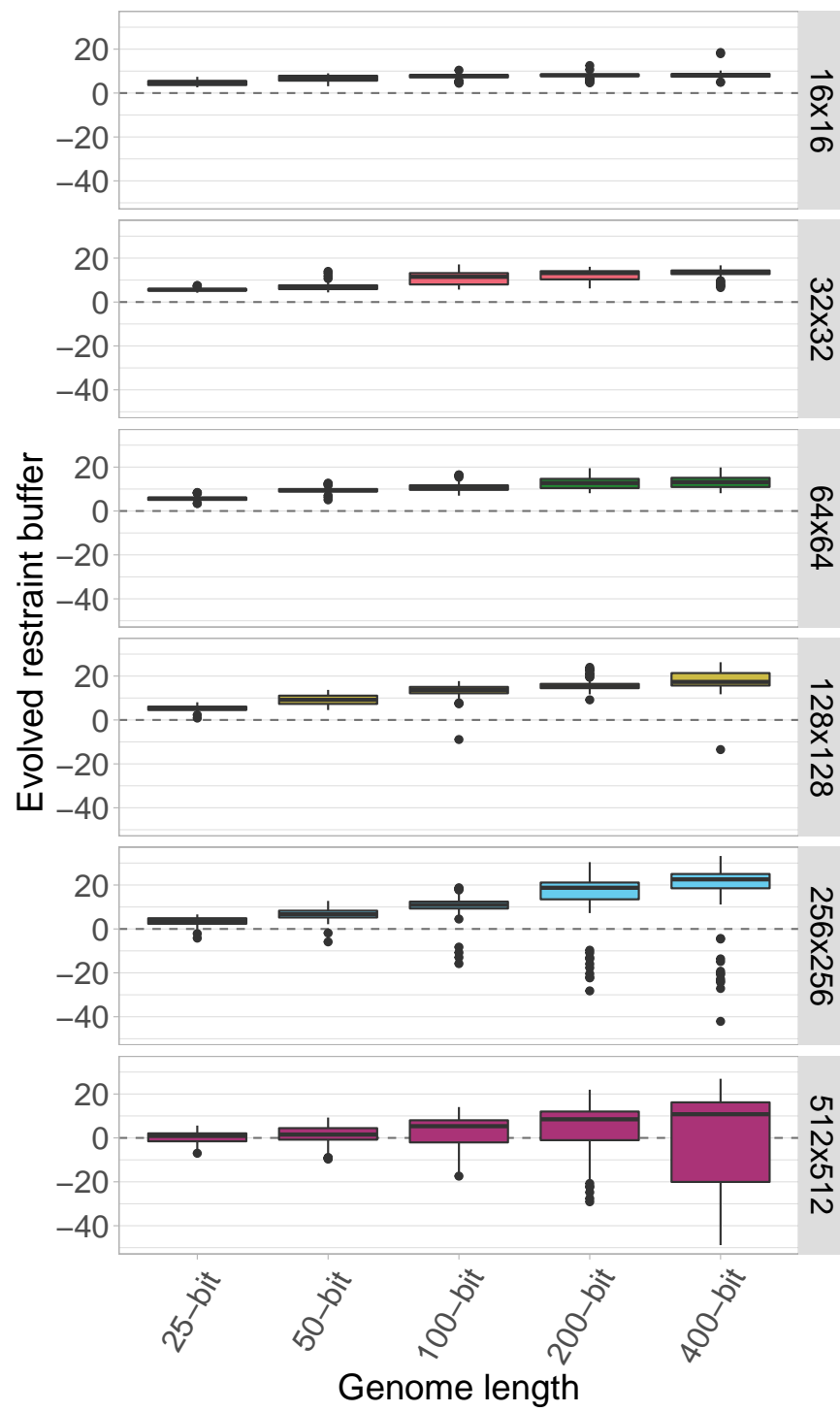


Here we plot the same data, only we allow the y-axis to vary between rows.

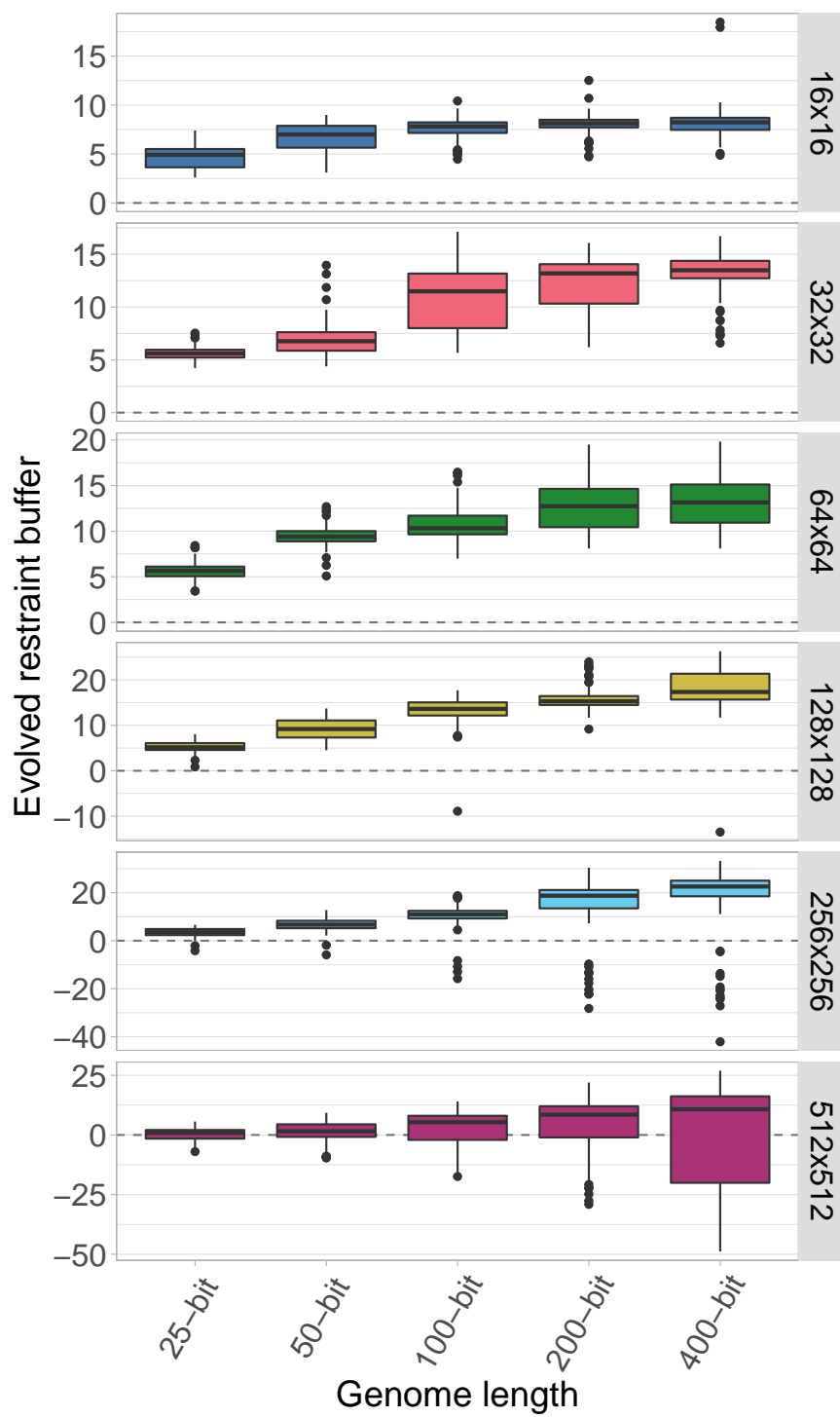


8.3.2 Facet by organism size

Here we plot the same data again, only now each row shows an organisms size while genome length varies on the x-axis.



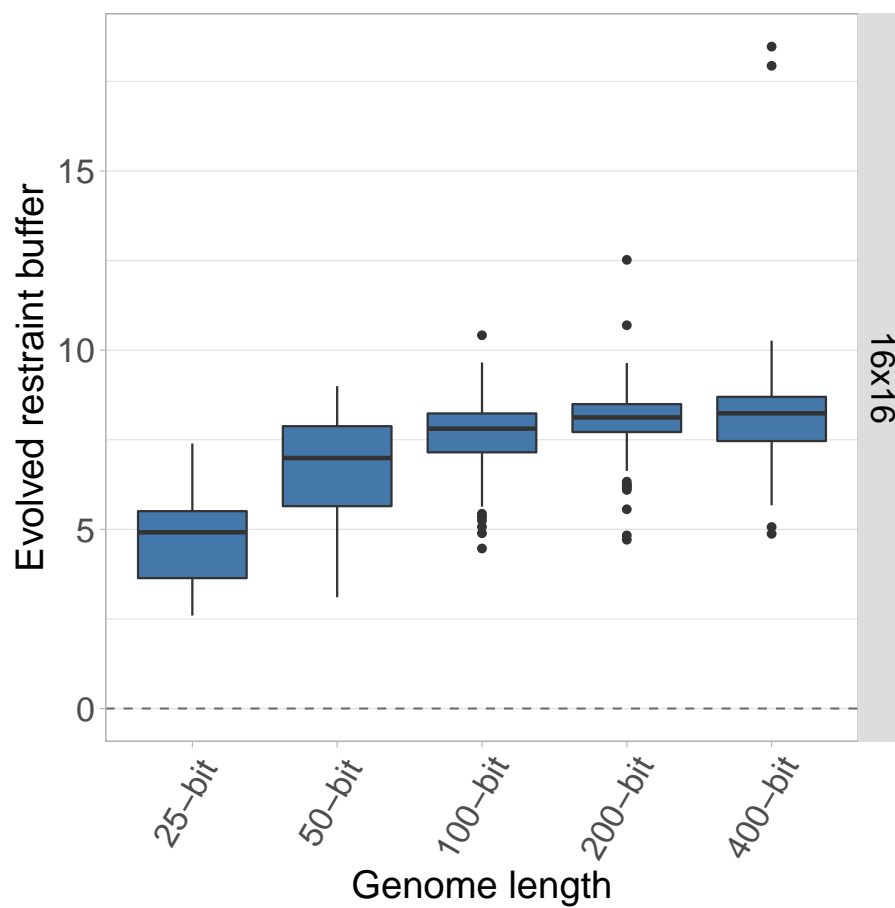
Here is the identical plot but now we allow the y-axis to vary between the rows.



