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Power Analysis for Regression Coefficients: The Role of Multiple Predictors and Power to Detect all Coefficients Simultaneously

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Abstract ■ Many tools exist for power analyses focused on R^2 Model (the variance explained by all the predictors together) but tools for estimating power for coefficients often require complicated inputs that are neither intuitive nor simple to estimate. Further compounding this issue is the recognition that power to detect effects for all predictors in a model tends to be substantially lower than power to detect individual effects. In short, most available power analysis approaches ignore the probability of detecting all effects and focus on probability of detecting individual effects. The consequences of this are designs that are underpowered to detect effects. The present work presents tools for addressing these issues via simulation approaches provided by the pwr2ppl package (Aberson, 2019) and an associated Shiny app.

Keywords ■ Put keywords here, in a comma separated list. **Tools** ■ R.

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Introduction

Power analysis came to prominence with Jacob Cohen's seminal work (Cohen, 1977). Since then, considerable literature and numerous software packages focused on power (e.g., G*Power, PASS, nQuery, Sample Power) emerged. Despite advances, surveys across fields such as abnormal psychology (Sedlmeier & Gigerenzer, 1989), consulting, clinical, and social psychology (Rossi, 1990), and neuroscience (Button et al., 2013) suggest that low power remains common in published literature.

Most tools for multiple regression power focus on R^2 Model or R^2 change, but power analyses focused on multiple regression coefficients are still a challenge. Existing resources for detecting power for coefficients are of limited utility as most require input of complicated statistical values. For example, G*Power (Faul, Erdfelder, Lang, & Buchner, 2007) provides protocols to address power for a single predictor. This approach requires that users input either partial R^2 or its components. The partial R^2 is a function of the proportion of variance uniquely explained by the predictor (squared semi-partial correlation) and the variance explained in the dependent measure by the other predictors in the model. This value is not intuitive, nor is it provided by most commercial packages. This tool is accurate; however, the complexity of the required inputs limits its usability as it requires values unknown to most researchers. Without tools that are simple enough to produce reasonable power analyses, low power will continue to plague our field.

Another explanation for low power in designs with multiple predictors is a lack of recognition that power for detecting a set of outcomes differs from power for individual coefficients. Researchers using multiple regression models with three predictors commonly want to detect significant coefficients for all the predictors. However, even some tools for power analyses with multiple predictors estimated simultaneously typically yield an estimate of power for each predictor, but not power to detect all of them in the same study (e.g., MRC function in `pwr2ppl`; Aberson, 2019). Problematically, power to detect multiple effects can differ substantially from power for individual effects. In most situations, power to detect multiple effects is considerably lower than the power for individ-

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ual effects. The lack of attention to this form of power is a likely source of underpowered research in the behavioral sciences (Maxwell, 2004). This combination of factors, both a lack of tools for simultaneously calculating power over multiple predictors and a lack of awareness the problems associated with multiple predictors create a situation wherein multiple regression designs tend to have considerably less power than intended.

The present paper addresses these challenges with power analysis for multiple regression. The paper introduces tools to calculate simultaneous power estimates for up to five multiple regression coefficients (i.e., five predictors) and power for detecting significant effects on all coefficients in a model. In addition to code, I also present a Shiny app that requires no background in R. All tools require entry of zero-order correlations with several other optional values.

Typical Effect Sizes and their Relation to Power

In the area of social and personality psychology, a meta analysis of meta analyses found the typical effect size was equivalent to $r = .21$ (equivalent to $d = 0.43$; Richard, Bond, & Stokes-Zoota, 2003). Similarly in fields like intelligence research, effect sizes averaged $r = .17$ ($d = 0.35$; Mathur & VanderWeele, 2021), studies of interventions for children with externalizing behaviors was $r = .22$ ($d = 0.46$; Mingebach, Kamp-Becker, Christiansen, & Weber, 2018), and meta analyses published in Psychological Bulletin yielded an average $r = .16$ ($d = 0.32$; Cafri, Kromrey, & Brannick, 2010). Given these somewhat small typical sample size in psychology ($n = 107$; Marszalek, Barber, Kohlhart, & Holmes, 2011), this suggests much of the work in the field is deeply underpowered as the average effect size and sample size produce about 60% power. This, combined with the reduction in power for detecting all coefficients of interest suggests that, on average, power is even worse than previously understood.

