

BM5033 Final Exam

Submitted by:

BM23MTECH11002
BM23MTECH11006
BM23MTECH11007
EE20BTECH11016

Contents

| | | |
|----------|--|-----------|
| 1 | Import libraries | 2 |
| 2 | Data Info | 2 |
| 2.1 | Columns | 2 |
| 2.2 | Conditions | 2 |
| 3 | Convert dat files to Dataframe | 3 |
| 4 | Import DataFrame | 3 |
| 5 | Data Analysis | 4 |
| 6 | Statistical Tests | 31 |
| 7 | Final Inference | 72 |
| 8 | Suggesting changes in experimental methodology. | 72 |

1 Import libraries

```
[ ]: import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import altair as alt
import scipy
from sklearn.linear_model import LinearRegression
import statsmodels.api as sm
from scipy import stats
```

2 Data Info

2.1 Columns

- p1_lvl - Expression levels of P1 in each cell (in arbitrary units)
- p2_lvl - Expression levels of P2 in each cell (in arbitrary units)
- cell_area - Size of the molecule
- maj-axis - major axis length of each cell (approximating the shape of the cell cross-section to be elliptical)
- min_axis - minor axis length of each cell
- condition - Experimental Condition
- replication - Repetition count under each condition

2.2 Conditions

- e0x - Normal setup (WT) without any modifications
 - e1x - The expression levels of the protein P1 were reduced while keeping that of P2 intact
 - e2x - The expression levels of the protein P2 were reduced while keeping that of P1 intact
 - e3x - The expression levels of the protein P1 were increased while keeping that of P2 intact
 - e4x - The expression levels of the protein P2 were increased while keeping that of P1 intact
- x = 1, 2, 3 depending on the number of repetition

In entire code,

- e0 contains data of e01,e02,e03
 - e1 contains data of e11,e12,e13
 - e1 contains data of e21,e22,e23
 - e1 contains data of e31,e32,e33
 - e1 contains data of e41,e42,e43
-

3 Convert dat files to DataFrame

```
[ ]: def read_data_file(path, condition, replication):  
    """Reads data file based on condition, replications and returns a DataFrame  
  
    Args:  
        condition: Experimental condition.  
        replication: Replication number.  
  
    Returns: DataFrame containing the data from input file.  
    """  
  
    file_path = f'{path}{condition}{replication}.dat' # Data file path  
    data=[i.strip().split() for i in open(file_path).readlines()] # splits the  
    ↪ data based on spaces and them as nested lists  
  
    # Create DataFrame  
    df=pd.DataFrame(data,columns=columns)  
  
    # Append condition and replicaton value to respective data  
    df['condition'] = condition  
    df['replication'] = replication  
  
    return df  
  
[ ]: columns=['p1_lvl', 'p2_lvl', 'cell_area', 'maj_axis', 'min_axis'] # Column Names  
    conditions = ['e0', 'e1', 'e2', 'e3', 'e4'] # Various Conditions  
    replications = ['1', '2', '3'] # Value representing number of replications  
  
    path="/content/drive/MyDrive/Data/Q1DataSets/Q1DataSet2/" # Replace it with your  
    ↪ File path  
    file_lst=os.listdir(path) # Returns list of all files in the respective directory  
    file_lst.sort() # Sort the list values  
  
    # Create a list of DataFrames, one for each condition and replication  
    df = pd.concat([read_data_file(path, c, r) for c in conditions for r in  
    ↪ replications])  
  
    df.to_csv("DataSet2.csv", index=False)
```

4 Import DataFrame

```
[ ]: df=pd.read_csv('DataSet2.csv') # This dataframe includes all the 15 .dat file  
    ↪ combined together  
    df
```

```
[ ]:      p1_lvl      p2_lvl  cell_area  maj_axis  min_axis  condition  \
0      285.79645  318.38006   88.48058   9.73106   3.09819         e0
1      228.01462  316.57763   95.36651  10.02494   3.14376         e0
2      331.06314  352.47901   95.07759  10.57045   3.02686         e0
3      368.32333  345.23546   57.87355   8.17404   2.39859         e0
4      318.78085  348.54889   69.52686   9.03779   2.62459         e0
...      ...      ...      ...      ...      ...      ...
2953   247.09355  508.81594   75.22882  11.25593   2.23617         e4
2954   235.05288  506.63546   41.92317   8.41123   1.69518         e4
2955   240.23013  483.13104   24.83344   6.33961   1.37994         e4
2956   297.61694  490.77206   43.88618   8.48084   1.78321         e4
2957   230.33775  621.15607   26.73256   7.44577   1.25444         e4

      replication
0              1
1              1
2              1
3              1
4              1
...      ...
2953          3
2954          3
2955          3
2956          3
2957          3

[2958 rows x 7 columns]
```

5 Data Analysis

Important terminology

- distplot : It is suitable for comparing the range and distribution for groups of numerical data. Data is plotted as value points along an axis.
- heatmap : It provides an immediate visual summary of information across two axes, allowing users to quickly grasp the most important or relevant data points
- jointplot : It is a Python graph that visualizes the relationship between two variables.
- correlation : Relation between an attribute to every other attribute . It varies from -1 to 1 . Better the value better the relation .

```
[ ]: ## Distribution plot for p1 and p2 for all the 15 .dat file combined together

f, ax = plt.subplots(1, 1)

# Plot the distribution of the 'p1_lvl' column with a histogram, kernel density
↪estimate (KDE), and rug plot
sns.distplot(df['p1_lvl'],kde=True,hist=True,rug=True,label="p1")
```

```

# Plot the distribution of the 'p2_lvl' column with a histogram and KDE, but
↳without a rug plot
sns.distplot(df['p2_lvl'],kde=True,hist=True,rug=False,label="p2")
plt.xlabel("protien level")

ax.legend()

plt.show() # Display plot

```

<ipython-input-39-de1c6d2e9e1f>:6: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see <https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751>

```

sns.distplot(df['p1_lvl'],kde=True,hist=True,rug=True,label="p1")
<ipython-input-39-de1c6d2e9e1f>:9: UserWarning:

```

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

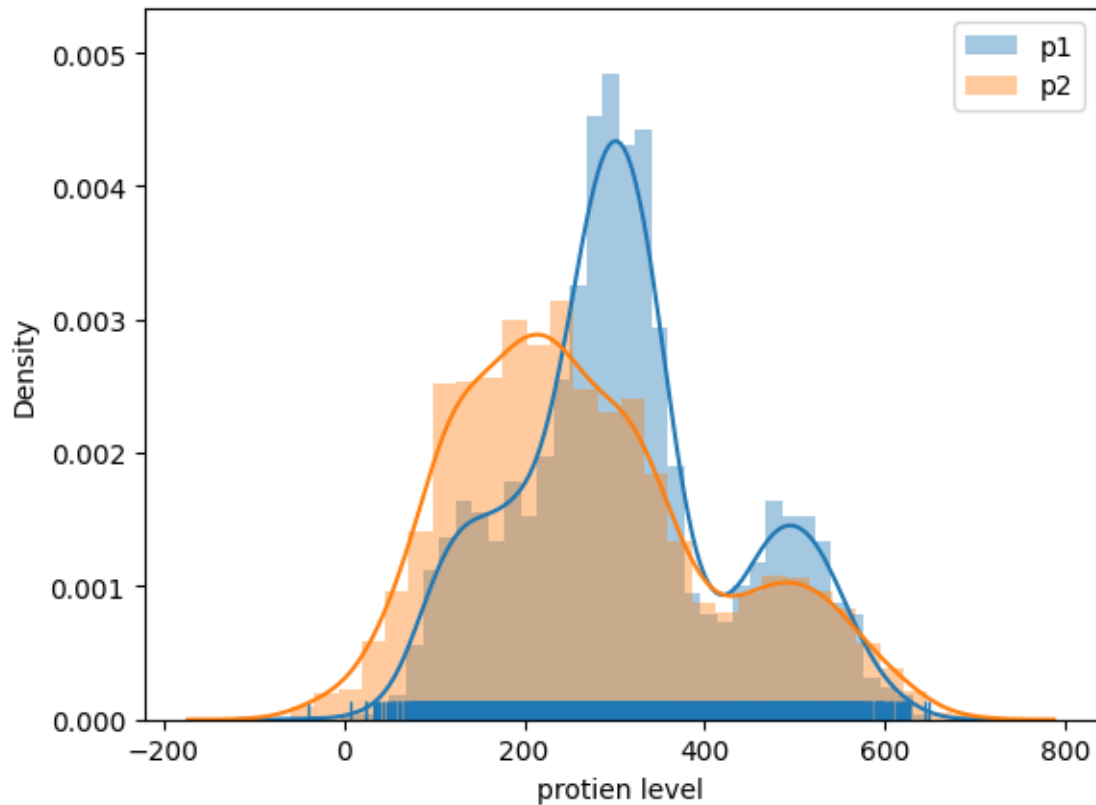
Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see <https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751>

```

sns.distplot(df['p2_lvl'],kde=True,hist=True,rug=False,label="p2")

```



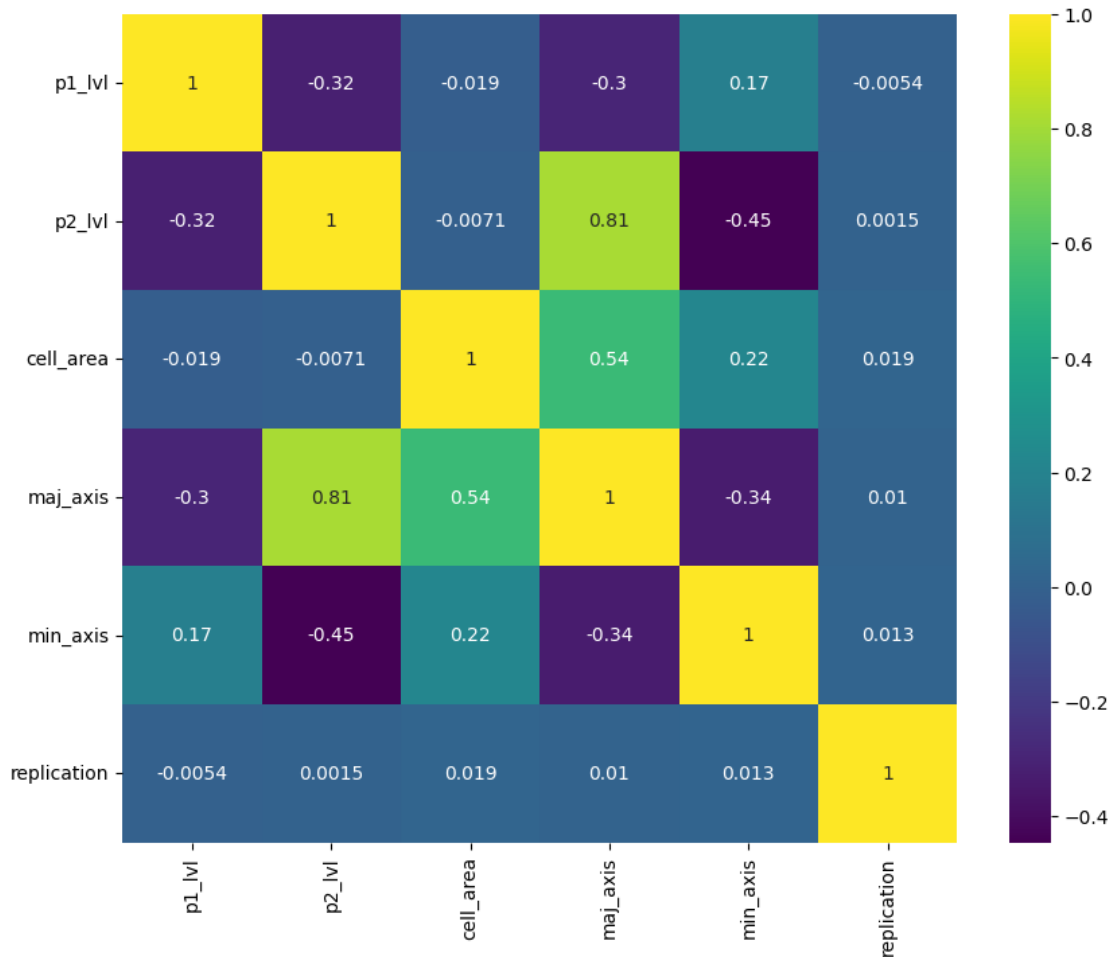
```
[ ]: ## heatmap for whole data (all 15 appended datasets) to have broader picture on  

     ↪ how data is correlated.
```

```
# Compute the correlation matrix  
corr_matrix = df.corr()  
  
# Plot the correlation heatmap  
sns.heatmap(corr_matrix, annot=True, cmap = 'viridis')  
  
# Set the figure size  
fig=plt.gcf()  
fig.set_size_inches(10,8)  
  
plt.show() # Display plot
```

<ipython-input-40-91cfcd2df138>:4: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.

```
corr_matrix = df.corr()
```



Inference : ->Close observation of the data reveals that, p1 and p2 are having near to zero correlation on cell area (size)

->P1 is having impact on major & min axes.

->P2 is having high corelation on major axis & mid negative correlation on minor axis.

```
[ ]: ## correlation under each condition

# Iterate over the unique experimental conditions
for i in df["condition"].value_counts()[df.condition.unique()].keys():
    # Drop replication column
    df1=df.drop(["replication"],axis=1)

    # Compute the correlation matrix and plot correlaton Heatmap
    sns.heatmap(df1[df1.condition==i].corr(), annot=True, cmap = 'viridis')

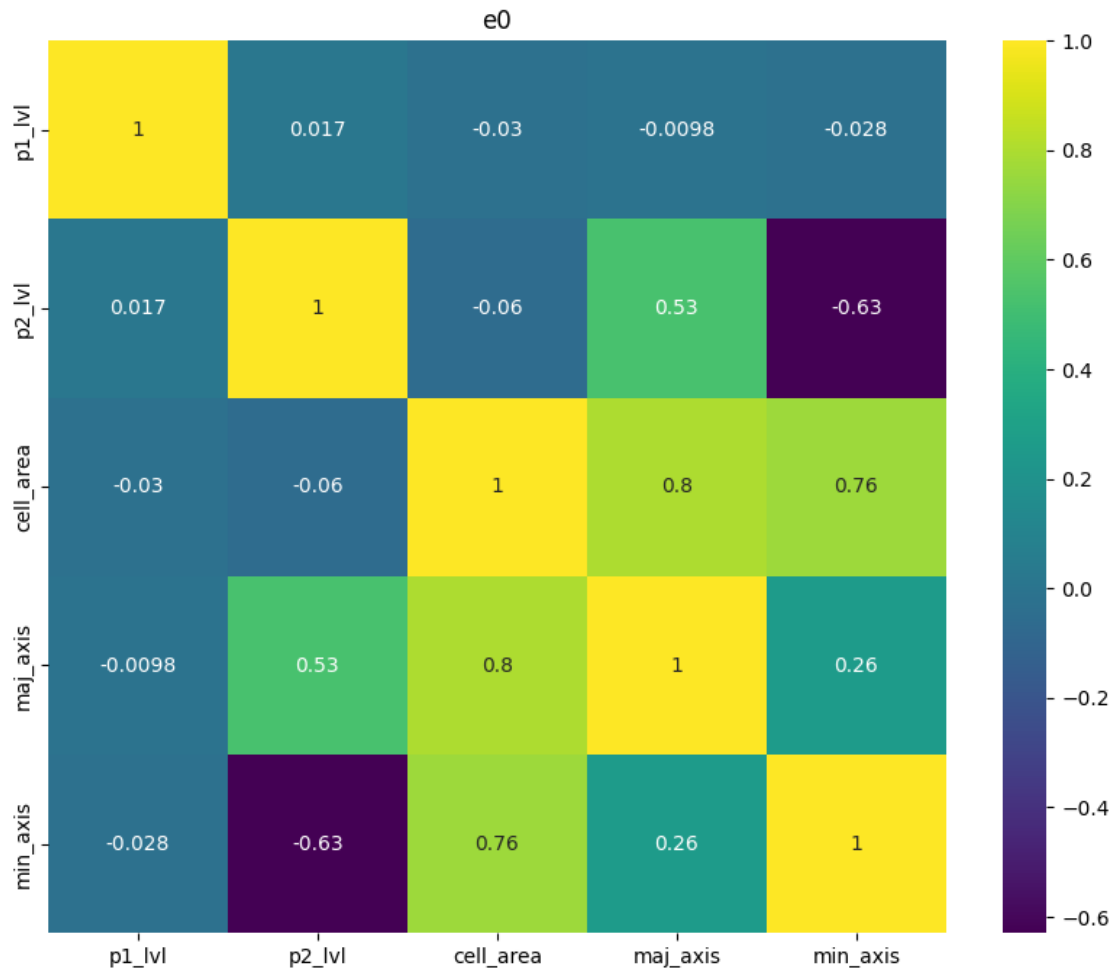
    # Set the figure size and title
```

```
fig=plt.gcf()
fig.set_size_inches(10,8)
plt.title(i)
```

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

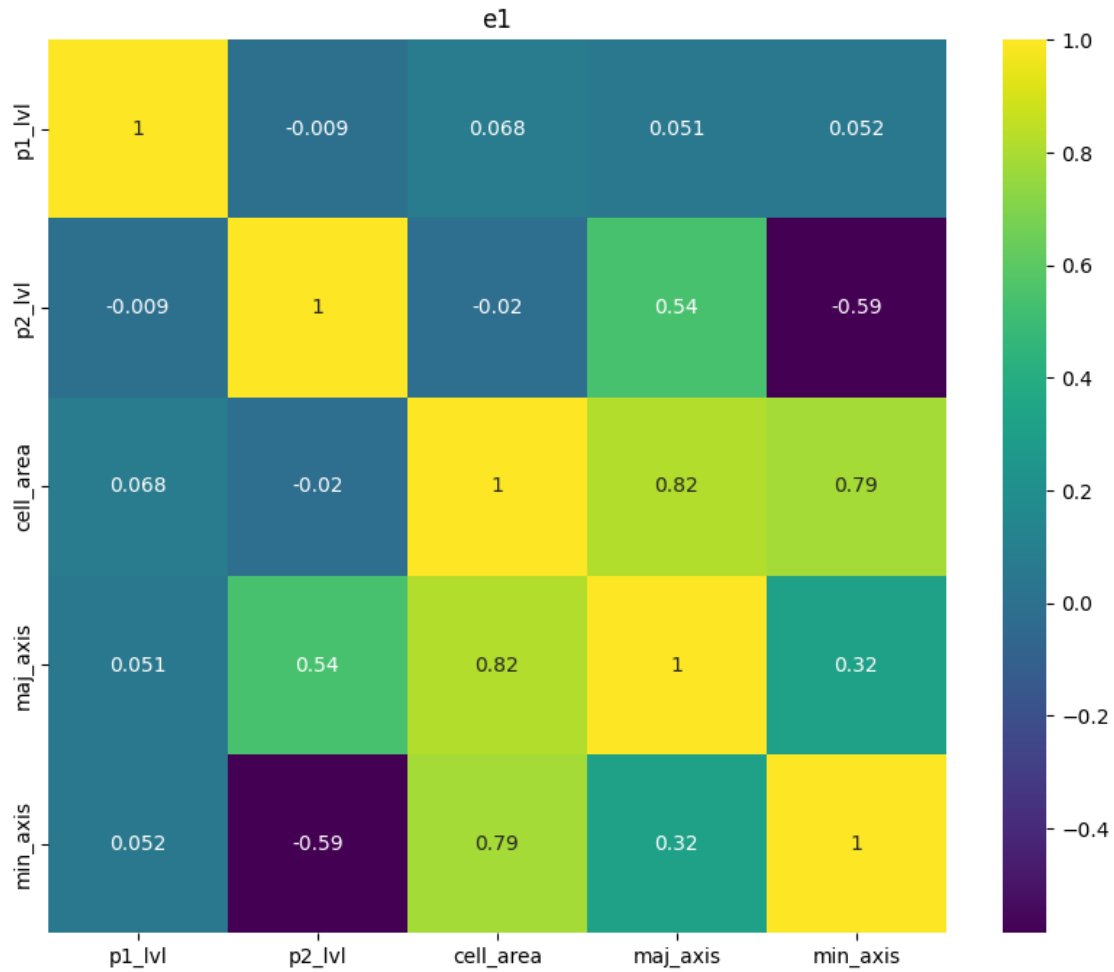
<ipython-input-41-521392304fce>:9: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.

```
sns.heatmap(df1[df1.condition==i].corr(), annot=True, cmap = 'viridis')
```



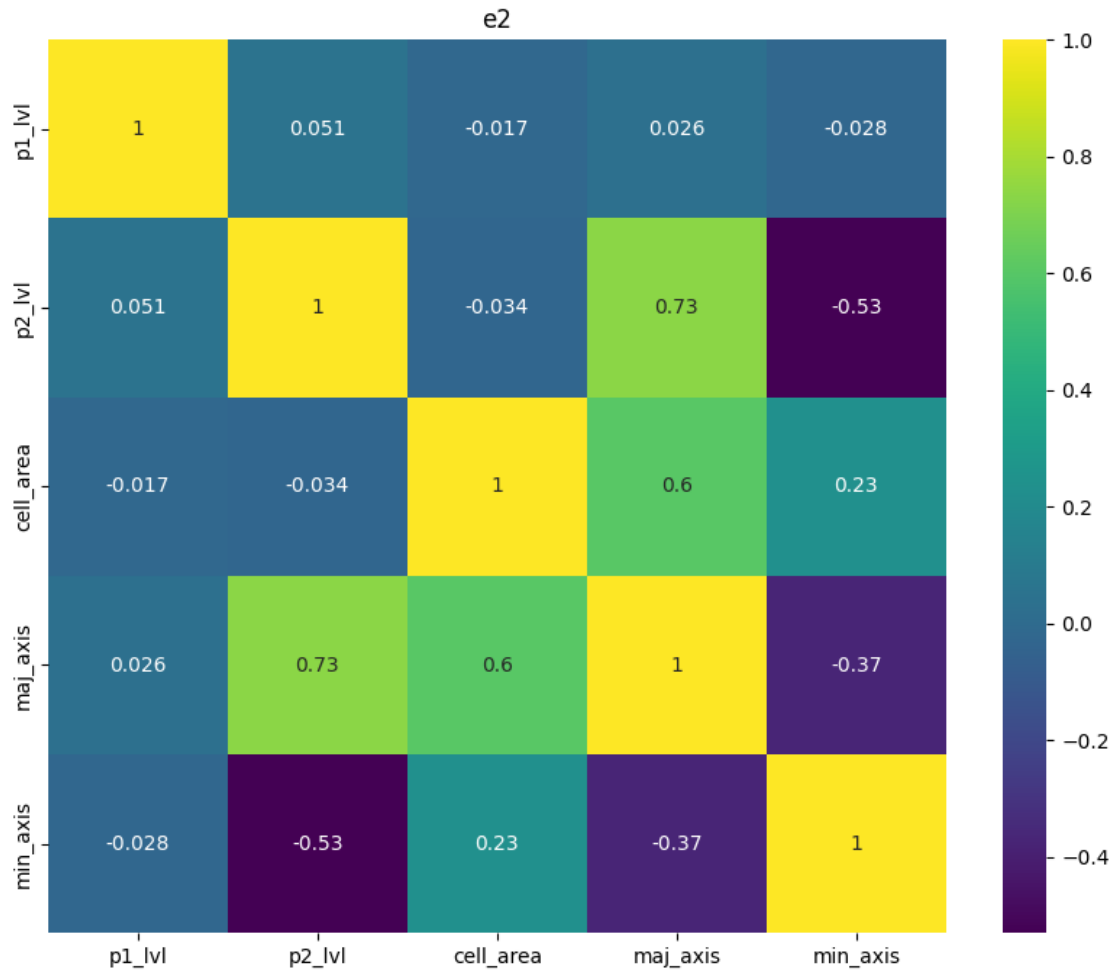
<ipython-input-41-521392304fce>:9: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.

```
sns.heatmap(df1[df1.condition==i].corr(), annot=True, cmap = 'viridis')
```

