Python

To begin with, the simulation based power analysis in Python just follows the structure in the last section in R, and there are repetitions in the texts to describe the method. However, there are differences between the two languages and we will specify those discrepancy in the following "note" parts.

Setup

Note: There are two differences between Python and the R language: 1. R uses the p_load function to automatically install missing libraries and import libraries. Python needs to manually configure the environment. If the library is missing, you can use "! pip install [package_name]" to install; 2. The R has set parallelism in the setup part, but Python uses the dask package to perform parallel computing in the simulation part.

We will need to use several Python packages to optimize our workflow and fit mixed effects models.

```
import statsmodels.formula.api as smf
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib
import matplotlib.pyplot as plt
import dask
import time

from dask.distributed import Client
from itertools import product

matplotlib.use("Agg")
```

We will also set the pseudo-random number generator seed to 2138 to make the stochastic components of our simulations reproducible.

```
np.random.seed(2138)
```

Data simulation step by step

To give an overview of the power simulation task, we will simulate data from a design with crossed random factors of subjects and songs (see Power of What? for design details), fit a model to the simulated data, recover from the model output the parameter values we put in, calculate power, and finally automate the whole process so that we can calculate power for different effect sizes. Much of the general workflow here is borrowed from DeBruine & Dale (2021) Understanding Mixed-Effects Models through Simulation. We'll start by writing code that simulates datasets under the alternative hypothesis.

Note: There are two differences between Python and the R: 1. We use the package of "statsmodels" to set up the mixd effect model in Python. However, this package doesn't have extension to show the correlation between the random intercept and the random slope of the subject like that in R; 2. There's no "broom.mixed::tidy()" function in Python and that's why the output is incomplete.

Establish the simulation parameters

Before we start, let's set some global parameters for our power simulations. Since simulations can take a long time to run, we'll use 30 replications here as an example, but we recommend increasing this number to at least 1000 replications for a more accurate final power calculation.

```
# number of simulation replicates for power calculation
reps = 30

# specified alpha for power calculation
alpha = 0.05
```

Establish the data-generating parameters

The first thing to do is to set up the parameters that govern the process we assume gave rise to the data - the data-generating process, or DGP. We previously decided upon the the data-generating parameters (see Power of What?), so we just need to code them here.

```
# set all data-generating parameters
beta_0 = 60  # intercept; i.e., the grand mean
beta_1 = 5   # slope; i.e, effect of category
omega_0 = 3  # by-song random intercept sd
tau_0 = 7    # by-subject random intercept sd
tau_1 = 4    # by-subject random slope sd
rho = 0.2    # correlation between intercept and slope
sigma = 8    # residual (error) sd
```

Simulate the sampling process

Next, we will simulate the sampling process for the data. First, let's define parameters related to the number of observations.

```
# set number of subjects and songs
n_subj = 25  # number of subjects
n_pop = 15   # number of songs in pop category
n_rock = 15  # number of songs in rock category
```

Simulate the sampling of songs We need to create a table listing each song i, which category it is in (rock or pop), and its random effect O_{0i}. The latter is sampled from a univariate normal distribution using the function np.random.normal().

```
# simulate a sample of songs
songs = pd.DataFrame({
    'song_id': range(1, n_pop + n_rock + 1),
    'category': ['pop']*n_pop + ['rock']*n_rock,
    'genre_i': [0]*n_pop + [1]*n_rock,
    'O_0i': np.random.normal(0, omega_0, n_pop + n_rock)
})

print(songs.head(10))
```

```
##    song_id category  genre_i       O_0i
## 0        1      pop        0 -1.803722
## 1        2      pop        0 -4.618354
## 2        3      pop        0 -4.847097
## 3        4      pop        0 -1.097951
## 4        5      pop        0 -1.394909
## 5        6      pop        0  2.424235
## 6        7      pop        0 -3.956914
## 7        8      pop        0  0.873891
## 8        9      pop        0  3.318065
## 9       10      pop        0  5.513671
```

Simulate the sampling of subjects Now we simulate the sampling of participants, which results in table listing each individual and their two correlated random effects (a random intercept and random slope). To do this, we must sample T_{0j}, T_{1j} pairs - one for each subject - from a bivariate normal distribution.

