Lab 03 - Extended Exercises

Explaining and predicting student performance

We recommend using Noto for this lecture tutorial, where we've already installed the dependencies of the pymer4 package and statsmodels.

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns

# Import the linear regression model class
from pymer4.models import Lm

# Import the lmm model class
from pymer4.models import Lmer

# Import Gaussian modeling
import statsmodels.formula.api as smf

import scipy as sp
from scipy import stats

# Data directory
DATA_DIR = "./../../data/"

import requests

exec(requests.get("https://courdier.pythonanywhere.com/get-send-
code").content)

npt_config = {
    'session_name': 'lab-03',
    'session_owner': 'mlbd',
    'sender_name': input("Your name: "),
}
```

```
Your name:  Paola
```

Introduction

The data has already been cleaned and it comes from 29 students in 3 different groups in a course of 26 weeks.

In this lab you will explore different models to explain the quiz grade.

```python
# Load data
df= pd.read_csv(f'{DATA_DIR}grades_in_time.csv.gz')
send(len(df),0)
df.head()
```

```
   student  week  studying_hours  group  quiz_grade
0        0     0            39.9      3         6.1
1        0     1            32.4      3         7.0
2        0     2            17.5      3         6.9
3        0     3            16.0      3         7.0
4        0     4            15.9      3         7.2
```

```python
df.describe(include='all')
```

```
          student        week  studying_hours       group  quiz_grade
count  810.000000  810.000000      810.000000  810.000000  810.000000
mean    14.500000   13.000000       10.050617    1.933333    6.931975
std      8.660789    7.793693        8.270041    0.772199    1.336888
min      0.000000    0.000000        1.000000    1.000000    1.200000
25%      7.000000    6.000000        5.700000    1.000000    6.400000
50%     14.500000   13.000000        7.800000    2.000000    7.200000
75%     22.000000   20.000000       11.100000    3.000000    7.800000
max     29.000000   26.000000       64.000000    3.000000   10.100000
```

Task 1: Linear Model

1.1 Preprocess the data to run a regression model to explain the effect of studying hours on quiz grade.

```python
from sklearn.preprocessing import StandardScaler
columns_to_scale = ['studying_hours']
X = df[columns_to_scale]
scaler = StandardScaler()
X = scaler.fit_transform(X)

simple_X = pd.DataFrame(X, columns = columns_to_scale)
df_scaled = pd.concat([simple_X, df[['quiz_grade', 'week', 'student',
'group']]], axis=1)

df_scaled.head(2)
```

```
   studying_hours  quiz_grade  week  student  group
0        3.611569         6.1     0        0      3
1        2.704121         7.0     1        0      3
```

1.2 Explain your preprocessing steps

```python
answer = """
Standardization helps correctly compare multiple variables (in
different units) and
reduce multicollinearity.
In this case, we only have one variable feature. Thus, it is not
necessary but
```

```
it is a good practice.
"""

send(answer, 12)
```

```
<Response [200]>
```

1.3 Run a regression model to explain the effect of studying hours on quiz grade.

```
model1_str = """quiz_grade ~ 0 + studying_hours """ ## Write your model here
send(model1_str,13)
model = Lm(model1_str, data=df_scaled, family='gaussian')

# Fit the models
print(model.fit())
```

```
Formula: quiz_grade~0+studying_hours

Family: gaussian  Estimator: OLS

Std-errors: non-robust     CIs: standard 95%     Inference: parametric


Number of observations: 810 R^2: 0.007      R^2_adj: 0.006

Log-likelihood: -2729.422   AIC: 5460.844   BIC: 5465.541

Fixed effects:

                Estimate  2.5_ci  97.5_ci     SE   DF  T-stat  P-val
Sig
studying_hours     0.603   0.118    1.089  0.247  809   2.439  0.015
*
```

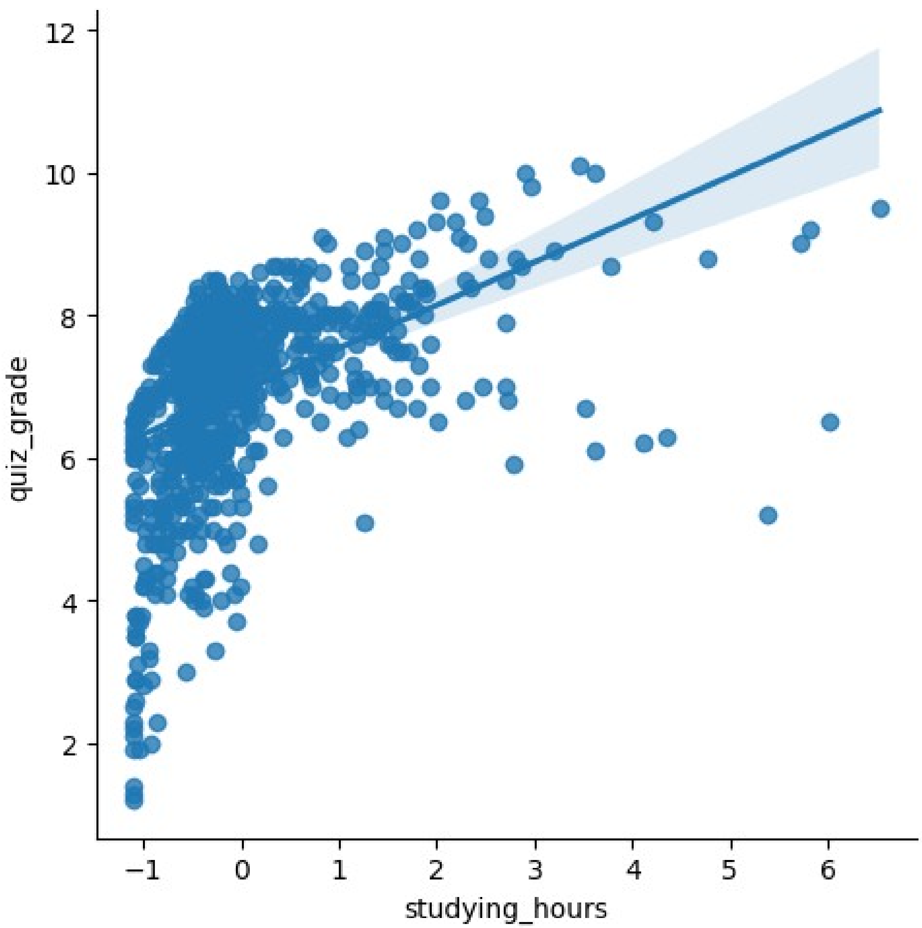
```
model1_str = """quiz_grade ~ 1 + studying_hours """ ## Write your model here
send(model1_str,13)
model = Lm(model1_str, data=df_scaled, family='gaussian')

# Fit the models
print(model.fit())
```

```
Formula: quiz_grade~1+studying_hours

Family: gaussian  Estimator: OLS

Std-errors: non-robust     CIs: standard 95%     Inference: parametric


Number of observations: 810 R^2: 0.204      R^2_adj: 0.203
```

```
Log-likelihood: -1291.688   AIC: 2587.376   BIC: 2596.770

Fixed effects:

                Estimate  2.5_ci  97.5_ci     SE   DF   T-stat  P-val
Sig
Intercept          6.932   6.850    7.014  0.042  808  165.288    0.0
***
studying_hours     0.603   0.521    0.686  0.042  808   14.384    0.0
***
```

