Thesis Simulation Results Analysis for Chapter 4

Dasha Asienga

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Contents

This file is intended to synthesize and analyze the results from the simulation.

Reading in the Result Data Sets

Logistic Regression

The results data set has 200 observations for each of the simulation trials, 50 from each sample size: $n = 500, 1000, 2500, 5000$.

```
lr_500 <- read.csv("/home/dasienga24/Statistics-Senior-Honors-Thesis/R/Simulation/LogisticRegression/Res
lr_1000 <- read.csv("/home/dasienga24/Statistics-Senior-Honors-Thesis/R/Simulation/LogisticRegression/Re
lr_2500 <- read.csv("/home/dasienga24/Statistics-Senior-Honors-Thesis/R/Simulation/LogisticRegression/Re
lr_5000 <- read.csv("/home/dasienga24/Statistics-Senior-Honors-Thesis/R/Simulation/LogisticRegression/Re

lr_500 <- lr_500 |>
  mutate(sample_size = 500) |>
```

```
  dplyr::select(-X)

lr_1000 <- lr_1000 |>
  mutate(sample_size = 1000) |>
  dplyr::select(-X)

lr_2500 <- lr_2500 |>
  mutate(sample_size = 2500) |>
  dplyr::select(-X)

lr_5000 <- lr_5000 |>
  mutate(sample_size = 5000) |>
  dplyr::select(-X)

logistic_results <- rbind(lr_500, lr_1000, lr_2500, lr_5000)
glimpse(logistic_results)
```

```
## Rows: 200
## Columns: 5
## $ dataset_id        <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 1~
## $ lr_convergence    <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1~
## $ lr_accuracy       <dbl> 0.790, 0.738, 0.778, 0.758, 0.788, 0.822, 0.776, 0.7~
## $ lr_discrimination <dbl> 0.2020, 0.2402, 0.2730, 0.3123, 0.2663, 0.2171, 0.31~
## $ sample_size       <dbl> 500, 500, 500, 500, 500, 500, 500, 500, 500, 500, 50~
```

Seldonian Solutions

The results data set has 200 observations for each of the simulation trials, 50 from each sample size: $n = 500, 1000, 2500, 5000$.

```
seldonian_results <- read.csv("/home/dasienga24/Statistics-Senior-Honors-Thesis/Python/COMPAS Simulatio
seldonian_results <- distinct(seldonian_results) #remove duplicate rows
glimpse(seldonian_results)
```

```
## Rows: 200
## Columns: 14
## $ sample_size       <int> 1000, 1000, 1000, 2500, 1000, 1000, 1000, 2500, 500,~
## $ dataset_id        <int> 25, 10, 22, 17, 34, 38, 36, 2, 49, 17, 7, 41, 8, 33,~
## $ passed_safety_02  <chr> "True", "True", "True", "True", "True", "True", "Tru~
## $ passed_safety_01  <chr> "True", "True", "True", "True", "True", "True", "Tru~
## $ passed_safety_005 <chr> "True", "True", "True", "True", "True", "True", "Tru~
## $ passed_safety_001 <chr> "True", "True", "True", "False", "True", "True", "Tr~
## $ sa_02_accuracy    <dbl> 0.6420, 0.6410, 0.6370, 0.7832, 0.5520, 0.6180, 0.73~
## $ sa_01_accuracy    <dbl> 0.5560, 0.5030, 0.5200, 0.4844, 0.4930, 0.5190, 0.49~
## $ sa_005_accuracy   <dbl> 0.5330, 0.5030, 0.5460, 0.4844, 0.4930, 0.5200, 0.49~
## $ sa_001_accuracy   <dbl> 0.5430, 0.5030, 0.5830, 0.4844, 0.4930, 0.5190, 0.49~
## $ sa_02_disc_stat   <dbl> 0.1791, 0.0995, 0.0948, 0.1428, 0.0787, 0.1081, 0.22~
## $ sa_01_disc_stat   <dbl> 0.0345, 0.0000, 0.0355, 0.0000, 0.0000, 0.0000, NA, ~
## $ sa_005_disc_stat  <dbl> 0.0184, 0.0000, 0.0496, 0.0000, 0.0000, NA, 0.0000, ~
## $ sa_001_disc_stat  <dbl> 0.0252, 0.0000, 0.0347, 0.0000, 0.0000, 0.0000, 0.00~
```

Combine the Data Sets from Both Simulations

```
sim_results <- inner_join(logistic_results, seldonian_results,
                          by = c("sample_size", "dataset_id"))

glimpse(sim_results)
```

```
## Rows: 200
## Columns: 17
## $ dataset_id        <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 1~
## $ lr_convergence    <int> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1~
## $ lr_accuracy       <dbl> 0.790, 0.738, 0.778, 0.758, 0.788, 0.822, 0.776, 0.7~
## $ lr_discrimination <dbl> 0.2020, 0.2402, 0.2730, 0.3123, 0.2663, 0.2171, 0.31~
## $ sample_size       <dbl> 500, 500, 500, 500, 500, 500, 500, 500, 500, 500, 50~
## $ passed_safety_02  <chr> "True", "True", "True", "True", "True", "True", "Tru~
## $ passed_safety_01  <chr> "True", "True", "False", "True", "True", "False", "T~
## $ passed_safety_005 <chr> "True", "True", "False", "True", "True", "False", "T~
## $ passed_safety_001 <chr> "True", "True", "False", "True", "True", "False", "T~
## $ sa_02_accuracy    <dbl> 0.526, 0.510, 0.528, 0.520, 0.512, 0.508, 0.608, 0.5~
## $ sa_01_accuracy    <dbl> 0.522, 0.510, 0.528, 0.520, 0.496, 0.508, 0.482, 0.5~
## $ sa_005_accuracy   <dbl> 0.522, 0.510, 0.528, 0.520, 0.496, 0.508, 0.756, 0.5~
## $ sa_001_accuracy   <dbl> 0.522, 0.510, 0.528, 0.520, 0.496, 0.508, 0.482, 0.5~
## $ sa_02_disc_stat   <dbl> NA, 0.0000, 0.0000, 0.0000, 0.0429, 0.0000, 0.0106, ~
## $ sa_01_disc_stat   <dbl> 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.00~
## $ sa_005_disc_stat  <dbl> 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.13~
## $ sa_001_disc_stat  <dbl> 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.00~
```

