R Notebook

A bit of stats

Does eating a banana makes you happier ? Lets assume happiness is distributed following a gaussian distribution. You have a way of measuring it reliably scored between 0 and 10.

- You are alone eating a banana:
  - what is the magnitude ?
  - what is the significance ?
- You are doing it with 4 friends
  - what is the magnitude ?
  - what is the significance ?
- You are doing it with 40000 people
  - Let's say you see a 3% increase in happiness
  - Would it be significant ?
- You are doing it with 40000 in china and 40000 in the US
  - Will the effect be significantly different ?
  - How will you know if that difference is really meaningful ?

```
before_happiness = rnorm(40000,7,5)

# First we eat a normal banana
sd = 1
after_happiness = before_happiness + rnorm(40000,0.5,sd)
mean(after_happiness - before_happiness)
```

```
## [1] 0.49237
```

```
# What about a the super weird banana
sd = 35
after_happiness_weird = before_happiness + rnorm(40000,0.5,sd)
```

And now, what test could we perform ? A t test ? which kind ? Should we do an anova ?

Power Analysis

What is the definition of power ?

A concrete example, you want to know how many subject are necessary for your comparative experiment. You have two groups: - Group 1 is doing A then B - Group 2 is doing B then A

Research questions: - Do you need groups to test if task B is correlated to task A ? - You are wondering how many subject are necessary to show a difference in performance between the two groups on task A and B - Is this difference larger for task A or task B. - How many subject would you need if you wanted to know the exact magnitude of the effect size with precision ?

```
# Comonly used values in clinical trial design
qnorm(0.05)
```

```
## [1] -1.644854
```

```
pnorm(1.644854)
```

```
## [1] 0.95
```

```r
power = 0.9

false_positive_error_rate = 0.05
alpha = false_positive_error_rate

# Specific to the problem
effect_size = 0.1
standard_deviation = 0.22
variance = standard_deviation^2

mean = 0.64
estimated_n = 364
n = estimated_n

quantile = qnorm(0.05, mean, standard_deviation)-(effect_size/(standard_deviation/sqrt(n)))
estimated_power = 1 - pnorm(quantile, mean, standard_deviation)
print(paste0("Estimated power: ", estimated_power))
```

```
## [1] "Estimated power: 1"
```

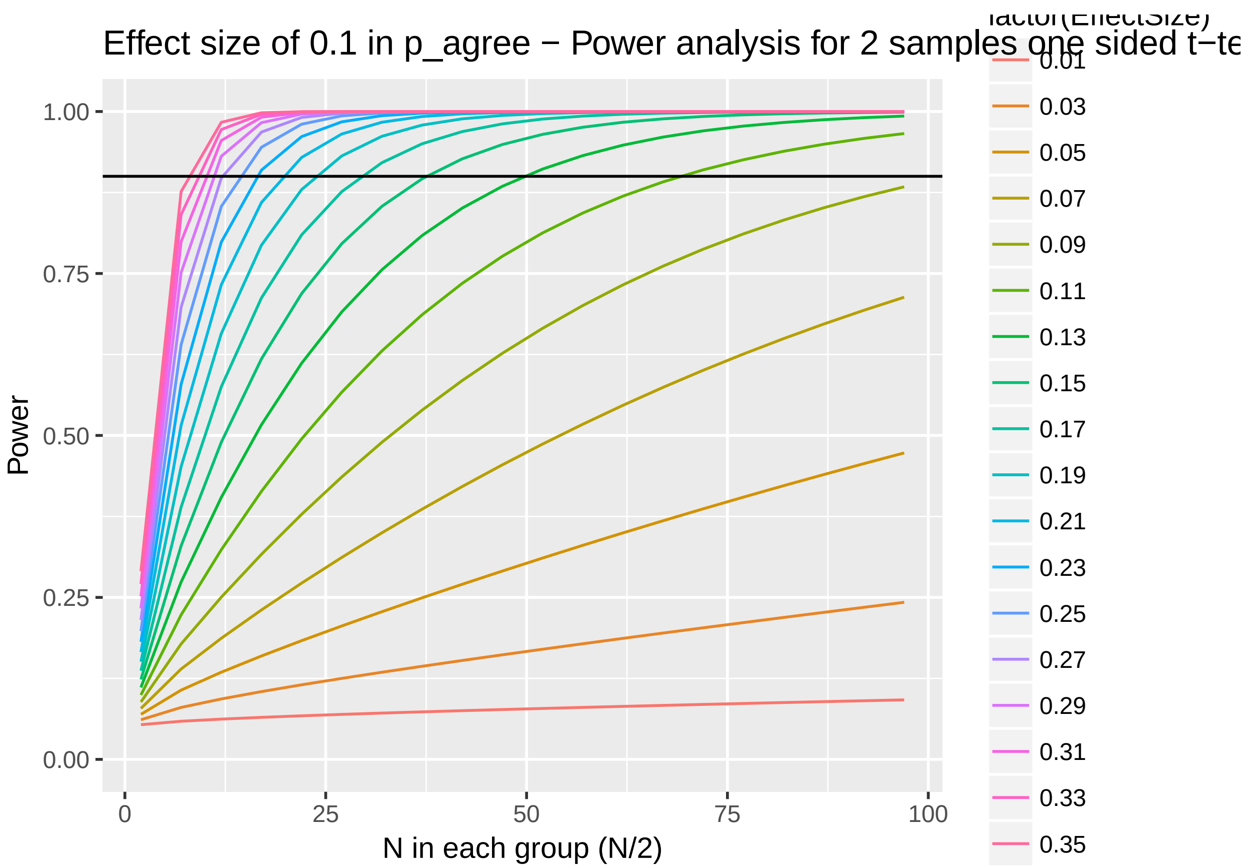
```r
# A bunch of very useful functions are present in the power library
power_test = power.t.test(n = n, delta = effect_size, sd = standard_deviation, sig.level = alpha,
             power = NULL,
             type = "two.sample",
             alternative = "one.sided")

return(power_test$power)
```

```
## [1] 0.9999963
```