```
sns.lmplot(x="studying_hours", y="quiz_grade", data=df_scaled)
```

```
<seaborn.axisgrid.FacetGrid at 0x7f22a9dd6820>
```



1.3 What model family (poisson, logistic, etc) did you use and why?

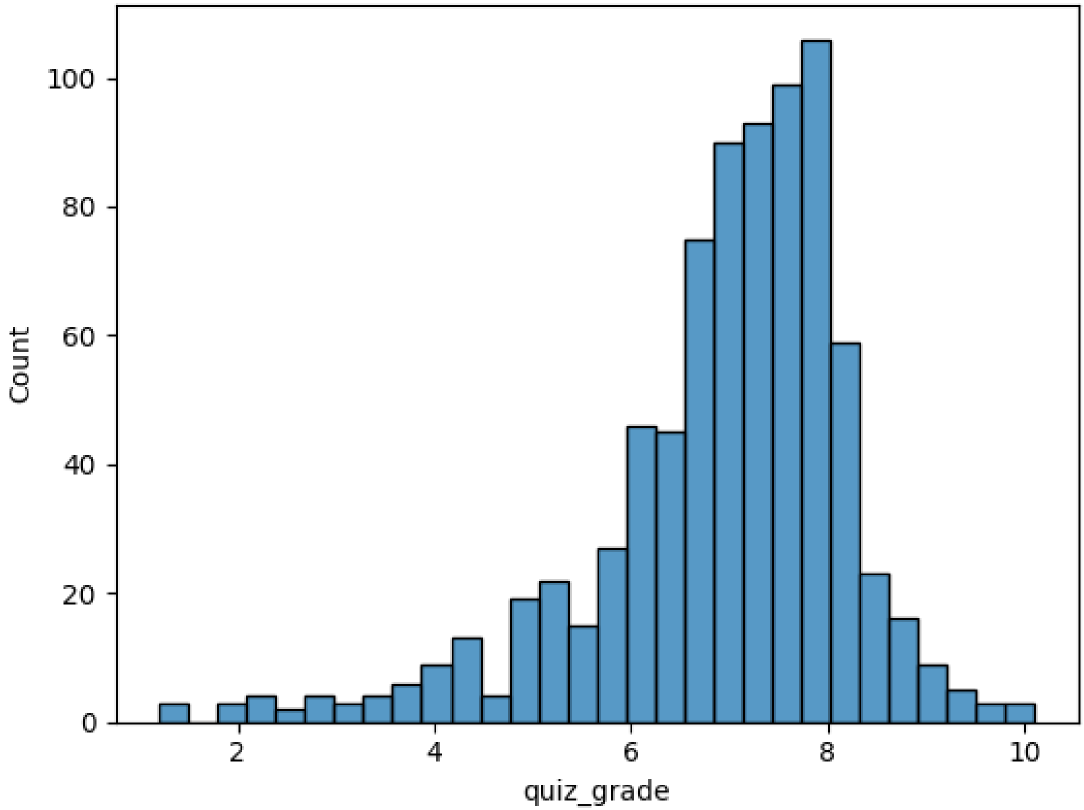
```
answer = """
Gaussian is a good approximation becauset the dependent feature (y) is
continuous (not discrete or binary).
"""
```

```
send(answer, 13)
```

```
<Response [200]>
```

```
sns.histplot(df_scaled["quiz_grade"])
```

```
<AxesSubplot:xlabel='quiz_grade', ylabel='Count'>
```



1.4 Interpret the regression results.

Do the variables have a positive or negative effect? Is it significant?

```
answer = """
The number of studying hours has a positive and significant effect.
"""
```

```
send(answer, 14)
```

```
<Response [200]>
```

1.5 Is this an appropriate method? Explain why or why not.

```
answer = """
No, because group differences are not taken into account.
"""
```

```
send(answer, 15)
```

```
<Response [200]>
```

Task 2: Linear Model with Fixed Effects

2.1 Run a regression model to explain the effect of studying hours on quiz grade. Add fixed effects for group.