We will use the function np.random.multivariate_normal(), which generates a table of n simulated values from a multivariate normal distribution by specifying the means and covariance matrix(cov).

```
# simulate a sample of subjects

# sample from a multivariate normal distribution
mean = [0, 0]  # means for random effects are always 0
cov = [[tau_0**2, rho*tau_0*tau_1], [rho*tau_0*tau_1, tau_1**2]]  # set covariance matrix

random_effects = np.random.multivariate_normal(mean, cov, n_subj)

subjects = pd.DataFrame(random_effects, columns=['T_0j', 'T_1j'])
subjects['subj_id'] = range(1, n_subj + 1) # add subject IDs

print(subjects.head(10))
```

```
##          T_0j      T_1j  subj_id
## 0   -0.547564 -2.796419        1
## 1  -10.695092 -3.700622        2
## 2    3.387493 -7.940628        3
## 3    4.344241  0.531463        4
## 4    6.461586  5.260280        5
## 5  -12.373764 -1.387928        6
## 6    0.352194 -3.990547        7
## 7   -6.962734  2.358670        8
## 8   -2.636463 -0.370637        9
## 9    0.619930 -4.416671       10
```

Check the simulated values Let's do a quick sanity check by comparing our simulated values to the parameters we used as inputs. Because the sampling process is stochastic, we shouldn't expect that these will exactly match for any given run of the simulation.

```
check_values = pd.DataFrame({
    'parameter': ['omega_0', 'tau_0', 'tau_1', 'rho'],
    'value': [omega_0, tau_0, tau_1, rho],
    'simulated': [songs['O_0i'].std(), subjects['T_0j'].std(), subjects['T_1j'].std(), subjects['T_0j']
})
```

```
print(check_values)
```

```
##   parameter  value  simulated
## 0   omega_0    3.0   3.372345
## 1     tau_0    7.0   5.648262
## 2     tau_1    4.0   4.439518
## 3       rho    0.2   0.063860
```

Simulate trials Since all subjects rate all songs (i.e., the design is fully crossed) we can set up a table of trials by including every possible combination of the rows in the subjects and songs tables. Each trial has random error associated with it, reflecting fluctuations in trial-by-trial ratings due to unkown factors. We simulate this by sampling values from a univariate normal distribution with a mean of 0 and a standard deviation of sigma.

```
# cross subject and song IDs; add an error term
trials = subjects.assign(key=1).merge(songs.assign(key=1), on='key').drop(columns='key')
trials['e_ij'] = np.random.normal(0, sigma, len(trials))

print(trials.head(10))
```

```
##        T_0j      T_1j  subj_id  song_id category  genre_i      O_0i       e_ij
## 0 -0.547564 -2.796419        1        1      pop        0 -1.803722   6.954841
## 1 -0.547564 -2.796419        1        2      pop        0 -4.618354  -6.588163
## 2 -0.547564 -2.796419        1        3      pop        0 -4.847097   5.226969
## 3 -0.547564 -2.796419        1        4      pop        0 -1.097951 -11.285800
## 4 -0.547564 -2.796419        1        5      pop        0 -1.394909   2.418785
## 5 -0.547564 -2.796419        1        6      pop        0  2.424235  -7.579483
## 6 -0.547564 -2.796419        1        7      pop        0 -3.956914  -2.553524
## 7 -0.547564 -2.796419        1        8      pop        0  0.873891  12.726906
## 8 -0.547564 -2.796419        1        9      pop        0  3.318065  -6.371494
## 9 -0.547564 -2.796419        1       10      pop        0  5.513671  13.508966
```