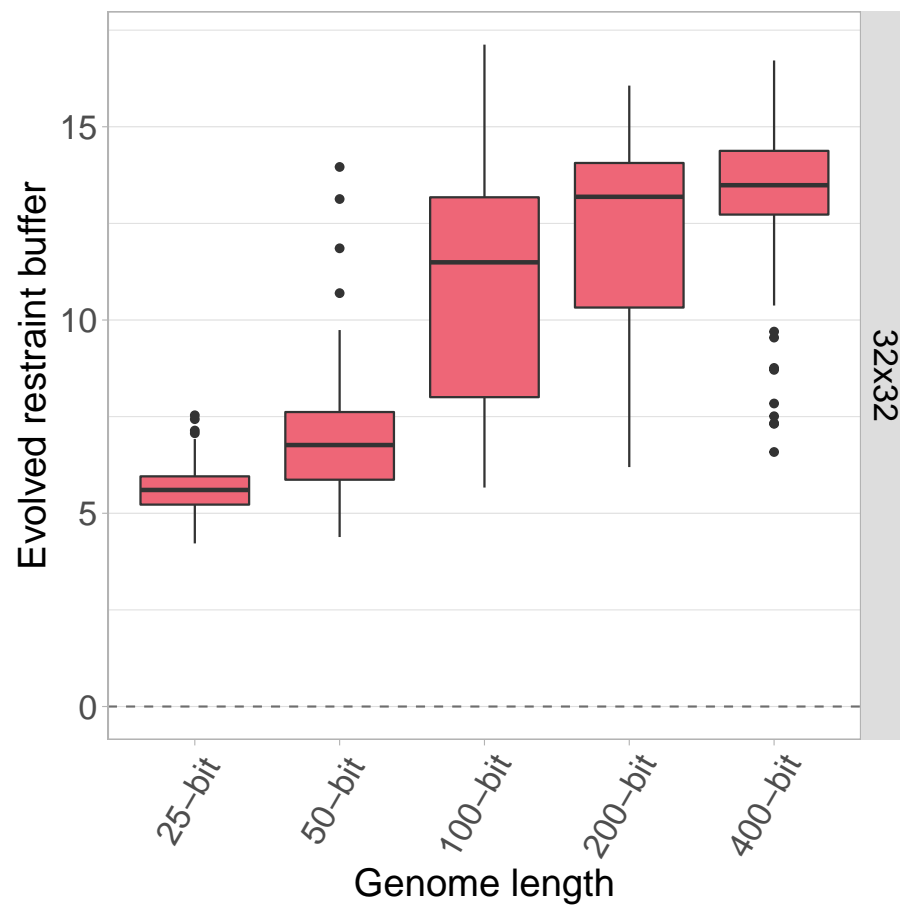
8.4 Single organism size plots

Here we plot each organism size independently, with the genome length on the x-axis.