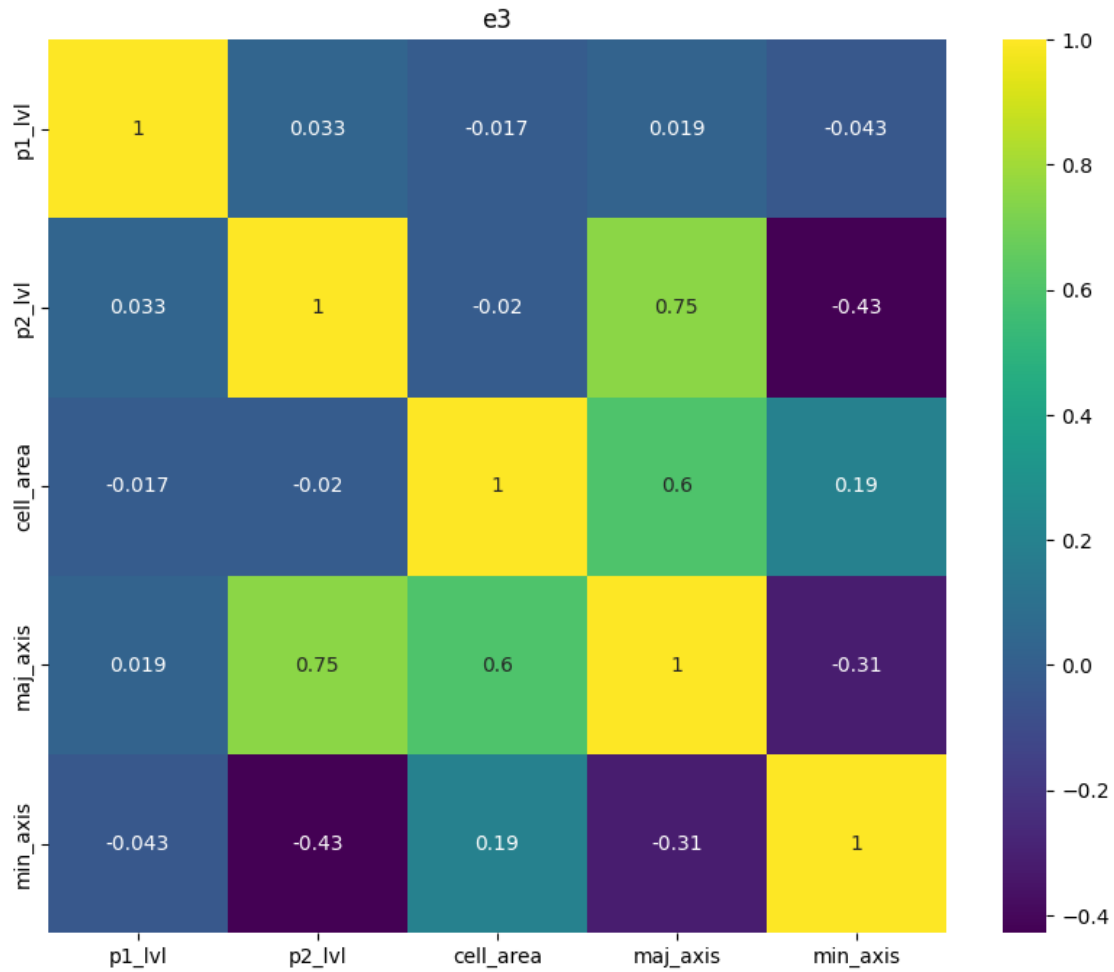
<ipython-input-41-521392304fce>:9: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.

```
sns.heatmap(df1[df1.condition==i].corr(), annot=True, cmap = 'viridis')
```



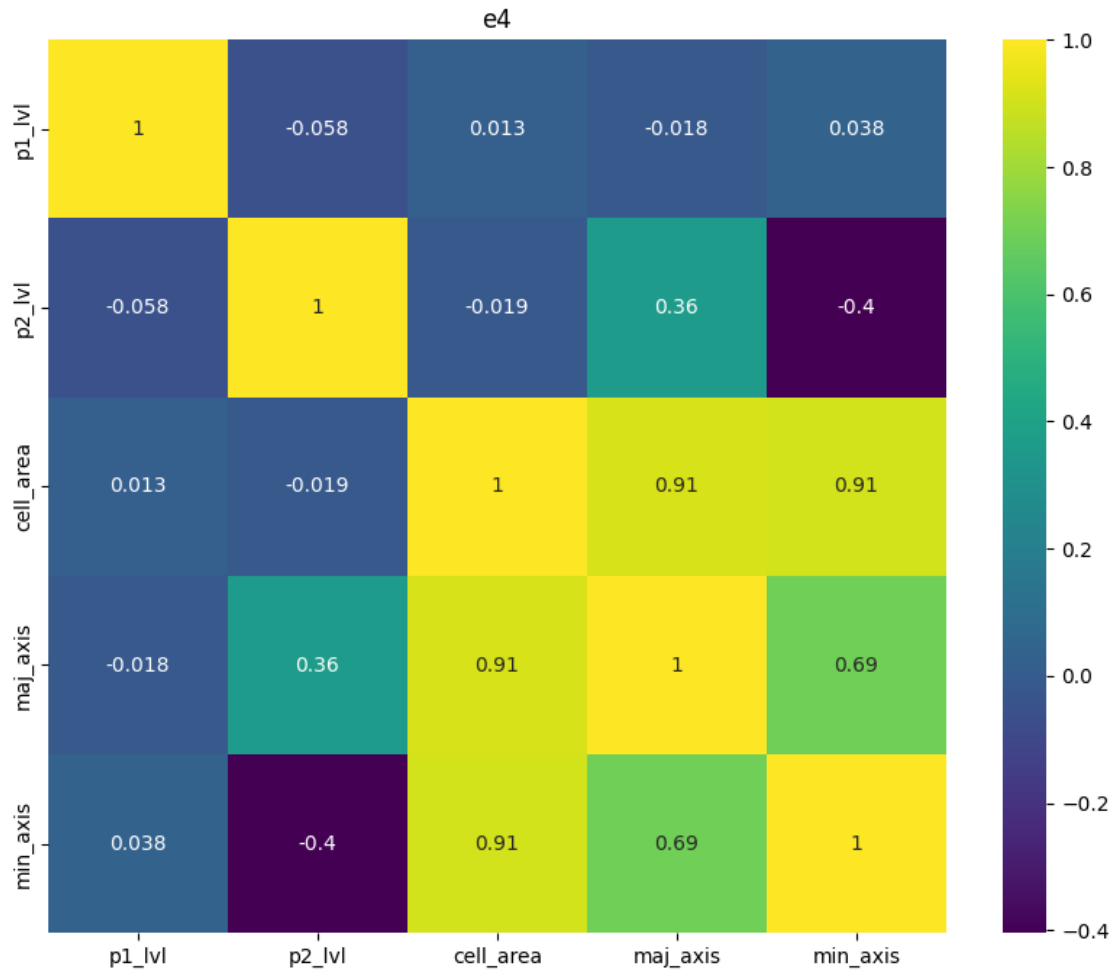
<ipython-input-41-521392304fce>:9: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.

```
sns.heatmap(df1[df1.condition==i].corr(), annot=True, cmap = 'viridis')
```



<ipython-input-41-521392304fce>:9: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.

```
sns.heatmap(df1[df1.condition==i].corr(), annot=True, cmap = 'viridis')
```



Inference :

As we have 5 different experimental conditions, we will be analyzing the data with each condition using heatmap. Overall, the impact of P1 & P2 on cell area has no change and is similar across all conditions. Similarly impact of P1 on major & minor axes follows the same. Also the impact of P2 on minor axis did not make much changes.

Changes were seen in P2 impact on major axis . We'll see impact in each condition :

e0,e1,e4 - Here it is around mid positive correlation

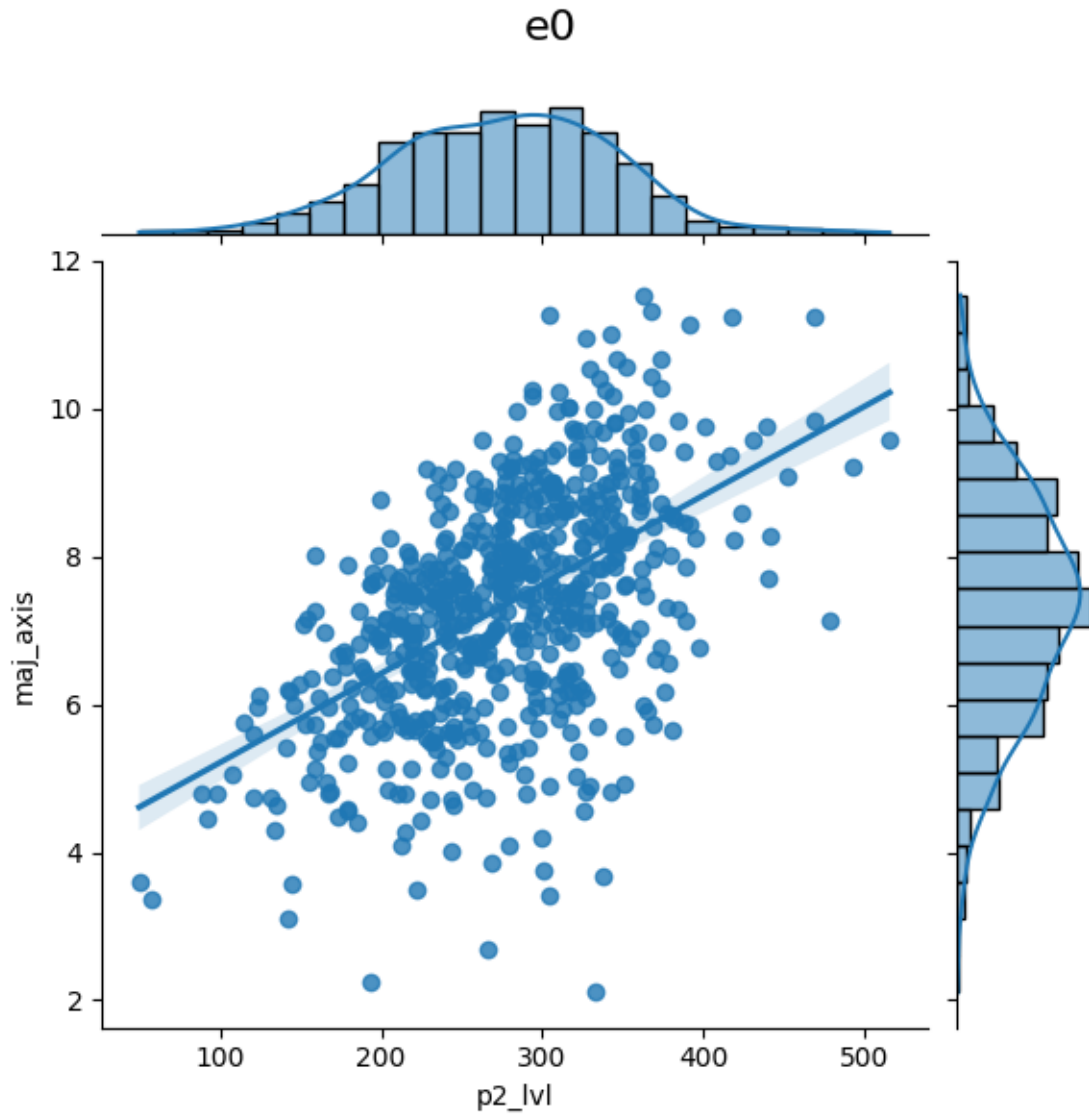
e2,e3 - It's showing high correlation in these two conditions i.e., when P2 is reduced keeping P1 intact or increasing P1 keeping P2 intact.

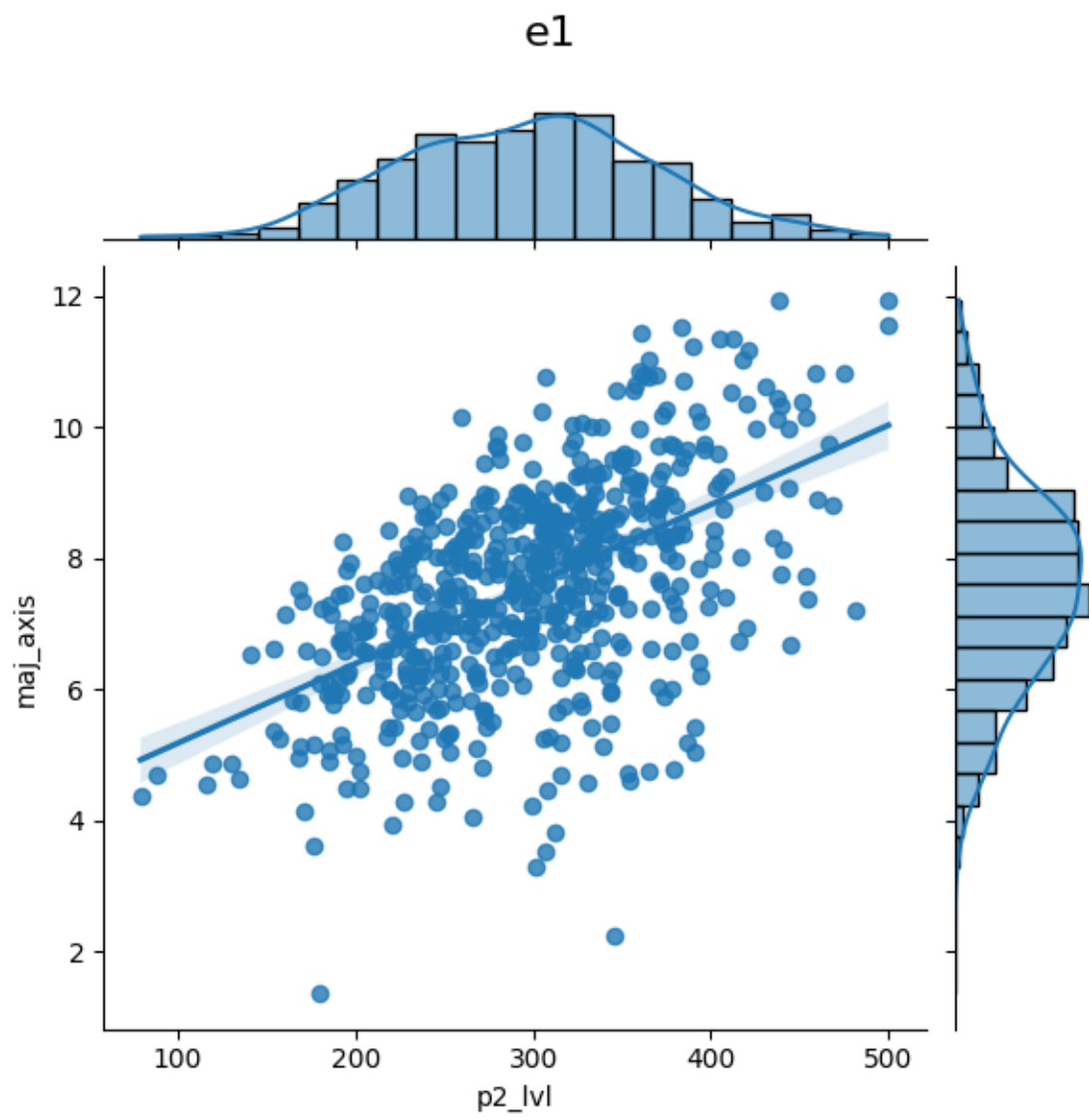
```
[ ]: ## p2 impact on major axis on each experimental condition (e0,e1,e2,e3,e4)

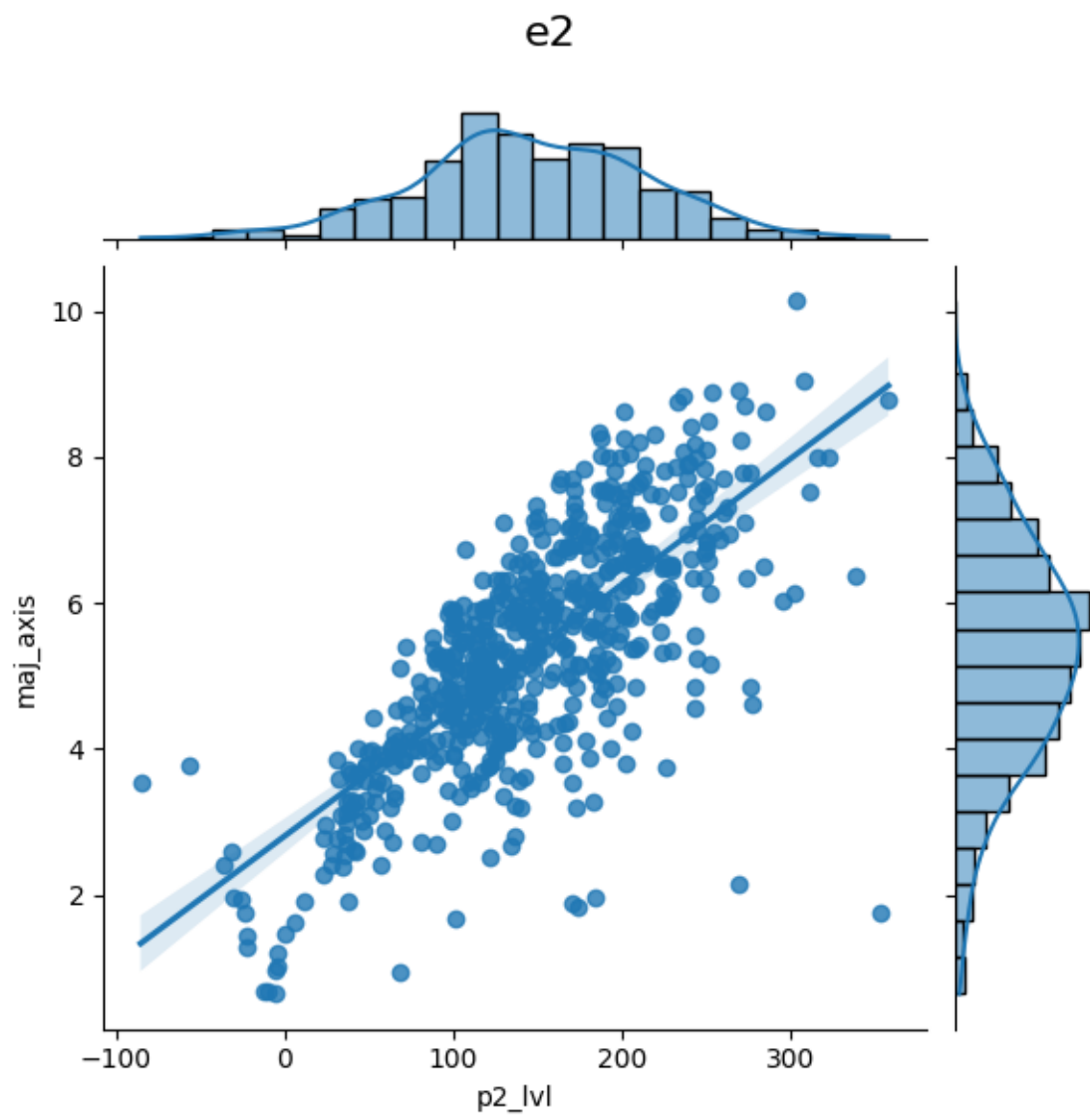
# Iterate over the unique experimental conditions
for i in df["condition"].value_counts()[df.condition.unique()].keys():
```