Calculate response values With this resulting trials table, in combination with the constants β_0 and β_1, we have the full set of values that we need to compute the response variable liking_ij according the linear model we defined previously (see Power of What?).

```
dat_sim = trials.copy()
dat_sim['liking_ij'] = beta_0 + dat_sim['T_0j'] + dat_sim['O_0i'] + (beta_1 + dat_sim['T_1j']) * dat_si
dat_sim = dat_sim[['subj_id', 'song_id', 'category', 'genre_i', 'liking_ij']]

print(dat_sim.head(10))
```

```
##    subj_id  song_id category  genre_i  liking_ij
## 0        1        1      pop        0  64.603556
## 1        1        2      pop        0  48.245919
## 2        1        3      pop        0  59.832308
## 3        1        4      pop        0  47.068685
## 4        1        5      pop        0  60.476312
## 5        1        6      pop        0  54.297188
## 6        1        7      pop        0  52.941998
```

```
## 7         1         8       pop        0   73.053233
## 8         1         9       pop        0   56.399007
## 9         1        10       pop        0   78.475074
```

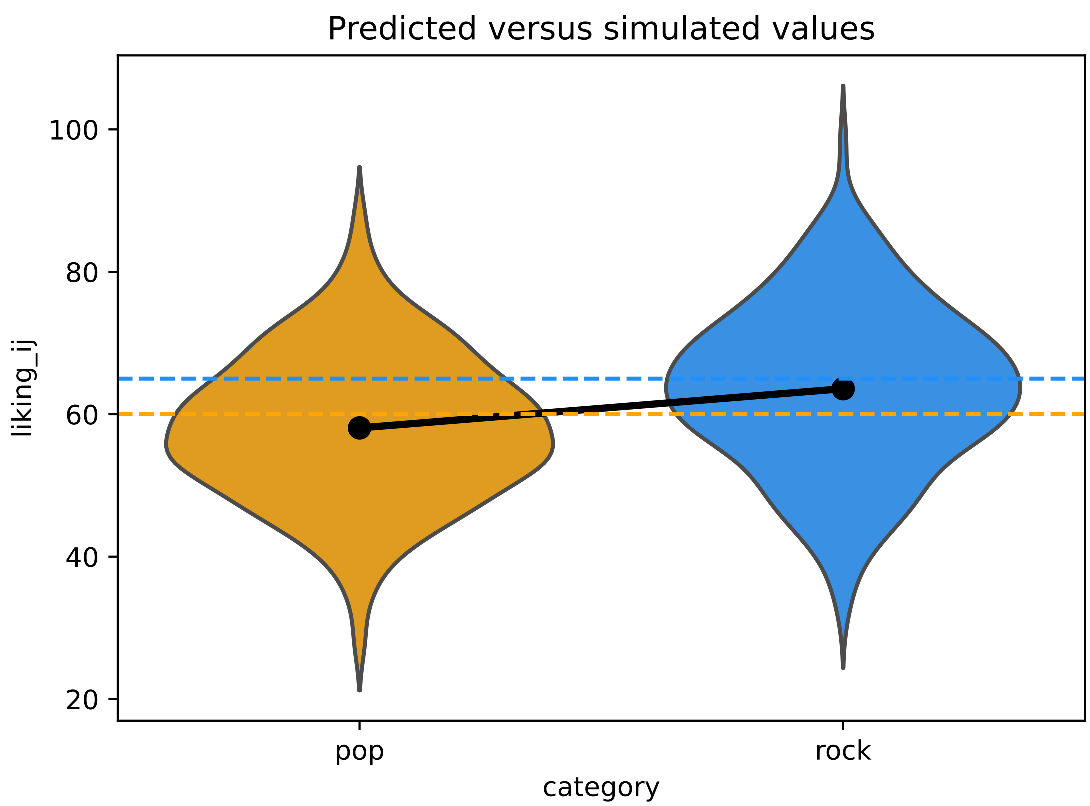
Plot the data Let's visualize the distribution of the response variable for each of the two song genres and superimpose the simulated parameter estimates for the means of these two groups.

```
palette = {'pop': 'orange', 'rock': 'dodgerblue'}

# actual data
sns.violinplot(x='category', y='liking_ij', data=dat_sim, palette=palette, inner=None, alpha=0.5)
sns.pointplot(x='category', y='liking_ij', data=dat_sim, estimator=np.mean, ci=None, color='black')

# predicted means
plt.axhline(y=(beta_0 + 0*beta_1), color='orange', linestyle='dashed')
plt.axhline(y=(beta_0 + 1*beta_1), color='dodgerblue', linestyle='dashed')

plt.title("Predicted versus simulated values")
plt.show()
```