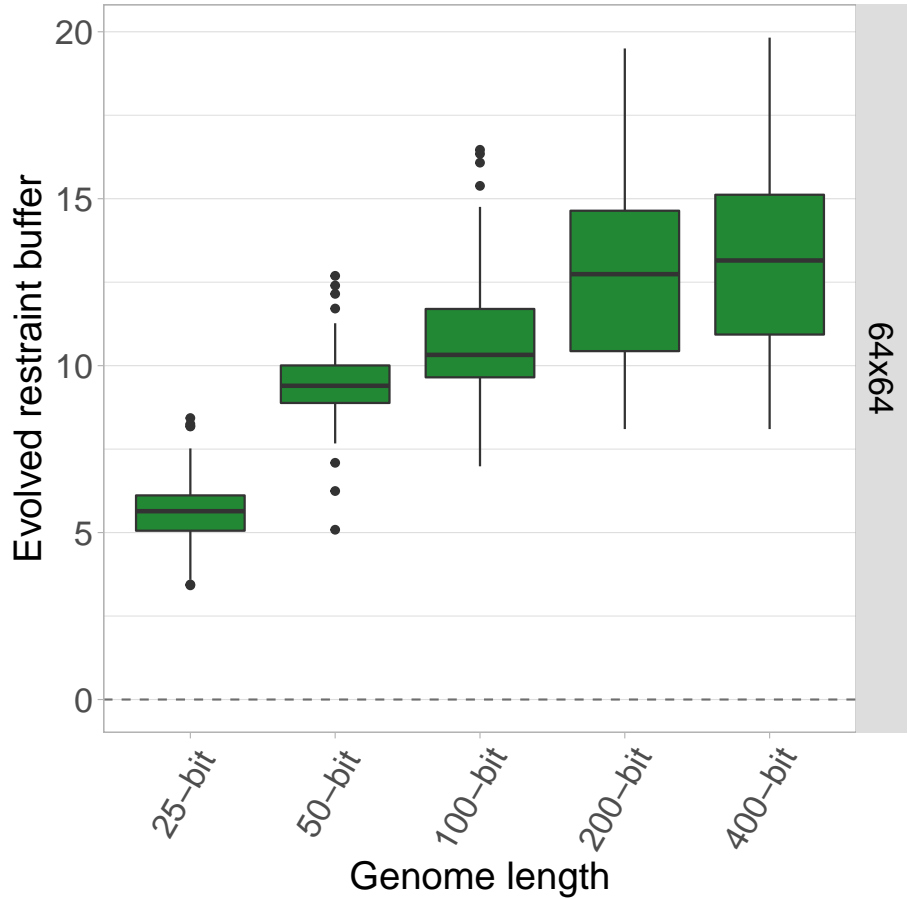
8.4.1 Organism size 16x16



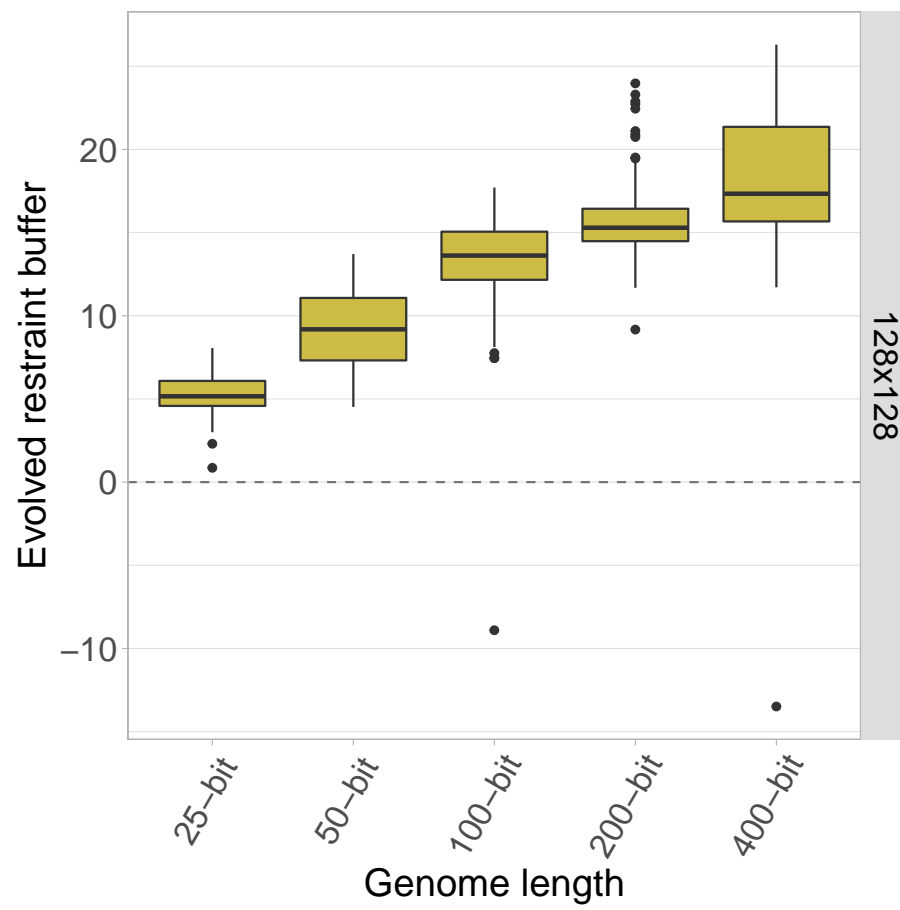
8.4.2 Organism size 32x32



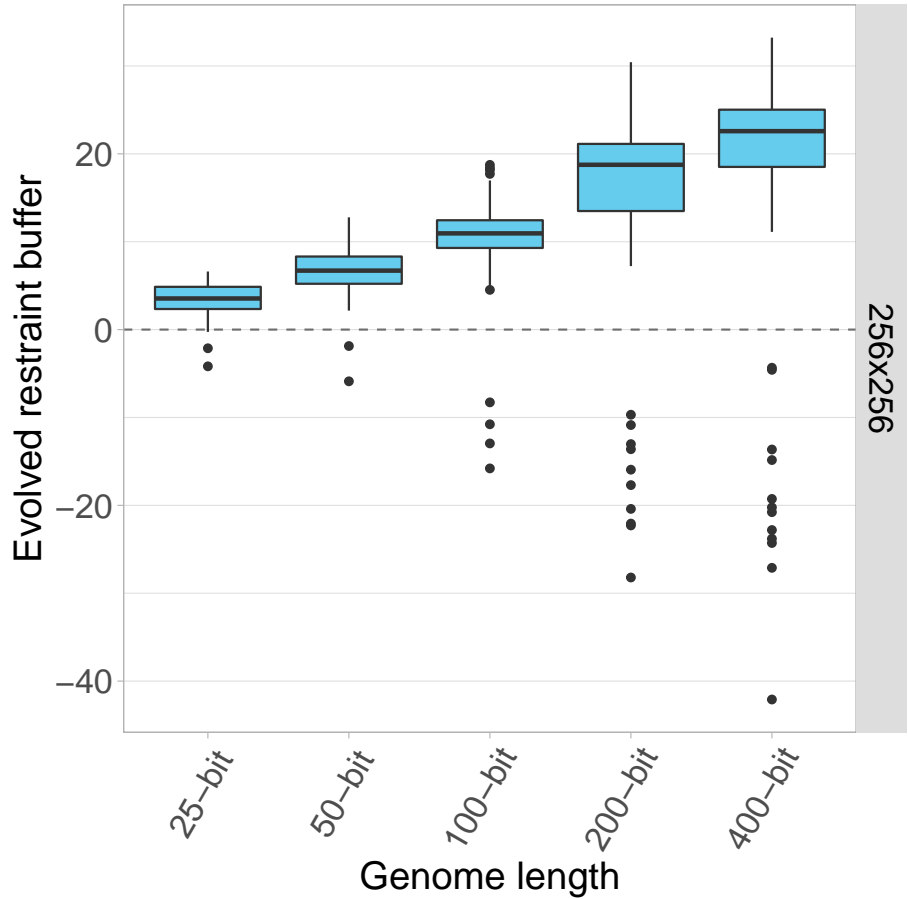
8.4.3 Organism size 64x64



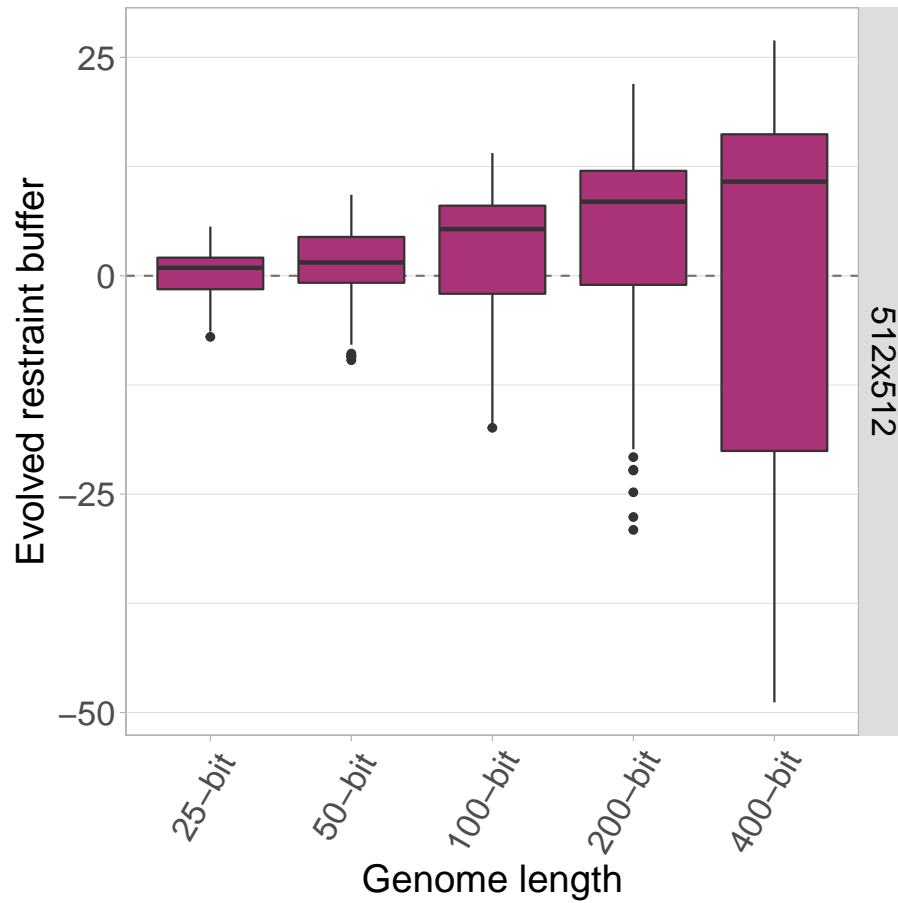
8.4.4 Organism size 128x128



8.4.5 Organism size 256x256



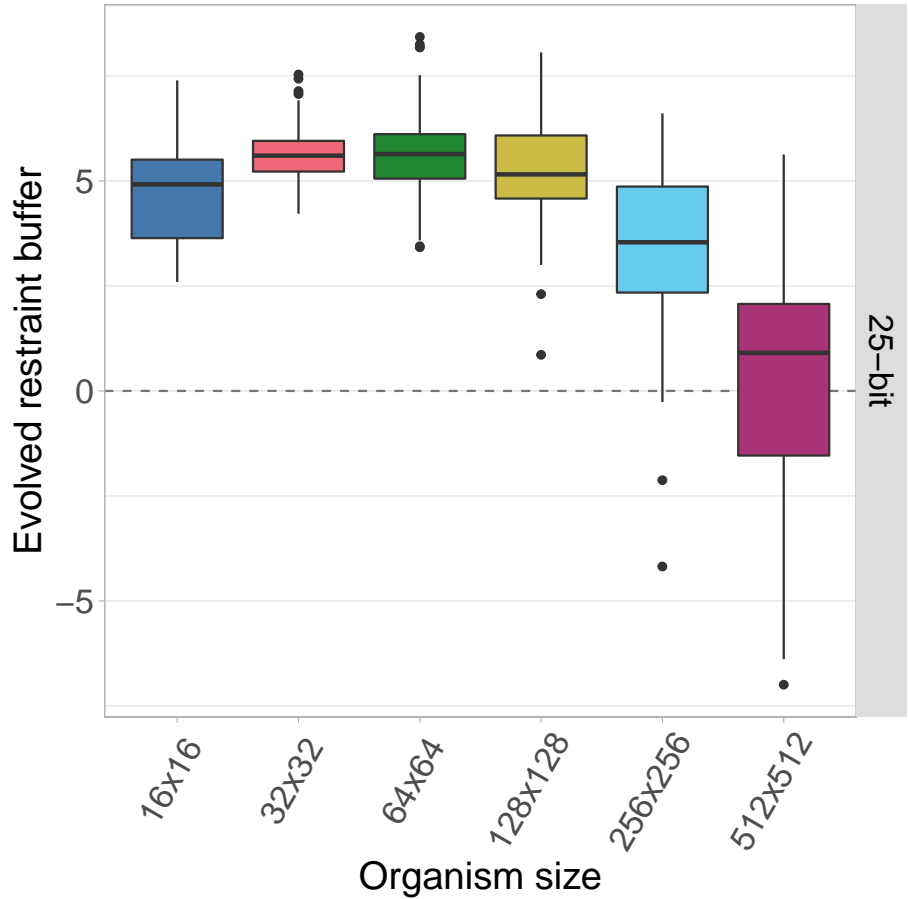
8.4.6 Organism size 512x512



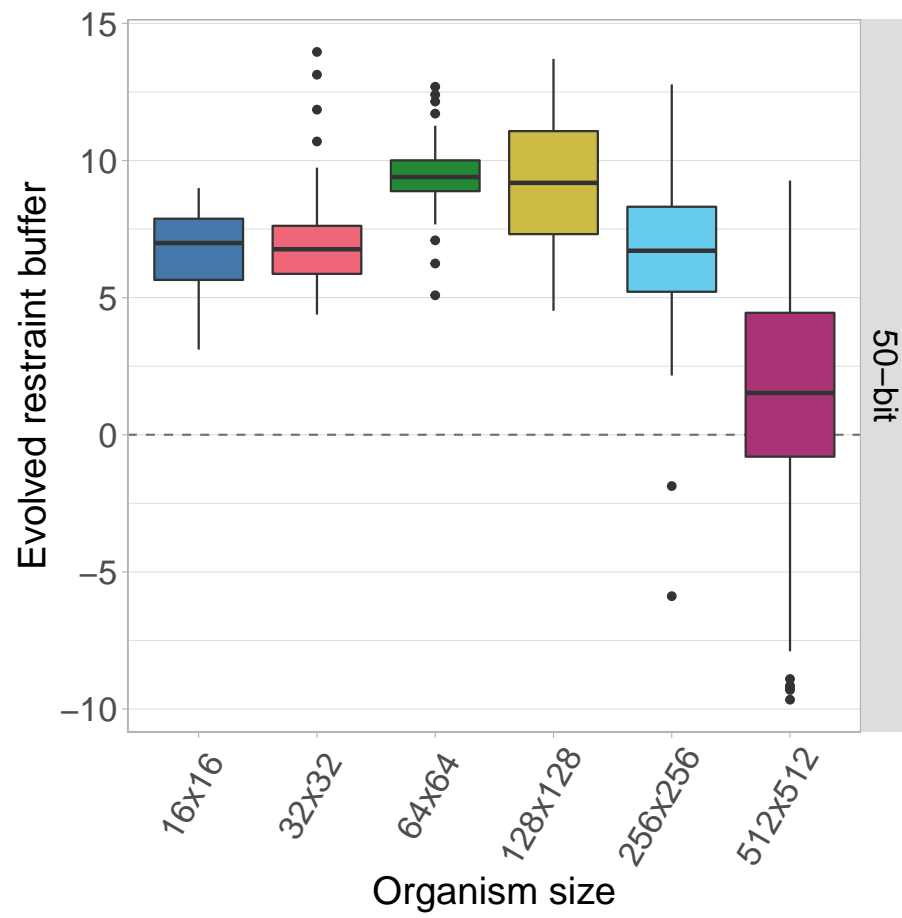
8.5 Single genome length plots

Here we plot each genome length independently, with the organism size on the x-axis.