Probability of a Solution

Table

This section assesses what proportion of the trials returned a solution. It is expected that all logistic regression trials will return a solution. However, for the Seldonian algorithms, while all trials will return a candidate solution (based on the logistic regression as a starting point), it is expected that not all candidate solutions will pass the safety test. The table below records the number of Seldonian solutions that passed the safety test in each sample size.

```
reps <- nrow(sim_results)/4

sim_results |>
  group_by(sample_size) |>
  summarise(LR = 100*count(lr_convergence == 1)/reps,
            `SA (0.2)` = 100*count(passed_safety_02 == "True")/reps,
            `SA (0.1)` = 100*count(passed_safety_01 == "True")/reps,
            `SA (0.05)` = 100*count(passed_safety_005 == "True")/reps,
            `SA (0.01)` = 100*count(passed_safety_001 == "True")/reps) |>
  rename("Sample Size" = sample_size) |>
  kable(caption = "Probability of a Solution")
```

Table 1: Probability of a Solution

Sample Size	LR	SA (0.2)	SA (0.1)	SA (0.05)	SA (0.01)
500	100	100	90	86	70

Sample Size	LR	SA (0.2)	SA (0.1)	SA (0.05)	SA (0.01)
1000	100	100	100	100	88
2500	100	100	100	100	52
5000	100	100	100	96	28

Accuracy

```r
# filter accuracy data out for only seldonian solutions that converged
sim_results_converged_accuracy <- sim_results |>
  mutate(sa_02_accuracy = ifelse(passed_safety_02 == "True", sa_02_accuracy, NA),
         sa_01_accuracy = ifelse(passed_safety_01 == "True", sa_01_accuracy, NA),
         sa_005_accuracy = ifelse(passed_safety_005 == "True", sa_005_accuracy, NA),
         sa_001_accuracy = ifelse(passed_safety_001 == "True", sa_001_accuracy, NA))
```

Table

```r
# table
sim_results_converged_accuracy |>
  group_by(sample_size) |>
  summarise(LR = round(100*mean(lr_accuracy, na.rm = TRUE),2),
            sd_lr = round(sd(lr_accuracy, na.rm = TRUE),2),
            `SA (0.2)` = round(100*mean(sa_02_accuracy, na.rm = TRUE),2),
            sd_02 = round(sd(sa_02_accuracy, na.rm = TRUE),2),
            `SA (0.1)` = round(100*mean(sa_01_accuracy, na.rm = TRUE),2),
            sd_01 = round(sd(sa_01_accuracy, na.rm = TRUE),2),
            `SA (0.05)` = round(100*mean(sa_005_accuracy, na.rm = TRUE),2),
            sd_005 = round(sd(sa_005_accuracy, na.rm = TRUE),2),
            `SA (0.01)` = round(100*mean(sa_001_accuracy, na.rm = TRUE),2),
            sd_001 = round(sd(sa_001_accuracy, na.rm = TRUE),2)) |>
  rename("Sample Size" = sample_size,
         "sd" = sd_lr,
         "sd " = sd_02,
         "sd  " = sd_01,
         "sd   " = sd_005,
         "sd    " = sd_001) |>
  kable(caption = "Accuracy of Convergent Solutions")
```

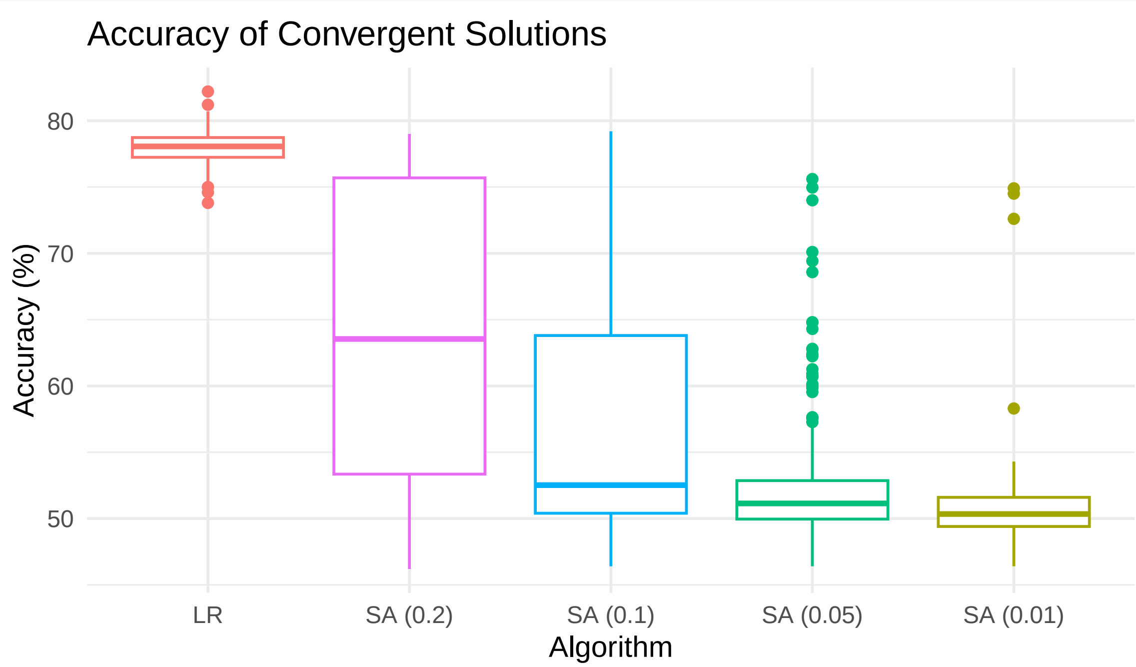
Table 2: Accuracy of Convergent Solutions

Sample Size	LR	sd	SA (0.2)	sd	SA (0.1)	sd	SA (0.05)	sd	SA (0.01)	sd
500	78.22	0.02	55.26	0.07	52.32	0.07	52.27	0.06	51.09	0.04
1000	77.89	0.01	58.21	0.08	52.24	0.05	51.55	0.04	51.54	0.05
2500	77.85	0.01	71.71	0.07	57.24	0.06	51.08	0.02	50.44	0.01
5000	78.04	0.01	71.12	0.07	65.31	0.09	55.71	0.06	50.04	0.01