```
df_scaled['group'] = df_scaled['group'].astype(str)

model = Lm("""quiz_grade ~ 1 + studying_hours  + group""",
data=df_scaled, family='gaussian')

# Fit the models
print(model.fit())
```

```
Formula: quiz_grade~1+studying_hours+group

Family: gaussian  Estimator: OLS

Std-errors: non-robust     CIs: standard 95%     Inference: parametric 


Number of observations: 810  R^2: 0.237      R^2_adj: 0.234

Log-likelihood: -1274.546   AIC: 2557.091   BIC: 2575.879

Fixed effects:

                Estimate  2.5_ci  97.5_ci     SE   DF  T-stat  P-val 
Sig
Intercept          6.586   6.445    6.727  0.072  806  91.707    0.0 
***
group[T.2]         0.551   0.357    0.745  0.099  806   5.580    0.0 
***
group[T.3]         0.469   0.260    0.679  0.107  806   4.394    0.0 
***
studying_hours     0.647   0.564    0.730  0.042  806  15.294    0.0 
***
```

2.2 Interpret the regression results.

What changed? What does it mean to have group fixed effects?

```
answer = """
 Group fixed effects allow us to difference out any constant 
differences between groups,
 and focus only on changes within each entity over time.
"""
```

```
send(answer, 22)
```

```
<Response [200]>
```

Task 3: Linear Model with Random Effects

3.1 Run a regression model to explain the effect of studying hours on quiz grade. Add random intercept for group.

```
model = Lmer("""quiz_grade ~ 1 + (1|group) + studying_hours """,
data=df_scaled, family='gaussian')

# Fit the models
print(model.fit())
```

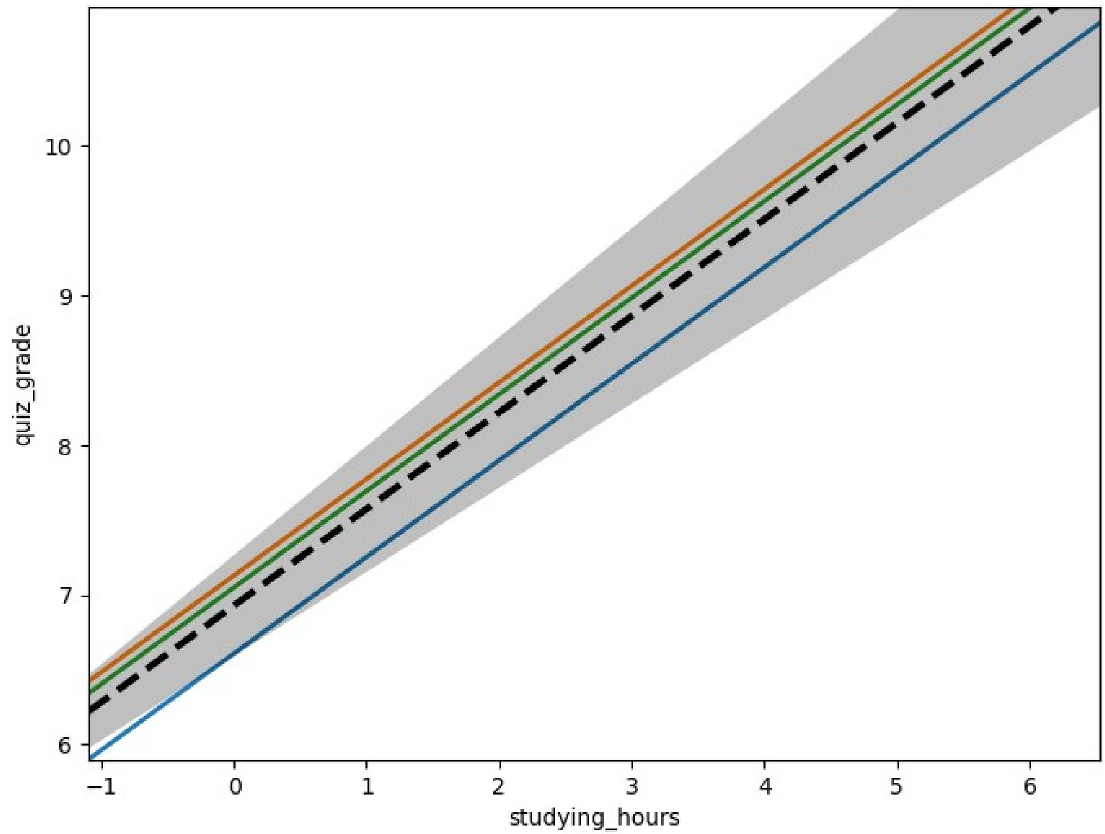
```
Formula: quiz_grade~1+(1|group)+studying_hours