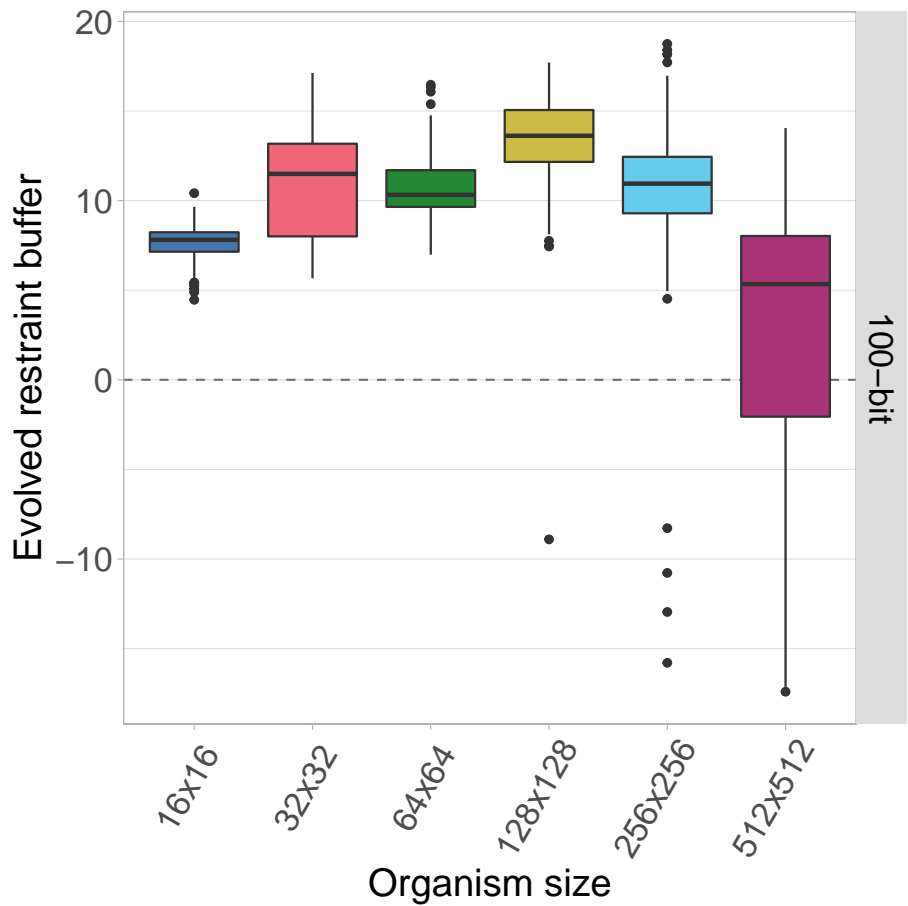
8.5.1 25-bit genomes



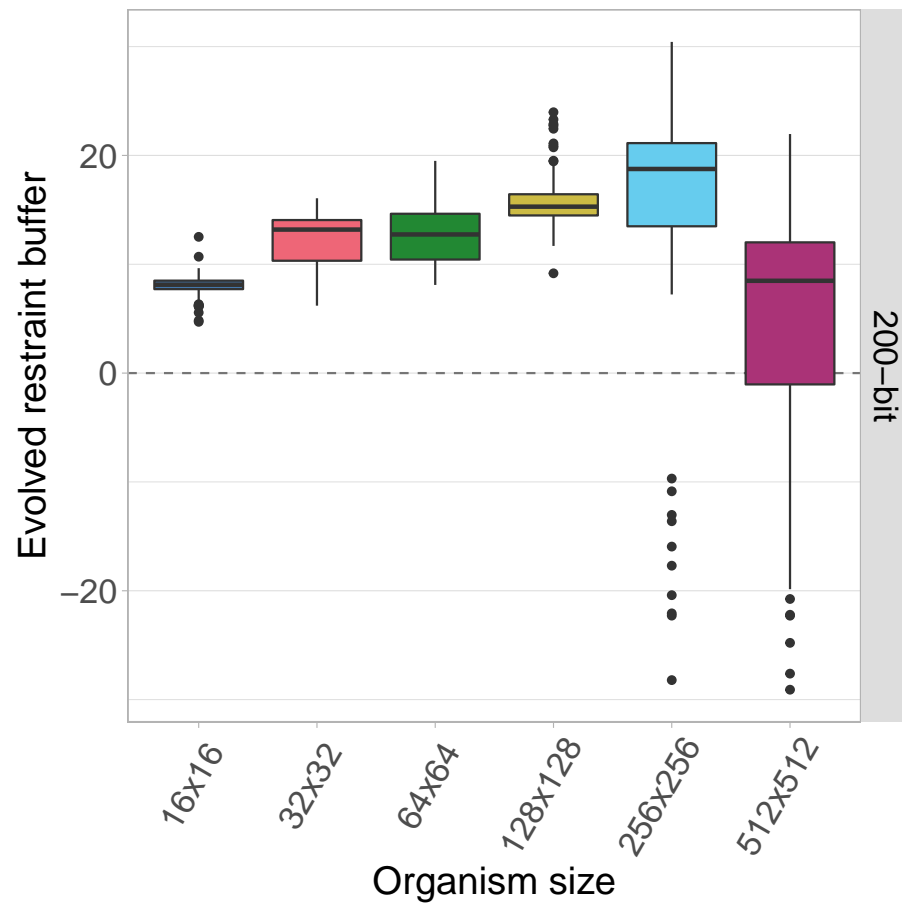
8.5.2 50-bit genomes



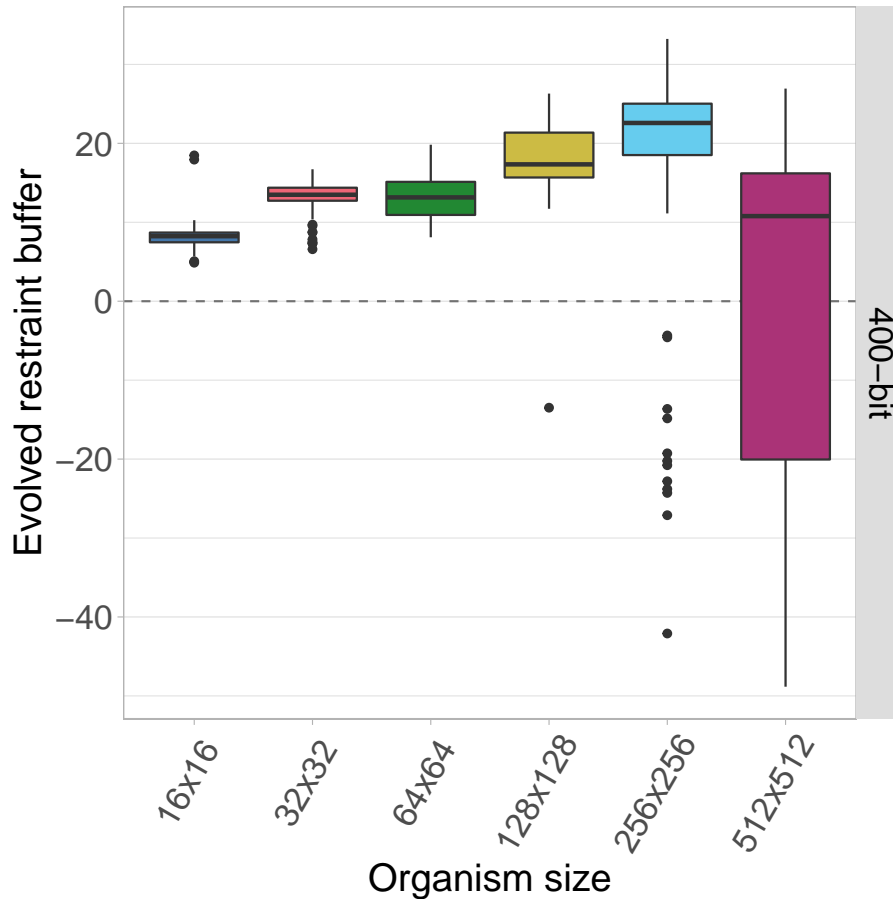
8.5.3 100-bit genomes



8.5.4 200-bit genomes



8.5.5 400-bit genomes



8.6 Statistics

Since organism size is our main point of comparison, we calculate statistics for each genome length.