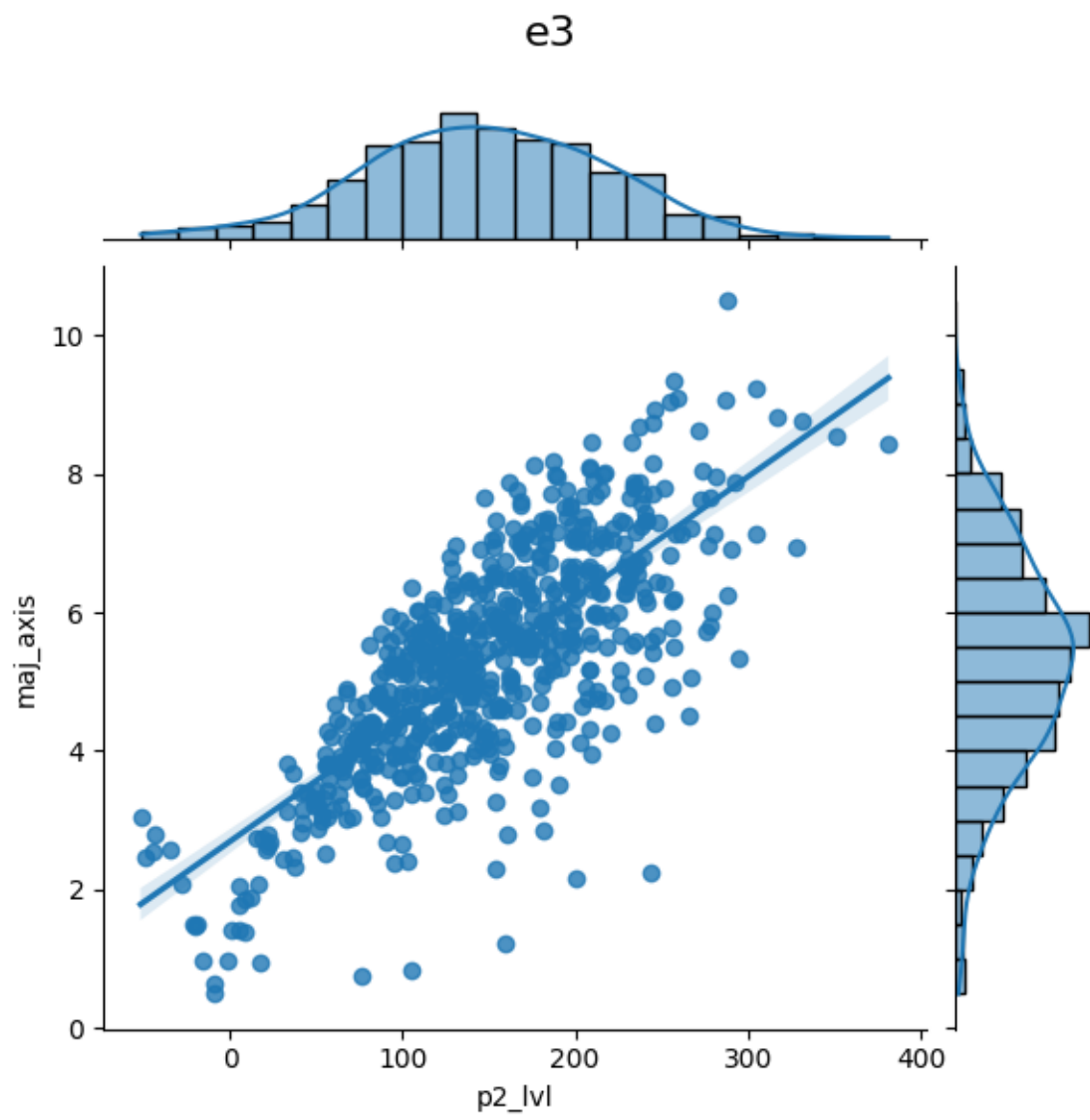
```
# Create a joint plot for the current condition
sns.jointplot(x='p2_lvl',y='maj_axis',data=df[df.condition==i],kind='reg')

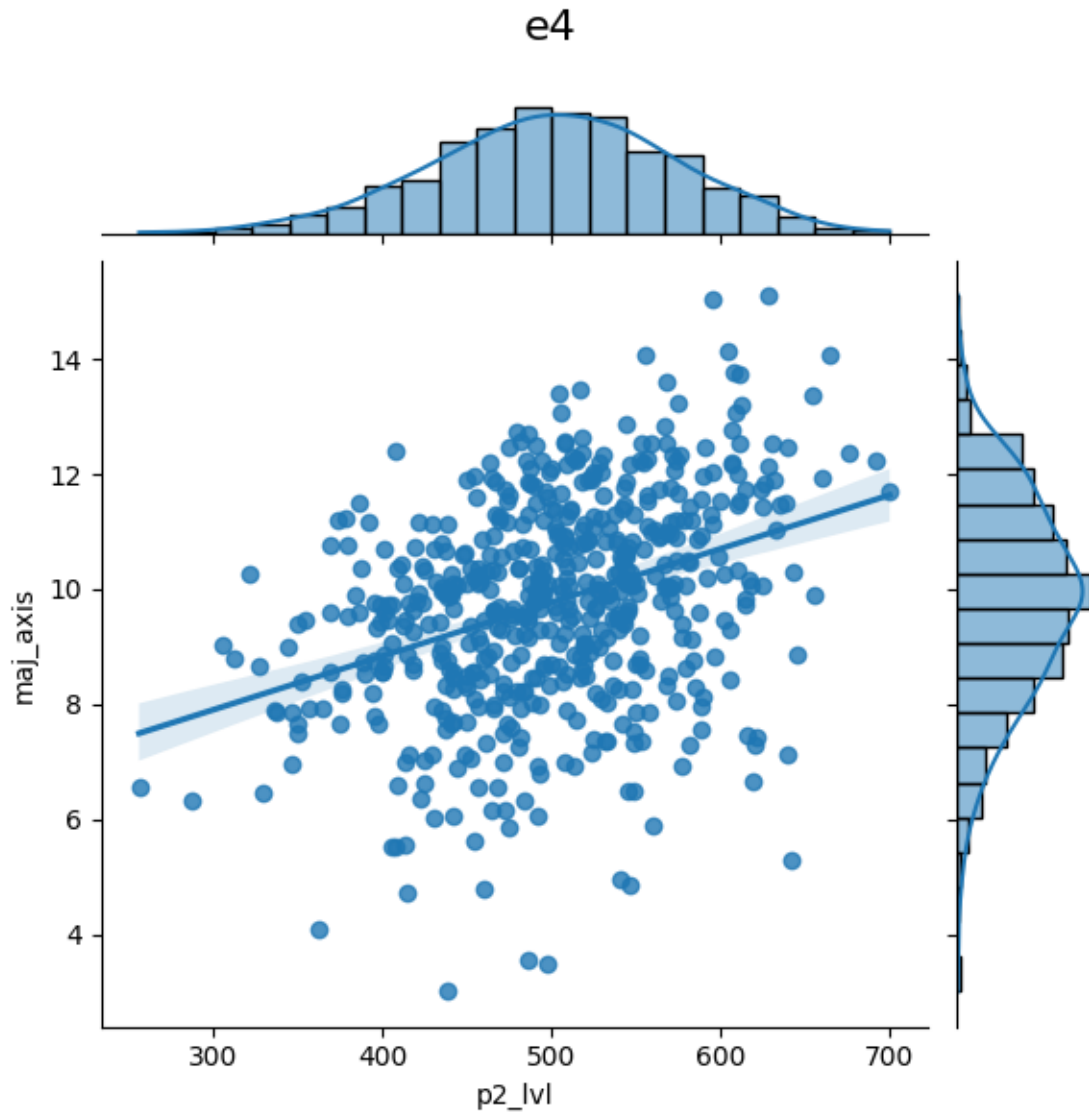
# Adjust the subplots and add centred title
plt.subplots_adjust(top=0.9)
plt.suptitle(i, fontsize = 16)
```











Inference :

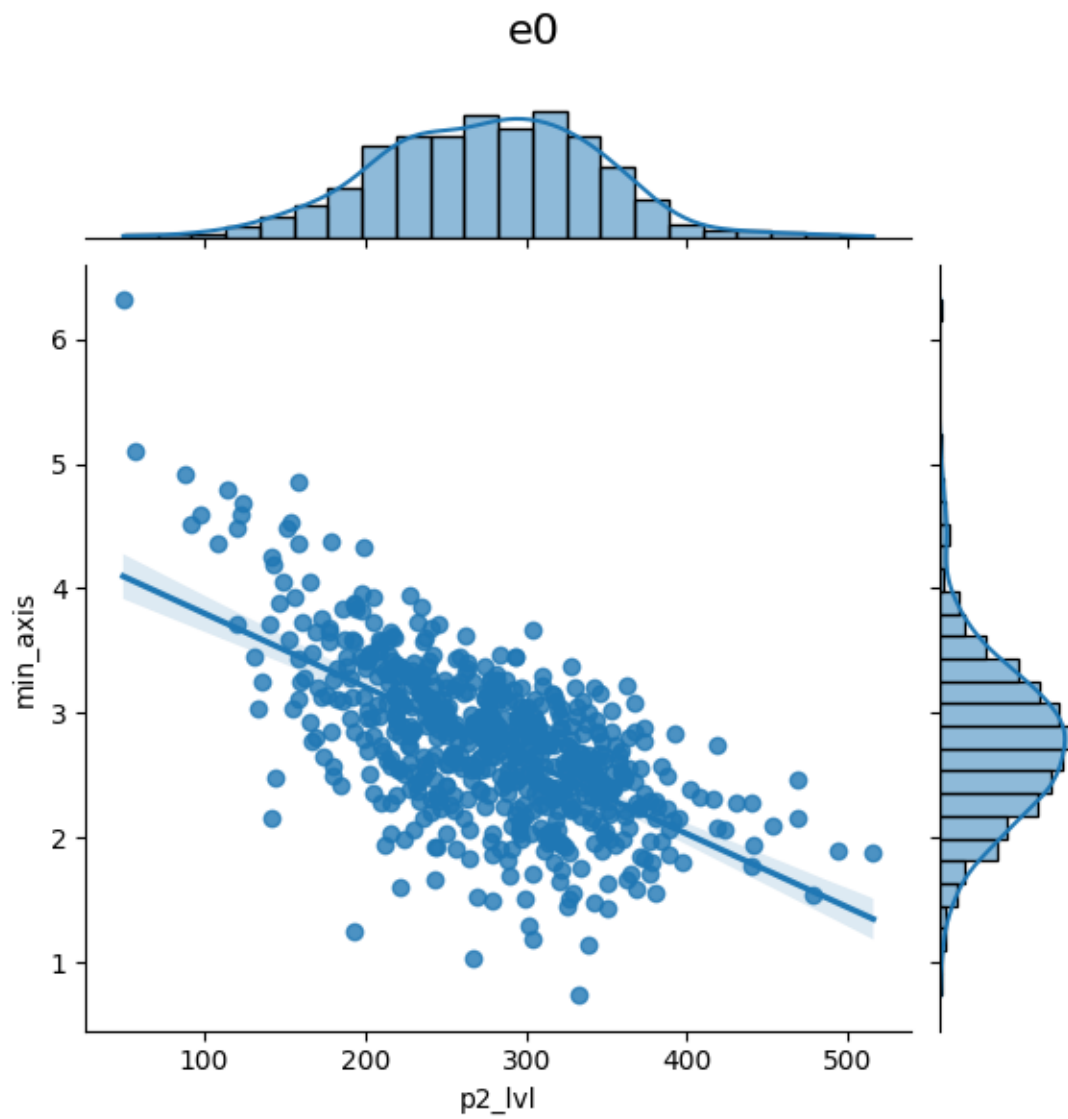
This is just a graphical representation of correlation value we saw in heatmap. Here we considered the impact of P2 on major axis under each condition.

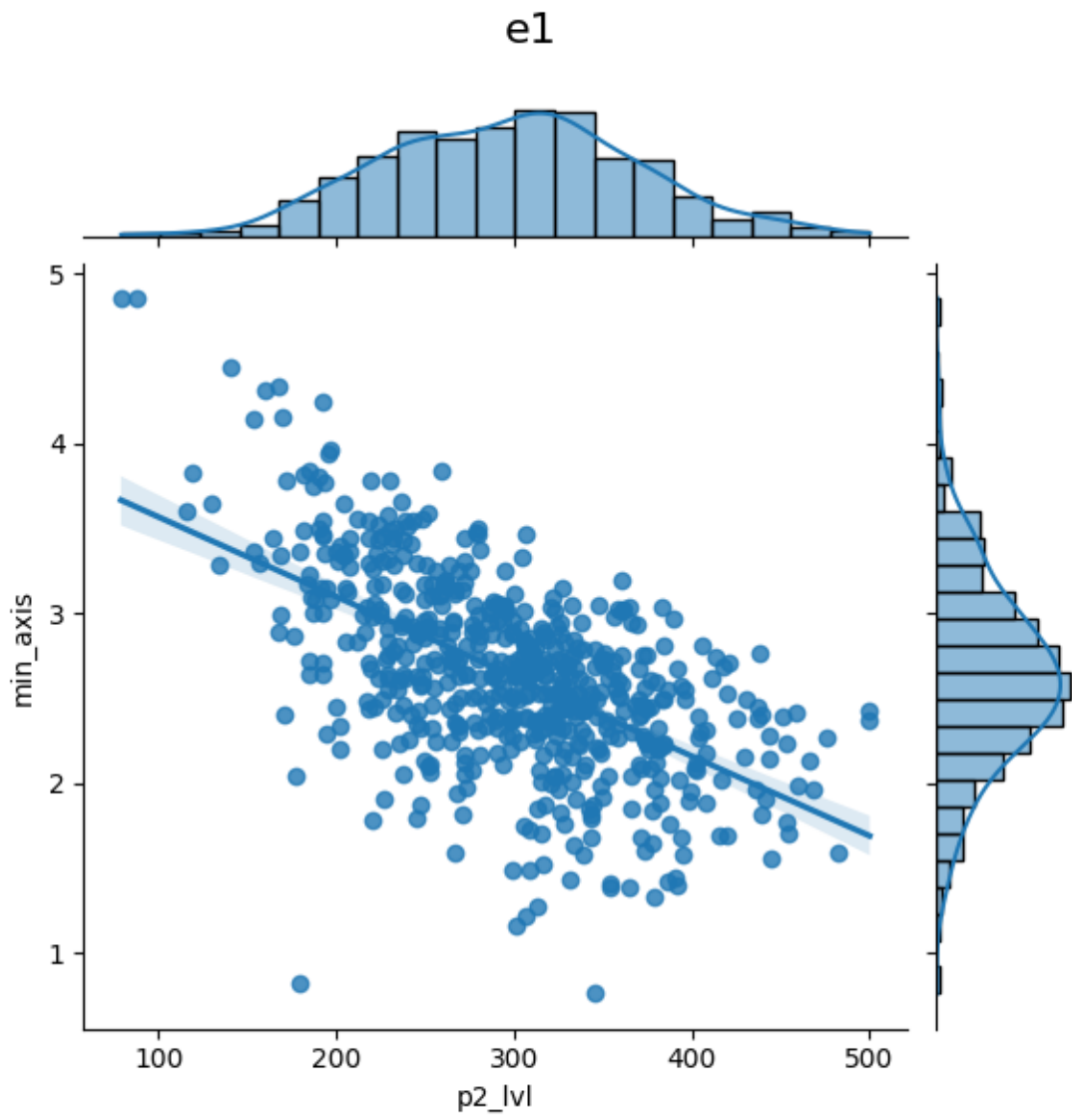
```
[ ]: ## p2 impact on minor axis on each experimental condition (e0,e1,e2,e3,e4)

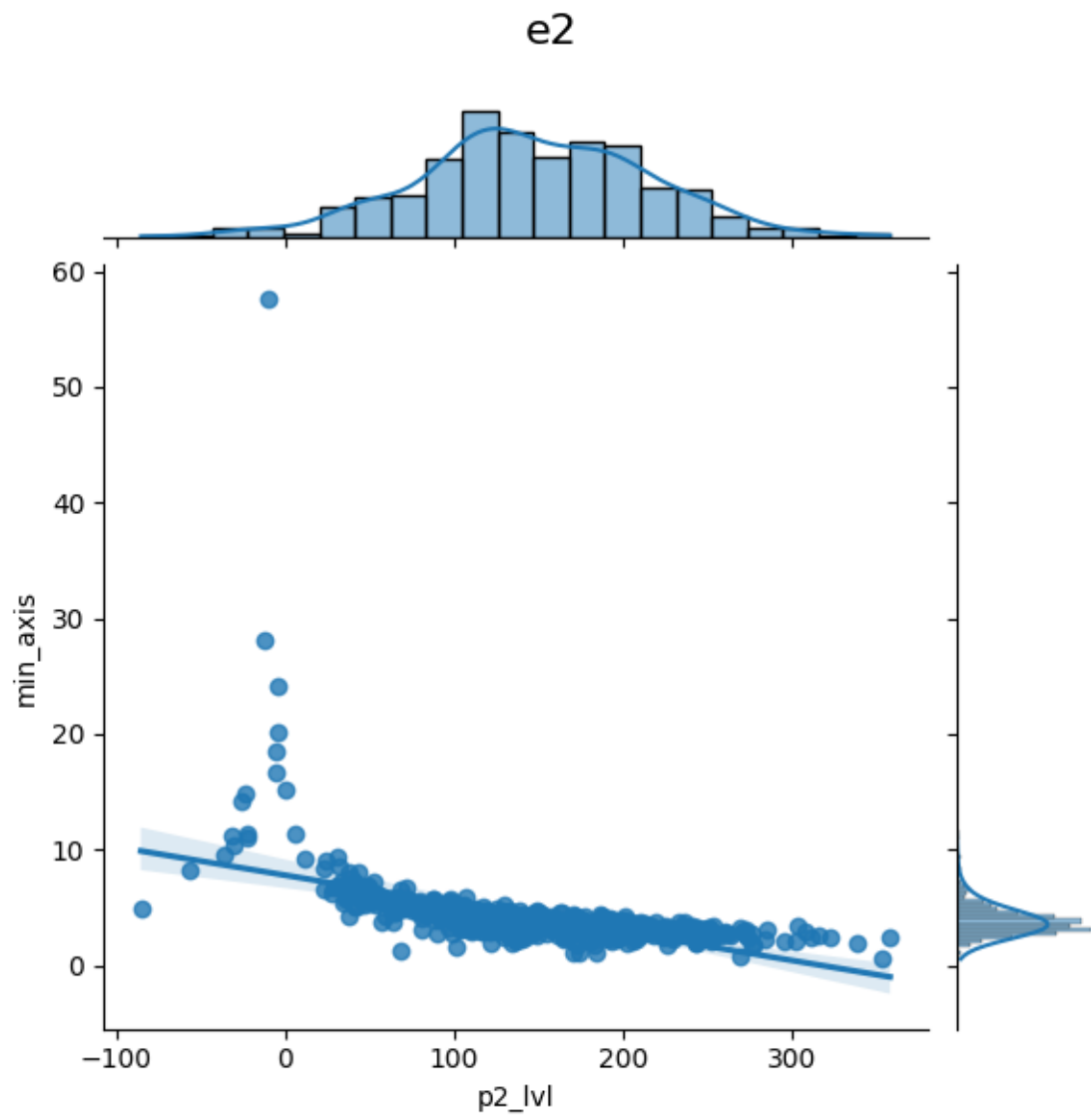
# Iterate over the unique experimental conditions
for i in df["condition"].value_counts()[df.condition.unique()].keys():

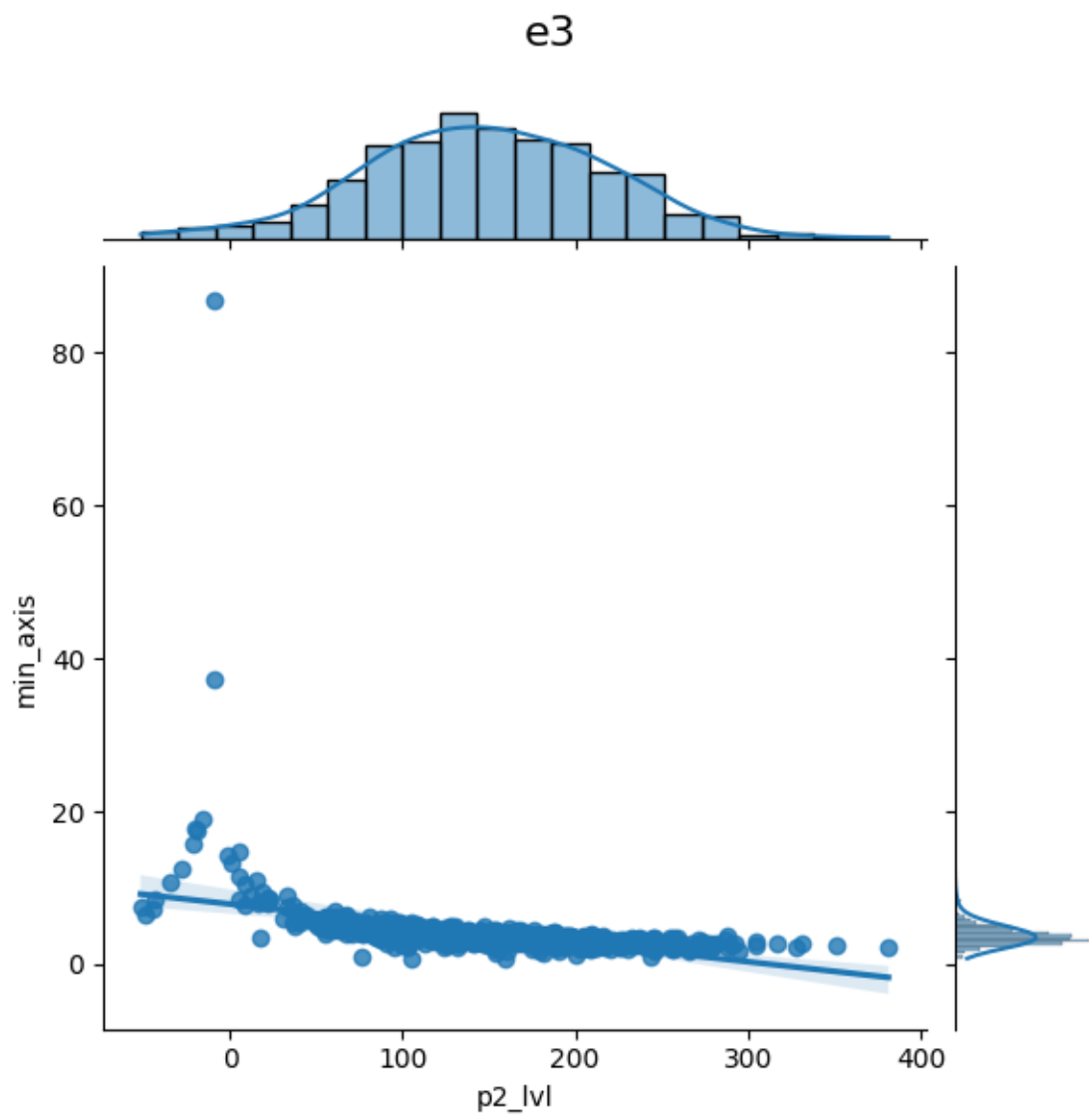
    # Create a joint plot for the current condition
    sns.jointplot(x='p2_lvl',y='min_axis',data=df[df.condition==i],kind='reg')
```