Equations for Multiple Regression

Calculating power for multiple regression involves correlations among all variables in a model. The calculation of the standardized regression coefficient (Eq. 1) involves both the correlations between the predictors (represented with numbers) and the criterion or dependent variable (represented with y). In this equation, r_{y_1} is the correlation between the predictor one and the dependent variable (dv), r_{y_2} is the correlation between the predictor two and the dv, and r_{12} is the correlation between the two predictors.

$$b^*_{y1.2} = \frac{r_{y1} - r_{y2}r_{12}}{1 - r^2_{12}} \tag{1}$$

The size of the coefficient increases when correlations between the predictor and DV are large but gets smaller when predictors correlate in the same direction as predictor-dv relationships.

Equation 1 demonstrates important concepts relevant to multiple predictors. Larger regression coefficients yield more power. Larger coefficients result from stronger correlations between predictors and the DV. Correlation between predictors drives coefficient size downward and thus reduces power. Broadly this means that multicollinearity reduces statistical power.

Power for Detecting Significant Effects for All Predictors in the Model

Most commonly, researchers using multiple regression want to detect significant effects for all of the predictors in a model. However, existing power analysis approaches only address power for individual predictors. This section details how power to detect effects for all of the predictors in a model differs from power to detect individual effects and present tools for addressing this form of power. The primary issue relevant to detecting significant effects for multiple predictor variables is the role of Beta error inflation (or Familywise Beta error; see Maxwell, 2004, for a technical discussion). This issue is similar to inflation of α or Type I error. When conducting multiple significance tests, Type I error rates for the family of tests (a.k.a., familywise alpha) increase. Equation 2 provides an estimate of familywise α error for multiple comparisons and is the conceptual basis for development of tests such as the Bonferroni adjustment. According to the formula, with three tests using a pairwise alpha (α_{pw}) of .05, familywise alpha (α_{fw}) is .14.

$$\alpha_{fw} = 1 - (1 - \alpha_{pw})^c \tag{2}$$

The same process is at work with the familywise probability of making a β or Type II error (Equation 3), a value we refer to as β_{fw}. For example, for a study designed to detect β of .10 (called β_{ind} for Beta individual) for each of its three predictors (Power = .90 for each predictor), the likelihood of making a single β error among those three tests is substantially higher than the error rate of .10 for the individual tests. Just as with α error, multiple tests inflate the chances to make a single β error among a set of significance tests. The β_{fw} value easily converts to power to detect all of the effects in the design by taking $1 - \beta_{fw}$. Throughout the paper, we term this value Power(All).

$$\beta_{fw} = 1 - (1 - \beta_{ind})^c \tag{3}$$

Table 1 shows β_{fw} and Power(All) for two through 10 predictors. One clear result here is that in models with four predictors or more, if the researcher designs for Power = .90 for each individual predictor, the study will, more likely than not, fail to find significance on at least one of the predictors. This table is useful for a conceptual understanding

Table 1 ■ Familywise Type II Error (Beta) Rates for Predictors using $\beta_{pw} = .10$ (Power = .90), assuming independence of predictors

Number of Predictors	β_{fw}	Power(All)
2	.190	.810
3	.261	.729
4	.344	.656
5	.410	.590
6	.469	.531
7	.522	.478
8	.570	.430
9	.613	.387
10	.651	.349

of β_{fw}, however these results (Eq. 3) are only accurate for calculations where all tests have the same power and predictors are uncorrelated.

Power (All) for Designs with Correlated Predictors

Calculation of β_{ind} and Power(All) is simple with uncorrelated predictors. In practice, predictors nearly always correlate to some degree in multiple regression models. How this influences Power(All) is a function of both the strength and direction of correlations between predictors. When predictors correlate positively with each other, Power(All) decreases. If predictors negatively correlate, Power(All) increases but this is a relatively rare occurrence with some values (as noted in Table 2) being impossible.