First, we perform a Kruskal-Wallis test across all organism sizes to indicate if variance exists at that mutation rate. If variance exists, we then perform a pairwise Wilcoxon Rank-Sum test to show which pairs of organism sizes significantly differ. Finally, we perform Bonferroni-Holm corrections for multiple comparisons.

```
length_vec = c(25, 50, 100, 200, 400)
df_kruskal = data.frame(data = matrix(nrow = 0, ncol = 4))
colnames(df_kruskal) = c('genome_length', 'p_value', 'chi_squared', 'df')
for(genome_length in length_vec){
```

```

df_test = df2[df2$LENGTH == genome_length,]
res = kruskal.test(df_test$restraint_value ~ df_test$MCSIZE, df_test)
df_kruskal[nrow(df_kruskal) + 1,] = c(genome_length, res$p.value, as.numeric(res$statistic))
}
df_kruskal$less_0.01 = df_kruskal$p_value < 0.01
print(df_kruskal)

```

```

## genome_length      p_value chi_squared df less_0.01
## 1          25 9.945818e-62    295.3623  5      TRUE
## 2          50 1.677718e-69    331.5020  5      TRUE
## 3         100 1.870502e-63    303.3893  5      TRUE
## 4         200 7.717483e-60    286.5693  5      TRUE
## 5         400 3.667815e-58    278.7645  5      TRUE

```

We see that significant variation exists within each genome length, so we perform pairwise Wilcoxon tests on each to see which pairs of sizes are significantly different.

```

size_vec = c(16, 32, 64, 128, 256, 512)
length_vec = c(25, 50, 100, 200, 400)
for(genome_length in length_vec){
  df_test = df2[df2$LENGTH == genome_length,]
  df_wilcox = data.frame(data = matrix(nrow = 0, ncol = 6))
  colnames(df_wilcox) = c('genome_length', 'size_a', 'size_b', 'p_value_corrected', 'p_value_raw', 'W')
  for(size_idx_a in 1:(length(size_vec) - 1)){
    size_a = size_vec[size_idx_a]
    for(size_idx_b in (size_idx_a + 1):length(size_vec)){
      size_b = size_vec[size_idx_b]
      res = wilcox.test(df_test[df_test$MCSIZE == size_a,]$restraint_value, df_test[df_test$MCSIZE == size_b,]$restraint_value)
      df_wilcox[nrow(df_wilcox) + 1,] = c(genome_length, size_a, size_b, 0, res$p.value, res$statistic)
    }
  }
  df_wilcox$p_value_corrected = p.adjust(df_wilcox$p_value_raw, method = 'holm')
  df_wilcox$less_0.01 = df_wilcox$p_value_corrected < 0.01
  print(paste0('Genome length: ', genome_length))
  print(df_wilcox)
}

```

```

## [1] "Genome length: 25"
## genome_length size_a size_b p_value_corrected p_value_raw      W less_0.01
## 1          25    16    32      3.071685e-07 4.388121e-08 2759.0      TRUE
## 2          25    16    64      2.643511e-06 4.405852e-07 2932.5      TRUE
## 3          25    16   128      2.296087e-02 7.653623e-03 3908.0     FALSE
## 4          25    16   256      4.468816e-06 8.937632e-07 7011.5      TRUE
## 5          25    16   512      1.225546e-26 1.021288e-27 9466.0      TRUE
## 6          25    32    64      8.795871e-01 8.795871e-01 4937.5     FALSE
## 7          25    32   128      1.781242e-02 4.453105e-03 6164.5     FALSE

```

```

## 8      25      32      256      8.642790e-19 7.857082e-20 8731.0      TRUE
## 9      25      32      512      1.295762e-31 8.638414e-33 9881.5      TRUE
## 10     25      64      128      2.755884e-02 1.377942e-02 6008.5      FALSE
## 11     25      64      256      8.087490e-17 8.087490e-18 8519.5      TRUE
## 12     25      64      512      7.929046e-31 5.663604e-32 9817.0      TRUE
## 13     25     128      256      1.175675e-11 1.469594e-12 7897.0      TRUE
## 14     25     128      512      9.159152e-29 7.045501e-30 9647.5      TRUE
## 15     25     256      512      9.448611e-16 1.049846e-16 8397.0      TRUE
## [1] "Genome length: 50"
##      genome_length size_a size_b p_value_corrected p_value_raw      W less_0.01
## 1           50      16      32      1.000000e+00 8.003516e-01 5104.0      FALSE
## 2           50      16      64      2.328801e-28 1.791386e-29  386.0      TRUE
## 3           50      16     128      8.546113e-13 1.220873e-13 1965.0      TRUE
## 4           50      16     256      1.000000e+00 6.285321e-01 5198.5      FALSE
## 5           50      16     512      2.425365e-23 2.425365e-24 9167.0      TRUE
## 6           50      32      64      3.889977e-24 3.536343e-25  757.0      TRUE
## 7           50      32     128      5.002137e-12 8.336895e-13 2071.0      TRUE
## 8           50      32     256      1.000000e+00 4.257132e-01 5326.5      FALSE
## 9           50      32     512      4.318415e-25 3.598679e-26 9331.5      TRUE
## 10          50      64     128      1.000000e+00 3.356981e-01 5394.5      FALSE
## 11          50      64     256      2.224828e-18 2.781035e-19 8674.5      TRUE
## 12          50      64     512      7.094686e-32 4.729791e-33 9902.0      TRUE
## 13          50     128     256      3.110374e-11 6.220748e-12 7814.0      TRUE
## 14          50     128     512      2.255738e-29 1.611242e-30 9700.0      TRUE
## 15          50     256     512      1.283931e-19 1.426590e-20 8806.0      TRUE
## [1] "Genome length: 100"
##      genome_length size_a size_b p_value_corrected p_value_raw      W less_0.01
## 1          100      16      32      2.153944e-14 2.692430e-15 1764.5      TRUE
## 2          100      16      64      2.038910e-29 1.359273e-30  294.0      TRUE
## 3          100      16     128      5.713029e-29 4.080735e-30  333.0      TRUE
## 4          100      16     256      1.058025e-17 1.175583e-18 1391.0      TRUE
## 5          100      16     512      3.828744e-06 9.571861e-07 7006.0      TRUE
## 6          100      32      64      1.000000e+00 7.740365e-01 5118.0      FALSE
## 7          100      32     128      1.546290e-09 2.577150e-10 2412.0      TRUE
## 8          100      32     256      1.000000e+00 9.522646e-01 4975.0      FALSE
## 9          100      32     512      3.415932e-19 3.105393e-20 8772.0      TRUE
## 10         100      64     128      4.799386e-14 6.856265e-15 1812.5      TRUE
## 11         100      64     256      1.000000e+00 3.718233e-01 4634.0      FALSE
## 12         100      64     512      1.603099e-22 1.335916e-23 9098.5      TRUE
## 13         100     128     256      1.394401e-08 2.788802e-09 7433.0      TRUE
## 14         100     128     512      1.814275e-28 1.395596e-29 9623.0      TRUE
## 15         100     256     512      4.379891e-18 4.379891e-19 8654.0      TRUE
## [1] "Genome length: 200"
##      genome_length size_a size_b p_value_corrected p_value_raw      W less_0.01
## 1          200      16      32      1.968049e-20 1.640041e-21 1101.0      TRUE
## 2          200      16      64      4.701928e-31 3.358520e-32  165.0      TRUE

```

```

## 3      200      16      128      4.881587e-33 3.254391e-34      8.0      TRUE
## 4      200      16      256      1.626707e-20 1.251313e-21 1089.5      TRUE
## 5      200      16      512      1.000000e+00 5.236501e-01 4738.5      FALSE
## 6      200      32      64       1.000000e+00 6.010522e-01 4785.5      FALSE
## 7      200      32      128      5.703607e-18 5.703607e-19 1358.0      TRUE
## 8      200      32      256      3.453153e-11 4.933076e-12 2172.5      TRUE
## 9      200      32      512      3.769973e-08 9.424932e-09 7350.0      TRUE
## 10     200      64      128      4.460538e-12 5.575672e-13 2048.5      TRUE
## 11     200      64      256      1.883098e-10 3.138497e-11 2282.0      TRUE
## 12     200      64      512      4.056747e-09 8.113493e-10 7514.5      TRUE
## 13     200     128      256      9.334382e-03 3.111461e-03 3789.5      TRUE
## 14     200     128      512      1.801191e-19 1.637446e-20 8800.0      TRUE
## 15     200     256      512      1.367136e-15 1.519040e-16 8379.0      TRUE
## [1] "Genome length: 400"
##      genome_length size_a size_b p_value_corrected p_value_raw      W less_0.01
## 1      400      16      32      1.535030e-25 1.180792e-26 626.0      TRUE
## 2      400      16      64      4.020270e-29 2.871622e-30 320.5      TRUE
## 3      400      16     128      2.139736e-30 1.426491e-31 215.0      TRUE
## 4      400      16     256      3.047545e-19 2.770496e-20 1223.0      TRUE
## 5      400      16     512      6.790903e-02 1.697726e-02 4022.5      FALSE
## 6      400      32      64      7.702973e-01 7.702973e-01 5120.0      FALSE
## 7      400      32     128      2.353267e-24 1.961056e-25 734.0      TRUE
## 8      400      32     256      3.922288e-16 4.358098e-17 1560.5      TRUE
## 9      400      32     512      7.607630e-02 3.803815e-02 5849.5      FALSE
## 10     400      64     128      3.142885e-18 3.142885e-19 1331.0      TRUE
## 11     400      64     256      6.103704e-16 7.629630e-17 1587.5      TRUE
## 12     400      64     512      6.790903e-02 2.149175e-02 5941.5      FALSE
## 13     400     128     256      2.106836e-06 4.213672e-07 2929.0      TRUE
## 14     400     128     512      3.669212e-11 6.115353e-12 7815.0      TRUE
## 15     400     256     512      9.548472e-15 1.364067e-15 8270.0      TRUE

```

Chapter 9

Infinite genome experiment

Building off the genome length experiment, we wanted to ensure our results were not an artifact of limited genome size. Genomes in biological organisms can be extremely large compared to our 400-bit genomes. Therefore, we extended the model to support infinite genomes. Organisms with infinite genomes have no limit on the restraint buffer values they can evolve. In an infinite genome, restraint threshold is set at zero, and thus all non-negative restraint values are restrained. Organisms begin with a restraint buffer of zero. Each mutation (both somatic and germ) *always* has a 60% probability of lowering restraint. In this way, the infinite genome has the same probability of a restraint-reducing mutation as finite genomes have at their restraint threshold. Furthermore, mutational pressure does not increase with the restraint buffer as it does in finite genomes.