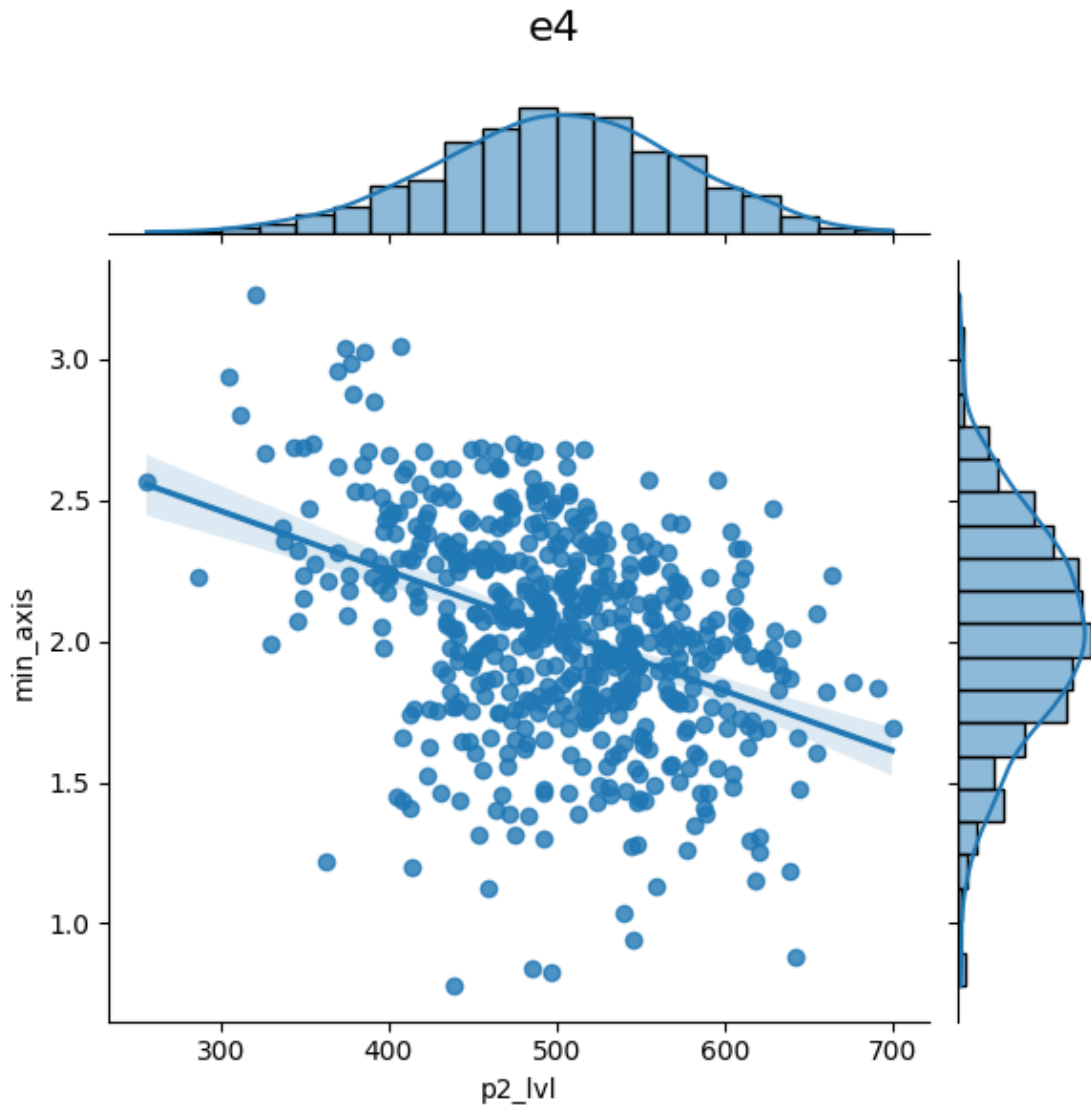
```
# Adjust the subplots and add centred title
plt.subplots_adjust(top=0.9)
plt.suptitle(i, fontsize = 16)
```











Inference :

This is just a graphical representation of correlation value we saw in heatmap. Here we considered the impact of P2 on minor axis under each condition.

```
[ ]: ## correlation under each replication of e2

# Iterate over the unique experimental conditions
for i in df["replication"].value_counts()[df.replication.unique()].keys():

    # Filter dataframe based on e2 condition
    df1=df[df.condition=='e2']
```

```

# Compute the correlation matrix and plot correlation Heatmap
sns.heatmap(df1[df1.replication==i].corr(), annot=True, cmap = 'viridis')

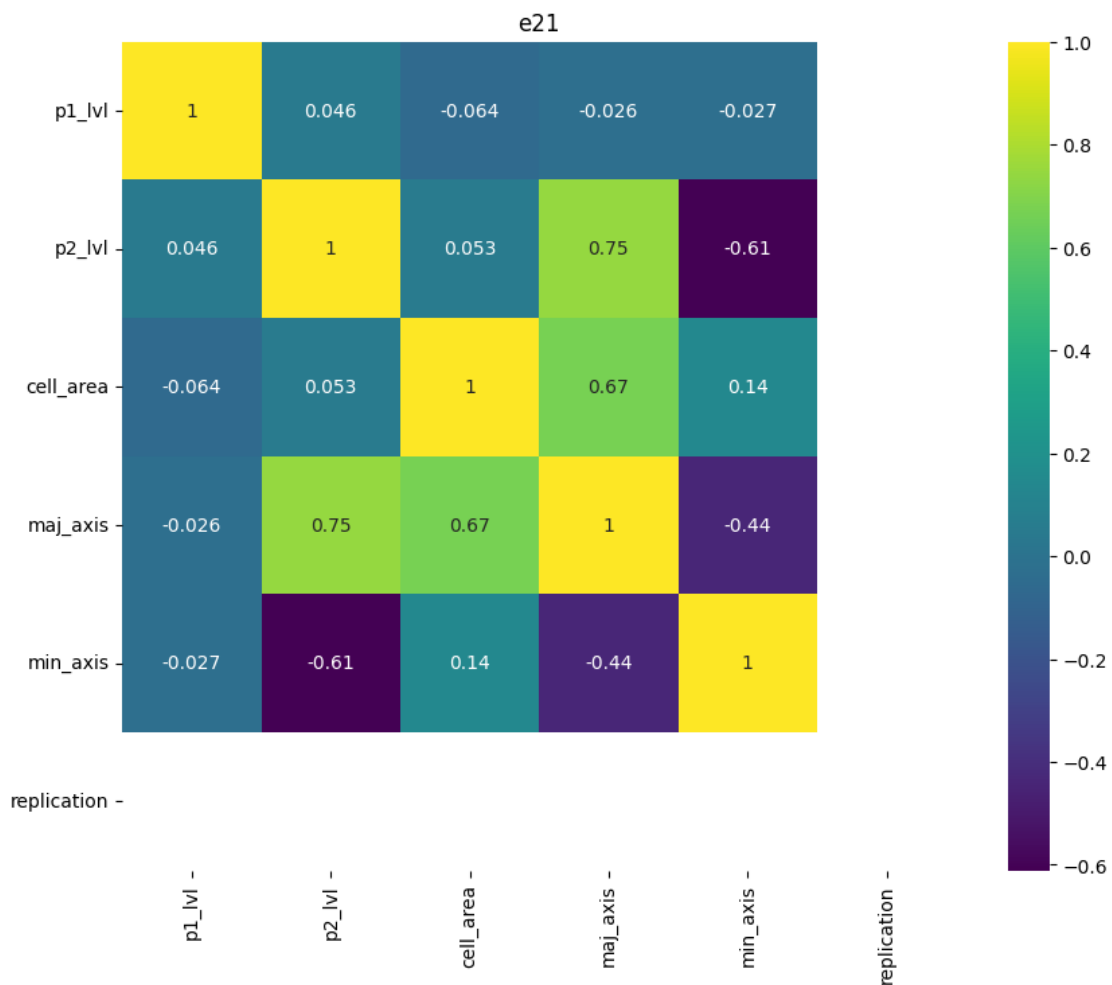
# Set the figure size and title
fig=plt.gcf()
fig.set_size_inches(10,8)
plt.title("e2"+str(i))

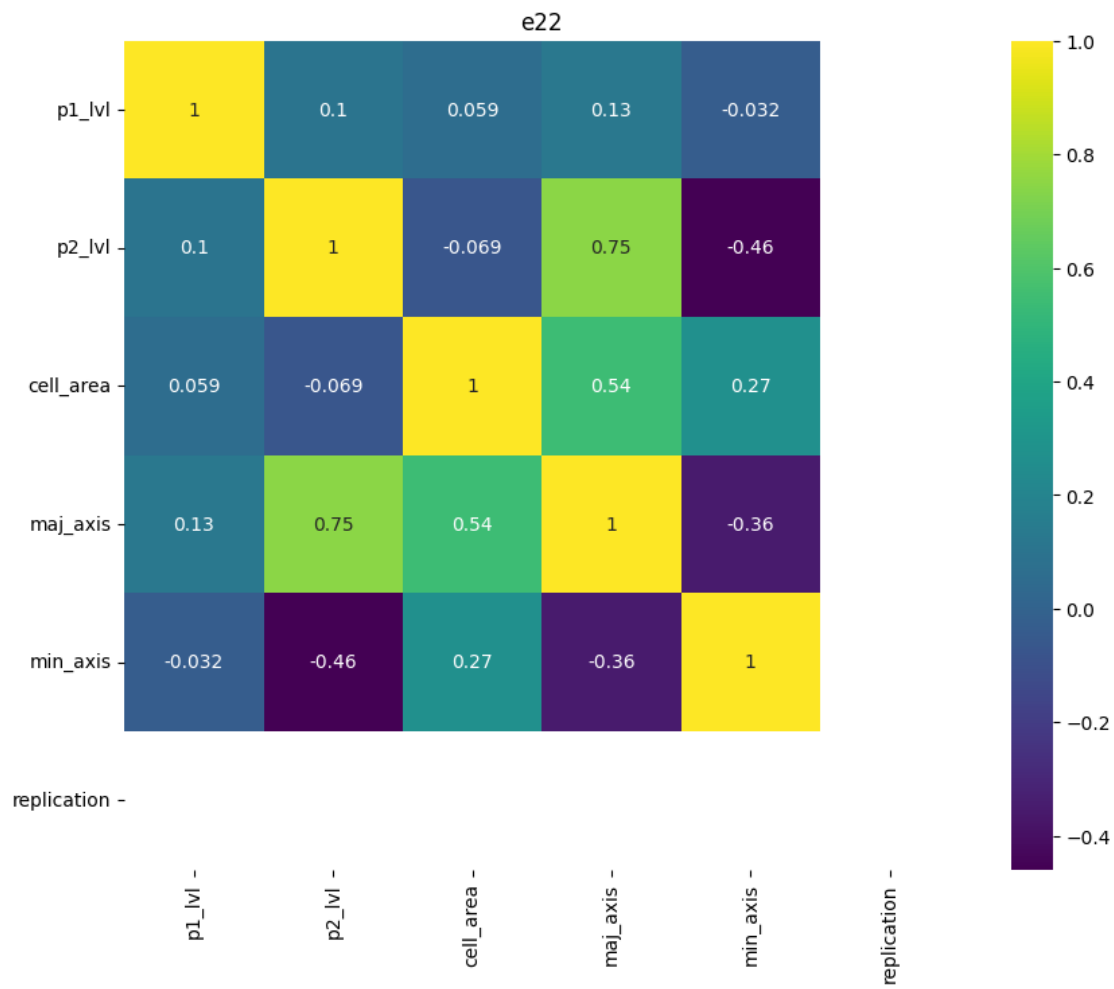
plt.show() # Display plot

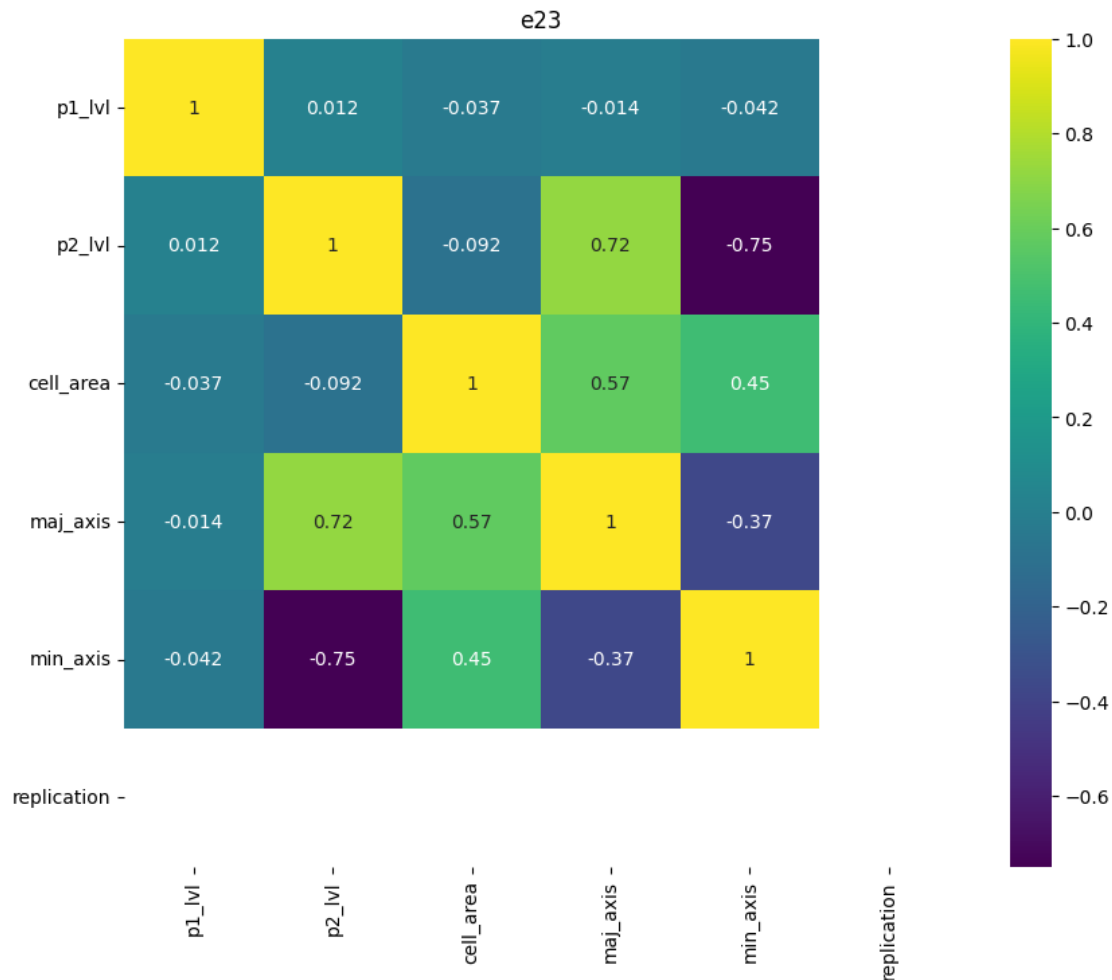
```

<ipython-input-44-40905197934d>:10: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.

```
sns.heatmap(df1[df1.replication==i].corr(), annot=True, cmap = 'viridis')
```







Inference :

Here we're trying to see how the data is behaving with each repetition under e2 condition. In this observation we'll be considering only the impact of P2 on shape as those are the only ones having good outcome.

If we observe under each repetition, the impact of P2 on major axis stayed same. But the impact of P2 on the minor axis has been fluctuating.

```
[ ]: ## correlation under each replications of e4 ( as we have similar results with
      ↳ e0,e1,e4 we've considered one of it)

      # Iterate over the unique replications
      for i in df["replication"].value_counts()[df.replication.unique()].keys():

          # Filter dataFrame based on e4 condition
          df1=df[df.condition=='e4']
```

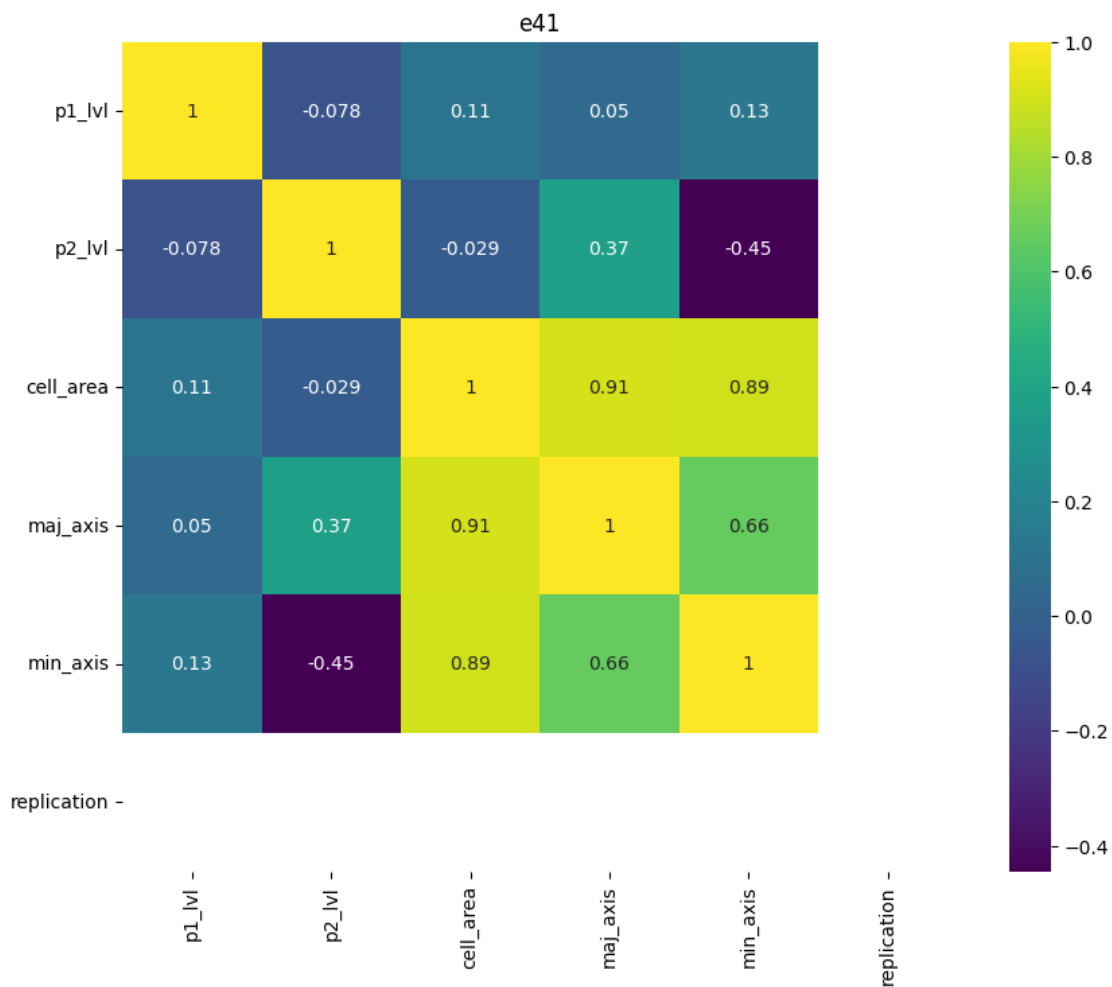
```
# Compute the correlation matrix and plot correlation Heatmap
sns.heatmap(df1[df1.replication==i].corr(), annot=True, cmap = 'viridis')

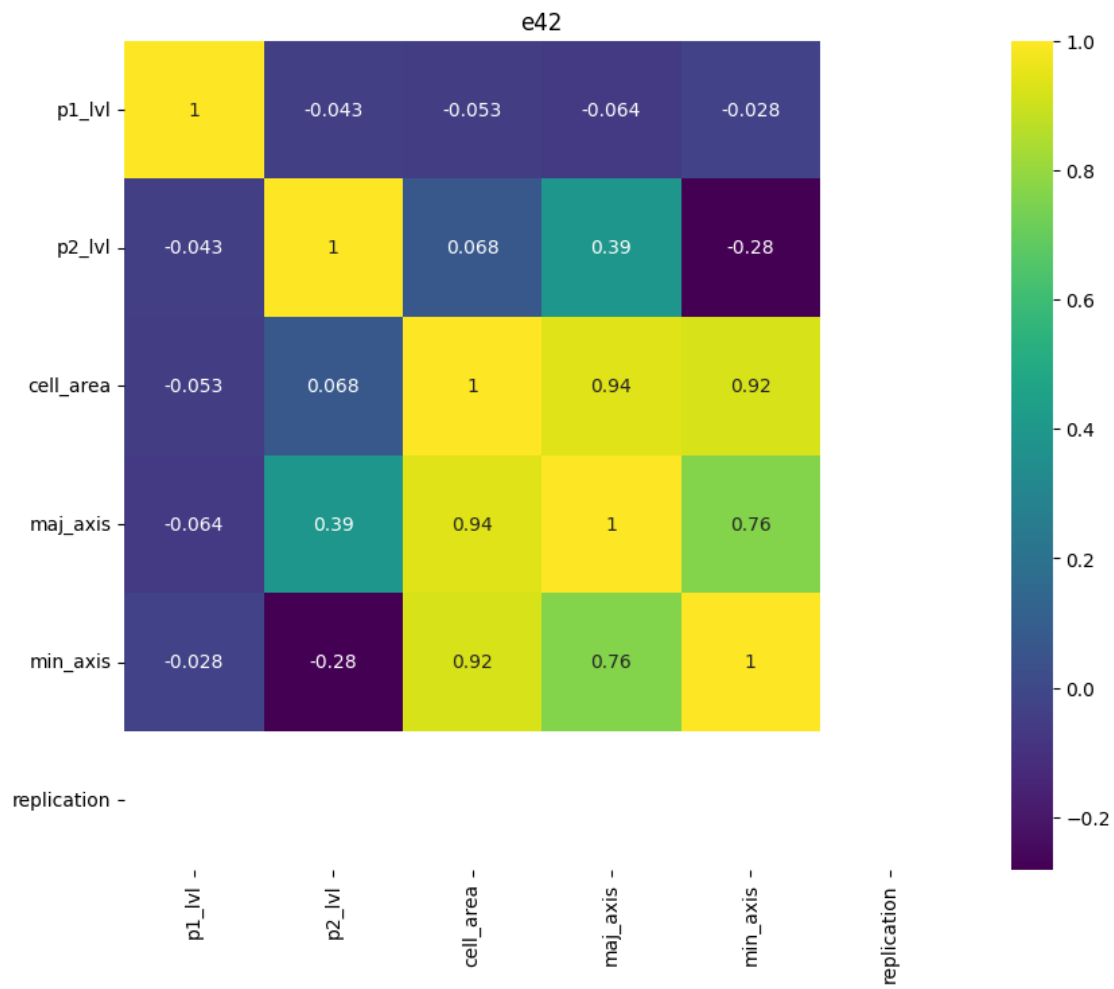
# Set the figure size and title
fig=plt.gcf()
fig.set_size_inches(10,8)
plt.title("e4"+str(i))

plt.show() # Display plot
```

<ipython-input-45-2717166e76e7>:10: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric_only to silence this warning.

```
sns.heatmap(df1[df1.replication==i].corr(), annot=True, cmap = 'viridis')
```







Inference :

Here we're trying to see the behaviour of the data with each repetition under e4 condition. In this observation we'll be considering only the impact of P2 on shape as those are the only ones having good outcome.

