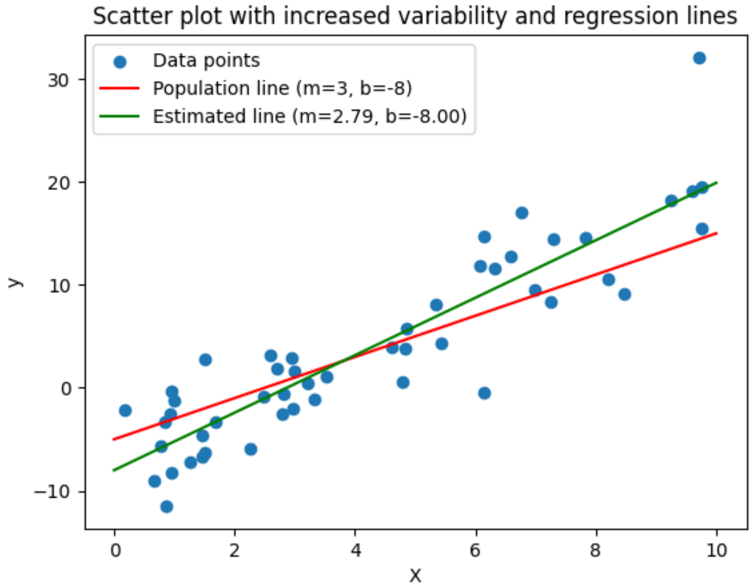
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression

# Generate the data
x = 10 * np.random.rand(50)
y = 3 * x - 8 + np.random.randn(50) * 4

# Fit a linear regression model
x = x.reshape(-1, 1)
model = LinearRegression()
model.fit(x, y)

# Calculate the predicted values
y_pred = model.predict(x)

# Plot the scatter plot and regression lines
plt.scatter(x, y, label="Data points")
plt.xlabel("X")
plt.ylabel("y")
plt.title("Scatter plot with increased variability and regression lines")

# Plot the actual population line
x_line = np.linspace(0, 10, 100)
y_actual = 2 * x_line - 5
plt.plot(x_line, y_actual, 'r', label="Population line (m=3, b=-8)")

# Plot the estimated regression line
y_estimated = model.coef_[0] * x_line + model.intercept_
plt.plot(x_line, y_estimated, 'g', label=f"Estimated line (m={model.coef_[0]:.2f}, b={model.intercept_:.2f})")

# Add legend and show the plot
plt.legend()
plt.show()
```



```
import pandas as pd
import statsmodels.api as sm

# Load the dataset
url = "https://raw.githubusercontent.com/justmarkham/scikit-learn-videos/master/data/Advertising.csv"
data = pd.read_csv(url, index_col=0)

# Define the independent variables (add a constant for the intercept)
X = data[['TV', 'Radio', 'Newspaper']]
X = sm.add_constant(X)

# Define the dependent variable
y = data['Sales']

# Fit the model using the independent and dependent variables
model = sm.OLS(y, X).fit()

# Print the summary of the model
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  Sales   R-squared:                       0.897
Model:                            OLS   Adj. R-squared:                  0.896
Method:                 Least Squares   F-statistic:                     570.3
Date:                Sat, 29 Apr 2023   Prob (F-statistic):           1.58e-96
Time:                        07:32:56   Log-Likelihood:                -386.18
No. Observations:                 200   AIC:                             780.4
Df Residuals:                     196   BIC:                             793.6
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          2.9389      0.312      9.422      0.000       2.324       3.554
TV             0.0458      0.001     32.809      0.000       0.043       0.049
Radio          0.1885      0.009     21.893      0.000       0.172       0.206
Newspaper     -0.0010      0.006     -0.177      0.860      -0.013       0.011
==============================================================================
Omnibus:                       60.414   Durbin-Watson:                   2.084
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              151.241
Skew:                          -1.327   Prob(JB):                     1.44e-33
Kurtosis:                       6.332   Cond. No.                         454.
==============================================================================

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

```
import numpy as np
import pandas as pd
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score

# Generate synthetic data
np.random.seed(42)
n = 100
x1 = np.random.normal(0, 1, n)
x2 = np.random.normal(0, 1, n)
irrelevant_predictors = np.random.normal(0, 1, (n, 10))

y = 2 * x1 + 3 * x2 + np.random.normal(0, 1, n)

# Helper function to calculate adjusted R-squared
def adjusted_r2(r2, n, k):
    return 1 - (1 - r2) * (n - 1) / (n - k - 1)

# Fit linear regression models with different predictors
X = pd.DataFrame({'x1': x1, 'x2': x2})
X_with_irrelevant = pd.concat([X] + [pd.Series(irrelevant_predictors[:, i], name=f"irrelevant_{i}") for i in range(10)], axi

model1 = LinearRegression().fit(X, y)
model2 = LinearRegression().fit(X_with_irrelevant, y)

# Calculate R-squared and adjusted R-squared for each model
models = [('Model with relevant predictors', model1, X.shape[1]), ('Model with irrelevant predictors', model2, X_with_irrele

for name, model, k in models:
    r2 = r2_score(y, model.predict(X_with_irrelevant.iloc[:, :k]))
    adj_r2 = adjusted_r2(r2, n, k)
    print(f"{name}: R-squared = {r2:.3f}, Adjusted R-squared = {adj_r2:.3f}")
```

```
Model with relevant predictors: R-squared = 0.912, Adjusted R-squared = 0.910
Model with irrelevant predictors: R-squared = 0.919, Adjusted R-squared = 0.908
```

```
X
```

	x1	x2
0	0.496714	-1.415371
1	-0.138264	-0.420645
2	0.647689	-0.342715
3	1.523030	-0.802277
4	-0.234153	-0.161286
...	...	...
95	-1.463515	0.385317
96	0.296120	-0.883857
97	0.261055	0.153725
98	0.005113	0.058209
99	-0.234587	-1.142970

100 rows × 2 columns

```
X_with_irrelevant
```