Here, we show the results of re-running the baseline experiment using an infinite genome. Since we are replicating the baseline experiment, we also include the 8x8 and 1024x1024 organism sizes. The configuration script and data for the experiment can be found under `2021_03_12__org_sizes_inf/` in the `experiments` directory of the git repository.

9.1 Data cleaning

Load necessary R libraries

```
library(dplyr)
library(ggplot2)
library(ggthemes)
library(scales)
library(khroma)
```

Load the data and trim to only include the final generation.

```
# Load the data
df = read.csv('../experiments/2021_03_12__org_sizes_inf/evolution/data/scraped_evoluti
# Trim off NAs (artifacts of how we scraped the data) and trim to only have gen 10,000
df2 = df[!is.na(df$MCSIZE) & df$generation == 10000,]
```

We group and summarize the data to make to ensure all replicates are present.

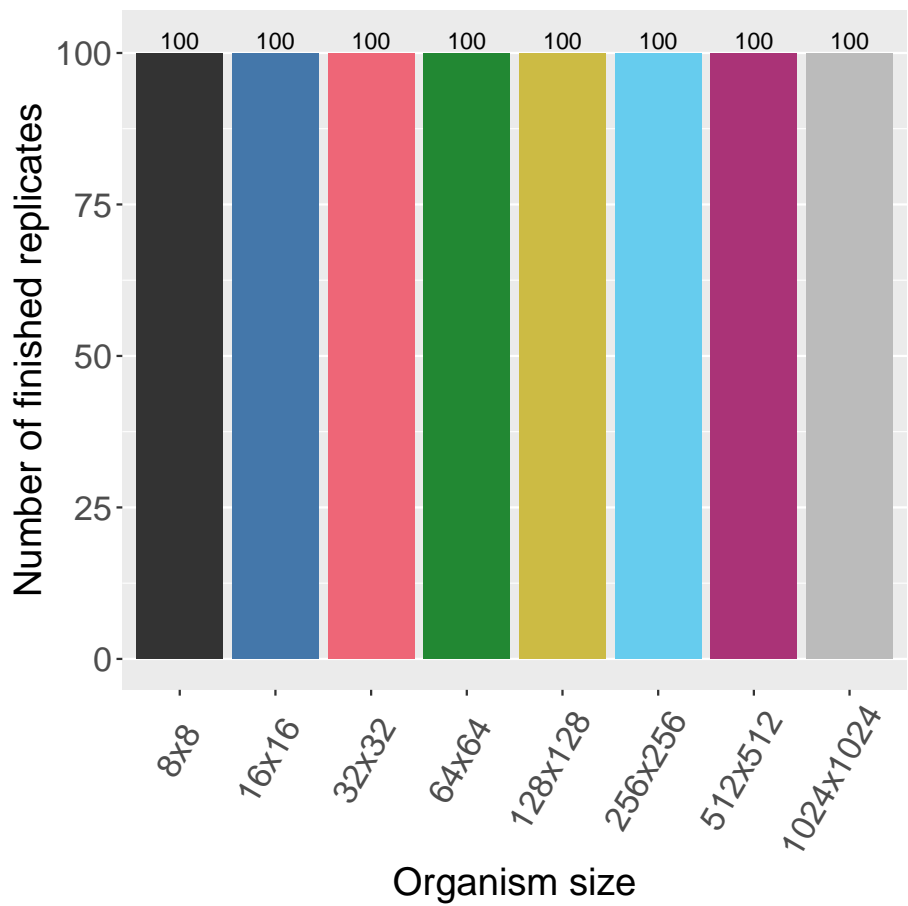
```
# Group the data by size and summarize
data_grouped = dplyr::group_by(df2, MCSIZE)
data_summary = dplyr::summarize(data_grouped, mean_ones = mean(ave_ones), n = dplyr::n
```

We clean the data and create a few helper variables to make plotting easier.

```
# Calculate restraint value (infinite genome there is no difference)
df2$restraint_value = df2$ave_ones
# Make a nice, clean factor for size
df2$size_str = paste0(df2$MCSIZE, 'x', df2$MCSIZE)
df2$size_factor = factor(df2$size_str, levels = c('8x8', '16x16', '32x32', '64x64', '128x128', '256x256', '512x512', '1024x1024'))
df2$size_factor_reversed = factor(df2$size_str, levels = rev(c('8x8', '16x16', '32x32', '64x64', '128x128', '256x256', '512x512', '1024x1024')))
data_summary$size_str = paste0(data_summary$MCSIZE, 'x', data_summary$MCSIZE)
data_summary$size_factor = factor(data_summary$size_str, levels = c('8x8', '16x16', '32x32', '64x64', '128x128', '256x256', '512x512', '1024x1024'))
# Create a map of colors we'll use to plot the different organism sizes
color_vec = as.character(khroma::color('bright')(7))
color_map = c(
  '8x8' = '#333333',
  '16x16' = color_vec[1],
  '32x32' = color_vec[2],
  '64x64' = color_vec[3],
  '128x128' = color_vec[4],
  '256x256' = color_vec[5],
  '512x512' = color_vec[6],
  '1024x1024' = color_vec[7]
)
# Set the sizes for text in plots
text_major_size = 18
text_minor_size = 16
```

9.2 Data integrity check

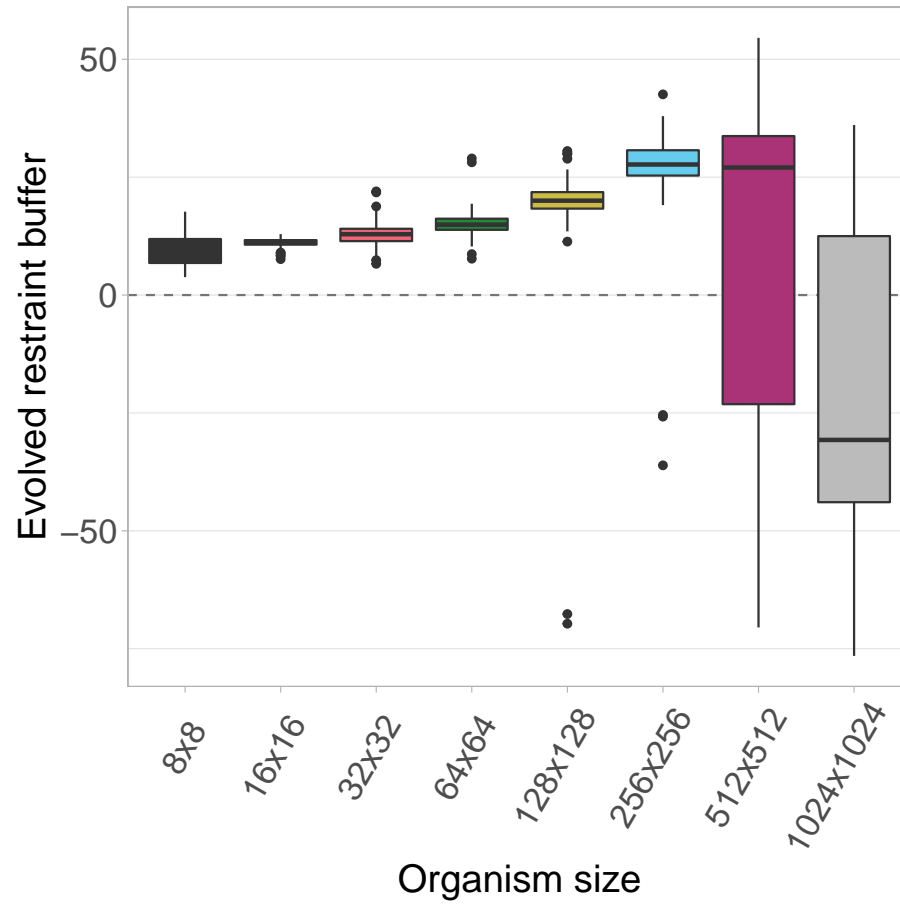
Now we plot the number of finished replicates for each treatment to make sure all data are present. Each bar/color shows a different organism size.



9.3 Plot

Here we plot all the data at once. Colors/boxplots represent different organism sizes.