Visualizations

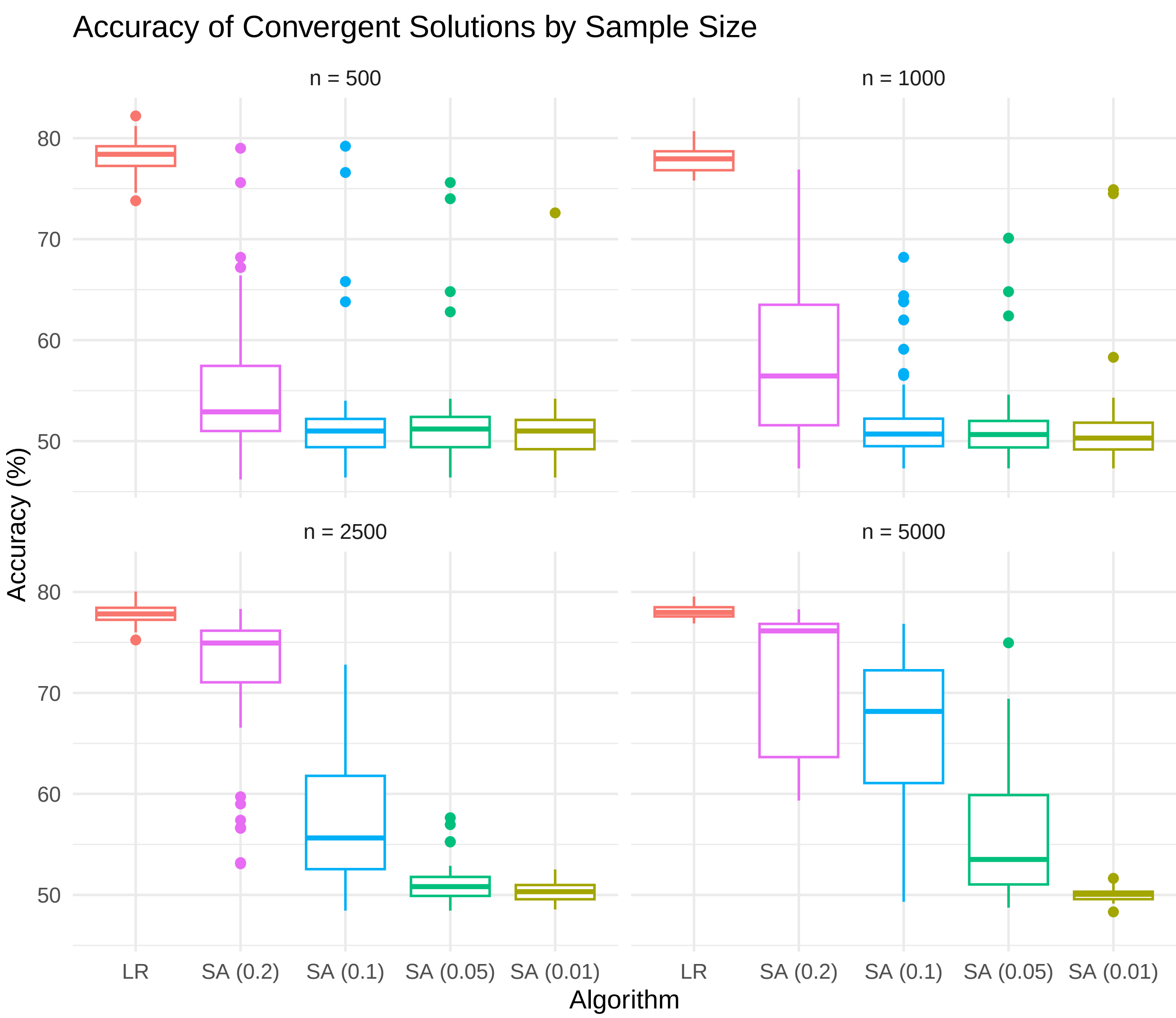
```r
# visualization
sim_results_converged_accuracy |>
```

```r
  dplyr::select(c(lr_accuracy, sa_02_accuracy, sa_01_accuracy, sa_005_accuracy,
                  sa_001_accuracy, sample_size)) |>
  rename("Sample Size" = sample_size,
         "LR" = lr_accuracy,
         "SA (0.2)" = sa_02_accuracy,
         "SA (0.1)" = sa_01_accuracy,
         "SA (0.05)" = sa_005_accuracy,
         "SA (0.01)" = sa_001_accuracy) |>
  pivot_longer(cols = -c(`Sample Size`),
               names_to = "model",
               values_to = "accuracy") |>
  mutate(accuracy = 100*accuracy) |>
  ggplot(mapping = aes(x = model, y = accuracy, color = model)) +
  geom_boxplot() +
  scale_x_discrete(limits = c("LR", "SA (0.2)", "SA (0.1)", "SA (0.05)", "SA (0.01)")) +
  theme_minimal() +
  guides(color = "none") +
  labs(x = "Algorithm",
       y = "Accuracy (%)",
       title = "Accuracy of Convergent Solutions")
```




```r
# visualization
sim_results_converged_accuracy |>
  dplyr::select(c(lr_accuracy, sa_02_accuracy, sa_01_accuracy, sa_005_accuracy,
                  sa_001_accuracy, sample_size)) |>
  mutate(sample_size = factor(case_when(sample_size == 500 ~ "n = 500",
                                        sample_size == 1000 ~ "n = 1000",
                                        sample_size == 2500 ~ "n = 2500",
                                        sample_size == 5000 ~ "n = 5000"
                                        ),
                              levels = c("n = 500", "n = 1000", "n = 2500", "n = 5000"))) |>
  rename("Sample Size" = sample_size,
         "LR" = lr_accuracy,
```

```r
         "SA (0.2)" = sa_02_accuracy,
         "SA (0.1)" = sa_01_accuracy,
         "SA (0.05)" = sa_005_accuracy,
         "SA (0.01)" = sa_001_accuracy) |>
  pivot_longer(cols = -c(`Sample Size`),
               names_to = "model",
               values_to = "accuracy") |>
  mutate(accuracy = 100*accuracy) |>
  ggplot(mapping = aes(x = model, y = accuracy, color = model)) +
  geom_boxplot() +
  scale_x_discrete(limits = c("LR", "SA (0.2)", "SA (0.1)", "SA (0.05)", "SA (0.01)")) +
  theme_minimal() +
  guides(color = "none") +
  facet_wrap(~`Sample Size`) +
  labs(x = "Algorithm",
       y = "Accuracy (%)",
       title = "Accuracy of Convergent Solutions by Sample Size")
```



