Supplementary

In this document, we demonstrate the programming to reproduce the result we have in the supplementary material.

```
source(here::here('src/optimization/w_optimization.R'))
```

1 Optimal Bonferroni weights table

In this section, we provide two tables of optimal α_1 under different marginal powers regarding to maximize disjunctive and conjunctive power of two independent hypotheses.

```
alpha = 0.025
mp_1 <- mp_2 <- seq(0.95, 0.5, by = -0.05)
opt_alpha_disj <- data.frame(matrix(nrow = length(mp_1),
                                    ncol = length(mp_2)),
                             row.names = mp_1)
colnames(opt_alpha_disj) <- mp_2
opt_alpha_conj <- opt_alpha_disj

for (p1 in mp_1) {
  for (p2 in mp_2) {
    opt_alpha_disj[as.character(p1),
                   as.character(p2)] = optim_w_dp(alpha = alpha,
                                                  mp = c(p1, p2))$w[1]
    opt_alpha_conj[as.character(p1),
                   as.character(p2)] = optim_w_cp(alpha = alpha,
                                                  mp = c(p1, p2))$w[1]
  }
}
```

Table 1: Optimal Bonferroni weights table for disjunctive power

	0.95	0.9	0.85	0.8	0.75	0.7	0.65	0.6	0.55	0.5
0.95	0.500	0.566	0.616	0.659	0.699	0.736	0.771	0.804	0.837	0.868
0.9	0.434	0.500	0.552	0.597	0.639	0.679	0.718	0.755	0.793	0.829
0.85	0.384	0.448	0.500	0.546	0.589	0.631	0.672	0.713	0.753	0.794
0.8	0.341	0.403	0.454	0.500	0.544	0.587	0.629	0.672	0.715	0.759
0.75	0.301	0.361	0.411	0.456	0.500	0.543	0.587	0.631	0.677	0.723
0.7	0.264	0.321	0.369	0.413	0.457	0.500	0.544	0.589	0.636	0.685
0.65	0.229	0.282	0.328	0.371	0.413	0.456	0.500	0.546	0.594	0.645
0.6	0.196	0.245	0.287	0.328	0.369	0.411	0.454	0.500	0.549	0.601
0.55	0.163	0.207	0.247	0.285	0.323	0.364	0.406	0.451	0.500	0.553
0.5	0.132	0.171	0.206	0.241	0.277	0.315	0.355	0.399	0.447	0.500

Table 2: Optimal Bonferroni weights table for conjunctive power

	0.95	0.9	0.85	0.8	0.75	0.7	0.65	0.6	0.55	0.5
0.95	0.500	0.410	0.358	0.322	0.294	0.271	0.253	0.237	0.222	0.210
0.9	0.590	0.500	0.445	0.404	0.373	0.347	0.325	0.306	0.289	0.273
0.85	0.642	0.555	0.500	0.459	0.426	0.399	0.375	0.354	0.336	0.318
0.8	0.678	0.596	0.541	0.500	0.467	0.439	0.414	0.393	0.373	0.355
0.75	0.706	0.627	0.574	0.533	0.500	0.472	0.447	0.425	0.404	0.385
0.7	0.729	0.653	0.601	0.561	0.528	0.500	0.475	0.452	0.432	0.412
0.65	0.747	0.675	0.625	0.586	0.553	0.525	0.500	0.477	0.456	0.437
0.6	0.763	0.694	0.646	0.607	0.575	0.548	0.523	0.500	0.479	0.459
0.55	0.778	0.711	0.664	0.627	0.596	0.568	0.544	0.521	0.500	0.480
0.5	0.790	0.727	0.682	0.645	0.615	0.588	0.563	0.541	0.520	0.500