Results are pretty much similar to what we inferred in the above scenario on e2.

```
[ ]: ## p2 impact on minor axis in condition under each repetition of e3 ( as we have
      ↳ similar results with e2,e3 we've considered one of it)

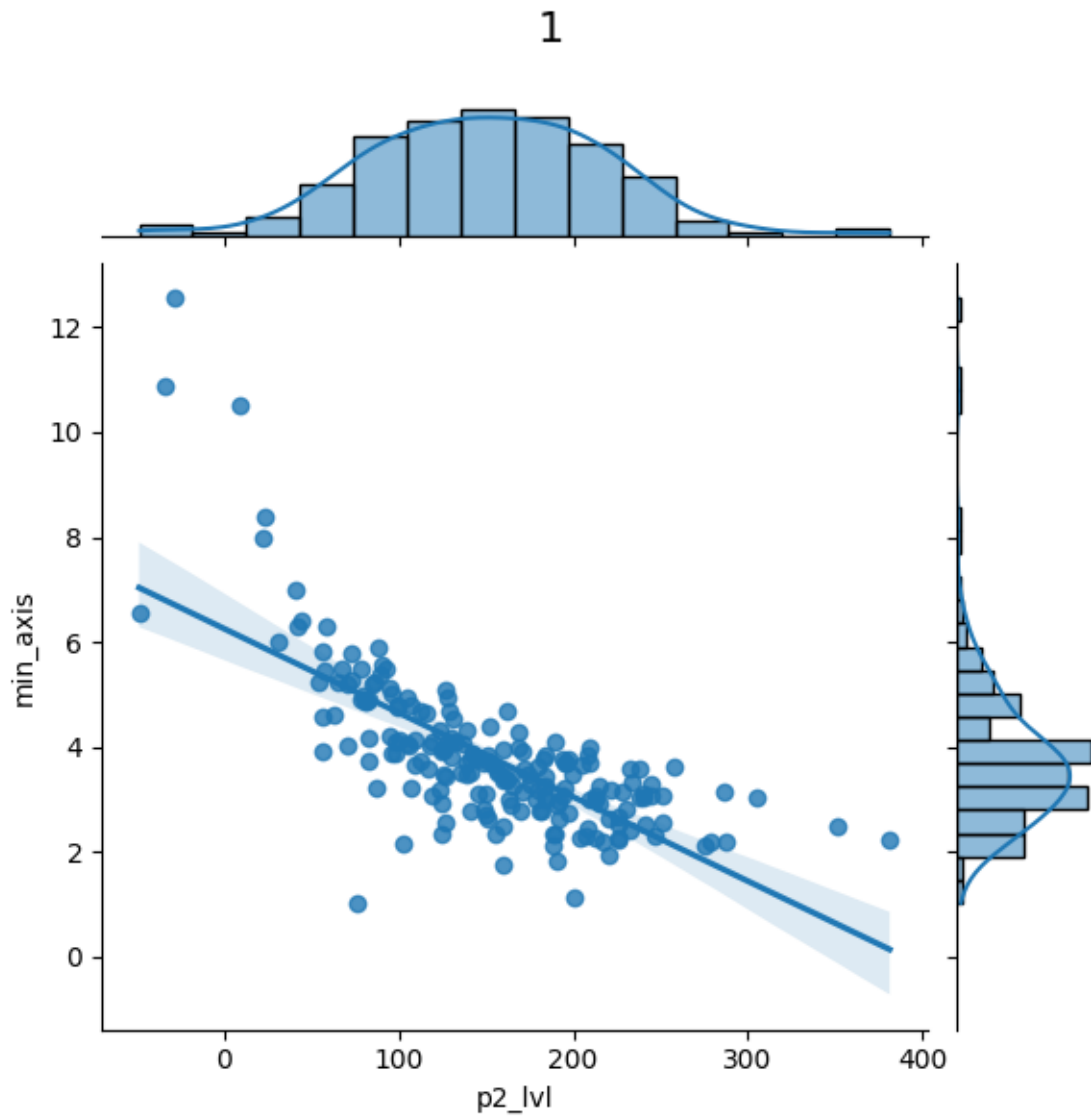
      # Iterate over the unique replications
      for i in df["replication"].value_counts()[df.replication.unique()].keys():

          # Filter dataFrame based on e3 condition
          df1=df[df.condition=='e3']

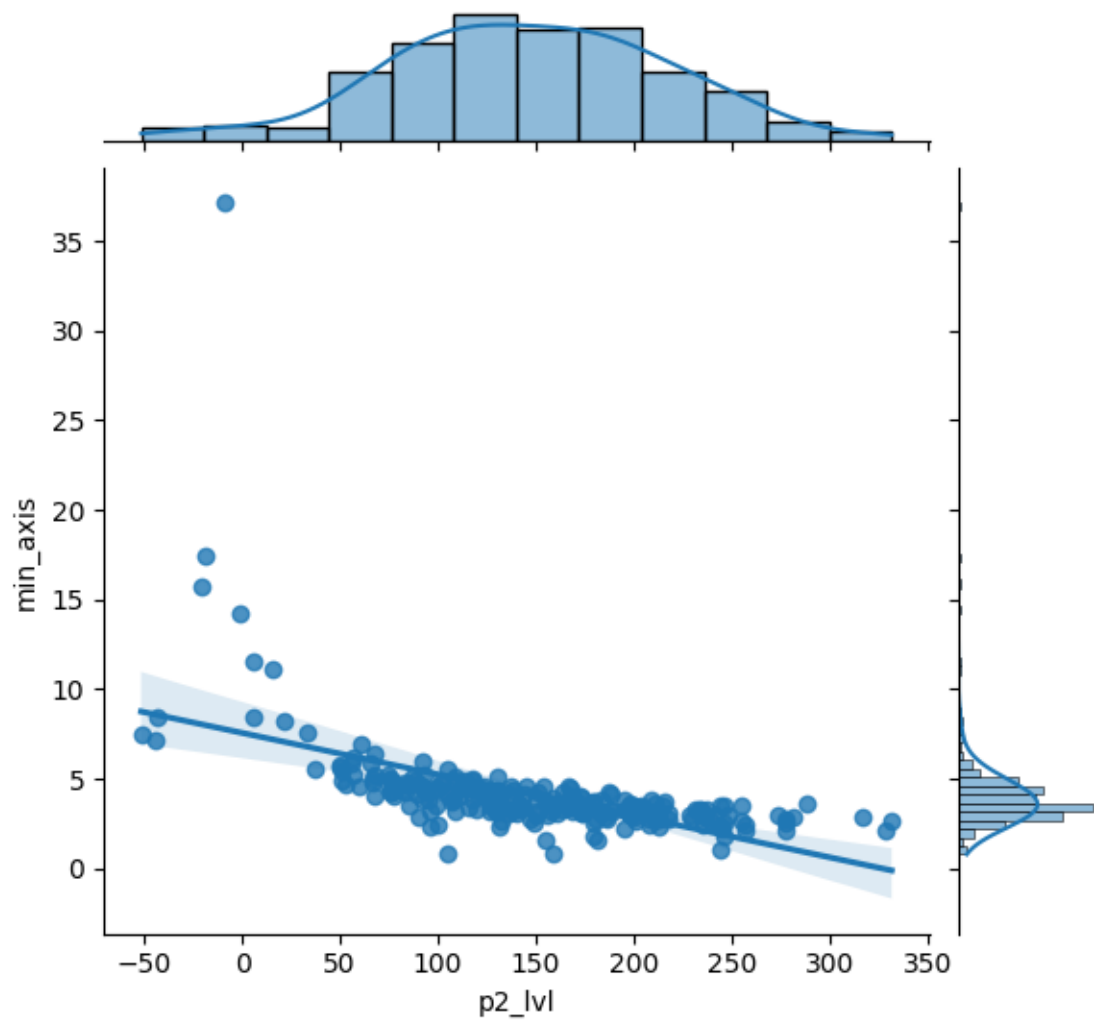
          # Create a joint plot for the current condition
```

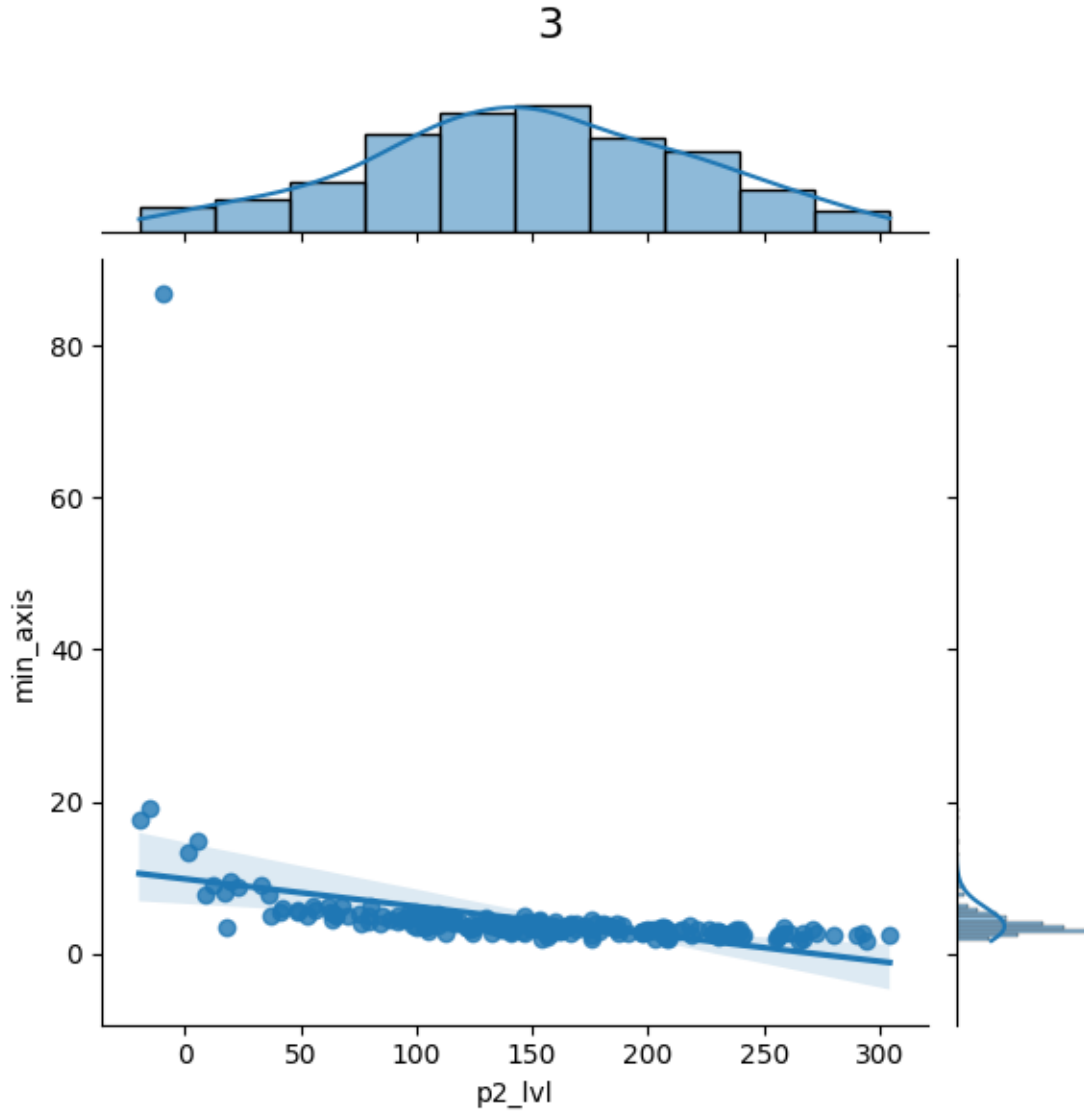
```
sns.jointplot(x='p2_lv1',y='min_axis',data=df1[df1.replication==i],kind='reg')

# Adjust the subplots and add centred title
plt.subplots_adjust(top=0.9)
plt.suptitle(i, fontsize = 16)
```



2





Inference :

As we saw fluctuations in the impact of P2 on minor axis in each condition, we decided to analyse on the reason for fluctuations. For that, we used jointplot between these 2 under each repetition.

As per the graphs we got, we found outliers as the key reason for these fluctuations.

6 Statistical Tests

1. Conducting a linear model analysis for each of the three datasets under all conditions

linear regression(ols) applied to e0 contains e01,e02,e03

linear regression(ols) applied to e1 contains e11,e12,e13

linear regression(ols) applied to e1 contains e21,e22,e23

linear regression(ols) applied to e1 contains e31,e32,e33

linear regression(ols) applied to e1 contains e41,e42,e43

- i) It allows the model to the characteristics and patterns specific to each dataset. So, it can captures unique relationships and variations that may be present in individual datasets.
- ii) Test-specific variations may be captured, and you can examine whether the relationships differ across tests.
- iii) Smaller sample sizes within each dataset may result in reduced statistical power. It results that the limited ability to detect significant effects or associations due to limited data.
- iv) Conducting multiple hypothesis tests (one for each dataset) without correction may increase the risk of making a Type I error.
- v) If multiple models need to be interpreted, it can increase the complexity of the overall analysis. Difficulty in providing a unified interpretation when dealing with multiple models.

2. Combining all datasets into a single model and conducting the linear model analysis.

Assumptions

- a. Assumes that the relationships and characteristics across datasets are homogenous
- b. The residuals (the differences between observed and predicted values) are normally distributed.

Advantages

- i) Combining datasets leads to a larger sample size, enhancing statistical power and improving the precision of parameter estimates. Greater ability to detect significant effects and relationships.
- ii) Simplifies the analysis by treating all datasets as a single entity, streamlining model development and interpretation. Easier to manage and communicate results.
- iii) Estimates of coefficients and other parameters are based on a larger dataset, potentially leading to more reliable and stable results.

Draw backs

- iv) The combined model may become complex, especially if datasets have different structures or patterns. Challenges in interpreting a complex model and potential overfitting.
- v) Outliers in one dataset may disproportionately influence the combined model. Sensitivity to extreme values, potentially affecting the robustness of the analysis.

```
[ ]: df.describe() # Returns description of the data in the DataFrame
```

```
[ ]:
count    2958.000000    2958.000000    2958.000000    2958.000000    2958.000000
mean      311.740225     269.658793     59.790264      7.012926      3.184773
std       123.479216     145.441257     20.217504      2.331285      2.535062
```


| | | | | | |
|-----|------------|------------|------------|-----------|-----------|
| min | -40.024410 | -85.400030 | 1.391440 | 0.489870 | 0.560590 |
| 25% | 236.763385 | 160.295973 | 46.033330 | 5.380665 | 2.276547 |
| 50% | 300.931940 | 245.970225 | 59.601295 | 6.951340 | 2.816520 |
| 75% | 368.821860 | 352.039562 | 73.545325 | 8.559145 | 3.548015 |
| max | 649.025540 | 699.673480 | 125.802950 | 15.110750 | 86.944080 |

| | replication |
|-------|-------------|
| count | 2958.000000 |
| mean | 1.993915 |
| std | 0.810376 |
| min | 1.000000 |
| 25% | 1.000000 |
| 50% | 2.000000 |
| 75% | 3.000000 |
| max | 3.000000 |

```
[ ]: def ols(x,y):
    """ Performs an ordinary least squares (OLS) regression on two variables.

    Args:
        x: Independent variable.
        y: Dependent variable.

    """

    # Adds a constant term to independent variable
    X2 = sm.add_constant(x)

    # Creates OLS model
    est = sm.OLS(y, X2)

    # Fits OLS model
    est2 = est.fit()

    print("R-Squared : "+ str(est.fit().rsquared))
    print("\n")
    print(est2.summary())
```

```
[ ]: ## On cell_area

X=df[['p1_lv1','p2_lv1']] # Independent variables
y=df['cell_area'] # Dependent variable

ols(X,y) # Call custom Ordinary Least Squares function
```

R-Squared : 0.0005716013235134154

OLS Regression Results

```

=====
Dep. Variable:          cell_area    R-squared:                0.001
Model:                  OLS          Adj. R-squared:           -0.000
Method:                 Least Squares  F-statistic:              0.8450
Date:                  Thu, 19 Oct 2023  Prob (F-statistic):       0.430
Time:                  11:57:07      Log-Likelihood:           -13089.
No. Observations:      2958          AIC:                     2.618e+04
Df Residuals:          2955          BIC:                     2.620e+04
Df Model:               2
Covariance Type:       nonrobust
=====

```

```

=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
const         61.5766      1.453      42.375      0.000      58.727      64.426
p1_lvl        -0.0039      0.003      -1.241      0.215      -0.010      0.002
p2_lvl        -0.0021      0.003      -0.765      0.444      -0.007      0.003
=====

```

```

=====
Omnibus:            4.159    Durbin-Watson:           2.010
Prob(Omnibus):      0.125    Jarque-Bera (JB):           3.675
Skew:               -0.004    Prob(JB):                  0.159
Kurtosis:           2.827    Cond. No.                   1.67e+03
=====

```

Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 1.67e+03. This might indicate that there are strong multicollinearity or other numerical problems.

```

[ ]: ## on cell area with each condition

for i in df["condition"].value_counts()[df.condition.unique()].keys():
    df1=df[df.condition==i]
    X=df1[['p1_lvl','p2_lvl']] # Independent variables
    y=df1['cell_area'] # Dependent variable
    print('\033[1m'"condition = "+i+'\033[0m\n')
    ols(X,y) # Call custom Ordinary Least Squares function
    print("\n")

```

condition = e0

R-Squared : 0.00440136126296764

OLS Regression Results

```

=====
Dep. Variable:          cell_area    R-squared:                0.004

```

```

Model:                OLS      Adj. R-squared:      0.001
Method:               Least Squares  F-statistic:      1.344
Date:                 Thu, 19 Oct 2023  Prob (F-statistic): 0.262
Time:                 11:57:07    Log-Likelihood:    -2707.3
No. Observations:     611      AIC:              5421.
Df Residuals:         608      BIC:              5434.
Df Model:              2
Covariance Type:      nonrobust

```

```

=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
const          68.8900        5.925      11.628      0.000      57.255      80.525
p1_lvl         -0.0118        0.016       -0.720      0.472     -0.044      0.020
p2_lvl         -0.0176        0.012       -1.461      0.145     -0.041      0.006
=====

Omnibus:                0.594    Durbin-Watson:           2.093
Prob(Omnibus):          0.743    Jarque-Bera (JB):           0.691
Skew:                   0.024    Prob(JB):                0.708
Kurtosis:               2.843    Cond. No.                2.96e+03
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 2.96e+03. This might indicate that there are strong multicollinearity or other numerical problems.

condition = e1

R-Squared : 0.0050087454605418635

OLS Regression Results

```

=====
Dep. Variable:          cell_area  R-squared:           0.005
Model:                 OLS      Adj. R-squared:       0.002
Method:               Least Squares  F-statistic:         1.467
Date:                 Thu, 19 Oct 2023  Prob (F-statistic): 0.231
Time:                 11:57:07    Log-Likelihood:     -2576.1
No. Observations:     586      AIC:                5158.
Df Residuals:         583      BIC:                5171.
Df Model:              2
Covariance Type:      nonrobust

```

```

=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
const          57.3082        4.296      13.340      0.000      48.871      65.746

```

| | | | | | | |
|--------|---------|-------|--------|-------|--------|-------|
| p1_lvl | 0.0270 | 0.016 | 1.647 | 0.100 | -0.005 | 0.059 |
| p2_lvl | -0.0052 | 0.011 | -0.457 | 0.648 | -0.028 | 0.017 |

| | | | |
|----------------|--------|-------------------|----------|
| Omnibus: | 0.752 | Durbin-Watson: | 1.899 |
| Prob(Omnibus): | 0.687 | Jarque-Bera (JB): | 0.835 |
| Skew: | -0.029 | Prob(JB): | 0.659 |
| Kurtosis: | 2.824 | Cond. No. | 1.79e+03 |

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 1.79e+03. This might indicate that there are strong multicollinearity or other numerical problems.

condition = e2

R-Squared : 0.0013884102004716459

OLS Regression Results

| | | | |
|-------------------|------------------|---------------------|---------|
| Dep. Variable: | cell_area | R-squared: | 0.001 |
| Model: | OLS | Adj. R-squared: | -0.002 |
| Method: | Least Squares | F-statistic: | 0.4102 |
| Date: | Thu, 19 Oct 2023 | Prob (F-statistic): | 0.664 |
| Time: | 11:57:07 | Log-Likelihood: | -2635.4 |
| No. Observations: | 593 | AIC: | 5277. |
| Df Residuals: | 590 | BIC: | 5290. |
| Df Model: | 2 | | |
| Covariance Type: | nonrobust | | |

| | coef | std err | t | P> t | [0.025 | 0.975] |
|--------|---------|---------|--------|-------|--------|--------|
| ----- | ----- | ----- | ----- | ----- | ----- | ----- |
| const | 63.5399 | 5.171 | 12.288 | 0.000 | 53.385 | 73.695 |
| p1_lvl | -0.0062 | 0.016 | -0.378 | 0.706 | -0.038 | 0.026 |
| p2_lvl | -0.0099 | 0.012 | -0.803 | 0.422 | -0.034 | 0.014 |

| | | | |
|----------------|--------|-------------------|----------|
| Omnibus: | 0.753 | Durbin-Watson: | 2.028 |
| Prob(Omnibus): | 0.686 | Jarque-Bera (JB): | 0.851 |
| Skew: | -0.053 | Prob(JB): | 0.653 |
| Kurtosis: | 2.848 | Cond. No. | 2.06e+03 |

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 2.06e+03. This might indicate that there are strong multicollinearity or other numerical problems.

condition = e3

R-Squared : 0.0006569729794903001

| OLS Regression Results | | | | | | |
|------------------------|------------------|-------------------|---------------------|----------|---------|--------|
| ===== | | | | | | |
| Dep. Variable: | cell_area | | R-squared: | | 0.001 | |
| Model: | OLS | | Adj. R-squared: | | -0.003 | |
| Method: | Least Squares | | F-statistic: | | 0.2012 | |
| Date: | Thu, 19 Oct 2023 | | Prob (F-statistic): | | 0.818 | |
| Time: | 11:57:07 | | Log-Likelihood: | | -2726.8 | |
| No. Observations: | 615 | | AIC: | | 5460. | |
| Df Residuals: | 612 | | BIC: | | 5473. | |
| Df Model: | 2 | | | | | |
| Covariance Type: | nonrobust | | | | | |
| ===== | | | | | | |
| | coef | std err | t | P> t | [0.025 | 0.975] |
| ----- | | | | | | |
| const | 62.6593 | 8.153 | 7.686 | 0.000 | 46.649 | 78.670 |
| p1_lvl | -0.0065 | 0.016 | -0.406 | 0.685 | -0.038 | 0.025 |
| p2_lvl | -0.0056 | 0.012 | -0.474 | 0.636 | -0.029 | 0.018 |
| ===== | | | | | | |
| Omnibus: | 0.784 | Durbin-Watson: | | 2.027 | | |
| Prob(Omnibus): | 0.676 | Jarque-Bera (JB): | | 0.873 | | |
| Skew: | 0.044 | Prob(JB): | | 0.646 | | |
| Kurtosis: | 2.838 | Cond. No. | | 5.19e+03 | | |
| ===== | | | | | | |

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 5.19e+03. This might indicate that there are strong multicollinearity or other numerical problems.

condition = e4

R-Squared : 0.0004969588608149111

| OLS Regression Results | | | |
|------------------------|-----------|------------|-------|
| ===== | | | |
| Dep. Variable: | cell_area | R-squared: | 0.000 |

```

Model: OLS Adj. R-squared: -0.003
Method: Least Squares F-statistic: 0.1367
Date: Thu, 19 Oct 2023 Prob (F-statistic): 0.872
Time: 11:57:07 Log-Likelihood: -2438.4
No. Observations: 553 AIC: 4883.
Df Residuals: 550 BIC: 4896.
Df Model: 2
Covariance Type: nonrobust

```

| | coef | std err | t | P> t | [0.025 | 0.975] |
|----------------|---------|---------|-------------------|-------|----------|--------|
| const | 60.7716 | 8.305 | 7.318 | 0.000 | 44.459 | 77.085 |
| p1_lvl | 0.0052 | 0.018 | 0.286 | 0.775 | -0.030 | 0.041 |
| p2_lvl | -0.0050 | 0.012 | -0.421 | 0.674 | -0.028 | 0.018 |
| Omnibus: | 0.705 | | Durbin-Watson: | | 2.014 | |
| Prob(Omnibus): | 0.703 | | Jarque-Bera (JB): | | 0.786 | |
| Skew: | 0.008 | | Prob(JB): | | 0.675 | |
| Kurtosis: | 2.816 | | Cond. No. | | 5.76e+03 | |

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 5.76e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Expression Level of the protein P1

H0: $\beta_{P1}=0$ (There is no significant linear between expression level P1 and the cell size)

HA: β_{P10} (There is significant relationship between expression level P1 and the cell size)

Expression Level of the protein P2

H0: $\beta_{P2}=0$ (There is no significant linear between expression level P1 and the cell size)

HA: β_{P20} (There is significant relationship between expression level P1 and the cell size)

1. Condition = e0 (Normal setup (WT) without any modifications)

For the Expression level of P1 & P2 the p-value was greater than 0.05, so null hypotheses cannot be rejected the relationship between expression level of P1 & P2 with 'Cells' is not statistically significant. But, Expression level of P2 the p-value was slightly near to 0.05, so expression level of P2 and 'Cells' has some relation.

2. Condition = e1 (The expression levels of the protein P1 were reduced while keeping that of P2 intact)

For the Expression level of P1 & P2 the p-value was greater than 0.05, so null hypotheses cannot be rejected the relationship between expression level of P1 & P2 with 'Cells' is not statistically

significant. But, Expression level of P1 the p-value was slightly near to 0.05, so expression level of P1 and 'Cells' has some relation.

3. Condition = e2 (The expression levels of the protein P2 were reduced while keeping that of P1 intact)

For the Expression level of P1 & P2 the p-value was greater than 0.05, so null hypotheses cannot be rejected and the relationship between expression level of P1 & P2 with 'Cells' is not statistically significant.

4. Condition = e3 (The expression levels of the protein P1 were increased while keeping that of P2 intact)

For the Expression level of P1 & P2 the p-value was greater than 0.05, so null hypotheses cannot be rejected and the relationship between expression level of P1 & P2 with 'Cells' is not statistically significant.

5. Condition = e4 (The expression levels of the protein P2 were increased while keeping that of P1 intact)

For the Expression level of P1 & P2 the p-value was greater than 0.05, so null hypotheses cannot be rejected and the relationship between expression level of P1 & P2 with 'Cells' is not statistically significant.