Calculations of Power(All) involve simulation. Simulations draw independent samples of size n from a population with parameters used in the power analysis. Multiple regression is performed on each resample, allowing for a simple count how of many samples allowed rejection of null hypotheses for all the predictors in the study. The proportion of samples rejecting all hypotheses is Power(All). Equation 4 provides a 95% confidence interval for the power estimate.

$$95\%CI = \text{power} \times t_{.95} \times \sqrt{\frac{p(1-p)}{n_{sims}}} \qquad (4)$$

Table 2 demonstrates how predictor correlations affect Power(All) for a three-predictor model. Power for each predictor is.90 (the predictor-DV correlations vary to create this level of power) and the sample size is 100. Reject All reflects Power(All) estimates derived by simulation of 10,000 samples. Since this approach is empirical, there is some deviation from theoretical probabilities. For example, Power(All) for two predictors with Power = .80 and no correlation between predictors is theoretically .64. A simulation, however, might provide a value of .635. The range of values for Power(All) is .72 to .82 with more power generated as correlations between predictors move from strongly positive to strongly negative. Obviously, this is substantially smaller than the Power of .90 for individual coefficients. These values suggest that negative correlations between predictors are advantageous. However, relatively strong negative correlations between predictors under conditions wherein the predictors show substantial positive correlation with the criterion is about as likely as seeing Bigfoot.

Also of note is that some values in Table 2, represented as n/a, are impossible. For example, there is no predictor-DV correlation where it is possible to have correlations of -.60 or -.80 between the predictors. Additionally, models with substantial positive correlations among multiple predictors likely violate regression assumptions regarding multicollinearity.

The previous section demonstrated how correlations between predictors influence Power(All). However, the values presented in those tables are limited as they reflect situations wherein correlations between predictors and power for individual predictors are constant. Practically, predictors might show various levels of power and correlation. The `MCR_all` function included in `pwr2ppl` (Aberson, 2019), allows for such input and address Power(All) for designs with two to five predictors.

Three Predictor Example

The example that follows demonstrates use of the function `MRC_all` to determine adequate sample size. This example uses the values in Table 3 to establish population correlations.

Using the correlation matrix from Table 3, we demonstrate use of `MCR_all` function from the `pwr2ppl` R package (Aberson, 2019). Listing 1 contains code and output. The code is straightforward with the subscripts 1, 2, and 3 representing predictor variables and y representing the outcome. Other options include alpha. Alpha defaults to .05. Presently, the code is limited to five predictors.

Table 2 ■ Power(All) for Three Predictors with Power=.90 and Varying Levels of Correlation Between Predictors

Correlation between predictors	Required x-y correlations	Reject None	Reject One	Reject Two	Reject All	N for 90% Power(ALL)
-.80	n/a					
-.60	n/a					
-.40	.093	.024	.046	.111	.819	123
-.20	.194	.006	.040	.183	.771	131
.00	.294	.001	.026	.223	.750	132
.20	.399	.000	.016	.255	.729	135
.40	.517	.000	.012	.268	.720	136
.60	.650	.000	.008	.284	.708	137
.80	.809	.000	.005	.276	.719	135

Note. Required x-y correlation is the correlation between each predictor and the dv to produce Power = .90 with $n = 100$.

Table 3 ■ Correlations between Variables in Three Predictor Example

	x_1	x_2	x_3
x_1	.45 (r_{y_1})		
x_2	-.39 (r_{y_2})	-.42 (r_{12})	
x_3	-.31 (r_{y_3})	-.22 (r_{13})	.11 (r_{23})

For $n = 173$, power for the individual predictors are .985, .916, and .907 respectively but Power(All) is only .816. To get to Power(All) = .90, we need a sample of 210. This represents a 21 percent increase over the original sample size estimate.