2 Optimal α splitting under different correlation

In this section, we illustrate how correlation affect the disjunctive/conjunctive power in the two hypotheses scenario.

```
mp2_eq <- c(0.9, 0.9)
corr2s <- list(disj = c(0., 0.25, 0.5, 0.815, 0.9),
               conj = c(0., 0.25, 0.5, 0.75, 0.99))
ws <- seq(0, 1, by=0.01)
disj_pow_eq <- data.frame(matrix(ncol=6, nrow=length(ws)))
colnames(disj_pow_eq) <- c("w1", corr2s$disj)
disj_pow_eq['w1'] = ws
conj_pow_eq <- data.frame(matrix(ncol=6, nrow=length(ws)))
colnames(conj_pow_eq) <- c("w1", corr2s$conj)
conj_pow_eq['w1'] = ws

for (i in 1:5) {
  dps = c()
  cps = c()
  for (w in ws) {
    dps = c(dps, disjunctive_power_corr(c(w, 1-w),
                                        alpha = alpha,
                                        mp = mp2_eq,
                                        rho = corr2s$disj[i]))
    cps = c(cps, conjunctive_power_corr(c(w, 1-w),
                                        alpha = alpha,
                                        mp = mp2_eq,
                                        rho = corr2s$conj[i]))
  }
  disj_pow_eq[i+1] = dps
  conj_pow_eq[i+1] = cps
}

df_disj_eq = reshape2::melt(disj_pow_eq, id.vars='w1', variable.name='correlation')
names(df_disj_eq)[3] <- "disjunctive.power"
df_conj_eq = reshape2::melt(conj_pow_eq, id.vars='w1', variable.name='correlation')
names(df_conj_eq)[3] <- "conjunctive.power"

opt_disj_eq <- data.frame()
opt_conj_eq <- data.frame()
for (i in 1:5) {
  opt_disj_eq <- rbind(opt_disj_eq,
                       df_disj_eq %>%
                         filter(correlation == corr2s$disj[i]) %>%
                         slice_max(disjunctive.power))
  opt_conj_eq <- rbind(opt_conj_eq,
                       df_conj_eq %>%
                         filter(correlation == corr2s$conj[i]) %>%
                         slice_max(conjunctive.power))
}

dp.corr <- ggplot(df_disj_eq, aes(w1, disjunctive.power)) +
  geom_line(aes(lty = correlation), size=1) +
  labs(x = expression(w[1]), y = "disjunctive power") +
```

```
  theme(text = element_text(size=15)) +
  geom_point(aes(x=w1, y=disjunctive.power, colour = "Optima"),
             data = opt_disj_eq,
             shape=17, size=3) +
  scale_colour_manual(name="Optima",
                      labels = c("Optima"),
                      values=c("black"))

cp.corr <- ggplot(df_conj_eq, aes(w1, conjunctive.power)) +
  geom_line(aes(lty = correlation), size=1) +
  labs(x = expression(w[1]), y = "conjunctive power") +
  theme(text = element_text(size=15)) +
  geom_point(aes(x=w1, y=conjunctive.power, colour = "Optima"),
             data = opt_conj_eq,
             shape=17, size=3) +
  scale_colour_manual(name="Optima",
                      labels = c("Optima"),
                      values=c("black"))
```

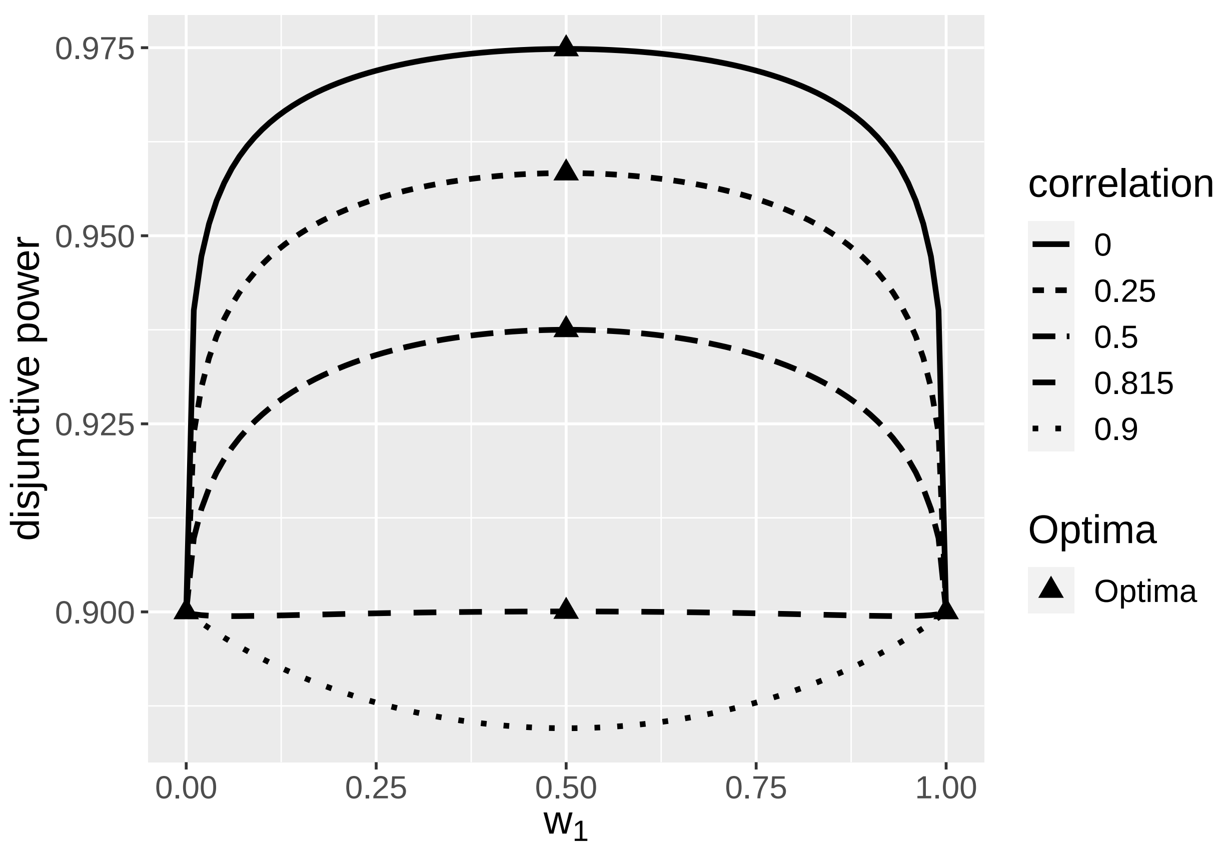

Figure 1: Disjunctive power of two hypotheses with equal marginal power of 90% under different w_1

```
mp2_uneq <- c(0.9, 0.7)
corr2s <- list(disj = c(0., 0.25, 0.5, 0.815, 0.9),
               conj = c(0., 0.25, 0.5, 0.75, 0.99))
```