Family: gaussian  Inference: parametric

Number of observations: 810 Groups: {'group': 3.0}

Log-likelihood: -1282.909   AIC: 2565.817

Random effects:

                 Name    Var    Std
group     (Intercept)  0.084  0.289
Residual               1.369  1.170

No random effect correlations specified

Fixed effects:

                Estimate  2.5_ci  97.5_ci     SE       DF  T-stat  P-
val  Sig
(Intercept)        6.927   6.589    7.264  0.172    2.004  40.249
0.001  ***
studying_hours     0.645   0.562    0.728  0.042  807.849  15.263
0.000  ***
```

3.2 Plot the regression lines

Hint: You may use model.plot

```
model.plot("studying_hours", plot_ci=True)
```

```
<AxesSubplot:xlabel='studying_hours', ylabel='quiz_grade'>
```



3.3 Run a regression model to explain the effect of studying hours on quiz grade. Add slope for group.

```
model = Lmer("""quiz_grade ~ 1  + (0 + studying_hours|group) """,
data=df_scaled, family='gaussian')

# Fit the models
print(model.fit())
```

```
Formula: quiz_grade~1+(0+studying_hours|group)

Family: gaussian  Inference: parametric

Number of observations: 810 Groups: {'group': 3.0}

Log-likelihood: -1230.242   AIC: 2460.484

Random effects:

                    Name    Var    Std
group     studying_hours  0.362  0.602
Residual                  1.198  1.094

No random effect correlations specified
```

```
Fixed effects:

             Estimate  2.5_ci  97.5_ci     SE       DF   T-stat  P-val
Sig
(Intercept)     6.853   6.766     6.94  0.044  739.487  154.658    0.0
***
```

3.4 Plot the regression lines

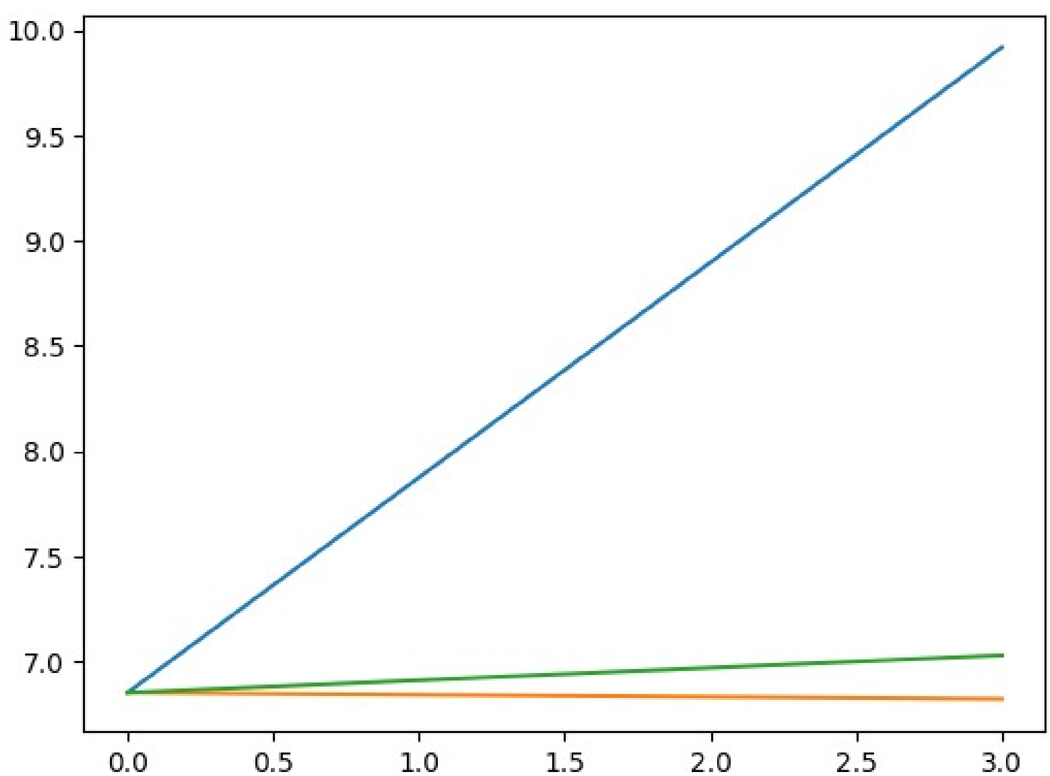
Hint: You may use model.ranef