```
[ ]: ## p1 & p2 on major_axis

X=df[['p1_lvl','p2_lvl']] # Independent variables
y=df['maj_axis'] # Dependent variable

ols(X,y) # Call custom Ordinary Least Squares function
```

R-Squared : 0.6595729479514083

| OLS Regression Results | | | | | | |
|------------------------|------------------|---------|---------------------|-----------|--------|--------|
| ===== | | | | | | |
| Dep. Variable: | maj_axis | | R-squared: | 0.660 | | |
| Model: | OLS | | Adj. R-squared: | 0.659 | | |
| Method: | Least Squares | | F-statistic: | 2863. | | |
| Date: | Thu, 19 Oct 2023 | | Prob (F-statistic): | 0.00 | | |
| Time: | 11:57:07 | | Log-Likelihood: | -5106.7 | | |
| No. Observations: | 2958 | | AIC: | 1.022e+04 | | |
| Df Residuals: | 2955 | | BIC: | 1.024e+04 | | |
| Df Model: | 2 | | | | | |
| Covariance Type: | nonrobust | | | | | |
| ===== | | | | | | |
| | coef | std err | t | P> t | [0.025 | 0.975] |
| ----- | | | | | | |
| const | 3.8221 | 0.098 | 39.083 | 0.000 | 3.630 | 4.014 |
| p1_lvl | -0.0008 | 0.000 | -3.825 | 0.000 | -0.001 | -0.000 |
| p2_lvl | 0.0128 | 0.000 | 70.362 | 0.000 | 0.012 | 0.013 |

```
=====
Omnibus:                253.912    Durbin-Watson:                1.984
Prob(Omnibus):           0.000    Jarque-Bera (JB):           407.967
Skew:                    -0.639    Prob(JB):                   2.58e-89
Kurtosis:                4.296    Cond. No.                   1.67e+03
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 1.67e+03. This might indicate that there are strong multicollinearity or other numerical problems.

```
[ ]: ## p1 & p2 on major_axis under each condition

for i in df["condition"].value_counts()[df.condition.unique()].keys():
    df1=df[df.condition==i]
    X=df1[['p1_lvl','p2_lvl']] # Independent variables
    y=df1['maj_axis'] # Dependent variable
    print('\033[1m"+"condition = "+i+'\033[0m\n')
    ols(X,y) # Call custom Ordinary Least Squares function
    print("\n")
```

condition = e0

R-Squared : 0.2764628411349941

OLS Regression Results

```
=====
Dep. Variable:          maj_axis    R-squared:                0.276
Model:                  OLS         Adj. R-squared:           0.274
Method:                 Least Squares    F-statistic:             116.2
Date:                  Thu, 19 Oct 2023    Prob (F-statistic):       1.89e-43
Time:                  11:57:07          Log-Likelihood:          -1044.3
No. Observations:      611            AIC:                    2095.
Df Residuals:          608            BIC:                    2108.
Df Model:               2
Covariance Type:       nonrobust
=====
```

| | coef | std err | t | P> t | [0.025 | 0.975] |
|--------|---------|---------|--------|-------|--------|--------|
| const | 4.1873 | 0.390 | 10.748 | 0.000 | 3.422 | 4.952 |
| p1_lvl | -0.0006 | 0.001 | -0.544 | 0.586 | -0.003 | 0.002 |
| p2_lvl | 0.0120 | 0.001 | 15.239 | 0.000 | 0.010 | 0.014 |

```
=====
Omnibus:                36.219    Durbin-Watson:                2.066
Prob(Omnibus):           0.000    Jarque-Bera (JB):           44.161
```


| | | | |
|-----------|--------|-----------|----------|
| Skew: | -0.546 | Prob(JB): | 2.57e-10 |
| Kurtosis: | 3.737 | Cond. No. | 2.96e+03 |

=====

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 2.96e+03. This might indicate that there are strong multicollinearity or other numerical problems.

condition = e1

R-Squared : 0.2912451095026556

OLS Regression Results

=====

| | | | |
|-------------------|------------------|---------------------|----------|
| Dep. Variable: | maj_axis | R-squared: | 0.291 |
| Model: | OLS | Adj. R-squared: | 0.289 |
| Method: | Least Squares | F-statistic: | 119.8 |
| Date: | Thu, 19 Oct 2023 | Prob (F-statistic): | 2.63e-44 |
| Time: | 11:57:07 | Log-Likelihood: | -1006.5 |
| No. Observations: | 586 | AIC: | 2019. |
| Df Residuals: | 583 | BIC: | 2032. |
| Df Model: | 2 | | |
| Covariance Type: | nonrobust | | |

=====

| | coef | std err | t | P> t | [0.025 | 0.975] |
|--------|--------|---------|--------|-------|--------|--------|
| ----- | ----- | ----- | ----- | ----- | ----- | ----- |
| const | 3.6921 | 0.295 | 12.516 | 0.000 | 3.113 | 4.271 |
| p1_lvl | 0.0018 | 0.001 | 1.613 | 0.107 | -0.000 | 0.004 |
| p2_lvl | 0.0121 | 0.001 | 15.408 | 0.000 | 0.011 | 0.014 |

=====

| | | | |
|----------------|--------|-------------------|----------|
| Omnibus: | 44.729 | Durbin-Watson: | 1.936 |
| Prob(Omnibus): | 0.000 | Jarque-Bera (JB): | 57.616 |
| Skew: | -0.629 | Prob(JB): | 3.08e-13 |
| Kurtosis: | 3.881 | Cond. No. | 1.79e+03 |

=====

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 1.79e+03. This might indicate that there are strong multicollinearity or other numerical problems.

condition = e2

R-Squared : 0.5402680626783148

OLS Regression Results

```
=====
Dep. Variable:          maj_axis    R-squared:                0.540
Model:                  OLS         Adj. R-squared:           0.539
Method:                 Least Squares   F-statistic:              346.7
Date:                   Thu, 19 Oct 2023   Prob (F-statistic):       2.75e-100
Time:                   11:57:07         Log-Likelihood:           -894.65
No. Observations:      593            AIC:                     1795.
Df Residuals:          590            BIC:                     1808.
Df Model:               2
Covariance Type:       nonrobust
=====
```

```
=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
const          2.9119      0.275      10.605      0.000       2.373       3.451
p1_lvl        -0.0004      0.001      -0.414      0.679      -0.002       0.001
p2_lvl         0.0173      0.001      26.315      0.000       0.016       0.019
=====
```

```
=====
Omnibus:          139.662    Durbin-Watson:           2.047
Prob(Omnibus):    0.000     Jarque-Bera (JB):        493.327
Skew:             -1.066    Prob(JB):                7.51e-108
Kurtosis:         6.927     Cond. No.:               2.06e+03
=====
```

Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 2.06e+03. This might indicate that there are strong multicollinearity or other numerical problems.

condition = e3

R-Squared : 0.5675976872546724

OLS Regression Results

```
=====
Dep. Variable:          maj_axis    R-squared:                0.568
Model:                  OLS         Adj. R-squared:           0.566
Method:                 Least Squares   F-statistic:              401.7
Date:                   Thu, 19 Oct 2023   Prob (F-statistic):       3.82e-112
Time:                   11:57:07         Log-Likelihood:           -910.87
No. Observations:      615            AIC:                     1828.
=====
```

Df Residuals: 612 BIC: 1841.
Df Model: 2
Covariance Type: nonrobust

| | coef | std err | t | P> t | [0.025 | 0.975] |
|----------------|---------|---------|-------------------|----------|--------|--------|
| const | 2.7828 | 0.426 | 6.539 | 0.000 | 1.947 | 3.619 |
| p1_lvl | -0.0002 | 0.001 | -0.228 | 0.819 | -0.002 | 0.001 |
| p2_lvl | 0.0176 | 0.001 | 28.335 | 0.000 | 0.016 | 0.019 |
| Omnibus: | 47.756 | | Durbin-Watson: | 2.022 | | |
| Prob(Omnibus): | 0.000 | | Jarque-Bera (JB): | 67.924 | | |
| Skew: | -0.595 | | Prob(JB): | 1.78e-15 | | |
| Kurtosis: | 4.111 | | Cond. No. | 5.19e+03 | | |

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 5.19e+03. This might indicate that there are strong multicollinearity or other numerical problems.

condition = e4

R-Squared : 0.12994698934857396

OLS Regression Results

| | | | |
|-------------------|------------------|---------------------|----------|
| Dep. Variable: | maj_axis | R-squared: | 0.130 |
| Model: | OLS | Adj. R-squared: | 0.127 |
| Method: | Least Squares | F-statistic: | 41.07 |
| Date: | Thu, 19 Oct 2023 | Prob (F-statistic): | 2.37e-17 |
| Time: | 11:57:07 | Log-Likelihood: | -1090.1 |
| No. Observations: | 553 | AIC: | 2186. |
| Df Residuals: | 550 | BIC: | 2199. |
| Df Model: | 2 | | |
| Covariance Type: | nonrobust | | |

| | coef | std err | t | P> t | [0.025 | 0.975] |
|----------------|--------|---------|-------------------|--------|--------|--------|
| const | 5.0797 | 0.725 | 7.005 | 0.000 | 3.655 | 6.504 |
| p1_lvl | 0.0001 | 0.002 | 0.071 | 0.943 | -0.003 | 0.003 |
| p2_lvl | 0.0093 | 0.001 | 9.052 | 0.000 | 0.007 | 0.011 |
| Omnibus: | 32.699 | | Durbin-Watson: | 2.016 | | |
| Prob(Omnibus): | 0.000 | | Jarque-Bera (JB): | 37.960 | | |

| | | | |
|-----------|--------|-----------|----------|
| Skew: | -0.570 | Prob(JB): | 5.72e-09 |
| Kurtosis: | 3.592 | Cond. No. | 5.76e+03 |

=====

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 5.76e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Expression Level of the protein P1

H0: $\beta_{P1}=0$ (There is no significant linear between expression level P1 and the cell size)

HA: β_{P10} (There is significant relationship between expression level P1 and the cell size)

Expression Level of the protein P2

H0: $\beta_{P2}=0$ (There is no significant linear between expression level P1 and the cell size)

HA: β_{P20} (There is significant relationship between expression level P1 and the cell size)

1. Condition = e0 (Normal setup (WT) without any modifications)

For the Expression level of P1 the p-value was greater than 0.05, so null hypotheses cannot be rejected and the relationship between expression level of P1 with 'major axis' is not statistically significant. But the Expression level of P2 the p-value was less than 0.05, so null hypotheses can be rejected and the relationship between expression level of P2 with 'major axis' is statistically significant.

2. Condition = e1 (The expression levels of the protein P1 were reduced while keeping that of P2 intact)

For the Expression level of P1 the p-value was greater than 0.05, so null hypotheses cannot be rejected and the p-value was near to 0.05 expression level of P1 & 'major axis' may have slight statistical relation. But the Expression level of P2 the p-value was less than 0.05, so null hypotheses can be rejected and the relationship between expression level of P2 with 'major axis' is statistically significant.

3. Condition = e2 (The expression levels of the protein P2 were reduced while keeping that of P1 intact)

For the Expression level of P1 the p-value was greater than 0.05, so null hypotheses cannot be rejected and the relationship between expression level of P1 with 'major axis' is not statistically significant. But the Expression level of P2 the p-value was less than 0.05, so null hypotheses can be rejected and the relationship between expression level of P2 with 'major axis' is statistically significant

4. Condition = e3 (The expression levels of the protein P1 were increased while keeping that of P2 intact)

For the Expression level of P1 the p-value was greater than 0.05, so null hypotheses cannot be rejected and the relationship between expression level of P1 with 'major axis' is not statistically

significant. But the Expression level of P2 the p-value was less than 0.05, so null hypotheses can be rejected and the relationship between expression level of P2 with 'major axis' is statistically significant

5. Condition = e4 (The expression levels of the protein P2 were increased while keeping that of P1 intact)

For the Expression level of P1 the p-value was greater than 0.05, so null hypotheses cannot be rejected and the relationship between expression level of P1 with 'major axis' is not statistically significant. But the Expression level of P2 the p-value was less than 0.05, so null hypotheses can be rejected and the relationship between expression level of P2 with 'major axis' is statistically significant.

```
[ ]: ## p1 on major_axis

X=df[['p1_lvl']] # Independent variable
y=df['maj_axis'] # Dependent variable

ols(X,y) # Call custom Ordinary Least Squares function
```

R-Squared : 0.08921328749749202

| OLS Regression Results | | | | | | |
|------------------------|------------------|-------------------|---------------------|----------|-----------|--------|
| ===== | | | | | | |
| Dep. Variable: | maj_axis | | R-squared: | | 0.089 | |
| Model: | OLS | | Adj. R-squared: | | 0.089 | |
| Method: | Least Squares | | F-statistic: | | 289.5 | |
| Date: | Thu, 19 Oct 2023 | | Prob (F-statistic): | | 5.10e-62 | |
| Time: | 11:57:07 | | Log-Likelihood: | | -6562.2 | |
| No. Observations: | 2958 | | AIC: | | 1.313e+04 | |
| Df Residuals: | 2956 | | BIC: | | 1.314e+04 | |
| Df Model: | 1 | | | | | |
| Covariance Type: | nonrobust | | | | | |
| ===== | | | | | | |
| | coef | std err | t | P> t | [0.025 | 0.975] |
| ----- | | | | | | |
| const | 8.7709 | 0.111 | 78.933 | 0.000 | 8.553 | 8.989 |
| p1_lvl | -0.0056 | 0.000 | -17.016 | 0.000 | -0.006 | -0.005 |
| ===== | | | | | | |
| Omnibus: | 31.424 | Durbin-Watson: | | 1.156 | | |
| Prob(Omnibus): | 0.000 | Jarque-Bera (JB): | | 32.146 | | |
| Skew: | 0.251 | Prob(JB): | | 1.05e-07 | | |
| Kurtosis: | 3.093 | Cond. No. | | 911. | | |
| ===== | | | | | | |

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```
[ ]: ## p1 on major_axis under each condition

for i in df["condition"].value_counts()[df.condition.unique()].keys():
    df1=df[df.condition==i]
    X=df1[['p1_lvl']] # Independent variables
    y=df1['maj_axis'] # Dependent variable
    print('\033[1m'+ "condition = "+i+'\033[0m\n')
    ols(X,y) # Call custom Ordinary Least Squares function
    print("\n")
```

condition = e0

R-Squared : 9.523890659746126e-05

```

                                OLS Regression Results
=====
Dep. Variable:                  maj_axis    R-squared:                   0.000
Model:                            OLS      Adj. R-squared:                -0.002
Method:                 Least Squares      F-statistic:                   0.05801
Date:                Thu, 19 Oct 2023      Prob (F-statistic):              0.810
Time:                11:57:07              Log-Likelihood:             -1143.1
No. Observations:                611      AIC:                           2290.
Df Residuals:                    609      BIC:                           2299.
Df Model:                          1
Covariance Type:                nonrobust
=====
               coef      std err          t      P>|t|      [0.025      0.975]
-----
const                7.4261        0.384     19.363     0.000        6.673        8.179
p1_lvl              -0.0003         0.001     -0.241     0.810       -0.003        0.002
=====
Omnibus:                 3.134    Durbin-Watson:                2.033
Prob(Omnibus):            0.209    Jarque-Bera (JB):                3.019
Skew:                    -0.171    Prob(JB):                        0.221
Kurtosis:                 3.045    Cond. No.                      1.83e+03
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 1.83e+03. This might indicate that there are strong multicollinearity or other numerical problems.

condition = e1

R-Squared : 0.002642302246965267

OLS Regression Results

```

=====
Dep. Variable:          maj_axis    R-squared:                0.003
Model:                  OLS         Adj. R-squared:           0.001
Method:                 Least Squares   F-statistic:             1.547
Date:                  Thu, 19 Oct 2023   Prob (F-statistic):       0.214
Time:                  11:57:07         Log-Likelihood:          -1106.6
No. Observations:      586            AIC:                    2217.
Df Residuals:          584            BIC:                    2226.
Df Model:               1
Covariance Type:       nonrobust
=====

```

| | coef | std err | t | P> t | [0.025 | 0.975] |
|--------|--------|---------|--------|-------|--------|--------|
| const | 7.3286 | 0.210 | 34.947 | 0.000 | 6.917 | 7.740 |
| p1_lvl | 0.0017 | 0.001 | 1.244 | 0.214 | -0.001 | 0.004 |

```

=====
Omnibus:                3.238    Durbin-Watson:           1.955
Prob(Omnibus):          0.198    Jarque-Bera (JB):        3.214
Skew:                   -0.111    Prob(JB):                0.201
Kurtosis:               3.286    Cond. No.:               499.
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

condition = e2

R-Squared : 0.0006780314617470529

OLS Regression Results

```

=====
Dep. Variable:          maj_axis    R-squared:                0.001
Model:                  OLS         Adj. R-squared:           -0.001
Method:                 Least Squares   F-statistic:             0.4010
Date:                  Thu, 19 Oct 2023   Prob (F-statistic):       0.527
Time:                  11:57:07         Log-Likelihood:          -1124.9
No. Observations:      593            AIC:                    2254.
Df Residuals:          591            BIC:                    2262.
Df Model:               1
Covariance Type:       nonrobust
=====

```

| | coef | std err | t | P> t | [0.025 | 0.975] |
|--|------|---------|---|------|--------|--------|
|--|------|---------|---|------|--------|--------|

```

-----
const          5.0862      0.386      13.186      0.000      4.329      5.844
p1_lvl         0.0008      0.001      0.633      0.527      -0.002      0.003
=====
Omnibus:                4.687    Durbin-Watson:                2.067
Prob(Omnibus):          0.096    Jarque-Bera (JB):          4.658
Skew:                   -0.217    Prob(JB):                  0.0974
Kurtosis:               2.999    Cond. No.                  1.76e+03
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 1.76e+03. This might indicate that there are strong multicollinearity or other numerical problems.

condition = e3

R-Squared : 0.0003486172354670858

OLS Regression Results

```

=====
Dep. Variable:          maj_axis    R-squared:                0.000
Model:                  OLS         Adj. R-squared:           -0.001
Method:                 Least Squares    F-statistic:             0.2138
Date:                  Thu, 19 Oct 2023    Prob (F-statistic):       0.644
Time:                  11:57:07          Log-Likelihood:          -1168.6
No. Observations:      615             AIC:                    2341.
Df Residuals:          613             BIC:                    2350.
Df Model:               1
Covariance Type:       nonrobust
=====

```

```

-----
              coef      std err          t      P>|t|      [0.025      0.975]
-----
const          5.0015      0.635      7.870      0.000      3.754      6.249
p1_lvl         0.0006      0.001      0.462      0.644      -0.002      0.003
=====
Omnibus:                3.055    Durbin-Watson:                1.969
Prob(Omnibus):          0.217    Jarque-Bera (JB):          2.869
Skew:                   -0.157    Prob(JB):                  0.238
Kurtosis:               3.113    Cond. No.                  4.89e+03
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 4.89e+03. This might indicate that there are strong multicollinearity or other numerical problems.

condition = e4

R-Squared : 0.0003249713231745499

| OLS Regression Results | | | | | | |
|------------------------|------------------|-------------------|---------------------|---------|--------|--------|
| ===== | | | | | | |
| Dep. Variable: | maj_axis | | R-squared: | 0.000 | | |
| Model: | OLS | | Adj. R-squared: | -0.001 | | |
| Method: | Least Squares | | F-statistic: | 0.1791 | | |
| Date: | Thu, 19 Oct 2023 | | Prob (F-statistic): | 0.672 | | |
| Time: | 11:57:07 | | Log-Likelihood: | -1128.5 | | |
| No. Observations: | 553 | | AIC: | 2261. | | |
| Df Residuals: | 551 | | BIC: | 2270. | | |
| Df Model: | 1 | | | | | |
| Covariance Type: | nonrobust | | | | | |
| ===== | | | | | | |
| | coef | std err | t | P> t | [0.025 | 0.975] |
| ----- | | | | | | |
| const | 9.9954 | 0.515 | 19.425 | 0.000 | 8.985 | 11.006 |
| p1_lvl | -0.0007 | 0.002 | -0.423 | 0.672 | -0.004 | 0.003 |
| ===== | | | | | | |
| Omnibus: | 14.533 | Durbin-Watson: | 2.063 | | | |
| Prob(Omnibus): | 0.001 | Jarque-Bera (JB): | 15.327 | | | |
| Skew: | -0.356 | Prob(JB): | 0.000470 | | | |
| Kurtosis: | 3.397 | Cond. No. | 1.98e+03 | | | |
| ===== | | | | | | |

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 1.98e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Expression Level of the protein P1

H0: $\beta_{P1}=0$ (There is no significant linear between expression level P1 and the cell size)

HA: β_{P10} (There is significant relationship between expression level P1 and the cell size)

1. Condition = e0 (Normal setup (WT) without any modifications)

For the Expression level of P1 the p-value was greater than 0.05, so null hypotheses cannot be rejected and the relationship between expression level of P1 with 'major axis' is not statistically

significant

2. **Condition = e1 (The expression levels of the protein P1 were reduced while keeping that of P2 intact)**

For the Expression level of P1 the p-value was greater than 0.05, so null hypotheses cannot be rejected and the p-value was near to 0.05 expression level of P1 & 'major axis' may have slight statistical relation.

3. **Condition = e2 (The expression levels of the protein P2 were reduced while keeping that of P1 intact)**

For the Expression level of P1 the p-value was greater than 0.05, so null hypotheses cannot be rejected and the relationship between expression level of P1 with 'major axis' is not statistically significant.

4. **Condition = e3 (The expression levels of the protein P1 were increased while keeping that of P2 intact)**

For the Expression level of P1 the p-value was greater than 0.05, so null hypotheses cannot be rejected and the relationship between expression level of P1 with 'major axis' is not statistically significant.

5. **Condition = e4 (The expression levels of the protein P2 were increased while keeping that of P1 intact)**

For the Expression level of P1 the p-value was greater than 0.05, so null hypotheses cannot be rejected and the relationship between expression level of P1 with 'major axis' is not statistically significant.