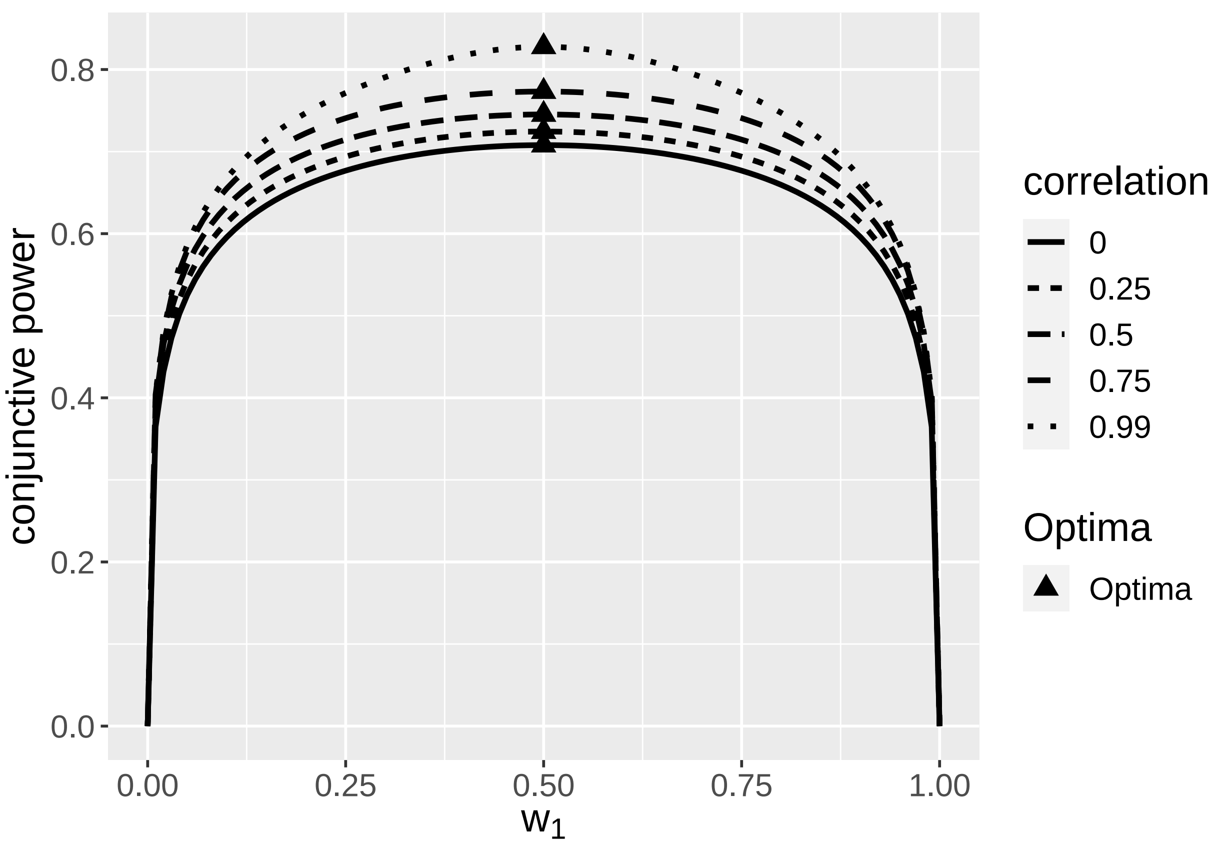

Figure 2: Conjunctive power of two hypotheses with equal marginal power of 90% under different w_1

```r
ws <- seq(0, 1, by=0.01)
disj_pow_uneq <- data.frame(matrix(ncol=6, nrow=length(ws)))
colnames(disj_pow_uneq) <- c("w1", corr2s$disj)
disj_pow_uneq['w1'] = ws
conj_pow_uneq <- data.frame(matrix(ncol=6, nrow=length(ws)))
colnames(conj_pow_uneq) <- c("w1", corr2s$conj)
conj_pow_uneq['w1'] = ws

for (i in 1:5) {
  dps = c()
  cps = c()
  for (w in ws) {
    dps = c(dps, disjunctive_power_corr(c(w, 1-w),
                                        alpha = alpha,
                                        mp = mp2_uneq,
                                        rho = corr2s$disj[i]))
    cps = c(cps, conjunctive_power_corr(c(w, 1-w),
                                        alpha = alpha,
                                        mp = mp2_uneq,
                                        rho = corr2s$conj[i]))
  }
  disj_pow_uneq[i+1] = dps
  conj_pow_uneq[i+1] = cps
}

df_disj_uneq = reshape2::melt(disj_pow_uneq, id.vars='w1', variable.name='correlation')
names(df_disj_uneq)[3] <- "disjunctive.power"
df_conj_uneq = reshape2::melt(conj_pow_uneq, id.vars='w1', variable.name='correlation')
names(df_conj_uneq)[3] <- "conjunctive.power"

opt_disj_uneq <- data.frame()
opt_conj_uneq <- data.frame()
for (i in 1:5) {
  opt_disj_uneq <- rbind(opt_disj_uneq,
                         df_disj_uneq %>%