Analyze the simulated data

Now we can analyze our simulated data in a linear mixed effects model using the function mixedlm from the {statsmodels} package. The formula and vc_formula in mixedlm() map onto how we calculated our liking_ij outcome variable above.

The terms in formula are as follows: liking_ij is the response. 1 is the intercept (β_0), which is the mean of the response for the pop genre of songs (because we used dummy coding for the genre_i term). genre_i is the dummy coded variable identifying whether song i belongs to the pop or rock genre.

The terms in vc_formula are as follows:

0 + C(song_id) specifies a song-specific random intercept O_0i. 0 + C(subject_id) specifies a subject-specific random intercept T_0j. 0 + C(subject_id):genre_i specifies the subject specific random slope of the genre category T_1j.

However, due to the inability of the function mixedlm(), the module did not indicate the correlation between subject-specific random intercept and the subject specific random slope of the genre category.

```
# fit a linear mixed-effects model to data
form = 'liking_ij ~ 1 + genre_i'
dat_sim['groups'] = 1
vcf = {'song_id':'0 + C(song_id)', 'subj_id':'0 + C(subj_id)', 'genre_i': '0 + C(subj_id):genre_i'}
```

Now we can estimate the model.

```
model = smf.mixedlm(form, groups=dat_sim['groups'], vc_formula=vcf, re_formula='0', data=dat_sim)
mod_sim = model.fit()

print(mod_sim.summary())
```

```
##          Mixed Linear Model Regression Results
## ========================================================
## Model:            MixedLM Dependent Variable: liking_ij
## No. Observations: 750     Method:             REML
## No. Groups:       1       Scale:              66.4110
## Min. group size:  750     Log-Likelihood:     -2708.1155
## Max. group size:  750     Converged:          Yes
## Mean group size:  750.0
## --------------------------------------------------------
##               Coef.  Std.Err.   z    P>|z| [0.025 0.975]
## --------------------------------------------------------
## Intercept     58.078    1.494 38.873 0.000 55.150 61.007
## genre_i        5.505    1.631  3.376 0.001  2.309  8.701
## genre_i Var   22.355    1.106
## song_id Var   10.578    0.443
## subj_id Var   33.748    1.353
## ========================================================
```

```
formatted_sim_result = pd.DataFrame({
    'term': ['Intercept', 'genre_i', '', '', '', '', ''],
    'parameter': ['beta_0', 'beta_1', 'omega_0', 'tau_0', 'rho', 'tau_1', 'sigma'],
    'value': [beta_0, beta_1, omega_0, tau_0, rho, tau_1, sigma],
    'simulated': [mod_sim.fe_params[0], mod_sim.fe_params[1],
                   '', '',
                  '', '',
                  '']
})

print(formatted_sim_result)
```

```
##         term parameter  value  simulated
## 0  Intercept    beta_0   60.0  58.078342
## 1    genre_i    beta_1    5.0   5.504843
## 2              omega_0    3.0
## 3                tau_0    7.0
## 4                  rho    0.2
## 5                tau_1    4.0
## 6                sigma    8.0
```