Now I want you to create a function or a bit of code that produce this figure:

```
##     EffectSize Needs_Minimum_N_Subjects
##  1:       0.11                       72
##  2:       0.13                       52
##  3:       0.15                       42
##  4:       0.17                       32
##  5:       0.19                       27
##  6:       0.21                       22
##  7:       0.23                       17
##  8:       0.25                       17
##  9:       0.27                       17
## 10:       0.29                       12
## 11:       0.31                       12
## 12:       0.33                       12
## 13:       0.35                       12
```

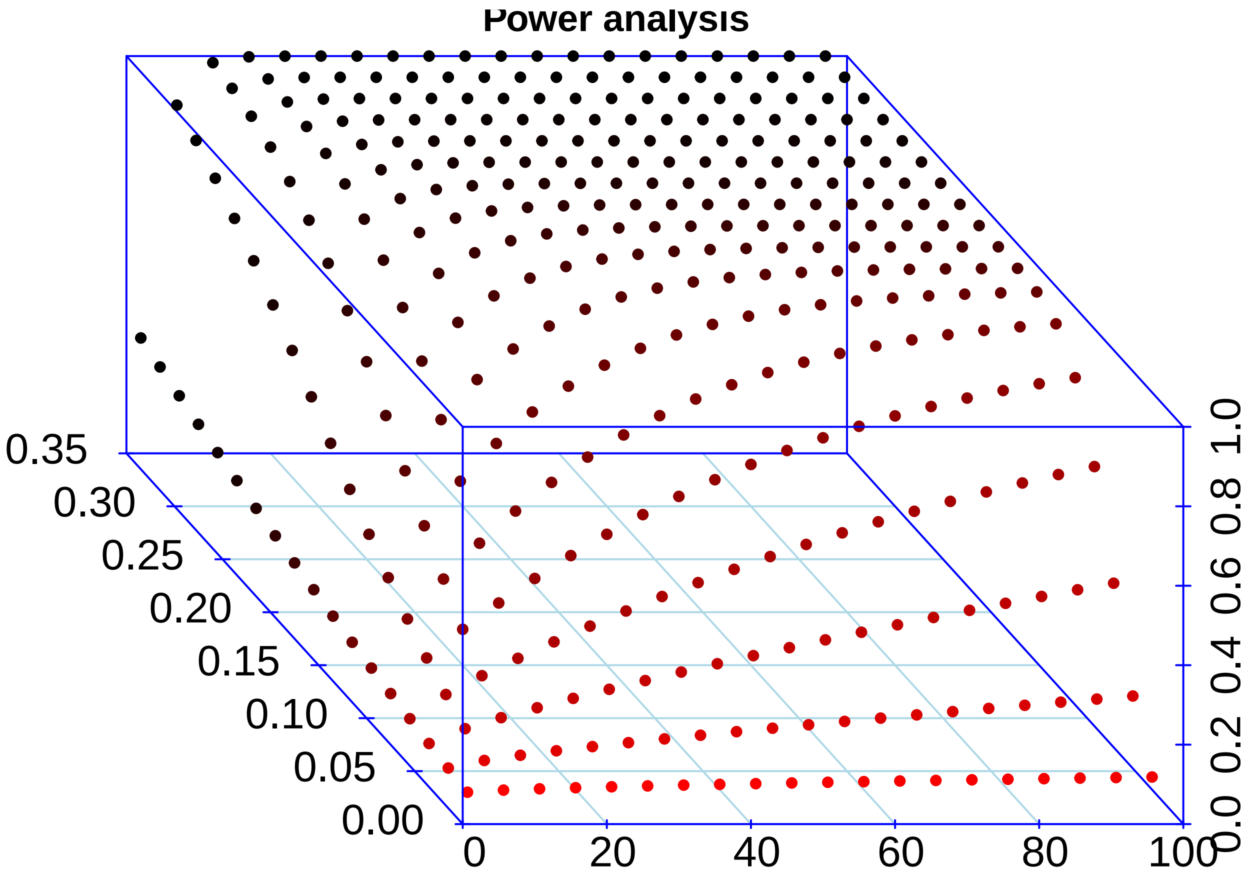


Try in 3D

Is 3D a better choice to plot these curve ?

```
N = x
effect_size = y
Power = z
threshold = rep(0.9, NROW(Power))

s3d = scatterplot3d(N, effect_size, Power, highlight.3d = TRUE, angle = 120,
col.axis = "blue", col.grid = "lightblue", cex.axis = 1.3,
cex.lab = 1.1, main = "Power analysis", pch = 20, mar = c(0.5, 0.3, 0.4, 0.3))
```




```
# s3d$points3d(effect_size, N, threshold, color = "blue", type = "l", angle = 70)
```

Definitions

Power analysis allows us to: * Determine the sample size required to detect an effect of a given size with a given degree of confidence. * Conversely, it allows us to determine the probability of detecting an effect of a given size with a given level of confidence, under sample size constraints.

If the probability is unacceptably low, we would be wise to alter or abandon the experiment.

The following four quantities have an intimate relationship:

- sample size
- effect size
- significance level = P(Type I error) = alpha = probability of finding an effect that is not there
- power = 1 - P(Type II error) = 1 - beta = probability of finding an effect that is there Given any three, we can determine the fourth.