Discrimination

```r
# filter discrimination data out for only seldonian solutions that converged
sim_results_converged_disc <- sim_results |>
  mutate(sa_02_disc_stat = ifelse(passed_safety_02 == "True", sa_02_disc_stat, NA),
         sa_01_disc_stat = ifelse(passed_safety_01 == "True", sa_01_disc_stat, NA),
         sa_005_disc_stat = ifelse(passed_safety_005 == "True", sa_005_disc_stat, NA),
         sa_001_disc_stat = ifelse(passed_safety_001 == "True", sa_001_disc_stat, NA))
```

Tables

```r
# table
sim_results_converged_disc |>
  group_by(sample_size) |>
  summarise(LR = round(100*mean(lr_discrimination, na.rm = TRUE),2),
            sd_lr = round(sd(lr_discrimination, na.rm = TRUE),2),
            `SA (0.2)` = round(100*mean(sa_02_disc_stat, na.rm = TRUE),2),
            sd_02 = round(sd(sa_02_disc_stat, na.rm = TRUE),2),
            `SA (0.1)` = round(100*mean(sa_01_disc_stat, na.rm = TRUE),2),
            sd_01 = round(sd(sa_01_disc_stat, na.rm = TRUE),2),
            `SA (0.05)` = round(100*mean(sa_005_disc_stat, na.rm = TRUE),2),
            sd_005 = round(sd(sa_005_disc_stat, na.rm = TRUE),2),
            `SA (0.01)` = round(100*mean(sa_001_disc_stat, na.rm = TRUE),2),
            sd_001 = round(sd(sa_001_disc_stat, na.rm = TRUE),2)) |>
  rename("Sample Size" = sample_size,
         "sd" = sd_lr,
         "sd " = sd_02,
         "sd  " = sd_01,
         "sd   " = sd_005,
         "sd     " = sd_001) |>
  kable(caption = "Discrimination of Convergent Solutions")
```

Table 3: Discrimination of Convergent Solutions

Sample Size	LR	sd	SA (0.2)	sd	SA (0.1)	sd	SA (0.05)	sd	SA (0.01)	sd
500	24.03	0.08	5.07	0.07	2.34	0.07	1.80	0.06	0.65	0.03
1000	24.20	0.05	8.31	0.07	2.21	0.05	1.19	0.04	0.97	0.04
2500	24.13	0.04	16.48	0.07	6.79	0.06	1.27	0.02	0.06	0.00
5000	24.88	0.03	13.57	0.06	13.17	0.08	5.60	0.06	0.02	0.00

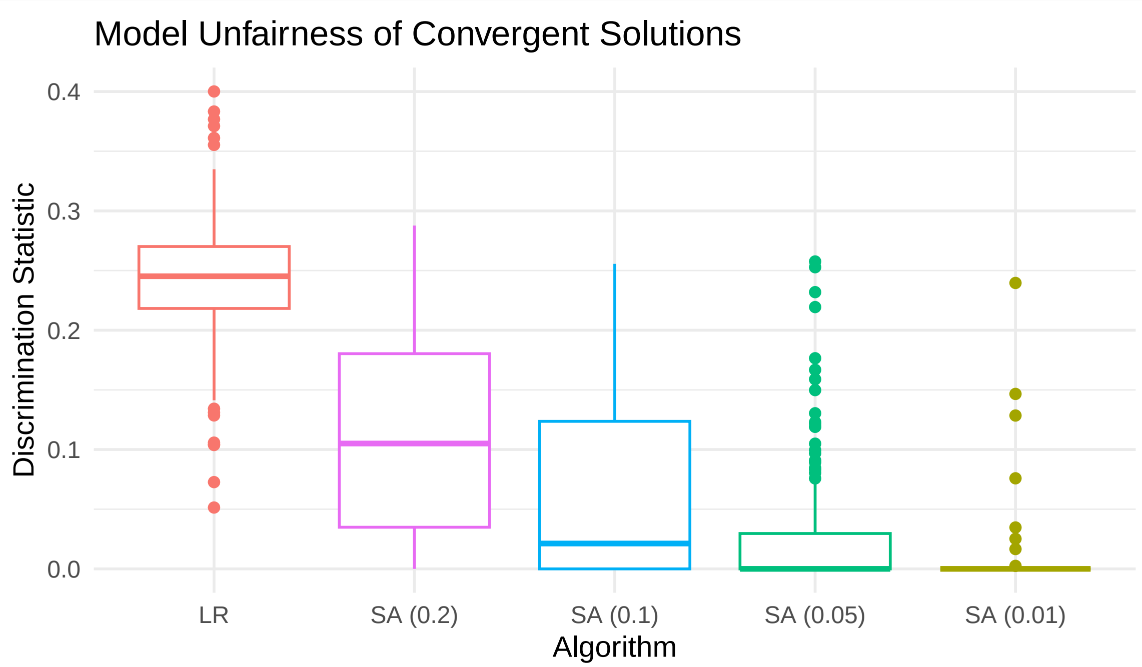
```r
# table
sim_results_converged_disc |>
  group_by(sample_size) |>
  summarise(`SA (0.2)` = round(100*count(sa_02_disc_stat < 0.2)/count(passed_safety_02 == "True"),2),
            `SA (0.1)` = round(100*count(sa_01_disc_stat < 0.1)/count(passed_safety_01 == "True"),2),
            `SA (0.05)` = round(100*count(sa_005_disc_stat < 0.05)/count(passed_safety_005 == "True"),2
            `SA (0.01)` = round(100*count(sa_001_disc_stat < 0.01)/count(passed_safety_001 == "True"),2
  rename("Sample Size" = sample_size) |>
  kable(caption = "Satisfaction of the Behavioral Constraint by Convergent Solutions")
```