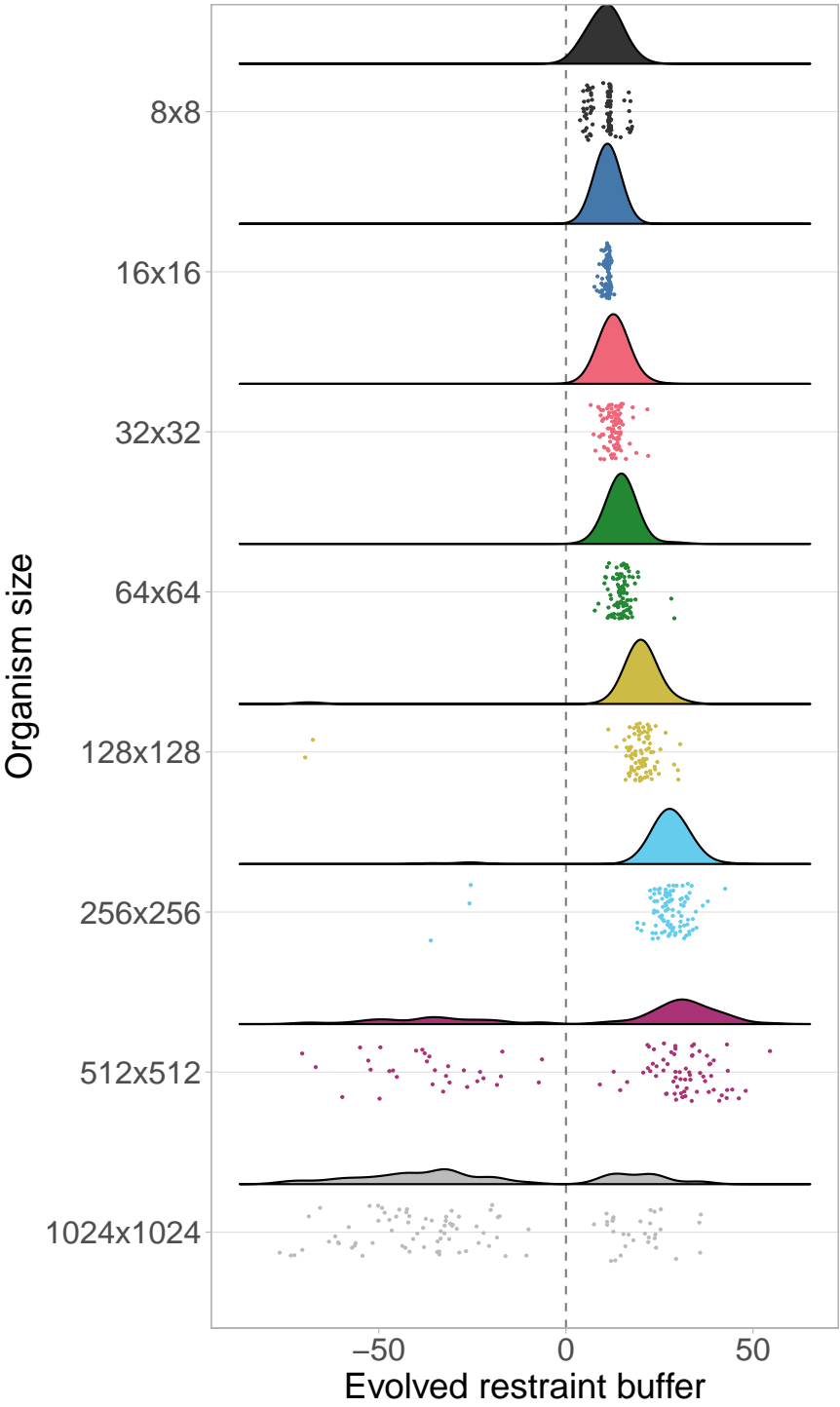
9.3.1 Boxplots



9.3.2 Raincloud plots

We can plot the same data via raincloud plots.

```
## Picking joint bandwidth of 3.57
```

These plots show that the same trend observed in the baseline experiment (that evolved restraint buffers initially increase and then decrease with increasing organisms size) still appears when organism genomes are not limited in length.

9.4 Statistics

First, we perform a Kruskal-Wallis test across all organism sizes to indicate if variance exists. If variance exists, we then perform a pairwise Wilcoxon Rank-Sum test to show which pairs of organism sizes significantly differ. Finally, we perform Bonferroni-Holm corrections for multiple comparisons.

```
res = kruskal.test(df2$restraint_value ~ df2$MCSIZE, df2)
df_kruskal = data.frame(data = matrix(nrow = 0, ncol = 3))
colnames(df_kruskal) = c('p_value', 'chi_squared', 'df')
df_kruskal[nrow(df_kruskal) + 1,] = c(res$p.value, as.numeric(res$statistic)[1], as.numeric(res$df))
df_kruskal$less_0.01 = df_kruskal$p_value < 0.01
print(df_kruskal)
```

```
##           p_value chi_squared df less_0.01
## 1 6.606587e-79      383.9432  7         TRUE
```

We see that significant variation exists, so we perform pairwise Wilcoxon tests on each to see which pairs of sizes are significantly different.

```
size_vec = c(16, 32, 64, 128, 256, 512)
df_test = df2
df_wilcox = data.frame(data = matrix(nrow = 0, ncol = 5))
colnames(df_wilcox) = c('size_a', 'size_b', 'p_value_corrected', 'p_value_raw', 'W')
for(size_idx_a in 1:(length(size_vec) - 1)){
  size_a = size_vec[size_idx_a]
  for(size_idx_b in (size_idx_a + 1):length(size_vec)){
    size_b = size_vec[size_idx_b]
    res = wilcox.test(df_test[df_test$MCSIZE == size_a,]$restraint_value, df_test[df_test$MCSIZE == size_b,]$restraint_value)
    df_wilcox[nrow(df_wilcox) + 1,] = c(size_a, size_b, 0, res$p.value, as.numeric(res$statistic))
  }
}
df_wilcox$p_value_corrected = p.adjust(df_wilcox$p_value_raw, method = 'holm')
df_wilcox$less_0.01 = df_wilcox$p_value_corrected < 0.01
print(df_wilcox)
```

```
##      size_a size_b p_value_corrected  p_value_raw      W less_0.01
## 1       16    32      3.317841e-10 4.739773e-11 2307.0      TRUE
## 2       16    64      3.767632e-24 3.767632e-25  759.5      TRUE
## 3       16   128      5.749859e-30 3.833239e-31  249.5      TRUE
## 4       16   256      2.254278e-29 1.610199e-30  300.0      TRUE
## 5       16   512      1.575007e-04 3.150014e-05 3296.0      TRUE
## 6       32    64      4.352278e-10 7.253796e-11 2333.0      TRUE
```

## 7	32	128	1.138873e-26	1.035339e-27	534.5	TRUE
## 8	32	256	2.625866e-29	2.019897e-30	308.0	TRUE
## 9	32	512	2.824927e-04	7.062318e-05	3373.0	TRUE
## 10	64	128	1.477957e-23	1.642174e-24	817.5	TRUE
## 11	64	256	5.981331e-28	4.984443e-29	423.0	TRUE
## 12	64	512	7.003790e-04	2.334597e-04	3493.5	TRUE
## 13	128	256	5.681587e-23	7.101983e-24	876.0	TRUE
## 14	128	512	4.314526e-03	2.157263e-03	3744.0	TRUE
## 15	256	512	3.971985e-01	3.971985e-01	5347.0	FALSE

Chapter 10

Infinite population experiments

10.1 Finite genome experiment

The population size experiment showed that increasing population size also increases selection pressure and leads to the evolution of higher restraint buffers. However, even at a population size of 2,000 individuals, we still see the turning point in evolved restraint. To determine if an even higher population size would prevent the turning point trend, we created a population genetics model to simulate an infinite population. We plugged the average of 100 fitness samples at each restraint buffer into the following formula:

$$p'_n = \frac{(1 - \mu_{t-} - \mu_{t+})F_n p_n + \mu_{f+} F_{(n+1)} p_{(n+1)} + \mu_{f-} F_{(n-1)} p_{(n-1)}}{\text{normalizing factor}}$$

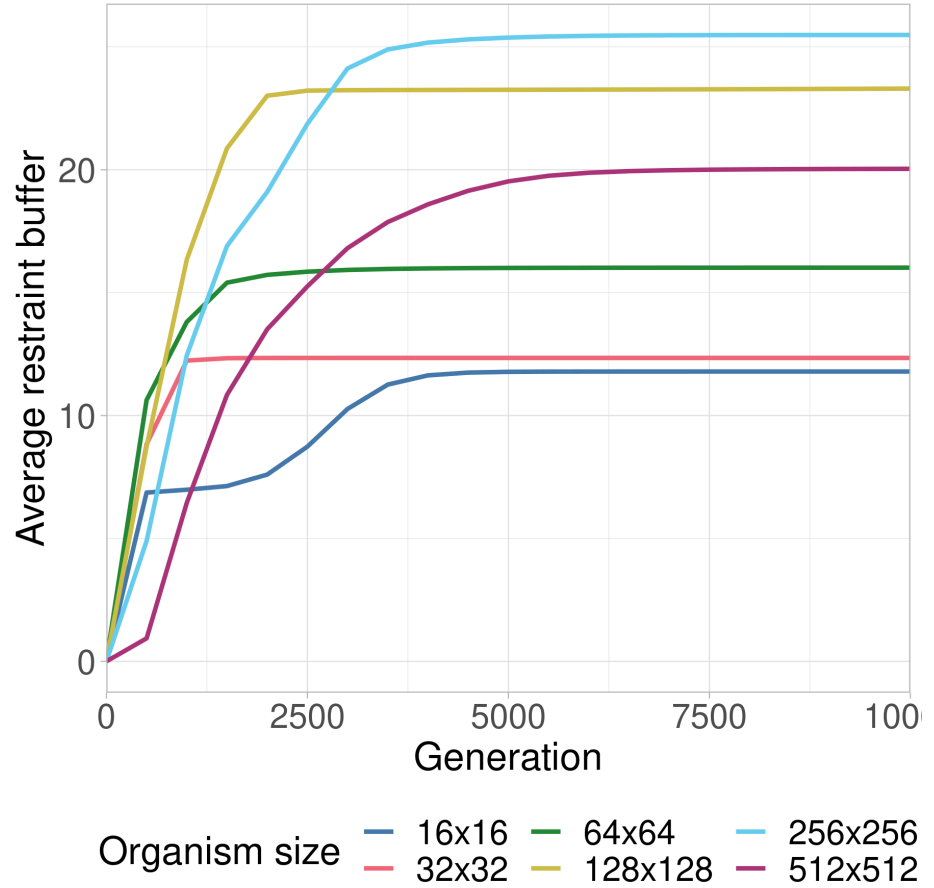
Definitions:

- p_n : fraction of the population at n ones
- F_n : average fitness at n ones
- μ_{t-} : probability of mutation to $n - 1$ ones from n ones
- μ_{f-} : probability of mutation from $n - 1$ to n ones
- μ_{t+} : probability of mutation to $n + 1$ ones from n ones
- μ_{f+} : probability of mutation from $n + 1$ to n ones

The simulation script, plotting script, and timing data for this experiment can be found under `2021_03_07__inf_population/` in the experiments directory of the git repository.