                           filter(correlation == corr2s$disj[i]) %>%
                           slice_max(disjunctive.power))
  opt_conj_uneq <- rbind(opt_conj_uneq,
                         df_conj_uneq %>%
                           filter(correlation == corr2s$conj[i]) %>%
                           slice_max(conjunctive.power))
}

dp.corr.uneq <- ggplot(df_disj_uneq, aes(w1, disjunctive.power)) +
  geom_line(aes(lty = correlation), size=1) +
  labs(x = expression(w[1]), y = "disjunctive power") +
  theme(text = element_text(size=15)) +
  geom_point(aes(x=w1, y=disjunctive.power, colour = "Optima"),
             data = opt_disj_uneq,
             shape=17, size=3) +
  scale_colour_manual(name="Optima",
                      labels = c("Optima"),
                      values=c("black"))
```

```
cp.corr.uneq <- ggplot(df_conj_uneq, aes(w1, conjunctive.power)) +
  geom_line(aes(lty = correlation), size=1) +
  labs(x = expression(w[1]), y = "conjunctive power") +
  theme(text = element_text(size=15)) +
  geom_point(aes(x=w1, y=conjunctive.power, colour = "Optima"),
             data = opt_conj_uneq,
             shape=17, size=3) +
  scale_colour_manual(name="Optima",
                      labels = c("Optima"),
                      values=c("black"))
```

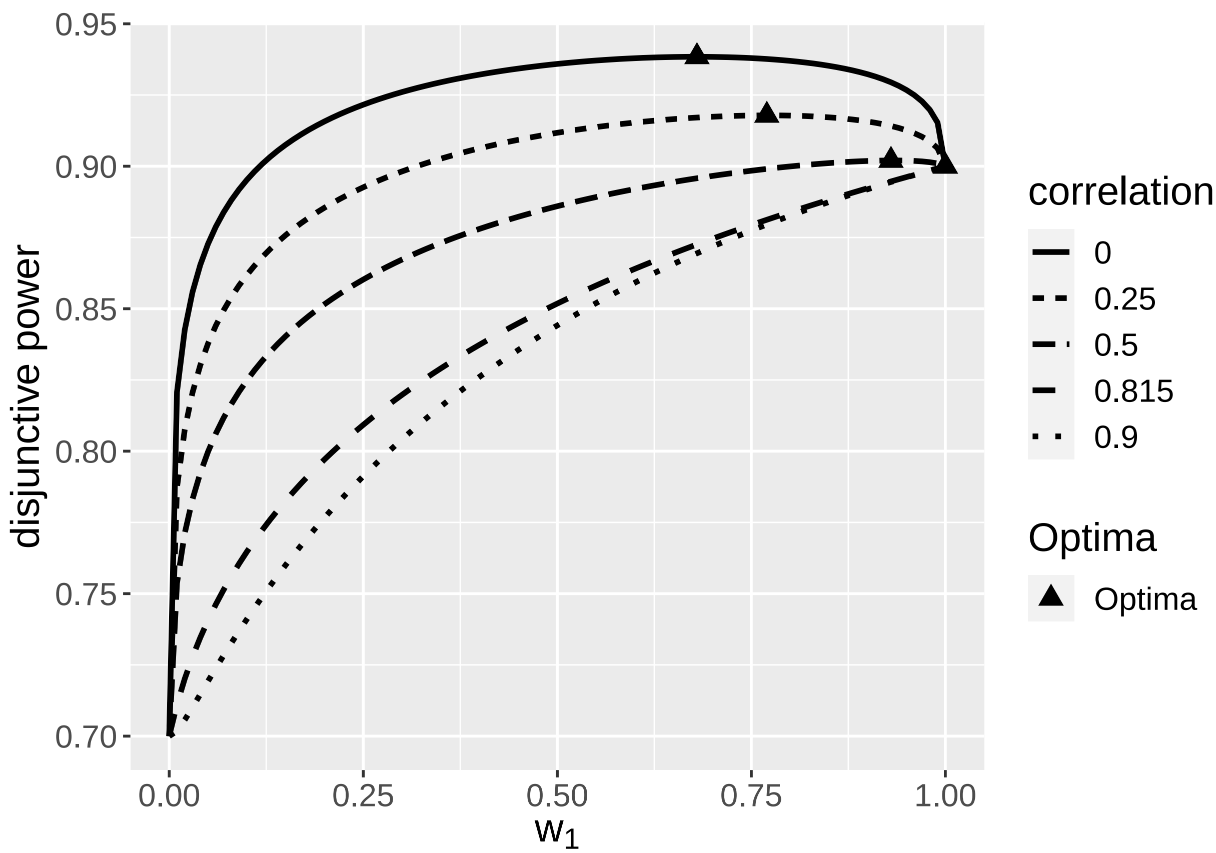

Figure 3: Disjunctive power of two hypotheses with unequal marginal power of 90% under different w_1