Table 4: Satisfaction of the Behavioral Constraint by Convergent Solutions

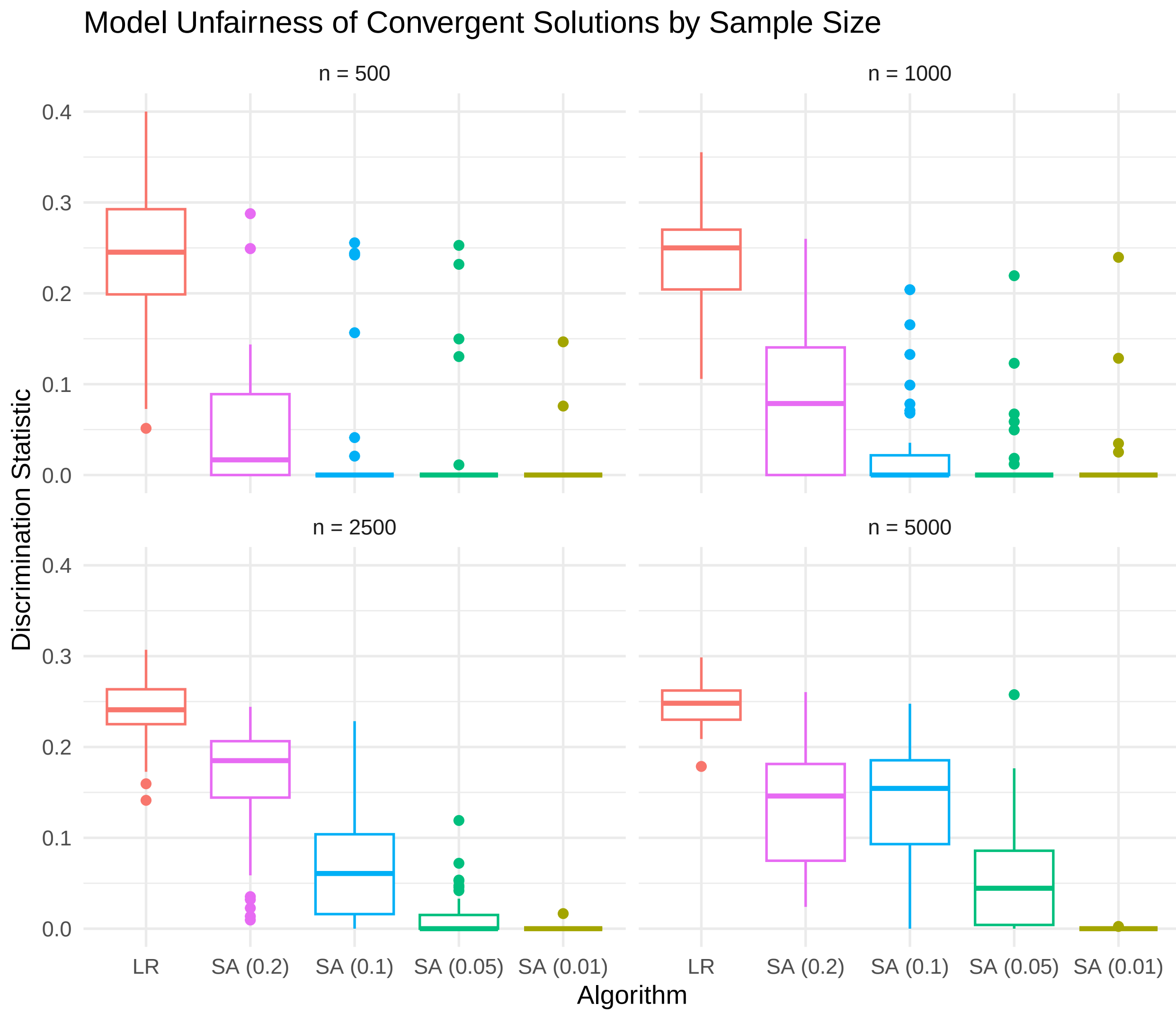
Sample Size	SA (0.2)	SA (0.1)	SA (0.05)	SA (0.01)
500	84	82.22	90.70	91.43
1000	88	84.00	84.00	90.91
2500	70	70.00	82.00	96.15
5000	82	30.00	52.08	100.00

Visualizations

```r
# visualization
sim_results_converged_disc |>
  dplyr::select(c(lr_discrimination, sa_02_disc_stat, sa_01_disc_stat, sa_005_disc_stat,
                  sa_001_disc_stat, sample_size)) |>
  rename("Sample Size" = sample_size,
         "LR" = lr_discrimination,
         "SA (0.2)" = sa_02_disc_stat,
         "SA (0.1)" = sa_01_disc_stat,
         "SA (0.05)" = sa_005_disc_stat,
         "SA (0.01)" = sa_001_disc_stat) |>
  pivot_longer(cols = -c(`Sample Size`),
               names_to = "model",
               values_to = "discrimination") |>
  ggplot(mapping = aes(x = model, y = discrimination, color = model)) +
  geom_boxplot() +
  scale_x_discrete(limits = c("LR", "SA (0.2)", "SA (0.1)", "SA (0.05)", "SA (0.01)")) +
  theme_minimal() +
  guides(color = "none") +
  labs(x = "Algorithm",
       y = "Discrimination Statistic",
       title = "Model Unfairness of Convergent Solutions")
```



```r
# visualization
sim_results_converged_disc |>
  dplyr::select(c(lr_discrimination, sa_02_disc_stat, sa_01_disc_stat, sa_005_disc_stat,
                sa_001_disc_stat, sample_size)) |>
  mutate(sample_size = factor(case_when(sample_size == 500 ~ "n = 500",
                              sample_size == 1000 ~ "n = 1000",
                              sample_size == 2500 ~ "n = 2500",
                              sample_size == 5000 ~ "n = 5000"
                              ),
                              levels = c("n = 500", "n = 1000", "n = 2500", "n = 5000"))) |>
  rename("Sample Size" = sample_size,
         "LR" = lr_discrimination,
         "SA (0.2)" = sa_02_disc_stat,
         "SA (0.1)" = sa_01_disc_stat,
         "SA (0.05)" = sa_005_disc_stat,
         "SA (0.01)" = sa_001_disc_stat) |>
  pivot_longer(cols = -c(`Sample Size`),
               names_to = "model",
               values_to = "discrimination") |>
  ggplot(mapping = aes(x = model, y = discrimination, color = model)) +
  geom_boxplot() +
  scale_x_discrete(limits = c("LR", "SA (0.2)", "SA (0.1)", "SA (0.05)", "SA (0.01)")) +
  theme_minimal() +
  guides(color = "none") +
  facet_wrap(~`Sample Size`) +
  labs(x = "Algorithm",
       y = "Discrimination Statistic",
       title = "Model Unfairness of Convergent Solutions by Sample Size")
```