Users might want to change the number of samples draw to get a quick sense of how large a sample will be needed before using the default 10,000 replications. Listing 2 demonstrates how to use this code in conjunction with a loop. Do note that a loop using 10,000 samples will take a bit of time. When looping, we suggest beginning with a small number of replications (e.g., 100) to get a reasonable estimate of the sample sizes that achieve adequate power and then move to 10,000 replications focused on a smaller range of sample sizes. For this analysis, x stands for predictor-predictor correlations and `i` stands for predictor-dv correlations (alternatively, users may enter values directly, replacing `x` or `i` with the number). The command for `j in seq(128,132,1)` indicates that the analysis should start with an n of 128 and add one until we hit 132.

A Tour of the Code

The table of the Appendix at the end of the article presents annotated `MRC_all` code. The code takes a sample of size n (specified by the user) and generates an analysis predicting the DV from the set of IVs for that sample. Mutliple regression is performed and results stored. This repeats 10,000 times via resampling. Finally, the code compiles rejection rates and provides output representing power for individual coefficients (total times rejecting null divided by total number of replications) and power for rejecting zero to all coefficients. Users may change the number of replications. However, more replications substantially increased processing time.

Shiny App

These protocols are also available via a Shiny app. Figure 1 shows the look and feel of the app. To initialize the app use the code `shiny::runGitHub("MRC_all-Shiny", "chrisaberson")`. Presently the app only handles up to three predictors.

Conclusion

Researchers often misunderstand power for multiple regression models. Specifically, the difference between power for detecting a single coefficient as opposed to power for detecting all coefficients. This misunderstanding results in underpowered designs. The tools discussed in this paper provide researchers with tools for estimating both power for individual coefficients and power to detect all coefficients in a model.

Listing 1 ■ Using `MRC_all`

```
pwr2ppl::MRC_all(ry1=.45,ry2=-.39,ry3=-.31,r12=-.42,r13=-.22,r23=.11,n=173)
## Sample size is 173
## Power R2 = 1
## Power b1 = 0.9835
## Power b2 = 0.9139
## Power b3 = 0.9018
## Proportion Rejecting None = 0
## Proportion Rejecting One = 0.0066
## Proportion Rejecting Two = 0.1876
## Power ALL (Proportion Rejecting All) = 0.8058

pwr2ppl::MRC_all(ry1=.45,ry2=-.39,ry3=-.31,r12=-.42,r13=-.22,r23=.11,n=210)
## Sample size is 210
## Power R2 = 1
## Power b1 = 0.9941
## Power b2 = 0.9588
## Power b3 = 0.9467
## Proportion Rejecting None = 0
## Proportion Rejecting One = 0.0023
## Proportion Rejecting Two = 0.0958
## Power ALL (Proportion Rejecting All) = 0.9019
```

References

Aberson, C. L. (2019). *Applied power analysis for the behavioral sciences (2nd edition)*. Taylor & Francis Group: Routledge.

Button, K. S., Ioannidis, J. P. A., Mokrysz, C., Nosek, B. A., Flint, J., Robinson, E. S. J., & Munafò, M. R. (2013). Power failure: Why small sample size undermines the reliability of neuroscience. *Nature Reviews Neuroscience*, *14*(5), 365–376. doi:10.1038/nrn3475

Cafri, G., Kromrey, J. D., & Brannick, M. T. (2010). A meta-meta-analysis: Empirical review of statistical power, type i error rates, effect sizes, and model selection of meta-analyses published in psychology. *Multivariate Behavioral Research*, *45*(2), 239–270. doi:10.1080/00273171003680187

Cohen, J. (1977). *Statistical power analysis for the behavioral sciences, rev ed (1987-98267-000)*. Inc: Lawrence Erlbaum Associates. Retrieved from http://ezproxy.humboldt.edu/login?url=https://search.ebscohost.com/login.aspx?direct=true&db=psyh&AN=1987-98267-000&site=ehost-live

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). Gpower 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2), 175–191. doi:10.3758/BF03193146

Marszalek, J., Barber, C., Kohlhart, J., & Holmes, C. (2011). Sample size in psychological research over the past 30 years. *Perceptual and Motor Skills*, *112*, 331–348. doi:10.2466/03.11.PMS.112.2.331-348

Mathur, M. B., & VanderWeele, T. J. (2021). Estimating publication bias in meta-analyses of peer-reviewed studies: A meta-meta-analysis across disciplines and journal tiers. *Research Synthesis Methods*, *12*(2), 176–191. doi:10.1002/jrsm.1464