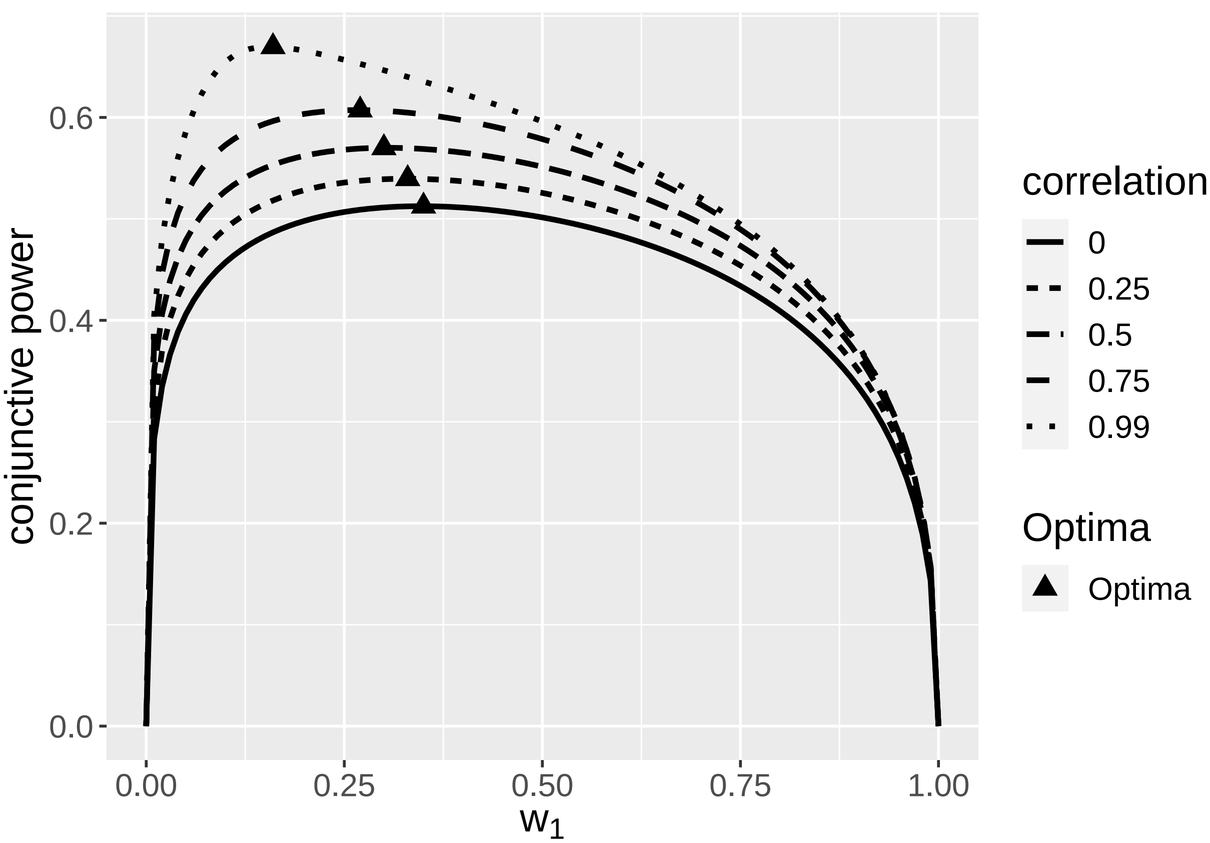

Figure 4: Conjunctive power of two hypotheses with unequal marginal power of 90% under different w_1

3 Optimal Bonferroni weights for disjunctive power with four hypotheses

```
mps4 <- list(rep(0.9, 4),
             rep(0.8, 4),
             c(0.9, 0.8, 0.7, 0.6),
             c(0.9, 0.75, 0.6, 0.45),
             c(0.9, 0.7, 0.5, 0.1),
             c(0.9, 0.5, 0.5, 0.5),
             c(0.9, 0.1, 0.1, 0.1))

opt_disj <- data.frame(marginal_power = character(),
                       w1 = numeric(),
                       w2 = numeric(),
                       w3 = numeric(),
                       w4 = numeric(),
                       disjunctive_power = numeric())

opt_conj <- data.frame(marginal_power = character(),
                       w1 = numeric(),
                       w2 = numeric(),
                       w3 = numeric(),
                       w4 = numeric(),
                       conjunctive_power = numeric())

for (mp in mps4) {
  indopt_dp <- optim_w_dp(alpha = alpha,
                          mp = mp)
  indopt_cp <- optim_w_cp(alpha = alpha,
                          mp = mp)
  opt_disj <- opt_disj %>%
    add_row(marginal_power = paste(mp, collapse = ", "),
            w1 = indopt_dp$w[1],
            w2 = indopt_dp$w[2],
            w3 = indopt_dp$w[3],
            w4 = indopt_dp$w[4],
            disjunctive_power = -indopt_dp$optima$objective * 100)
  opt_conj <- opt_conj %>%
    add_row(marginal_power = paste(mp, collapse = ", "),
            w1 = indopt_cp$w[1],
            w2 = indopt_cp$w[2],
            w3 = indopt_cp$w[3],
            w4 = indopt_cp$w[4],
            conjunctive_power = -indopt_cp$optima$objective * 100)
}
```