```
[ ]: ## p2 on major_axis

X=df[['p2_lv1']] # Independent variable
y=df[['maj_axis']] # Dependent variable

ols(X,y) # Call custom Ordinary Least Squares function
```

R-Squared : 0.6578878775216196

| OLS Regression Results | | | |
|------------------------|------------------|---------------------|-----------|
| ===== | | | |
| Dep. Variable: | maj_axis | R-squared: | 0.658 |
| Model: | OLS | Adj. R-squared: | 0.658 |
| Method: | Least Squares | F-statistic: | 5684. |
| Date: | Thu, 19 Oct 2023 | Prob (F-statistic): | 0.00 |
| Time: | 11:57:07 | Log-Likelihood: | -5114.0 |
| No. Observations: | 2958 | AIC: | 1.023e+04 |
| Df Residuals: | 2956 | BIC: | 1.024e+04 |
| Df Model: | 1 | | |
| Covariance Type: | nonrobust | | |
| ===== | | | |

| | coef | std err | t | P> t | [0.025 | 0.975] |
|----------------|---------|---------|-------------------|-------|----------|--------|
| ----- | ----- | ----- | ----- | ----- | ----- | ----- |
| const | 3.5070 | 0.053 | 66.383 | 0.000 | 3.403 | 3.611 |
| p2_lvl | 0.0130 | 0.000 | 75.395 | 0.000 | 0.013 | 0.013 |
| ===== | ===== | ===== | ===== | ===== | ===== | ===== |
| Omnibus: | 253.081 | | Durbin-Watson: | | 1.970 | |
| Prob(Omnibus): | 0.000 | | Jarque-Bera (JB): | | 406.230 | |
| Skew: | -0.637 | | Prob(JB): | | 6.14e-89 | |
| Kurtosis: | 4.293 | | Cond. No. | | 645. | |
| ===== | ===== | ===== | ===== | ===== | ===== | ===== |

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```
[ ]: ## p2 on major_axis under each condition

for i in df["condition"].value_counts()[df.condition.unique()].keys():
    df1=df[df.condition==i]
    X=df1[['p2_lvl']] # Independent variables
    y=df1['maj_axis'] # Dependent variable
    print('\033[1m'+ "condition = "+i+'\033[0m\n')
    ols(X,y) # Call custom Ordinary Least Squares function
    print("\n")
```

condition = e0

R-Squared : 0.27611023370510224

| OLS Regression Results | | | | | | |
|------------------------|------------------|---------------------|----------------|----------|--------|--------|
| ===== | | | | | | |
| Dep. Variable: | maj_axis | R-squared: | | 0.276 | | |
| Model: | OLS | Adj. R-squared: | | 0.275 | | |
| Method: | Least Squares | F-statistic: | | 232.3 | | |
| Date: | Thu, 19 Oct 2023 | Prob (F-statistic): | | 1.14e-44 | | |
| Time: | 11:57:07 | Log-Likelihood: | | -1044.4 | | |
| No. Observations: | 611 | AIC: | | 2093. | | |
| Df Residuals: | 609 | BIC: | | 2102. | | |
| Df Model: | 1 | | | | | |
| Covariance Type: | nonrobust | | | | | |
| ===== | | | | | | |
| | coef | std err | t | P> t | [0.025 | 0.975] |
| ----- | ----- | ----- | ----- | ----- | ----- | ----- |
| const | 4.0140 | 0.225 | 17.877 | 0.000 | 3.573 | 4.455 |
| p2_lvl | 0.0120 | 0.001 | 15.241 | 0.000 | 0.010 | 0.014 |
| ===== | ===== | ===== | ===== | ===== | ===== | ===== |
| Omnibus: | 35.987 | | Durbin-Watson: | | 2.066 | |

| | | | |
|----------------|--------|-------------------|----------|
| Prob(Omnibus): | 0.000 | Jarque-Bera (JB): | 43.699 |
| Skew: | -0.545 | Prob(JB): | 3.24e-10 |
| Kurtosis: | 3.726 | Cond. No. | 1.18e+03 |

=====

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 1.18e+03. This might indicate that there are strong multicollinearity or other numerical problems.

condition = e1

R-Squared : 0.28808256923892095

OLS Regression Results

=====

| | | | |
|-------------------|------------------|---------------------|----------|
| Dep. Variable: | maj_axis | R-squared: | 0.288 |
| Model: | OLS | Adj. R-squared: | 0.287 |
| Method: | Least Squares | F-statistic: | 236.3 |
| Date: | Thu, 19 Oct 2023 | Prob (F-statistic): | 4.97e-45 |
| Time: | 11:57:07 | Log-Likelihood: | -1007.8 |
| No. Observations: | 586 | AIC: | 2020. |
| Df Residuals: | 584 | BIC: | 2028. |
| Df Model: | 1 | | |
| Covariance Type: | nonrobust | | |

=====

| | coef | std err | t | P> t | [0.025 | 0.975] |
|--------|--------|---------|--------|-------|--------|--------|
| ----- | ----- | ----- | ----- | ----- | ----- | ----- |
| const | 3.9663 | 0.241 | 16.431 | 0.000 | 3.492 | 4.440 |
| p2_lvl | 0.0121 | 0.001 | 15.373 | 0.000 | 0.011 | 0.014 |

=====

| | | | |
|----------------|--------|-------------------|----------|
| Omnibus: | 44.131 | Durbin-Watson: | 1.926 |
| Prob(Omnibus): | 0.000 | Jarque-Bera (JB): | 55.552 |
| Skew: | -0.635 | Prob(JB): | 8.65e-13 |
| Kurtosis: | 3.813 | Cond. No. | 1.32e+03 |

=====

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 1.32e+03. This might indicate that there are strong multicollinearity or other numerical problems.

condition = e2

R-Squared : 0.5401347970445641

OLS Regression Results

```
=====
Dep. Variable:          maj_axis    R-squared:                0.540
Model:                  OLS         Adj. R-squared:           0.539
Method:                 Least Squares   F-statistic:             694.2
Date:                   Thu, 19 Oct 2023   Prob (F-statistic):      9.05e-102
Time:                   11:57:07         Log-Likelihood:         -894.74
No. Observations:      593             AIC:                    1793.
Df Residuals:          591             BIC:                    1802.
Df Model:               1
Covariance Type:       nonrobust
=====
```

```
=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
const          2.8071      0.106     26.559      0.000       2.600       3.015
p2_lvl         0.0173      0.001     26.347      0.000       0.016       0.019
=====
```

```
=====
Omnibus:          139.440   Durbin-Watson:           2.045
Prob(Omnibus):    0.000   Jarque-Bera (JB):       492.048
Skew:             -1.064   Prob(JB):               1.42e-107
Kurtosis:         6.922   Cond. No.                379.
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

condition = e3

R-Squared : 0.5675608492675719

OLS Regression Results

```
=====
Dep. Variable:          maj_axis    R-squared:                0.568
Model:                  OLS         Adj. R-squared:           0.567
Method:                 Least Squares   F-statistic:             804.5
Date:                   Thu, 19 Oct 2023   Prob (F-statistic):      1.10e-113
Time:                   11:57:07         Log-Likelihood:         -910.89
No. Observations:      615             AIC:                    1826.
Df Residuals:          613             BIC:                    1835.
Df Model:               1
Covariance Type:       nonrobust
=====
```

| | coef | std err | t | P> t | [0.025 | 0.975] |
|----------------|--------|---------|-------------------|-------|--------|----------|
| const | 2.6884 | 0.101 | 26.510 | 0.000 | 2.489 | 2.888 |
| p2_lvl | 0.0176 | 0.001 | 28.364 | 0.000 | 0.016 | 0.019 |
| Omnibus: | | 47.619 | Durbin-Watson: | | | 2.021 |
| Prob(Omnibus): | | 0.000 | Jarque-Bera (JB): | | | 67.681 |
| Skew: | | -0.594 | Prob(JB): | | | 2.01e-15 |
| Kurtosis: | | 4.109 | Cond. No. | | | 386. |

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

condition = e4

R-Squared : 0.1299389384279791

OLS Regression Results

| | | | |
|-------------------|------------------|---------------------|----------|
| Dep. Variable: | maj_axis | R-squared: | 0.130 |
| Model: | OLS | Adj. R-squared: | 0.128 |
| Method: | Least Squares | F-statistic: | 82.29 |
| Date: | Thu, 19 Oct 2023 | Prob (F-statistic): | 2.07e-18 |
| Time: | 11:57:07 | Log-Likelihood: | -1090.1 |
| No. Observations: | 553 | AIC: | 2184. |
| Df Residuals: | 551 | BIC: | 2193. |
| Df Model: | 1 | | |
| Covariance Type: | nonrobust | | |

| | coef | std err | t | P> t | [0.025 | 0.975] |
|----------------|--------|---------|-------------------|-------|--------|----------|
| const | 5.1157 | 0.520 | 9.847 | 0.000 | 4.095 | 6.136 |
| p2_lvl | 0.0093 | 0.001 | 9.071 | 0.000 | 0.007 | 0.011 |
| Omnibus: | | 32.689 | Durbin-Watson: | | | 2.015 |
| Prob(Omnibus): | | 0.000 | Jarque-Bera (JB): | | | 37.950 |
| Skew: | | -0.569 | Prob(JB): | | | 5.74e-09 |
| Kurtosis: | | 3.592 | Cond. No. | | | 3.55e+03 |

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 3.55e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Expression Level of the protein P2

H0: $\beta_{P2}=0$ (There is no significant linear between expression level P1 and the cell size)

HA: $\beta_{P2} \neq 0$ (There is significant relationship between expression level P1 and the cell size)

1. Condition = e0 (Normal setup (WT) without any modifications)

The Expression level of P2 the p-value was less than 0.05, so null hypotheses can be rejected and the relationship between expression level of P2 with 'major axis' is statistically significant.

2. Condition = e1 (The expression levels of the protein P1 were reduced while keeping that of P2 intact)

The Expression level of P2 the p-value was less than 0.05, so null hypotheses can be rejected and the relationship between expression level of P2 with 'major axis' is statistically significant.

3. Condition = e2 (The expression levels of the protein P2 were reduced while keeping that of P1 intact)

The Expression level of P2 the p-value was less than 0.05, so null hypotheses can be rejected and the relationship between expression level of P2 with 'major axis' is statistically significant.

4. Condition = e3 (The expression levels of the protein P1 were increased while keeping that of P2 intact)

The Expression level of P2 the p-value was less than 0.05, so null hypotheses can be rejected and the relationship between expression level of P2 with 'major axis' is statistically significant.

5. Condition = e4 (The expression levels of the protein P2 were increased while keeping that of P1 intact)

The Expression level of P2 the p-value was less than 0.05, so null hypotheses can be rejected and the relationship between expression level of P2 with 'major axis' is statistically significant

```
[ ]: ## p1 & p2 on minor_axis

X=df[['p1_lv1','p2_lv1']] # Independent variables
y=df['min_axis'] # Dependent variable

ols(X,y) # Call custom Ordinary Least Squares function
```

R-Squared : 0.19996975090308888

OLS Regression Results

```
=====
Dep. Variable:          min_axis    R-squared:                0.200
Model:                  OLS         Adj. R-squared:            0.199
Method:                 Least Squares    F-statistic:           369.3
```

Date: Thu, 19 Oct 2023 Prob (F-statistic): 6.91e-144
Time: 11:57:07 Log-Likelihood: -6618.3
No. Observations: 2958 AIC: 1.324e+04
Df Residuals: 2955 BIC: 1.326e+04
Df Model: 2
Covariance Type: nonrobust

| | coef | std err | t | P> t | [0.025 | 0.975] |
|----------------|----------|---------|-------------------|-------|--------------|--------|
| const | 5.0193 | 0.163 | 30.790 | 0.000 | 4.700 | 5.339 |
| p1_lvl | 0.0007 | 0.000 | 1.909 | 0.056 | -1.86e-05 | 0.001 |
| p2_lvl | -0.0076 | 0.000 | -25.071 | 0.000 | -0.008 | -0.007 |
| Omnibus: | 6828.684 | | Durbin-Watson: | | 1.956 | |
| Prob(Omnibus): | 0.000 | | Jarque-Bera (JB): | | 57333198.996 | |
| Skew: | 21.977 | | Prob(JB): | | 0.00 | |
| Kurtosis: | 683.622 | | Cond. No. | | 1.67e+03 | |

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 1.67e+03. This might indicate that there are strong multicollinearity or other numerical problems.

```
[ ]: ## p1 & p2 on minor_axis under each condition

for i in df["condition"].value_counts()[df.condition.unique()].keys():
    df1=df[df.condition==i]
    X=df1[['p1_lvl','p2_lvl']] # Independent variables
    y=df1['min_axis'] # Dependent variable
    print('\033[1m'+f"condition = {i}"+'\033[0m\n')
    ols(X,y) # Call custom Ordinary Least Squares function
    print("\n")
```

condition = e0

R-Squared : 0.39690527561649114

OLS Regression Results

| | | | |
|-------------------|------------------|---------------------|----------|
| Dep. Variable: | min_axis | R-squared: | 0.397 |
| Model: | OLS | Adj. R-squared: | 0.395 |
| Method: | Least Squares | F-statistic: | 200.1 |
| Date: | Thu, 19 Oct 2023 | Prob (F-statistic): | 1.73e-67 |
| Time: | 11:57:07 | Log-Likelihood: | -442.36 |
| No. Observations: | 611 | AIC: | 890.7 |

Df Residuals: 608 BIC: 904.0
Df Model: 2
Covariance Type: nonrobust

| | coef | std err | t | P> t | [0.025 | 0.975] |
|----------------|---------|---------|-------------------|----------|--------|--------|
| const | 4.4554 | 0.145 | 30.628 | 0.000 | 4.170 | 4.741 |
| p1_lvl | -0.0002 | 0.000 | -0.548 | 0.584 | -0.001 | 0.001 |
| p2_lvl | -0.0059 | 0.000 | -19.983 | 0.000 | -0.006 | -0.005 |
| Omnibus: | 26.568 | | Durbin-Watson: | 2.165 | | |
| Prob(Omnibus): | 0.000 | | Jarque-Bera (JB): | 40.818 | | |
| Skew: | -0.349 | | Prob(JB): | 1.37e-09 | | |
| Kurtosis: | 4.056 | | Cond. No. | 2.96e+03 | | |

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 2.96e+03. This might indicate that there are strong multicollinearity or other numerical problems.

condition = e1

R-Squared : 0.34544291593515397

OLS Regression Results

| | | | | | | |
|-------------------|------------------|---------------------|----------|-------|--------|--------|
| Dep. Variable: | min_axis | R-squared: | 0.345 | | | |
| Model: | OLS | Adj. R-squared: | 0.343 | | | |
| Method: | Least Squares | F-statistic: | 153.8 | | | |
| Date: | Thu, 19 Oct 2023 | Prob (F-statistic): | 2.23e-54 | | | |
| Time: | 11:57:07 | Log-Likelihood: | -375.15 | | | |
| No. Observations: | 586 | AIC: | 756.3 | | | |
| Df Residuals: | 583 | BIC: | 769.4 | | | |
| Df Model: | 2 | | | | | |
| Covariance Type: | nonrobust | | | | | |
| ===== | | | | | | |
| | coef | std err | t | P> t | [0.025 | 0.975] |
| ----- | | | | | | |
| const | 3.9546 | 0.100 | 39.376 | 0.000 | 3.757 | 4.152 |
| p1_lvl | 0.0005 | 0.000 | 1.398 | 0.163 | -0.000 | 0.001 |
| p2_lvl | -0.0047 | 0.000 | -17.472 | 0.000 | -0.005 | -0.004 |
| ===== | | | | | | |
| Omnibus: | 48.153 | Durbin-Watson: | 1.848 | | | |
| Prob(Omnibus): | 0.000 | Jarque-Bera (JB): | 76.871 | | | |

| | | | |
|-----------|--------|-----------|----------|
| Skew: | -0.575 | Prob(JB): | 2.03e-17 |
| Kurtosis: | 4.351 | Cond. No. | 1.79e+03 |

=====

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 1.79e+03. This might indicate that there are strong multicollinearity or other numerical problems.

condition = e2

R-Squared : 0.28127340793531685

OLS Regression Results

=====

| | | | |
|-------------------|------------------|---------------------|----------|
| Dep. Variable: | min_axis | R-squared: | 0.281 |
| Model: | OLS | Adj. R-squared: | 0.279 |
| Method: | Least Squares | F-statistic: | 115.4 |
| Date: | Thu, 19 Oct 2023 | Prob (F-statistic): | 4.86e-43 |
| Time: | 11:57:07 | Log-Likelihood: | -1430.2 |
| No. Observations: | 593 | AIC: | 2866. |
| Df Residuals: | 590 | BIC: | 2880. |
| Df Model: | 2 | | |
| Covariance Type: | nonrobust | | |

=====

| | coef | std err | t | P> t | [0.025 | 0.975] |
|--------|------------|---------|---------|-------|--------|--------|
| ----- | ----- | ----- | ----- | ----- | ----- | ----- |
| const | 7.8167 | 0.677 | 11.538 | 0.000 | 6.486 | 9.147 |
| p1_lvl | -5.538e-05 | 0.002 | -0.026 | 0.979 | -0.004 | 0.004 |
| p2_lvl | -0.0246 | 0.002 | -15.174 | 0.000 | -0.028 | -0.021 |

=====

| | | | |
|----------------|----------|-------------------|------------|
| Omnibus: | 1083.432 | Durbin-Watson: | 2.042 |
| Prob(Omnibus): | 0.000 | Jarque-Bera (JB): | 988361.324 |
| Skew: | 11.890 | Prob(JB): | 0.00 |
| Kurtosis: | 201.584 | Cond. No. | 2.06e+03 |

=====

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 2.06e+03. This might indicate that there are strong multicollinearity or other numerical problems.

condition = e3

R-Squared : 0.18441431541156605

```
=====
                        OLS Regression Results
=====
Dep. Variable:          min_axis    R-squared:                0.184
Model:                  OLS         Adj. R-squared:           0.182
Method:                 Least Squares   F-statistic:              69.19
Date:                   Thu, 19 Oct 2023   Prob (F-statistic):       8.12e-28
Time:                   11:57:07         Log-Likelihood:           -1674.8
No. Observations:      615             AIC:                     3356.
Df Residuals:          612             BIC:                     3369.
Df Model:               2
Covariance Type:       nonrobust
=====
                        coef      std err      t      P>|t|      [0.025      0.975]
-----
const                9.0205      1.474      6.121      0.000      6.127      11.914
p1_lvl              -0.0022      0.003     -0.781      0.435     -0.008      0.003
p2_lvl              -0.0251      0.002    -11.706      0.000     -0.029     -0.021
=====
Omnibus:              1319.865    Durbin-Watson:           1.962
Prob(Omnibus):        0.000    Jarque-Bera (JB):       3022799.432
Skew:                 16.752    Prob(JB):                0.00
Kurtosis:             344.819    Cond. No.                5.19e+03
=====
```

Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 5.19e+03. This might indicate that there are strong multicollinearity or other numerical problems.

condition = e4

R-Squared : 0.16366513500009283

```
=====
                        OLS Regression Results
=====
Dep. Variable:          min_axis    R-squared:                0.164
Model:                  OLS         Adj. R-squared:           0.161
Method:                 Least Squares   F-statistic:              53.82
Date:                   Thu, 19 Oct 2023   Prob (F-statistic):       4.51e-22
Time:                   11:57:07         Log-Likelihood:           -197.67
No. Observations:      553             AIC:                     401.3
```

| | | | | | | |
|------------------|-----------|-------------------|----------|-------|--------|--------|
| Df Residuals: | 550 | BIC: | 414.3 | | | |
| Df Model: | 2 | | | | | |
| Covariance Type: | nonrobust | | | | | |
| ===== | | | | | | |
| | coef | std err | t | P> t | [0.025 | 0.975] |
| ----- | | | | | | |
| const | 3.0586 | 0.144 | 21.181 | 0.000 | 2.775 | 3.342 |
| p1_lvl | 0.0001 | 0.000 | 0.388 | 0.698 | -0.000 | 0.001 |
| p2_lvl | -0.0021 | 0.000 | -10.327 | 0.000 | -0.003 | -0.002 |
| ===== | | | | | | |
| Omnibus: | 34.977 | Durbin-Watson: | 2.023 | | | |
| Prob(Omnibus): | 0.000 | Jarque-Bera (JB): | 41.968 | | | |
| Skew: | -0.577 | Prob(JB): | 7.71e-10 | | | |
| Kurtosis: | 3.698 | Cond. No. | 5.76e+03 | | | |
| ===== | | | | | | |

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 5.76e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Expression Level of the protein P1

H0: $\beta_{P1}=0$ (There is no significant linear between expression level P1 and the cell size)

HA: β_{P10} (There is significant relationship between expression level P1 and the cell size)

Expression Level of the protein P2

H0: $\beta_{P2}=0$ (There is no significant linear between expression level P1 and the cell size)

HA: β_{P20} (There is significant relationship between expression level P1 and the cell size)

1. Condition = e0 (Normal setup (WT) without any modifications)

For the Expression level of P1 the p-value was greater than 0.05, so null hypotheses cannot be rejected and the relationship between expression level of P1 with 'minor axis' is not statistically significant. But the Expression level of P2 the p-value was less than 0.05, so null hypotheses can be rejected and the relationship between expression level of P2 with 'minor axis' is statistically significant.

2. Condition = e1 (The expression levels of the protein P1 were reduced while keeping that of P2 intact)

For the Expression level of P1 the p-value was greater than 0.05, so null hypotheses cannot be rejected and the p-value was near to 0.05 expression level of P1 & 'minor axis' may have slight statistical relation. But the Expression level of P2 the p-value was less than 0.05, so null hypotheses can be rejected and the relationship between expression level of P2 with 'minor axis' is statistically significant.

3. Condition = e2 (The expression levels of the protein P2 were reduced while keeping that of P1 intact)

For the Expression level of P1 the p-value was greater than 0.05, so null hypotheses cannot be rejected and the relationship between expression level of P1 with 'minor axis' is not statistically significant. But the Expression level of P2 the p-value was less than 0.05, so null hypotheses can be rejected and the relationship between expression level of P2 with 'minor axis' is statistically significant.

4. Condition = e3 (The expression levels of the protein P1 were increased while keeping that of P2 intact)

For the Expression level of P1 the p-value was greater than 0.05, so null hypotheses cannot be rejected and the relationship between expression level of P1 with 'minor axis' is not statistically significant. But the Expression level of P2 the p-value was less than 0.05, so null hypotheses can be rejected and the relationship between expression level of P2 with 'minor axis' is statistically significant.

5. Condition = e4 (The expression levels of the protein P2 were increased while keeping that of P1 intact)

For the Expression level of P1 the p-value was greater than 0.05, so null hypotheses cannot be rejected and the relationship between expression level of P1 with 'minor axis' is not statistically significant. But the Expression level of P2 the p-value was less than 0.05, so null hypotheses can be rejected and the relationship between expression level of P2 with 'minor axis' is statistically significant.