Maxwell, S. E. (2004). The persistence of underpowered studies in psychological research: Causes, consequences, and remedies. *Psychological Methods*, *9*(2), 147–163. doi:10.1037/1082-989X.9.2.147

Mingebach, T., Kamp-Becker, I., Christiansen, H., & Weber, L. (2018). Meta-meta-analysis on the effectiveness of parent-based interventions for the treatment of child externalizing behavior problems. *PLoS ONE*, *13*, 9–19. doi:10.1371/journal.pone.0202855

Richard, F. D., Bond, C. F., & Stokes-Zoota, J. J. (2003). One hundred years of social psychology quantitatively described. *Review of General Psychology*, *7*(4), 331–363. doi:10.1037/1089-2680.7.4.331

Rossi, J. S. (1990). Statistical power of psychological research: What have we gained in 20 years? *Journal of Consulting and Clinical Psychology*, *58*(5), 646–656. doi:10.1037/0022-006X.58.5.646

Sedlmeier, P., & Gigerenzer, G. (1989). Do studies of statistical power have an effect on the power of studies? *Psychological Bulletin*, *105*(2), 309–316. doi:10.1037/0033-2909.105.2.309

Listing 2 ■ Looping Analyses

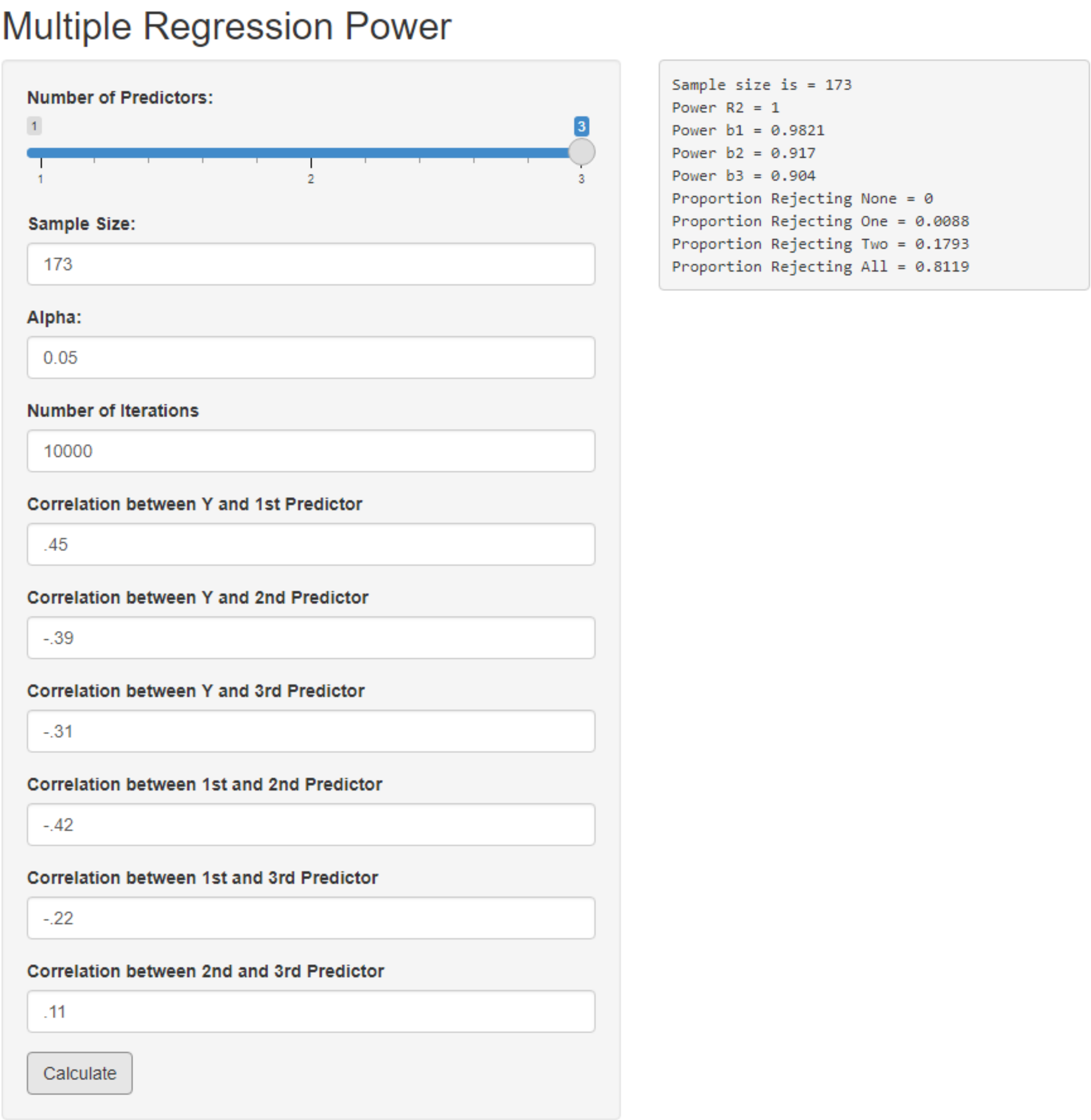
```
x <- -.20
i <- .194
for (j in seq(128,132,1))
{
  print(j)
  pwr2ppl::MRC_all(ry1=i,ry2=i,ry3=i,r12=x,r13=x,r23=x,n=j, rep=10000)
}
## [1] 128
## Sample size is 128
## Power R2 = 0.9954
## Power b1 = 0.9615
## Power b2 = 0.9576
## Power b3 = 0.9588
## Proportion Rejecting None = 0.0011
## Proportion Rejecting One = 0.0109
## Proportion Rejecting Two = 0.097
## Power ALL (Proportion Rejecting All) = 0.891

## [1] 129
## Sample size is 129
## Power R2 = 0.996
## Power b1 = 0.964
## Power b2 = 0.9618
## Power b3 = 0.9626
## Proportion Rejecting None = 6e-04
## Proportion Rejecting One = 0.0102
## Proportion Rejecting Two = 0.0894
## Power ALL (Proportion Rejecting All) = 0.8998

## [1] 130
## Sample size is 130
## Power R2 = 0.9969
## Power b1 = 0.9624
## Power b2 = 0.9667
## Power b3 = 0.9663
## Proportion Rejecting None = 6e-04
## Proportion Rejecting One = 0.0082
## Proportion Rejecting Two = 0.0864
## Power ALL (Proportion Rejecting All) = 0.9048

(Remaining output deleted)
```