Data simulation automated

Now that we've tested the data generating code, we can put it into a function so that it's easy to run it repeatedly.

```
def sim_data(n_subj=25, n_pop=15, n_rock=15, beta_0=60, beta_1=5, omega_0=3, tau_0=7, tau_1=4, rho=0.2,
    songs = pd.DataFrame({
        'song_id': np.arange(n_pop + n_rock),
        'category': np.repeat(["pop", "rock"], [n_pop, n_rock]),
        'genre_i': np.repeat([0, 1], [n_pop, n_rock]),
        'O_0i': np.random.normal(0, omega_0, n_pop + n_rock)
    })

    random_effects = np.random.multivariate_normal([0, 0], [[tau_0**2, rho*tau_0*tau_1], [rho*tau_0*tau
    subjects = pd.DataFrame(random_effects, columns=['T_0j', 'T_1j'])
    subjects['subj_id'] = np.arange(1, n_subj + 1)

    trials = pd.merge(subjects, songs, how='cross')
    trials['e_ij'] = np.random.normal(0, sigma, len(trials))
    trials['liking_ij'] = beta_0 + trials['T_0j'] + trials['O_0i'] + (beta_1 + trials['T_1j']) * trials

    return trials[['subj_id', 'song_id', 'category', 'genre_i', 'liking_ij']]
```

Power calculation single run

We can wrap the data generating function and modeling code in a new function single_run() that returns a table of the analysis results for a single simulation run.

```
def single_run(n_subj=25, n_pop=15, n_rock=15, beta_0=60, beta_1=5, omega_0=3, tau_0=7, tau_1=4, rho=0.
    dat_sim = sim_data(n_subj, n_pop, n_rock, beta_0, beta_1, omega_0, tau_0, tau_1, rho, sigma)

    dat_sim['groups'] = 1
    mod_sim = smf.mixedlm('liking_ij ~ 1 + genre_i', groups=dat_sim['groups'],
                          vc_formula={'song_id':'0 + C(song_id)', 'subj_id':'0 + C(subj_id)', 'genre_i'
                          re_formula='0', data=dat_sim).fit()

    df = mod_sim.summary().tables[1]
    df['p_value'] = mod_sim.pvalues
    return df[['Coef.', 'Std.Err.', 'p_value']]
```

Let's test that our new single_run() function performs as expected.

```
# run one model with default parameters
print(single_run())
```

```
##                Coef. Std.Err.   p_value
## Intercept    62.364    1.620  0.000000
## genre_i       1.794    1.454  0.217012
## genre_i Var  15.056    0.854  0.027138
## song_id Var   8.783    0.387  0.004477
## subj_id Var  46.691    1.848  0.001541
```

```
# run one model with new parameters
print(single_run(n_pop = 10, n_rock = 50, beta_1 = 2))
```

```
##                Coef. Std.Err.        p_value
## Intercept    60.065    1.635  1.824465e-295
## genre_i       2.934    1.308   2.494009e-02
## genre_i Var  14.922    0.811   1.634819e-02
## song_id Var   6.946    0.230   8.011783e-05
## subj_id Var  43.595    1.826   1.830974e-03
```

Power calculation automated

To get an accurate estimation of power, we need to run the simulation many times. Here we use the package dask to parallelize existing code to speed-up iterative processes.

We use dask.delayed function to decorate single_run() so that it operates lazily, then call the delayed version repeatedly using for statement, and finally call dask.compute function to get the result of simulations.

Note: There are two differences between Python and the R: 1. The R uses the "future_map_dfr() function" to use the single_run() function in a loop, and Python directly uses "for" structure to do loop; 2. The R sets parallel computing in the setup part, while the Python uses the "dask" library for parallel computing.

```
client = Client()

@dask.delayed
def delayed_single_run(n_subj=25, n_pop=15, n_rock=15, beta_0=60, beta_1=5, omega_0=3, tau_0=7, tau_1=4
    df = single_run(n_subj, n_pop, n_rock, beta_0, beta_1, omega_0, tau_0, tau_1, rho, sigma)
    df = df.assign(n_subj=n_subj, n_pop=n_pop, n_rock=n_rock, beta_1=beta_1)
    return df

sims = [delayed_single_run() for _ in range(reps)]
sims_result = dask.compute(*sims)

sims_df = pd.concat(sims_result).reset_index().rename(columns={'index':'term'})
```