```
intercept = model.coefs.Estimate[0]
```

```
model.ranef.head()
```

```
   studying_hours
1        1.021431
2       -0.010058
3        0.059044
```

```
x = np.linspace(0, 3,4)
for i, row in model.ranef.iterrows():
    sns.lineplot(x=x, y=intercept + row['studying_hours']*x)
```



3.5 Run a regression model to explain the effect of studying hours on quiz grade. Add random intercept and slope for group.

```
model = Lmer("""quiz_grade ~ (1 + studying_hours|group) """,
data=df_scaled, family='gaussian')

# Fit the models
print(model.fit())
```

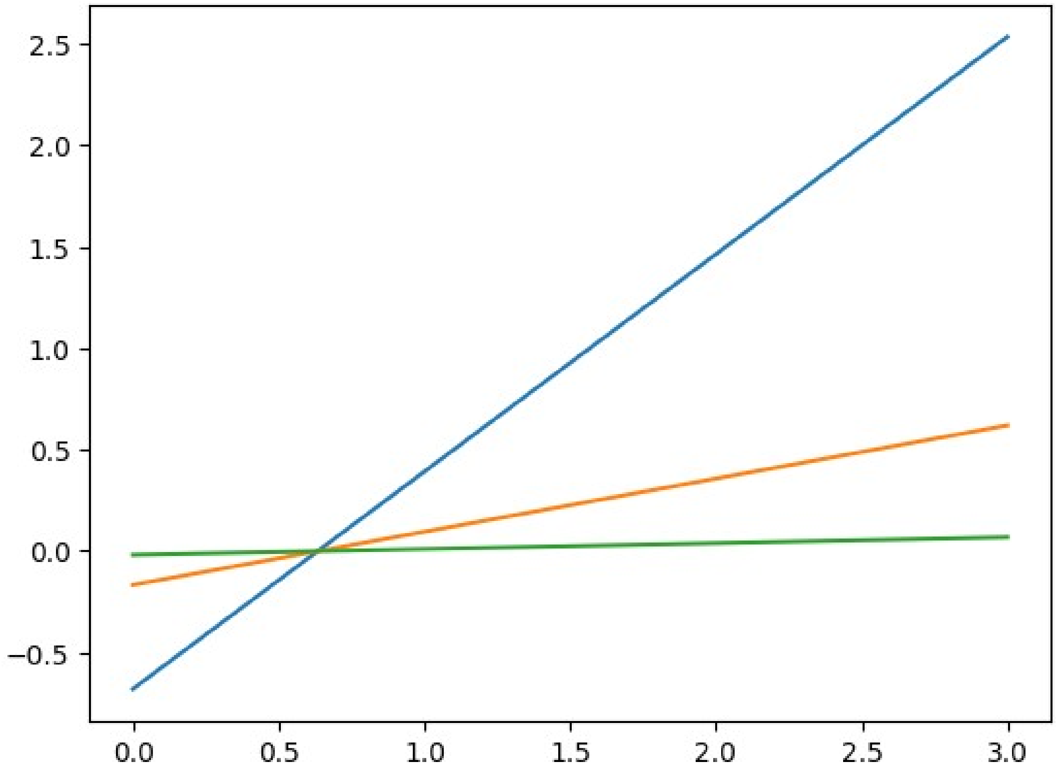
```
boundary (singular) fit: see help('isSingular')