Figure 1 ■ Shiny App for Multiple Regression Power for All Predictors



Number of Predictors: 3

Sample Size: 173

Alpha: 0.05

Number of Iterations: 10000

Correlation between Y and 1st Predictor: .45

Correlation between Y and 2nd Predictor: -.39

Correlation between Y and 3rd Predictor: -.31

Correlation between 1st and 2nd Predictor: -.42

Correlation between 1st and 3rd Predictor: -.22

Correlation between 2nd and 3rd Predictor: .11

```
Sample size is = 173
Power R2 = 1
Power b1 = 0.9821
Power b2 = 0.917
Power b3 = 0.904
Proportion Rejecting None = 0
Proportion Rejecting One = 0.0088
Proportion Rejecting Two = 0.1793
Proportion Rejecting All = 0.8119
```

Appendix: Inside the `MRC_all` function

Code | Comment

```
MRC_all<-function(ry1=NULL, ry2=NULL, ry3=NULL,
  ry4=NULL, ry5=NULL, r12=NULL, r13=NULL,r14=NULL,
  r15=NULL, r23=NULL, r24=NULL, r25=NULL, r34=NULL,
  r35=NULL, r45=NULL, n=NULL, alpha=.05, rep = 10000)
{
```

Initializes the function

```
  pred<-NA
  pred[!is.null(ry2)]<-2
  pred[!is.null(ry3)]<-3
  pred[!is.null(ry4)]<-4
  pred[!is.null(ry5)]<-5
```