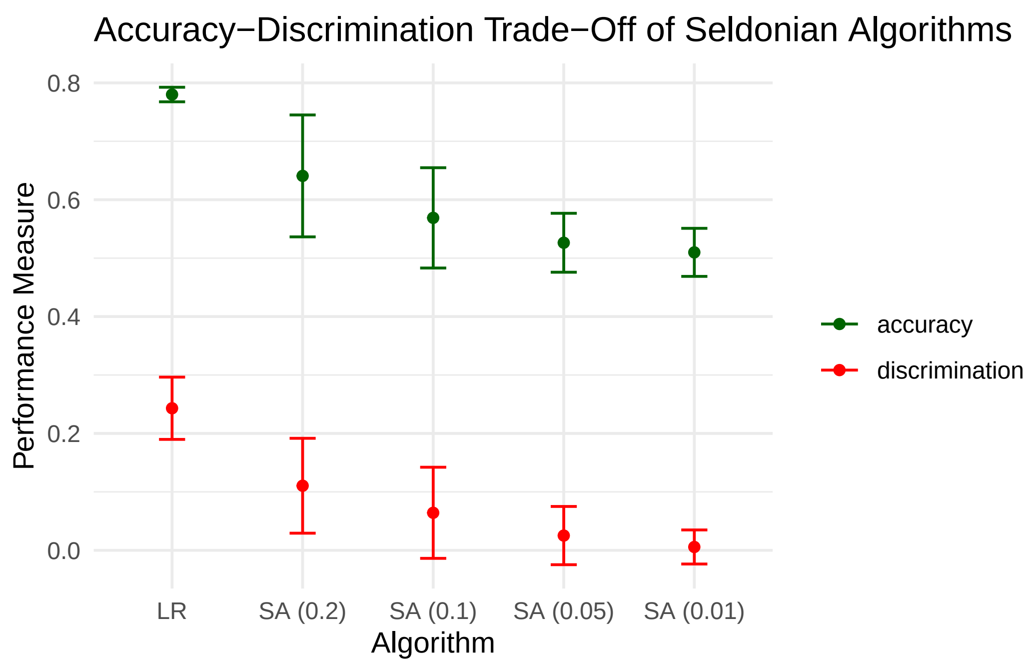
Accuracy-Discrimination Trade-Off

This section aims to visualize the accuracy-discrimination trade-off for each of the models, by sample-size.

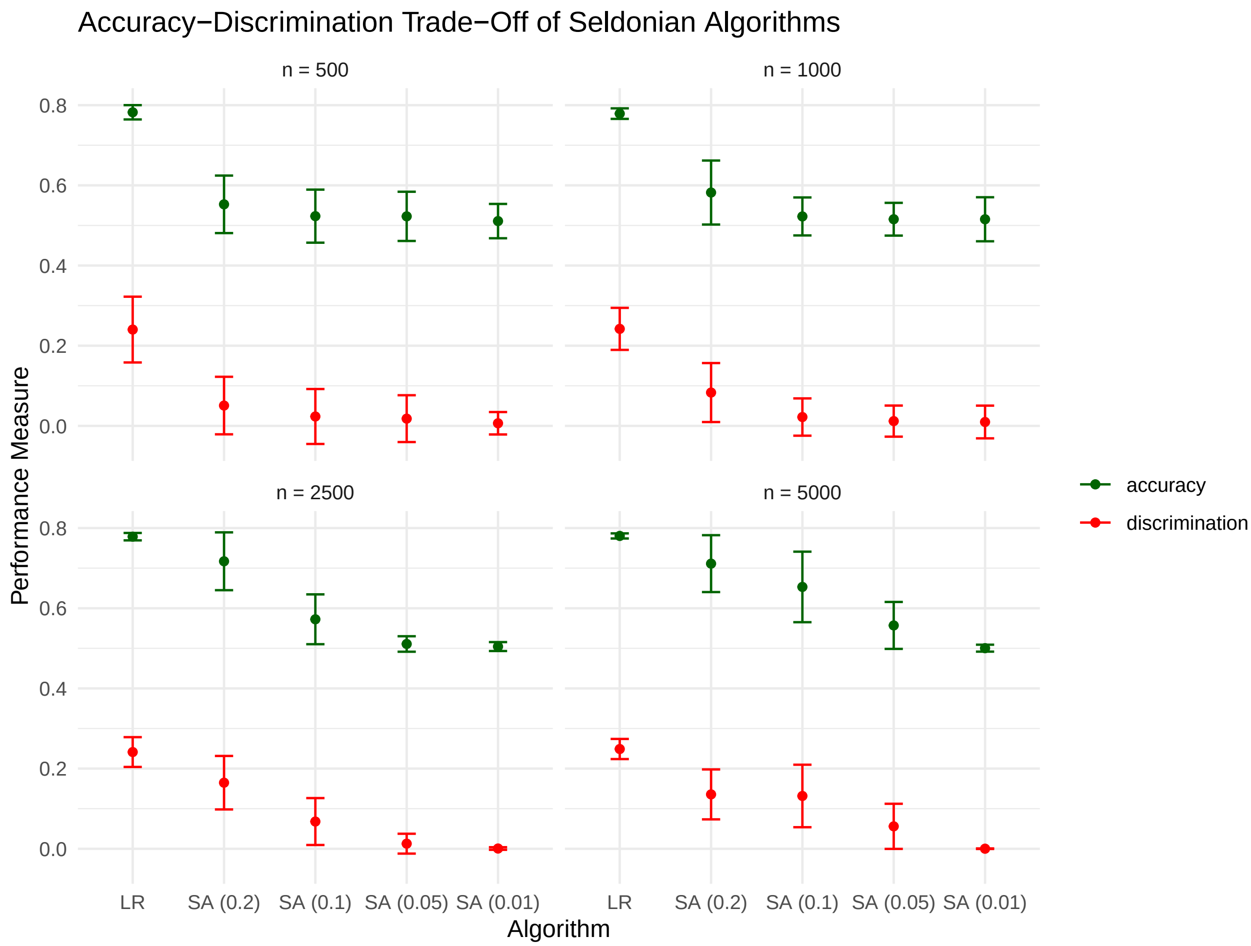
```r
# get long discrimination data set for plotting (1000 rows)
sim_results_converged_disc_long <- sim_results_converged_disc |>
  dplyr::select(c(lr_discrimination, sa_02_disc_stat, sa_01_disc_stat, sa_005_disc_stat,
                  sa_001_disc_stat, sample_size, dataset_id)) |>
  mutate(sample_size = factor(case_when(sample_size == 500 ~ "n = 500",
                                        sample_size == 1000 ~ "n = 1000",
                                        sample_size == 2500 ~ "n = 2500",
                                        sample_size == 5000 ~ "n = 5000"
                                        ),
                                    levels = c("n = 500", "n = 1000", "n = 2500", "n = 5000"))) |>
  rename("Sample Size" = sample_size,
         "LR" = lr_discrimination,
         "SA (0.2)" = sa_02_disc_stat,
         "SA (0.1)" = sa_01_disc_stat,
         "SA (0.05)" = sa_005_disc_stat,
```

```r
         "SA (0.01)" = sa_001_disc_stat) |>
  pivot_longer(cols = -c(`Sample Size`, dataset_id),
               names_to = "model",
               values_to = "discrimination")

# get long accuracy data set for plotting (1000 rows)
sim_results_converged_accuracy_long <- sim_results_converged_accuracy |>
  dplyr::select(c(lr_accuracy, sa_02_accuracy, sa_01_accuracy, sa_005_accuracy,
                  sa_001_accuracy, sample_size, dataset_id)) |>
  mutate(sample_size = factor(case_when(sample_size == 500 ~ "n = 500",
                                        sample_size == 1000 ~ "n = 1000",
                                        sample_size == 2500 ~ "n = 2500",
                                        sample_size == 5000 ~ "n = 5000"
                                        ),
                              levels = c("n = 500", "n = 1000", "n = 2500", "n = 5000"))) |>
  rename("Sample Size" = sample_size,
         "LR" = lr_accuracy,
         "SA (0.2)" = sa_02_accuracy,
         "SA (0.1)" = sa_01_accuracy,