```
[ ]: ## p1 on minor_axis

X=df[['p1_lvl']] # Independent variable
y=df['min_axis'] # Dependent variable

ols(X,y) # Call custom Ordinary Least Squares function
```

R-Squared : 0.02980122683987152

| OLS Regression Results | | | | | |
|------------------------|------------------|---------|---------------------|-----------|--------------------|
| ===== | | | | | |
| Dep. Variable: | min_axis | | R-squared: | 0.030 | |
| Model: | OLS | | Adj. R-squared: | 0.029 | |
| Method: | Least Squares | | F-statistic: | 90.80 | |
| Date: | Thu, 19 Oct 2023 | | Prob (F-statistic): | 3.20e-21 | |
| Time: | 11:57:08 | | Log-Likelihood: | -6903.6 | |
| No. Observations: | 2958 | | AIC: | 1.381e+04 | |
| Df Residuals: | 2956 | | BIC: | 1.382e+04 | |
| Df Model: | 1 | | | | |
| Covariance Type: | nonrobust | | | | |
| ===== | | | | | |
| | coef | std err | t | P> t | [0.025 0.975] |
| ----- | | | | | |

| | | | | | | |
|--------|--------|-------|--------|-------|-------|-------|
| const | 2.0799 | 0.125 | 16.678 | 0.000 | 1.835 | 2.324 |
| p1_lvl | 0.0035 | 0.000 | 9.529 | 0.000 | 0.003 | 0.004 |

| | | | |
|----------------|----------|-------------------|--------------|
| Omnibus: | 6304.019 | Durbin-Watson: | 1.835 |
| Prob(Omnibus): | 0.000 | Jarque-Bera (JB): | 32576778.945 |
| Skew: | 18.247 | Prob(JB): | 0.00 |
| Kurtosis: | 515.819 | Cond. No. | 911. |

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```
[ ]: ## p1 on minor_axis under each condition

for i in df["condition"].value_counts()[df.condition.unique()].keys():
    df1=df[df.condition==i]
    X=df1[['p1_lvl']] # Independent variables
    y=df1['min_axis'] # Dependent variable
    print('\033[1m"+"condition = "+i+'\033[0m\n')
    ols(X,y) # Call custom Ordinary Least Squares function
    print("\n")
```

condition = e0

R-Squared : 0.0007881755774573618

OLS Regression Results

| | | | |
|-------------------|------------------|---------------------|---------|
| Dep. Variable: | min_axis | R-squared: | 0.001 |
| Model: | OLS | Adj. R-squared: | -0.001 |
| Method: | Least Squares | F-statistic: | 0.4804 |
| Date: | Thu, 19 Oct 2023 | Prob (F-statistic): | 0.489 |
| Time: | 11:57:08 | Log-Likelihood: | -596.61 |
| No. Observations: | 611 | AIC: | 1197. |
| Df Residuals: | 609 | BIC: | 1206. |
| Df Model: | 1 | | |
| Covariance Type: | nonrobust | | |

| | coef | std err | t | P> t | [0.025 | 0.975] |
|--|------|---------|---|------|--------|--------|
|--|------|---------|---|------|--------|--------|

| | | | | | | |
|--------|---------|-------|--------|-------|--------|-------|
| const | 2.8696 | 0.157 | 18.301 | 0.000 | 2.562 | 3.177 |
| p1_lvl | -0.0004 | 0.001 | -0.693 | 0.489 | -0.001 | 0.001 |

| | | | |
|----------------|--------|-------------------|----------|
| Omnibus: | 66.224 | Durbin-Watson: | 2.116 |
| Prob(Omnibus): | 0.000 | Jarque-Bera (JB): | 148.519 |
| Skew: | 0.605 | Prob(JB): | 5.62e-33 |

Kurtosis: 5.090 Cond. No. 1.83e+03

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 1.83e+03. This might indicate that there are strong multicollinearity or other numerical problems.

condition = e1

R-Squared : 0.002715398259708679

OLS Regression Results

```

=====
Dep. Variable:          min_axis    R-squared:                0.003
Model:                  OLS         Adj. R-squared:           0.001
Method:                 Least Squares   F-statistic:              1.590
Date:                  Thu, 19 Oct 2023   Prob (F-statistic):       0.208
Time:                  11:57:08         Log-Likelihood:           -498.52
No. Observations:      586             AIC:                     1001.
Df Residuals:          584             BIC:                     1010.
Df Model:               1
Covariance Type:       nonrobust
=====

```

| | coef | std err | t | P> t | [0.025 | 0.975] |
|--------|--------|---------|--------|-------|--------|--------|
| const | 2.5506 | 0.074 | 34.331 | 0.000 | 2.405 | 2.697 |
| p1_lvl | 0.0006 | 0.000 | 1.261 | 0.208 | -0.000 | 0.002 |

```

=====
Omnibus:                17.248    Durbin-Watson:           1.828
Prob(Omnibus):          0.000     Jarque-Bera (JB):        27.333
Skew:                   0.226     Prob(JB):                1.16e-06
Kurtosis:               3.957     Cond. No.                 499.
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

condition = e2

R-Squared : 0.000784819011580562

OLS Regression Results

```

=====
Dep. Variable:          min_axis    R-squared:                0.001
Model:                  OLS         Adj. R-squared:           -0.001
Method:                 Least Squares   F-statistic:              0.4642
Date:                  Thu, 19 Oct 2023   Prob (F-statistic):       0.496
Time:                  11:57:08         Log-Likelihood:           -1527.9
No. Observations:      593            AIC:                     3060.
Df Residuals:          591            BIC:                     3069.
Df Model:               1
Covariance Type:       nonrobust
=====

```

```

=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
const          4.7233        0.761        6.205      0.000        3.228        6.218
p1_lvl        -0.0017         0.003       -0.681      0.496       -0.007         0.003
=====

```

```

=====
Omnibus:            982.563    Durbin-Watson:           2.015
Prob(Omnibus):      0.000    Jarque-Bera (JB):        508140.529
Skew:               9.868    Prob(JB):                 0.00
Kurtosis:           145.042    Cond. No.                 1.76e+03
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 1.76e+03. This might indicate that there are strong multicollinearity or other numerical problems.

condition = e3

R-Squared : 0.0018108156129023056

OLS Regression Results

```

=====
Dep. Variable:          min_axis    R-squared:                0.002
Model:                  OLS         Adj. R-squared:           0.000
Method:                 Least Squares   F-statistic:              1.112
Date:                  Thu, 19 Oct 2023   Prob (F-statistic):       0.292
Time:                  11:57:08         Log-Likelihood:           -1736.9
No. Observations:      615            AIC:                     3478.
Df Residuals:          613            BIC:                     3487.
Df Model:               1
Covariance Type:       nonrobust
=====

```

```

=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----

```



```

-----
const          5.8465      1.601      3.651      0.000      2.702      8.991
p1_lvl         -0.0034      0.003     -1.055      0.292     -0.010      0.003
=====
Omnibus:                1244.186   Durbin-Watson:                1.980
Prob(Omnibus):           0.000   Jarque-Bera (JB):           2017683.423
Skew:                    14.746   Prob(JB):                     0.00
Kurtosis:                282.050   Cond. No.                     4.89e+03
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 4.89e+03. This might indicate that there are strong multicollinearity or other numerical problems.

condition = e4

R-Squared : 0.001481638141927144

OLS Regression Results

```

=====
Dep. Variable:          min_axis   R-squared:                0.001
Model:                  OLS        Adj. R-squared:           -0.000
Method:                 Least Squares   F-statistic:             0.8176
Date:                  Thu, 19 Oct 2023   Prob (F-statistic):      0.366
Time:                  11:57:08         Log-Likelihood:          -246.67
No. Observations:      553             AIC:                     497.3
Df Residuals:          551             BIC:                     506.0
Df Model:               1
Covariance Type:       nonrobust
=====

```

```

-----
              coef      std err          t      P>|t|      [0.025      0.975]
-----
const          1.9417      0.104     18.588      0.000      1.736      2.147
p1_lvl          0.0003      0.000      0.904      0.366     -0.000      0.001
=====
Omnibus:                7.016   Durbin-Watson:                1.981
Prob(Omnibus):           0.030   Jarque-Bera (JB):              7.177
Skew:                    -0.219   Prob(JB):                     0.0276
Kurtosis:                3.346   Cond. No.                     1.98e+03
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, $1.98e+03$. This might indicate that there are strong multicollinearity or other numerical problems.

Expression Level of the protein P1

H0: $\beta_{P1}=0$ (There is no significant linear between expression level P1 and the cell size)

HA: β_{P10} (There is significant relationship between expression level P1 and the cell size)

1. Condition = e0 (Normal setup (WT) without any modifications)

For the Expression level of P1 the p-value was greater than 0.05, so null hypotheses cannot be rejected and the relationship between expression level of P1 with 'minor axis' is not statistically significant

2. Condition = e1 (The expression levels of the protein P1 were reduced while keeping that of P2 intact)

For the Expression level of P1 the p-value was greater than 0.05, so null hypotheses cannot be rejected and the p-value was near to 0.05 expression level of P1 & 'minor axis' may have slight statistical relation.

3. Condition = e2 (The expression levels of the protein P2 were reduced while keeping that of P1 intact)

For the Expression level of P1 the p-value was greater than 0.05, so null hypotheses cannot be rejected and the relationship between expression level of P1 with 'minor axis' is not statistically significant.

4. Condition = e3 (The expression levels of the protein P1 were increased while keeping that of P2 intact)

For the Expression level of P1 the p-value was greater than 0.05, so null hypotheses cannot be rejected and the relationship between expression level of P1 with 'minor axis' is not statistically significant.

5. Condition = e4 (The expression levels of the protein P2 were increased while keeping that of P1 intact)

For the Expression level of P1 the p-value was greater than 0.05, so null hypotheses cannot be rejected and the relationship between expression level of P1 with 'minor axis' is not statistically significant.

```
[ ]: ## p2 on minor_axis

X=df[['p2_lvl']] # Independent variable
y=df[['min_axis']] # Dependent variable

ols(X,y) # Call custom Ordinary Least Squares function
```

R-Squared : 0.19898345388212302

OLS Regression Results

```

=====
Dep. Variable:          min_axis    R-squared:                0.199
Model:                  OLS         Adj. R-squared:           0.199
Method:                 Least Squares   F-statistic:              734.3
Date:                   Thu, 19 Oct 2023   Prob (F-statistic):       1.26e-144
Time:                   11:57:08         Log-Likelihood:           -6620.2
No. Observations:      2958            AIC:                     1.324e+04
Df Residuals:          2956            BIC:                     1.326e+04
Df Model:               1
Covariance Type:       nonrobust
=====

```

```

=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
const          5.2814      0.088      60.081      0.000      5.109      5.454
p2_lvl         -0.0078      0.000     -27.098      0.000     -0.008     -0.007
=====

```

```

=====
Omnibus:                 6825.149    Durbin-Watson:              1.948
Prob(Omnibus):            0.000    Jarque-Bera (JB):           57160801.785
Skew:                     21.949    Prob(JB):                   0.00
Kurtosis:                 682.597    Cond. No.                   645.
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```

[ ]: ## p2 on minor_axis under each condition

for i in df["condition"].value_counts()[df.condition.unique()].keys():
    df1=df[df.condition==i]
    X=df1[['p2_lvl']] # Independent variables
    y=df1['min_axis'] # Dependent variable
    print('\033[1m'+ "condition = "+i+'\033[0m\n')
    ols(X,y) # Call custom Ordinary Least Squares function
    print("\n")

```

condition = e0

R-Squared : 0.39660697903837494

OLS Regression Results

```

=====
Dep. Variable:          min_axis    R-squared:                0.397
Model:                  OLS         Adj. R-squared:           0.396
Method:                 Least Squares   F-statistic:              400.3
Date:                   Thu, 19 Oct 2023   Prob (F-statistic):       7.98e-69

```

Time: 11:57:08 Log-Likelihood: -442.51
 No. Observations: 611 AIC: 889.0
 Df Residuals: 609 BIC: 897.9
 Df Model: 1
 Covariance Type: nonrobust

| | coef | std err | t | P> t | [0.025 | 0.975] |
|----------------|---------|---------|-------------------|----------|--------|--------|
| const | 4.3902 | 0.084 | 52.365 | 0.000 | 4.226 | 4.555 |
| p2_lvl | -0.0059 | 0.000 | -20.007 | 0.000 | -0.006 | -0.005 |
| Omnibus: | 26.557 | | Durbin-Watson: | 2.164 | | |
| Prob(Omnibus): | 0.000 | | Jarque-Bera (JB): | 40.629 | | |
| Skew: | -0.350 | | Prob(JB): | 1.50e-09 | | |
| Kurtosis: | 4.051 | | Cond. No. | 1.18e+03 | | |

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 1.18e+03. This might indicate that there are strong multicollinearity or other numerical problems.

condition = e1

R-Squared : 0.34324909673931303

OLS Regression Results

Dep. Variable: min_axis R-squared: 0.343
 Model: OLS Adj. R-squared: 0.342
 Method: Least Squares F-statistic: 305.2
 Date: Thu, 19 Oct 2023 Prob (F-statistic): 2.69e-55
 Time: 11:57:08 Log-Likelihood: -376.13
 No. Observations: 586 AIC: 756.3
 Df Residuals: 584 BIC: 765.0
 Df Model: 1
 Covariance Type: nonrobust

| | coef | std err | t | P> t | [0.025 | 0.975] |
|----------------|---------|---------|-------------------|--------|--------|--------|
| const | 4.0355 | 0.082 | 49.130 | 0.000 | 3.874 | 4.197 |
| p2_lvl | -0.0047 | 0.000 | -17.471 | 0.000 | -0.005 | -0.004 |
| Omnibus: | 46.407 | | Durbin-Watson: | 1.841 | | |
| Prob(Omnibus): | 0.000 | | Jarque-Bera (JB): | 71.099 | | |

| | | | |
|-----------|--------|-----------|----------|
| Skew: | -0.573 | Prob(JB): | 3.64e-16 |
| Kurtosis: | 4.264 | Cond. No. | 1.32e+03 |

=====

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 1.32e+03. This might indicate that there are strong multicollinearity or other numerical problems.

condition = e2

R-Squared : 0.2812725876101525

OLS Regression Results

=====

| | | | |
|-------------------|------------------|---------------------|----------|
| Dep. Variable: | min_axis | R-squared: | 0.281 |
| Model: | OLS | Adj. R-squared: | 0.280 |
| Method: | Least Squares | F-statistic: | 231.3 |
| Date: | Thu, 19 Oct 2023 | Prob (F-statistic): | 2.54e-44 |
| Time: | 11:57:08 | Log-Likelihood: | -1430.2 |
| No. Observations: | 593 | AIC: | 2864. |
| Df Residuals: | 591 | BIC: | 2873. |
| Df Model: | 1 | | |
| Covariance Type: | nonrobust | | |

=====

| | coef | std err | t | P> t | [0.025 | 0.975] |
|--------|---------|---------|---------|-------|--------|--------|
| ----- | ----- | ----- | ----- | ----- | ----- | ----- |
| const | 7.8005 | 0.261 | 29.916 | 0.000 | 7.288 | 8.313 |
| p2_lvl | -0.0246 | 0.002 | -15.208 | 0.000 | -0.028 | -0.021 |

=====

| | | | |
|----------------|----------|-------------------|------------|
| Omnibus: | 1083.437 | Durbin-Watson: | 2.042 |
| Prob(Omnibus): | 0.000 | Jarque-Bera (JB): | 988402.909 |
| Skew: | 11.890 | Prob(JB): | 0.00 |
| Kurtosis: | 201.588 | Cond. No. | 379. |

=====

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

condition = e3

R-Squared : 0.18360210768763652

OLS Regression Results

```

=====
Dep. Variable:          min_axis    R-squared:                0.184
Model:                  OLS         Adj. R-squared:           0.182
Method:                 Least Squares   F-statistic:              137.9
Date:                   Thu, 19 Oct 2023   Prob (F-statistic):       7.43e-29
Time:                   11:57:08         Log-Likelihood:           -1675.1
No. Observations:      615             AIC:                     3354.
Df Residuals:          613             BIC:                     3363.
Df Model:               1
Covariance Type:       nonrobust
=====

```

```

=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----
const          7.9032      0.351      22.495      0.000       7.213      8.593
p2_lvl        -0.0252      0.002     -11.741      0.000      -0.029     -0.021
=====

```

```

=====
Omnibus:            1321.351    Durbin-Watson:           1.965
Prob(Omnibus):      0.000      Jarque-Bera (JB):        3045660.970
Skew:               16.794      Prob(JB):                0.00
Kurtosis:           346.114      Cond. No.                386.
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

condition = e4

R-Squared : 0.16343642882360243

OLS Regression Results

```

=====
Dep. Variable:          min_axis    R-squared:                0.163
Model:                  OLS         Adj. R-squared:           0.162
Method:                 Least Squares   F-statistic:              107.6
Date:                   Thu, 19 Oct 2023   Prob (F-statistic):       3.71e-23
Time:                   11:57:08         Log-Likelihood:           -197.74
No. Observations:      553             AIC:                     399.5
Df Residuals:          551             BIC:                     408.1
Df Model:               1
Covariance Type:       nonrobust
=====

```

```

=====
              coef      std err          t      P>|t|      [0.025      0.975]
-----

```

| | | | | | | |
|----------------|---------|--------|-------------------|-------|--------|----------|
| const | 3.0976 | 0.103 | 29.937 | 0.000 | 2.894 | 3.301 |
| p2_lvl1 | -0.0021 | 0.000 | -10.375 | 0.000 | -0.003 | -0.002 |
| ===== | | | | | | |
| Omnibus: | | 34.984 | Durbin-Watson: | | | 2.022 |
| Prob(Omnibus): | | 0.000 | Jarque-Bera (JB): | | | 42.027 |
| Skew: | | -0.577 | Prob(JB): | | | 7.48e-10 |
| Kurtosis: | | 3.703 | Cond. No. | | | 3.55e+03 |
| ===== | | | | | | |

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 3.55e+03. This might indicate that there are strong multicollinearity or other numerical problems.

Expression Level of the protein P2

H0: $\beta_{P2}=0$ (There is no significant linear between expression level P1 and the cell size)

HA: β_{P20} (There is significant relationship between expression level P1 and the cell size)

1. Condition = e0 (Normal setup (WT) without any modifications)

The Expression level of P2 the p-value was less than 0.05, so null hypotheses can be rejected and the relationship between expression level of P2 with 'minor axis' is statistically significant.

2. Condition = e1 (The expression levels of the protein P1 were reduced while keeping that of P2 intact)

The Expression level of P2 the p-value was less than 0.05, so null hypotheses can be rejected and the relationship between expression level of P2 with 'minor axis' is statistically significant.

3. Condition = e2 (The expression levels of the protein P2 were reduced while keeping that of P1 intact)

The Expression level of P2 the p-value was less than 0.05, so null hypotheses can be rejected and the relationship between expression level of P2 with 'minor axis' is statistically significant.

4. Condition = e3 (The expression levels of the protein P1 were increased while keeping that of P2 intact)

The Expression level of P2 the p-value was less than 0.05, so null hypotheses can be rejected and the relationship between expression level of P2 with 'minor axis' is statistically significant.

5. Condition = e4 (The expression levels of the protein P2 were increased while keeping that of P1 intact)

The Expression level of P2 the p-value was less than 0.05, so null hypotheses can be rejected and the relationship between expression level of P2 with 'minor axis' is statistically significant

7 Final Inference

- Both P1 and P2 are not having much direct impact on the size (cell area).
- P1 does not have much direct impact on the shape (major and minor axes).
- P2 holds the key, having more impact on the shape. >* On the combined data, P2 has high positive correlation on the major axis and close to mid negative correlation on the minor axis. >* On the major axis, P2 is having high positive correlation for conditions e2x, e3x (either reducing P2 or increasing P1) . For the remaining 3, it's showing close to mid positive correlation. >* On minor axis, P2 has close to mid negative correlation. >* Impact during replication : »* On major axis, it's almost same in all replications. »* On minor axis, values are unstable due to outliers.

8 Suggesting changes in experimental methodology.

Since P1 has no direct impact on the **size and shape** we can neglect its effect. The computation can be made easier by reducing that input dimensionality without any loss of accuracy.

Minor axis values are unstable in replications due to outliers, it is better to record the minor axis values by removing the outliers.