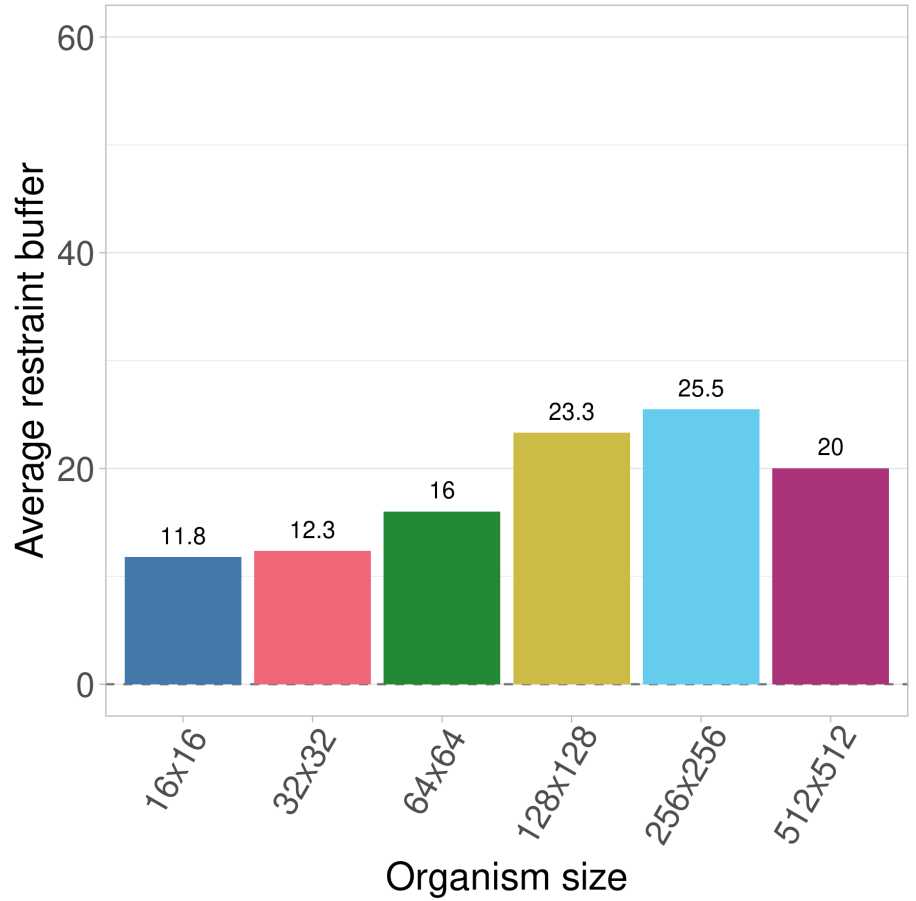
10.1.1 Plots

Here we show how the evolved restraint buffer values change through the course of



evolution.

Here we show the evolved restraint buffer values at the end of 10,000 generations. Bar plots are used because the simulation is deterministic; there is only one sample



needed for each organism size.

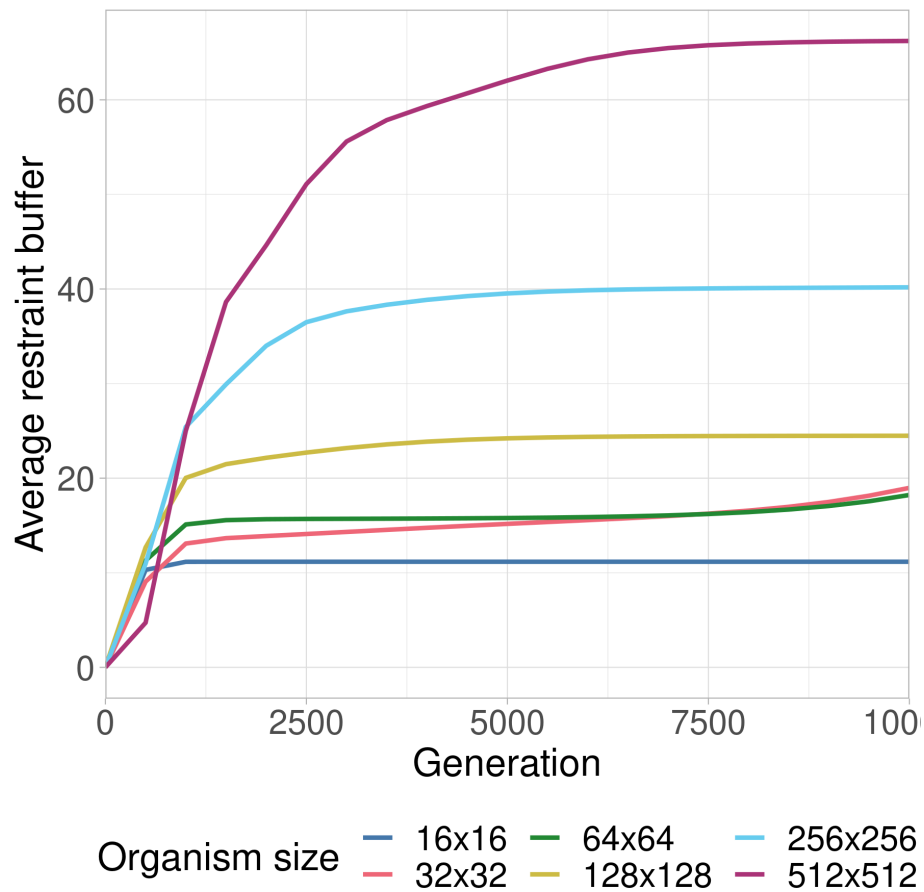
Thus, even with an infinite population and the higher selective pressures that come with it, we still see the turning point trend in the evolved restraint buffer values.

10.2 Infinite genome experiment

Knowing that an infinite population alone is not enough to negate the turning point trend, we then reran the infinite population model with an infinite genome. Functionally this experiment is identical to the one above, the only difference is that we now feed in fitness data from the infinite genome experiment (fitness data was calculated from restraint buffer values of -100 to 450, which preliminary experiments showed was sufficient). The simulation script, plotting script, and timing data for this experiment can be found under `2021_03_08__inf_genome_inf_pop/` in the experiments directory of the git repository.

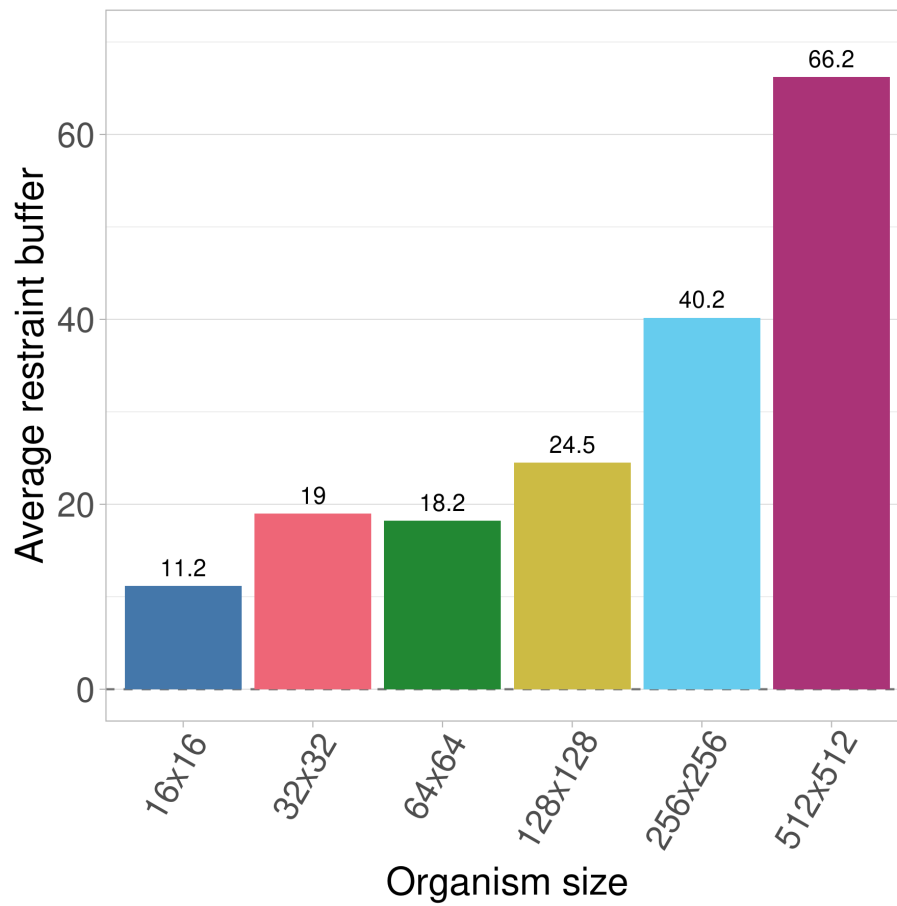
10.2.1 Plots

Here we show how the evolved restraint buffer values change through the course of



evolution.

Here we show the evolved restraint buffer values at the end of 10,000 generations. Again, we use bar plots because the simulation is deterministic.



Thus, we see that using *both* an infinite genome and an infinite population (and thus increasing selective pressure while decreasing mutational pressure) is enough to see evolved restraint buffers monotonically increase with organism size.