         "SA (0.05)" = sa_005_accuracy,
         "SA (0.01)" = sa_001_accuracy) |>
  pivot_longer(cols = -c(`Sample Size`, dataset_id),
               names_to = "model",
               values_to = "accuracy")

# join both data sets
accuracy_disc <- inner_join(sim_results_converged_disc_long, sim_results_converged_accuracy_long,
                            by = c("dataset_id", "Sample Size", "model")) |>
  pivot_longer(cols = -c(`Sample Size`, dataset_id, model),
               names_to = "statistic",
               values_to = "value")
```

```r
# plot error-bars
color <- c("darkgreen", "red")

accuracy_disc |>
  group_by(model, statistic) |>
  summarise(avg = mean(value, na.rm = TRUE),
            se = sd(value, na.rm = TRUE)) |>
  ggplot(mapping = aes(x = model, y = avg, color = statistic)) +
  geom_point() +
  geom_errorbar(mapping = aes(ymin = avg - se,
                              ymax = avg + se,
                              width = 0.2)) +
  theme_minimal() +
  scale_color_manual(values = c("accuracy" = color[1],
                                "discrimination" = color[2])) +
  scale_x_discrete(limits = c("LR", "SA (0.2)", "SA (0.1)", "SA (0.05)", "SA (0.01)")) +
  labs(x = "Algorithm",
       y = "Performance Measure",
       title = "Accuracy-Discrimination Trade-Off of Seldonian Algorithms",
       color = " ")
```




```r
# plot error-bars by sample size
accuracy_disc |>
  group_by(model, statistic, `Sample Size`) |>
  summarise(avg = mean(value, na.rm = TRUE),
            se = sd(value, na.rm = TRUE)) |>
  ggplot(mapping = aes(x = model, y = avg, color = statistic)) +
  geom_point() +
  geom_errorbar(mapping = aes(ymin = avg - se,
                              ymax = avg + se,
                              width = 0.2)) +
  theme_minimal() +
  scale_color_manual(values = c("accuracy" = color[1],
                                "discrimination" = color[2])) +
  scale_x_discrete(limits = c("LR", "SA (0.2)", "SA (0.1)", "SA (0.05)", "SA (0.01)")) +
  facet_wrap(~`Sample Size`) +
  labs(x = "Algorithm",
       y = "Performance Measure",
       title = "Accuracy-Discrimination Trade-Off of Seldonian Algorithms",
       color = " ")
```