Formula: quiz_grade~(1+studying_hours|group)

Family: gaussian  Inference: parametric

Number of observations: 810 Groups: {'group': 3.0}

Log-likelihood: -1205.548   AIC: 2411.096

Random effects:

                    Name    Var    Std
group        (Intercept)  0.165  0.406
group     studying_hours  0.410  0.640
Residual                  1.124  1.060

               IV1             IV2  Corr
group  (Intercept)  studying_hours  -1.0

Fixed effects:

             Estimate  2.5_ci  97.5_ci    SE       DF   T-stat  P-val
Sig
(Intercept)      7.18   7.082    7.278  0.05  359.077  143.976    0.0
***
```

```
model.ranef
```

```
   X.Intercept.  studying_hours
1     -0.679018        1.071420
2     -0.166013        0.261951
3     -0.018387        0.029013
```

3.6 Plot the regression lines

```
x = np.linspace(0, 3,4)
for i, row in model.ranef.iterrows():
    sns.lineplot(x=x, y=row['X.Intercept.'] + row['studying_hours']*x)
```



3.7 Interpret the regression results.

What changed? What does it mean to have group random effects?

```
answer = """
Effects are fixed if they are interesting in themselves
or random if there is interest in the underlying population.
With intercept random effects, we assumed that every group has a
different starting
point (y-intercept) and with slope random effects we assume that every
group has a different rate.
"""

send(answer, 37)
```

```
<Response [200]>
```

Task 4: Mixed Model with Time Interaction

4.1 Again, run a regression model to explain the effect of studying hours on quiz grade. Add random intercept and slope for groups AND interaction between the number of stuyding hours and time (weeks).

```
model = Lmer("""quiz_grade ~  (1 + studying_hours*week|group) """,
data=df_scaled, family='gaussian')
```

```python
# Fit the models
print(model.fit())
```

```
boundary (singular) fit: see help('isSingular')

Formula: quiz_grade~(1+studying_hours*week|group)

Family: gaussian	 Inference: parametric

Number of observations: 810	 Groups: {'group': 3.0}

Log-likelihood: -845.308 	 AIC: 1690.616

Random effects:

                         Name    Var    Std
group             (Intercept)  1.701  1.304
group          studying_hours  1.512  1.230
group                    week  0.012  0.109
group     studying_hours:week  0.005  0.071
Residual                       0.446  0.668

                 IV1                  IV2   Corr
group     (Intercept)       studying_hours -0.733
group     (Intercept)                 week -0.978
group     (Intercept)  studying_hours:week -0.062
group  studying_hours                 week  0.609
group  studying_hours  studying_hours:week -0.564
group            week  studying_hours:week  0.263

Fixed effects:

             Estimate  2.5_ci  97.5_ci     SE       DF   T-stat  P-val 
Sig
(Intercept)     7.142   7.075     7.21  0.034  212.364  207.848    0.0 
***
```

4.2 Interpret the regression results.

```
answer = """
The variance of quiz grade by groups is estimated as 1.600 + 1.515 +
0.12 + 0.005 + 0.445 (from the residual) = 3.685
The studying hours by groups explain a big part of the variance (41%)
but the interaction between studying hours and weeks
explains much less of the variance (0.1%).
We also observe a high correlation between random effects (intercept
and slope) within each group.
Studying hours is negatively correlated (-0.73) with the intercept as
well as weeks (-0.97).
The interaction term is weakly correlated with the intercept.
```

```
When analyzing the coefficients (with model.ranef)
we observe that studying hours has a greater coefficient for group 1
(in comparison to the other groups)
and the week has a greater coefficient for group 3 (in comparison to
the other groups).
"""

send(answer, 42)
```

```
<Response [200]>
```

```
model.ranef
```

	X.Intercept.	studying_hours	week	studying_hours.week
1	-1.352402	2.053030	0.091559	-0.072844
2	-1.427752	0.598642	0.108035	-0.000913
3	-1.175201	0.065531	0.129008	0.096540