Establishes the number of predictors.

```
  vary<-1; var1<-1; var2<-1; var3 <-1; var4 <-1; var5 <-1
```

Establishes the variances. This assumes normality

```
  if (pred=="2") {
    nruns = rep
    int = numeric(nruns)
    b1 = numeric(nruns)
    b2 = numeric(nruns)
    R2 = numeric(nruns)
    F = numeric(nruns)
    df1 = numeric(nruns)
    df2 = numeric(nruns)
```

Creates each value used for calculations as a variable with rows equal to the number of replications.

```
    for (i in 1:nruns) {
```

Initializes a loop

```
    samp <- data.frame(MASS::mvrnorm(n, mu = c(0, 0, 0),
               Sigma = matrix(c(vary, ry1, ry2,
                                ry1, var1, r12,
                                ry2, r12, var2),
                                ncol = 3),
               empirical =FALSE)
            )
```

Draws a sample of the specified n from the population.

```
    test <- stats::lm(formula = X1 ~ X2+ X3, data = samp)
```

This applies multiple regression.

```
    c<-summary(test)
    int[i] = stats::coef(summary(test))[1,4]
    b1[i] = stats::coef(summary(test))[2,4]
    #grabs p from each analysis
    b2[i] = stats::coef(summary(test))[3,4]
    R2[i] = c$r.squared
    F[i]<-c$fstatistic[1]
```

Captures results including intercept, b1 and b2 (unstandardized coefficients), R squared, F, and df.

```
    df1[i]<-c$fstatistic[2]
    df2[i]<-c$fstatistic[3]
  }
```

Creates a data frame to store results.

```
  Powerall = data.frame(int = int, b1 = b1, b2 = b2)
  Powerall[4:5, "rejectb1"]<-NA
  Powerall$rejectb1 [ b1 < alpha] <- 1
  Powerall$rejectb1 [ b1 >= alpha] <- 0
  Powerall[4:5, "rejectb2"]<-NA
  Powerall$rejectb2 [ b2 < alpha] <- 1
  Powerall$rejectb2 [ b2 >= alpha] <- 0
```

Assigned the row a 1 if we can reject null for each predictor.

```
  Powerall[4:5, "rejecttotal"]<-NA
  Powerall$rejectall <- (Powerall$rejectb1 +
                           Powerall$rejectb2)
```

Calculates the number of cases rejecting all null hypotheses. Calculates the other values

```
  Reject.None <-NA
  Reject.None [Powerall$rejectall == 0]<-1
  Reject.None [Powerall$rejectall > 0]<-0
  Reject.One <-NA
  Reject.One [Powerall$rejectall == 1]<-1
  Reject.One [Powerall$rejectall != 1]<-0
  Reject.All <-NA
  Reject.All [Powerall$rejectall == 2]<-1
  Reject.All [Powerall$rejectall != 2]<-0
  is.numeric(Reject.None)
  is.numeric(Reject.One)
  is.numeric(Reject.All)
```

Converts raw numbers to probability.

```
  Power_b1<-mean(Powerall$rejectb1)
  Power_b2<-mean(Powerall$rejectb2)
  pR2<-1-stats::pf(F,df1, df2)
  Powerall$rejectR2 [pR2 < alpha] <- 1
  Powerall$rejectR2 [pR2 >= alpha] <- 0
  Power_R2<-mean(Powerall$rejectR2)
  PowerAll_R0<-mean(Reject.None)
  PowerAll_R1<-mean(Reject.One)
  PowerAll_R2<-mean(Reject.All)
```

Compile the results

```
  message("Sample size is ",n)
  message("Power R2 = ", Power_R2)
  message("Power b1 = ", Power_b1)
  message("Power b2 = ", Power_b2)
  message("Proportion Rejecting None = ", PowerAll_R0)
  message("Proportion Rejecting One = ", PowerAll_R1)
  message("Power ALL (Proportion Rejecting All) = ",
    PowerAll_R2)
}
```

Report the results

Note. This is a shortened version of the code. For full code see https://github.com/chrisaberson/pwr2ppl.

Open practices

The *Open Material* badge was earned because supplementary material(s) are available on osf.io/zbrhx/

Citation

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