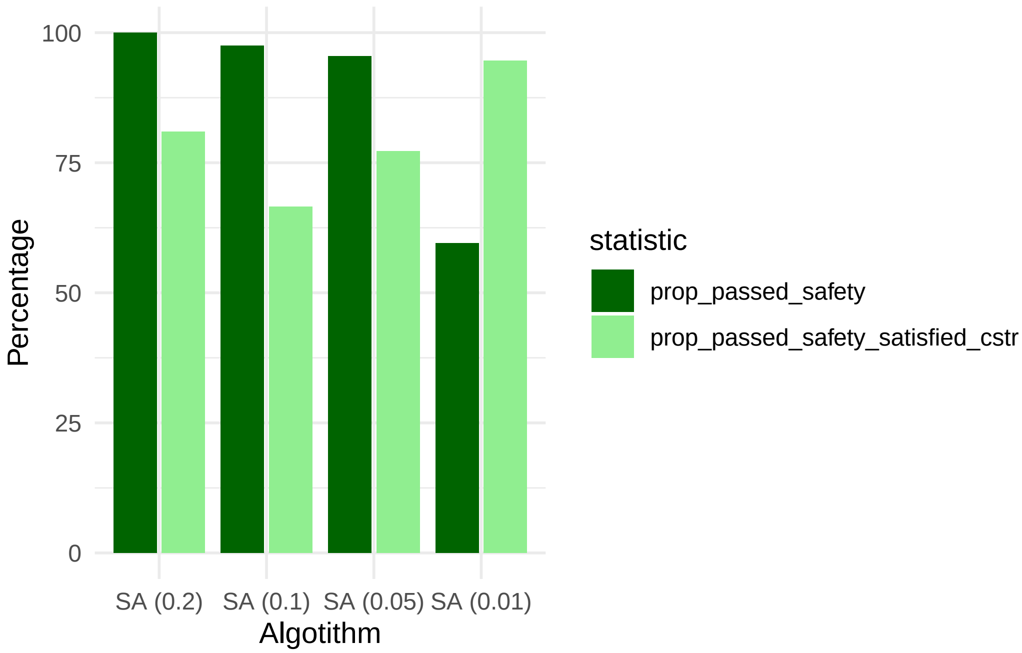
Convergence-Discrimination Trade-Off

This section examines whether there is a trade-off in the proportion of solutions that pass the safety test and the proportion of Seldonian solutions that satisfy the fairness constraint. I need to brainstorm better ways of visualizing this relationship.

```
# get long convergence data for plotting
sim_converged_long <- sim_results |>
  group_by(sample_size) |>
  summarise(`SA (0.2)` = 100*count(passed_safety_02 == "True")/reps,
            `SA (0.1)` = 100*count(passed_safety_01 == "True")/reps,
            `SA (0.05)` = 100*count(passed_safety_005 == "True")/reps,
            `SA (0.01)` = 100*count(passed_safety_001 == "True")/reps) |>
  pivot_longer(cols = -c(sample_size),
               names_to = "model",
               values_to = "prop_passed_safety")

# get long discrimination data for plotting
sim_satisfied_cstr_long <- sim_results_converged_disc |>
  group_by(sample_size) |>
  summarise(`SA (0.2)` = round(100*count(sa_02_disc_stat < 0.2)/count(passed_safety_02 == "True"),2),
            `SA (0.1)` = round(100*count(sa_01_disc_stat < 0.1)/count(passed_safety_01 == "True"),2),
            `SA (0.05)` = round(100*count(sa_005_disc_stat < 0.05)/count(passed_safety_005 == "True"),2
```

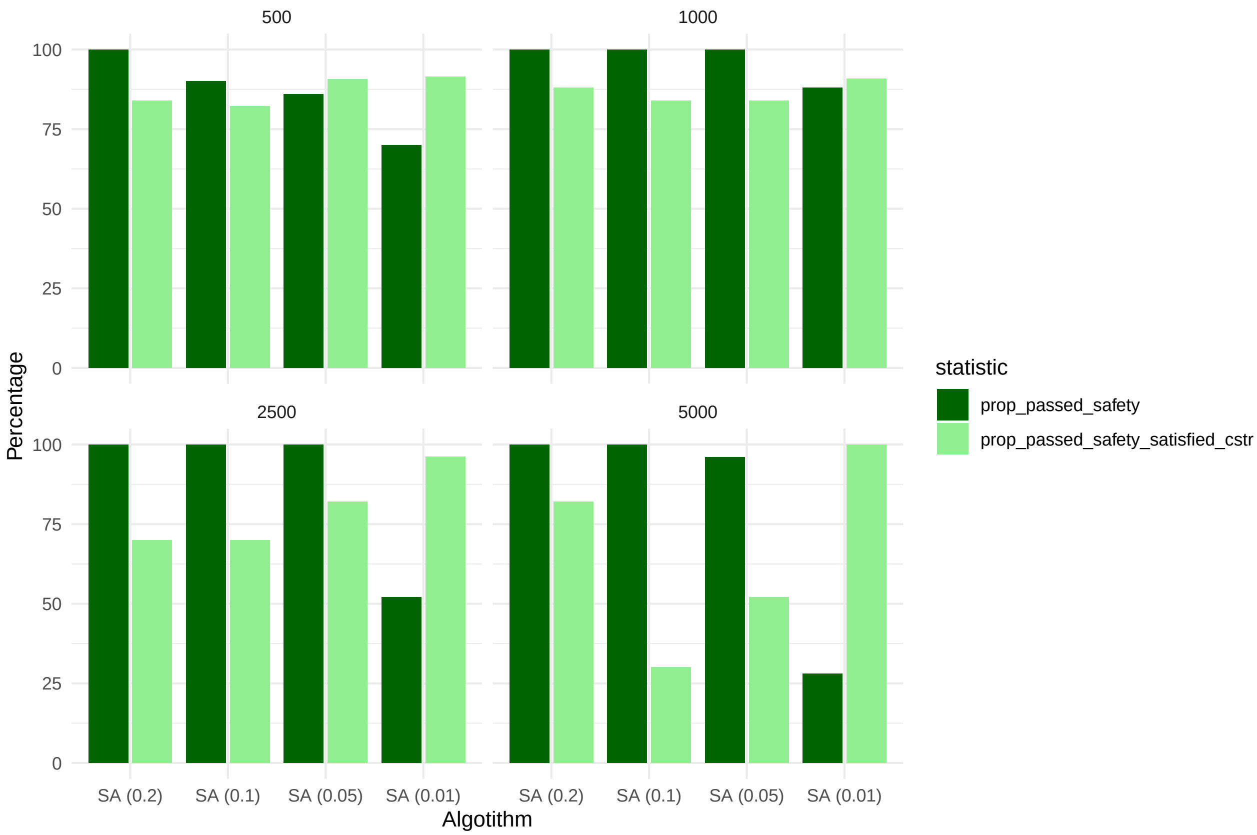
```r
              `SA (0.01)` = round(100*count(sa_001_disc_stat < 0.01)/count(passed_safety_001 == "True"),2)
  pivot_longer(cols = -c(sample_size),
               names_to = "model",
               values_to = "prop_passed_safety_satisfied_cstr")

# join both data sets
conv_disc <- inner_join(sim_converged_long, sim_satisfied_cstr_long,
                        by = c("sample_size", "model")) |>
  pivot_longer(cols = -c(sample_size, model),
               names_to = "statistic",
               values_to = "value")
```

```r
# plot error-bars
color <- c("darkgreen", "lightgreen")

conv_disc |>
  mutate(model = factor(model,
                        levels = c("SA (0.2)", "SA (0.1)", "SA (0.05)", "SA (0.01)"))) |>
  group_by(model, statistic) |>
  summarise(avg = mean(value, na.rm = TRUE)) |>
  ggplot(mapping = aes(x = model, y = avg, fill = statistic)) +
  geom_col(position = position_dodge2()) +
  theme_minimal() +
  scale_fill_manual(values = c("prop_passed_safety" = color[1],
                               "prop_passed_safety_satisfied_cstr" = color[2])) +
  labs(y = "Percentage",
       x = "Algotithm")
```




```r
# plot
color <- c("darkgreen", "lightgreen")

conv_disc |>
  mutate(model = factor(model,
```

```r
                         levels = c("SA (0.2)", "SA (0.1)", "SA (0.05)", "SA (0.01)"))) |>
  ggplot(mapping = aes(x = model, y = value, fill = statistic)) +
  geom_col(position = position_dodge2()) +
  theme_minimal() +
  scale_fill_manual(values = c("prop_passed_safety" = color[1],
                               "prop_passed_safety_satisfied_cstr" = color[2])) +
  facet_wrap(~sample_size) +
  labs(y = "Percentage",
       x = "Algotithm")
```



NSF

compare these solutions with logistic regression