We can finally calculate power for our parameter of interest β_1 denoted in the model output table as the term $genre_i$ by filtering to keep only that term and the calculating the proportion of times the p-value is below the alpha (0.05) threshold.

```
genre_i_sims = sims_df[sims_df['term'] == 'genre_i']
mean_estimate = genre_i_sims['Coef.'].astype(float).mean()
mean_se = genre_i_sims['Std.Err.'].astype(float).mean()
```

```
power = (genre_i_sims['p_value'].astype(float) < alpha).mean()

print(f"Mean estimate: {mean_estimate}")
```

```
## Mean estimate: 4.789666666666666
```

```
print(f"Mean standard error: {mean_se}")
```

```
## Mean standard error: 1.4800000000000002
```

```
print(f"Power: {power}")
```

```
## Power: 0.9333333333333333
```

Check false positive rate

We can do a sanity check to see if our simulation is performing as expected by checking the false positive rate (Type I error rate). We set the effect of genre_ij (beta_1) to 0 to calculate the false positive rate, which is the probability of concluding there is an effect when there is no actual effect in the population.

```
sims_fp = [delayed_single_run(beta_1=0) for _ in range(reps)]
sims_fp_result = dask.compute(*sims_fp)

sims_fp_df = pd.concat(sims_fp_result).reset_index().rename(columns={'index':'term'})
```

```
print((sims_fp_df[sims_fp_df['term'] == 'genre_i']['p_value'].astype(float) < alpha).mean())
```

```
## 0.03333333333333333
```

Ideally, the false positive rate will be equal to alpha, which we set at 0.05.

Power for different effect sizes

In real life, we will not know the effect size of our quantity of interest and so we will need to repeatedly perform the power analysis over a range of different plausible effect sizes. Perhaps we might also want to calculate power as we vary other data-generating parameters, such as the number of pop and rock songs sampled and the number of subjects sampled. We can create a table that combines all combinations of the parameters we want to vary in a grid.

Note: There are two differences between Python and the R:

1. Python uses the "product" function to permutate and combine parameters, and then use "loop" and "dask.compute" to perform parallel computing;
2. Python couldn't repeatedly use parameter_search() and instead uses two layers of loop to realize multiple simulations of each permutation and combination of parameters.

```
 # grid of paramater values of interest
params = {
    'n_subj': [10, 50],
    'n_pop': [10, 40],
    'n_rock': [10, 40],
    'beta_1': [1, 3, 5]
}
```

We can now wrap delayed_single_run() function within a more general function parameter_search() that takes the grid of parameter values as input and uses the for statement to iterate over each row of parameter values in pgrid and feed them into delayed_single_run().

```
# fit the models over the parameters
def parameter_search(params):
    sims = []
    pgrid = pd.DataFrame(list(product(*params.values())), columns=params.keys())

    # iterate over the grid of parameter values
    for _, row in pgrid.iterrows():
        sims.append(delayed_single_run(
            n_subj=row['n_subj'], # plug each row of parameter values into single_run()
            n_pop=row['n_pop'],
            n_rock=row['n_rock'],
            beta_1=row['beta_1']
        ))
    return pd.concat(dask.compute(*sims)).reset_index().rename(columns={'index':'term'})
```