Table 3: Optimal Bonferroni weights to maximize the disjunctive power with four independent hypotheses

marginal power	w_1	w_2	w_3	w_4	disjunctive power(%)
0.9, 0.9, 0.9, 0.9	0.250	0.250	0.250	0.250	99.727
0.8, 0.8, 0.8, 0.8	0.250	0.250	0.250	0.250	97.901
0.9, 0.8, 0.7, 0.6	0.415	0.276	0.187	0.122	97.519
0.9, 0.75, 0.6, 0.45	0.502	0.279	0.152	0.066	96.024
0.9, 0.7, 0.5, 0.1	0.498	0.313	0.189	0.000	94.453
0.9, 0.5, 0.5, 0.5	0.633	0.122	0.122	0.122	93.417
0.9, 0.1, 0.1, 0.1	1.000	0.000	0.000	0.000	90.000

Table 4: Optimal Bonferroni weights to maximize the conjunctive power with four independent hypotheses

marginal power	w_1	w_2	w_3	w_4	conjunctive power(%)
0.9, 0.9, 0.9, 0.9	0.250	0.250	0.250	0.250	35.429
0.8, 0.8, 0.8, 0.8	0.250	0.250	0.250	0.250	14.718
0.9, 0.8, 0.7, 0.6	0.158	0.224	0.281	0.337	9.579
0.9, 0.75, 0.6, 0.45	0.136	0.217	0.287	0.360	4.558
0.9, 0.7, 0.5, 0.1	0.104	0.181	0.250	0.465	0.499
0.9, 0.5, 0.5, 0.5	0.121	0.293	0.293	0.293	2.163
0.9, 0.1, 0.1, 0.1	0.074	0.309	0.309	0.309	0.004

This table could take more than 10 mins to run, please add `eval = FALSE` on the header of following two cells to skip this table.

```
mp4_1 <- rep(0.9, 4)
mp4_2 <- rep(0.8, 4)
mp4_3 <- c(0.9, 0.75, 0.6, 0.45)
rhos <- c(0.9, 0.8, 0.77, 0.7, 0.5)
sigma1 <- matrix(c(1, 0.8, 0.6, 0.4,
                   0.8, 1, 0.6, 0.4,
                   0.6, 0.6, 1, 0.4,
                   0.4, 0.4, 0.4, 1), nrow = 4)
sigma2 <- matrix(c(1, 0.9, 0.1, 0.4,
                   0.9, 1, 0.1, 0.4,
                   0.1, 0.1, 1, 0.4,
                   0.4, 0.4, 0.4, 1), nrow = 4)
mp4 <- list(mp4_1, mp4_2, mp4_3)
corr <- c(as.list(rhos), list(sigma1, sigma2))
corr <- setNames(corr, c(rhos, "$\\Sigma_1$", "$\\Sigma_2$"))

opt_disj_corr <- data.frame(marginal_power = character(),
                            correlation = character(),
                            w1 = numeric(),
                            w2 = numeric(),
                            w3 = numeric(),
                            w4 = numeric(),
                            disjunctive_power = numeric())
```

```
opt_conj_corr <- data.frame(marginal_power = character(),
                            correlation = character(),
                            w1 = numeric(),
                            w2 = numeric(),
                            w3 = numeric(),
                            w4 = numeric(),
                            conjunctive_power = numeric())

for (mp in mp4) {
  for (rho in names(corr)) {
    locopt <- optim_w_dp(alpha = alpha,
                         mp = mp)
    glopt <- go_optim_w_dp(alpha = alpha,
                           mp = mp,
                           rho = corr[[rho]])
    benchmark <- disjunctive_power_corr(w = locopt$w,
                                        alpha = alpha,
                                        mp = mp, rho = corr[[rho]])
    opt_disj_corr <- opt_disj_corr %>%
      add_row(marginal_power = paste(mp, collapse = ", "),
              correlation = as.character(rho),
              w1 = glopt[1, ]$w1,
              w2 = glopt[1, ]$w2,
              w3 = glopt[1, ]$w3,
              w4 = glopt[1, ]$w4,
              disjunctive_power = glopt[1, ]$optimal_value * 100)
    opt_disj_corr <- opt_disj_corr %>%
      add_row(marginal_power = paste(mp, collapse = ", "),
              correlation = "Benchmark",
              w1 = locopt$w[1],
              w2 = locopt$w[2],
              w3 = locopt$w[3],
              w4 = locopt$w[4],
              disjunctive_power = benchmark * 100)

    locopt <- optim_w_cp(alpha = alpha,
                         mp = mp)
    glopt <- optim_w_cp(alpha = alpha,
                        mp = mp,
                        rho = corr[[rho]])
    benchmark <- conjunctive_power_corr(w = locopt$w,
                                        alpha = alpha,
                                        mp = mp, rho = corr[[rho]])
    opt_conj_corr <- opt_conj_corr %>%
      add_row(marginal_power = paste(mp, collapse = ", "),
              correlation = as.character(rho),
              w1 = glopt$w[1],
              w2 = glopt$w[2],
              w3 = glopt$w[3],
              w4 = glopt$w[4],
              conjunctive_power = -glopt$optima$objective * 100)
    opt_conj_corr <- opt_conj_corr %>%
      add_row(marginal_power = paste(mp, collapse = ", "),
```

```
            correlation = "Benchmark",
            w1 = locopt$w[1],
            w2 = locopt$w[2],
            w3 = locopt$w[3],
            w4 = locopt$w[4],
            conjunctive_power = benchmark * 100)

  }
}
```