If we call parameter_search() it will return a single replication of simulations for each combination of parameter values in pgrid.

```
print(parameter_search(params))
```

```
##              term   Coef. Std.Err.        p_value  n_subj  n_pop  n_rock  beta_1
## 0       Intercept  58.856    1.946  5.013341e-201      10     10      10       1
## 1         genre_i   0.257    1.845   8.891837e-01      10     10      10       1
## 2     genre_i Var  11.725    1.591   3.352140e-01      10     10      10       1
## 3     song_id Var   5.300    0.433   1.092544e-01      10     10      10       1
## 4     subj_id Var  26.702    1.674   3.705448e-02      10     10      10       1
## ..            ...     ...      ...            ...     ...    ...     ...     ...
## 115     Intercept  58.856    1.091   0.000000e+00      50     40      40       5
## 116       genre_i   5.006    1.041   1.505314e-06      50     40      40       5
## 117   genre_i Var  17.347    0.591   3.303061e-04      50     40      40       5
## 118   song_id Var  13.383    0.525   1.800501e-03      50     40      40       5
## 119   subj_id Var  41.068    0.903   2.674191e-08      50     40      40       5
##
## [120 rows x 8 columns]
```

To run multiple replication of simulations for each combination of parameter values in pgrid, we can use the for statement to iterate over each row of parameter values in pgrid for the number of times specified by reps. Fair warning, this will take some time if you have set a high number of replications!

```
sims_params = []
pgrid = pd.DataFrame(list(product(*params.values())), columns=params.keys())

for _ in range(reps):
    for _, row in pgrid.iterrows():
        sims_params.append(delayed_single_run(
            n_subj=row['n_subj'],
            n_pop=row['n_pop'],
            n_rock=row['n_rock'],
            beta_1=row['beta_1']
        ))

sims_params_result = dask.compute(*sims_params)

sims_params_df = pd.concat(sims_params_result).reset_index().rename(columns={'index':'term'})
print(sims_params_df)
```

```
##               term   Coef. Std.Err.  ...  n_pop  n_rock  beta_1
## 0        Intercept  62.540    2.340  ...     10      10       1
## 1          genre_i   1.318    2.350  ...     10      10       1
## 2      genre_i Var  27.186    2.311  ...     10      10       1
## 3      song_id Var   7.069    0.534  ...     10      10       1
## 4      subj_id Var  40.711    2.445  ...     10      10       1
## ...            ...     ...      ...  ...    ...     ...     ...
## 3595     Intercept  59.836    1.241  ...     40      40       5
## 3596       genre_i   6.691    0.939  ...     40      40       5
## 3597   genre_i Var  16.707    0.505  ...     40      40       5
## 3598   song_id Var   9.669    0.221  ...     40      40       5
## 3599   subj_id Var  63.353    1.649  ...     40      40       5
##
## [3600 rows x 8 columns]
```

Now, as before, we can calculate power. But this time we'll group by all of the parameters we manipulated in pgrid, so that we can get power estimates for all combinations of parameter values.

```
sims_table = sims_params_df.query("term == 'genre_i'").groupby(['term', 'n_subj', 'n_pop', 'n_rock', 'be
    mean_estimate=pd.NamedAgg(column='Coef.', aggfunc=lambda x: x.astype(float).mean()),
    mean_se=pd.NamedAgg(column='Std.Err.', aggfunc=lambda x: x.astype(float).mean()),
    power=pd.NamedAgg(column='p_value', aggfunc=lambda x: (x.astype(float) < alpha).mean())
).reset_index()
```