Table 5: Optimal Bonferroni weights to maximize the disjunctive power with four hypotheses under dependence

marginal power	correlation	w_1	w_2	w_3	w_4	disjunctive power(%)
0.9, 0.9, 0.9, 0.9	0.9	1.000	0.000	0.000	0.000	90.000
0.9, 0.9, 0.9, 0.9	Benchmark	0.250	0.250	0.250	0.250	86.384
0.9, 0.9, 0.9, 0.9	0.8	0.500	0.500	0.000	0.000	90.238
0.9, 0.9, 0.9, 0.9	Benchmark	0.250	0.250	0.250	0.250	89.824
0.9, 0.9, 0.9, 0.9	0.77	0.333	0.333	0.333	0.000	90.721
0.9, 0.9, 0.9, 0.9	Benchmark	0.250	0.250	0.250	0.250	90.633
0.9, 0.9, 0.9, 0.9	0.7	0.250	0.250	0.250	0.250	92.277
0.9, 0.9, 0.9, 0.9	Benchmark	0.250	0.250	0.250	0.250	92.277
0.9, 0.9, 0.9, 0.9	0.5	0.250	0.250	0.250	0.250	95.732
0.9, 0.9, 0.9, 0.9	Benchmark	0.250	0.250	0.250	0.250	95.732
0.9, 0.9, 0.9, 0.9	Σ_1	0.000	0.288	0.288	0.424	95.499
0.9, 0.9, 0.9, 0.9	Benchmark	0.250	0.250	0.250	0.250	95.272
0.9, 0.9, 0.9, 0.9	Σ_2	0.000	0.411	0.411	0.178	97.305
0.9, 0.9, 0.9, 0.9	Benchmark	0.250	0.250	0.250	0.250	96.954
0.8, 0.8, 0.8, 0.8	0.9	1.000	0.000	0.000	0.000	80.000
0.8, 0.8, 0.8, 0.8	Benchmark	0.250	0.250	0.250	0.250	74.078
0.8, 0.8, 0.8, 0.8	0.8	1.000	0.000	0.000	0.000	80.000
0.8, 0.8, 0.8, 0.8	Benchmark	0.250	0.250	0.250	0.250	78.985
0.8, 0.8, 0.8, 0.8	0.77	0.500	0.500	0.000	0.000	80.584
0.8, 0.8, 0.8, 0.8	Benchmark	0.250	0.250	0.250	0.250	80.188
0.8, 0.8, 0.8, 0.8	0.7	0.250	0.250	0.250	0.250	82.704
0.8, 0.8, 0.8, 0.8	Benchmark	0.250	0.250	0.250	0.250	82.704
0.8, 0.8, 0.8, 0.8	0.5	0.250	0.250	0.250	0.250	88.483
0.8, 0.8, 0.8, 0.8	Benchmark	0.250	0.250	0.250	0.250	88.483
0.8, 0.8, 0.8, 0.8	Σ_1	0.287	0.000	0.287	0.426	88.084
0.8, 0.8, 0.8, 0.8	Benchmark	0.250	0.250	0.250	0.250	87.560
0.8, 0.8, 0.8, 0.8	Σ_2	0.000	0.410	0.410	0.180	91.441
0.8, 0.8, 0.8, 0.8	Benchmark	0.250	0.250	0.250	0.250	90.555
0.9, 0.75, 0.6, 0.45	0.9	1.000	0.000	0.000	0.000	90.000
0.9, 0.75, 0.6, 0.45	Benchmark	0.502	0.279	0.152	0.066	84.375
0.9, 0.75, 0.6, 0.45	0.8	1.000	0.000	0.000	0.000	90.000
0.9, 0.75, 0.6, 0.45	Benchmark	0.502	0.279	0.152	0.066	85.208
0.9, 0.75, 0.6, 0.45	0.77	1.000	0.000	0.000	0.000	90.000
0.9, 0.75, 0.6, 0.45	Benchmark	0.502	0.279	0.152	0.066	85.529
0.9, 0.75, 0.6, 0.45	0.7	1.000	0.000	0.000	0.000	90.000
0.9, 0.75, 0.6, 0.45	Benchmark	0.502	0.279	0.152	0.066	86.351
0.9, 0.75, 0.6, 0.45	0.5	0.866	0.134	0.000	0.000	90.538
0.9, 0.75, 0.6, 0.45	Benchmark	0.502	0.279	0.152	0.066	88.997

marginal power	correlation	w_1	w_2	w_3	w_4	disjunctive power(%)
0.9, 0.75, 0.6, 0.45	Σ_1	0.999	0.000	0.000	0.001	90.001
0.9, 0.75, 0.6, 0.45	Benchmark	0.502	0.279	0.152	0.066	86.223
0.9, 0.75, 0.6, 0.45	Σ_2	0.796	0.000	0.204	0.000	91.745
0.9, 0.75, 0.6, 0.45	Benchmark	0.502	0.279	0.152	0.066	88.793