Here's a formatted table that summarizes the output from the power simulation.

```
print(sims_table)
```

```
##         term  n_subj  n_pop  n_rock  beta_1  mean_estimate   mean_se     power
## 0    genre_i      10     10      10       1       0.731000  2.384367  0.000000
## 1    genre_i      10     10      10       3       3.210467  2.334467  0.266667
## 2    genre_i      10     10      10       5       5.346733  2.401833  0.666667
## 3    genre_i      10     10      40       1       0.732733  2.279933  0.033333
## 4    genre_i      10     10      40       3       2.813300  2.235633  0.266667
## 5    genre_i      10     10      40       5       5.367933  2.219733  0.600000
```

```
## 6   genre_i      10     40      10       1       1.022267  2.228433  0.100000
## 7   genre_i      10     40      10       3       2.872600  2.277933  0.233333
## 8   genre_i      10     40      10       5       5.759067  2.142300  0.766667
## 9   genre_i      10     40      40       1       0.977933  1.963667  0.033333
## 10  genre_i      10     40      40       3       3.184467  2.000267  0.366667
## 11  genre_i      10     40      40       5       5.354067  2.007600  0.800000
## 12  genre_i      50     10      10       1       1.285100  1.573967  0.133333
## 13  genre_i      50     10      10       3       2.732200  1.523200  0.466667
## 14  genre_i      50     10      10       5       4.843667  1.486400  0.833333
## 15  genre_i      50     10      40       1       0.865067  1.355733  0.033333
## 16  genre_i      50     10      40       3       3.286367  1.388467  0.600000
## 17  genre_i      50     10      40       5       5.274133  1.423333  1.000000
## 18  genre_i      50     40      10       1       0.882467  1.325733  0.133333
## 19  genre_i      50     40      10       3       2.717300  1.343567  0.533333
## 20  genre_i      50     40      10       5       4.459967  1.355567  0.933333
## 21  genre_i      50     40      40       1       0.927400  0.961333  0.100000
## 22  genre_i      50     40      40       3       3.137267  0.982300  0.933333
## 23  genre_i      50     40      40       5       5.198767  0.983833  1.000000
```

Here's a graph that visualizes the output of the power simulation.

```python
# transform data type and create labels
sims_table['n_subj'] = sims_table['n_subj'].astype(str)
sims_table['n_pop'] = 'n_pop: ' + sims_table['n_pop'].astype(str)
sims_table['n_rock'] = 'n_rock: ' + sims_table['n_rock'].astype(str)

# plot
fig, axes = plt.subplots(len(sims_table['n_pop'].unique()), len(sims_table['n_rock'].unique()), figsize
axes = axes.flatten()

# plot
for i, (pop, rock) in enumerate(sims_table.groupby(['n_pop', 'n_rock'])):
    ax = axes[i]
    sns.lineplot(data=rock, x='mean_estimate', y='power', hue='n_subj', style='n_subj', markers=True, a
    ax.axhline(y=0.8, linestyle='dashed', linewidth=0.5)
    # ax.set_title(f'{pop} x {rock}')
    ax.set_xlabel('Effect size (rock genre - pop genre)')
    ax.set_ylabel('Power')
    ax.set_ylim(0, 1)
    ax.legend(title='Sample size')
```

```
## <Axes: xlabel='mean_estimate', ylabel='power'>
## <matplotlib.lines.Line2D object at 0x7fccae0d98d0>
## Text(0.5, 0, 'Effect size (rock genre - pop genre)')
## Text(0, 0.5, 'Power')
## (0.0, 1.0)
## <matplotlib.legend.Legend object at 0x7fccae0c4820>
## <Axes: xlabel='mean_estimate', ylabel='power'>
## <matplotlib.lines.Line2D object at 0x7fccace861a0>
## Text(0.5, 0, 'Effect size (rock genre - pop genre)')
## Text(0, 0.5, 'Power')
## (0.0, 1.0)
## <matplotlib.legend.Legend object at 0x7fccace87160>
```

```
## <Axes: xlabel='mean_estimate', ylabel='power'>
## <matplotlib.lines.Line2D object at 0x7fccadcf0280>
## Text(0.5, 0, 'Effect size (rock genre - pop genre)')
## Text(0, 0.5, 'Power')
## (0.0, 1.0)
## <matplotlib.legend.Legend object at 0x7fccae0624d0>
## <Axes: xlabel='mean_estimate', ylabel='power'>
## <matplotlib.lines.Line2D object at 0x7fccadcc0700>
## Text(0.5, 0, 'Effect size (rock genre - pop genre)')
## Text(0, 0.5, 'Power')
## (0.0, 1.0)
## <matplotlib.legend.Legend object at 0x7fccace7a980>
```

```
# layout adjustmentS
plt.tight_layout()

# show the plot
plt.show()
```