Table 6: Optimal Bonferroni weights to maximize the conjunctive power with four hypotheses under dependence

marginal power	correlation	w_1	w_2	w_3	w_4	conjunctive power(%)
0.9, 0.9, 0.9, 0.9	0.9	0.250	0.250	0.250	0.250	66.633
0.9, 0.9, 0.9, 0.9	Benchmark	0.250	0.250	0.250	0.250	66.633
0.9, 0.9, 0.9, 0.9	0.8	0.250	0.250	0.250	0.250	61.813
0.9, 0.9, 0.9, 0.9	Benchmark	0.250	0.250	0.250	0.250	61.813
0.9, 0.9, 0.9, 0.9	0.77	0.250	0.250	0.250	0.250	60.570
0.9, 0.9, 0.9, 0.9	Benchmark	0.250	0.250	0.250	0.250	60.570
0.9, 0.9, 0.9, 0.9	0.7	0.250	0.250	0.250	0.250	57.875
0.9, 0.9, 0.9, 0.9	Benchmark	0.250	0.250	0.250	0.250	57.875
0.9, 0.9, 0.9, 0.9	0.5	0.250	0.250	0.250	0.250	51.068
0.9, 0.9, 0.9, 0.9	Benchmark	0.250	0.250	0.250	0.250	51.068
0.9, 0.9, 0.9, 0.9	Σ_1	0.224	0.224	0.255	0.297	52.800
0.9, 0.9, 0.9, 0.9	Benchmark	0.250	0.250	0.250	0.250	52.628
0.9, 0.9, 0.9, 0.9	Σ_2	0.217	0.217	0.308	0.257	49.773
0.9, 0.9, 0.9, 0.9	Benchmark	0.250	0.250	0.250	0.250	49.520
0.8, 0.8, 0.8, 0.8	0.9	0.250	0.250	0.250	0.250	49.135
0.8, 0.8, 0.8, 0.8	Benchmark	0.250	0.250	0.250	0.250	49.135
0.8, 0.8, 0.8, 0.8	0.8	0.250	0.250	0.250	0.250	43.503
0.8, 0.8, 0.8, 0.8	Benchmark	0.250	0.250	0.250	0.250	43.503
0.8, 0.8, 0.8, 0.8	0.77	0.250	0.250	0.250	0.250	42.070
0.8, 0.8, 0.8, 0.8	Benchmark	0.250	0.250	0.250	0.250	42.070
0.8, 0.8, 0.8, 0.8	0.7	0.250	0.250	0.250	0.250	38.990
0.8, 0.8, 0.8, 0.8	Benchmark	0.250	0.250	0.250	0.250	38.990
0.8, 0.8, 0.8, 0.8	0.5	0.250	0.250	0.250	0.250	31.367
0.8, 0.8, 0.8, 0.8	Benchmark	0.250	0.250	0.250	0.250	31.367
0.8, 0.8, 0.8, 0.8	Σ_1	0.220	0.220	0.255	0.304	33.083
0.8, 0.8, 0.8, 0.8	Benchmark	0.250	0.250	0.250	0.250	32.885
0.8, 0.8, 0.8, 0.8	Σ_2	0.215	0.215	0.317	0.253	29.292
0.8, 0.8, 0.8, 0.8	Benchmark	0.250	0.250	0.250	0.250	29.031
0.9, 0.75, 0.6, 0.45	0.9	0.039	0.135	0.289	0.536	29.291
0.9, 0.75, 0.6, 0.45	Benchmark	0.136	0.217	0.287	0.360	26.878
0.9, 0.75, 0.6, 0.45	0.8	0.055	0.155	0.294	0.497	24.936
0.9, 0.75, 0.6, 0.45	Benchmark	0.136	0.217	0.287	0.360	23.630
0.9, 0.75, 0.6, 0.45	0.77	0.059	0.159	0.295	0.488	23.826
0.9, 0.75, 0.6, 0.45	Benchmark	0.136	0.217	0.287	0.360	22.716
0.9, 0.75, 0.6, 0.45	0.7	0.067	0.168	0.296	0.470	21.447
0.9, 0.75, 0.6, 0.45	Benchmark	0.136	0.217	0.287	0.360	20.676
0.9, 0.75, 0.6, 0.45	0.5	0.087	0.186	0.295	0.432	15.675
0.9, 0.75, 0.6, 0.45	Benchmark	0.136	0.217	0.287	0.360	15.400
0.9, 0.75, 0.6, 0.45	Σ_1	0.065	0.169	0.297	0.469	15.365
0.9, 0.75, 0.6, 0.45	Benchmark	0.136	0.217	0.287	0.360	14.766
0.9, 0.75, 0.6, 0.45	Σ_2	0.068	0.198	0.336	0.398	12.871

marginal power	correlation	w_1	w_2	w_3	w_4	conjunctive power(%)
0.9, 0.75, 0.6, 0.45	Benchmark	0.136	0.217	0.287	0.360	12.496