# index

January 29, 2022

# 1 Polynomial Regression - Lab

## 1.1 Introduction

In this lab, you'll practice your knowledge on adding polynomial terms to your regression model!

## 1.2 Objectives

You will be able to:

- Use sklearn's built in capabilities to create polynomial features

## 1.3 Dataset

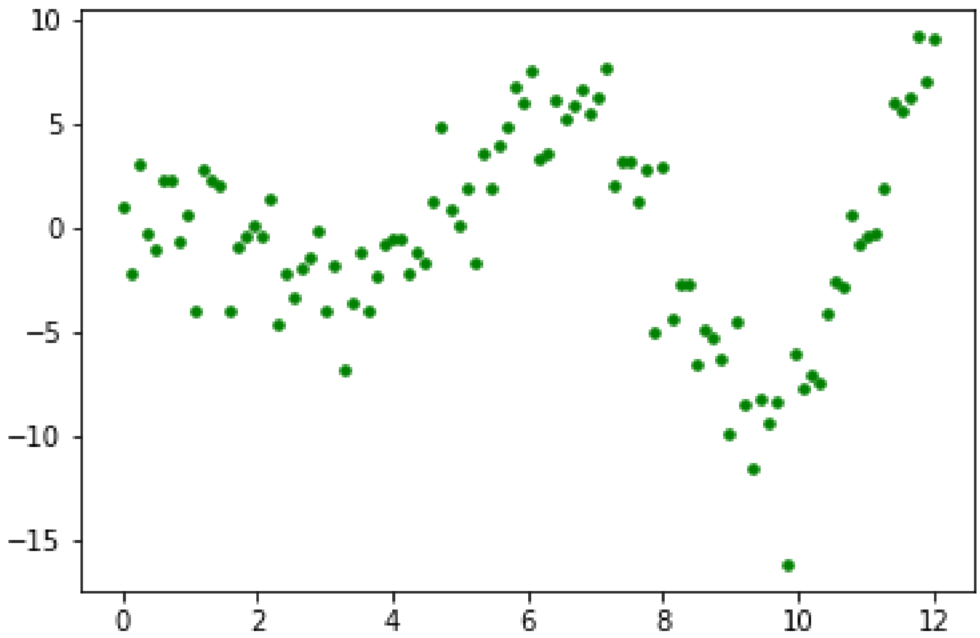
Here is the dataset you will be working with in this lab:

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

df = pd.read_csv('sample_data.csv')

df.head()
```

[1]:
```
          x         y
0  0.000000  0.942870
1  0.121212 -2.261629
2  0.242424  3.100749
3  0.363636 -0.285446
4  0.484848 -1.012210
```

Run the following line of code. You will notice that the data is clearly of non-linear shape. Begin to think about what degree polynomial you believe will fit it best.

[2]:
```
plt.scatter(df['x'], df['y'], color='green', s=50, marker='.');
```




## 1.4 Train-test split

The next step is to split the data into training and test sets. Set the `random_state` to 42 and assign 75% of the data in the training set.

[11]:
```
# Split data into 75-25 train-test split
from sklearn.model_selection import train_test_split
y = df['y']
X = df.drop(columns='y', axis=1)
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.75,
                                                    random_state = 42)
```

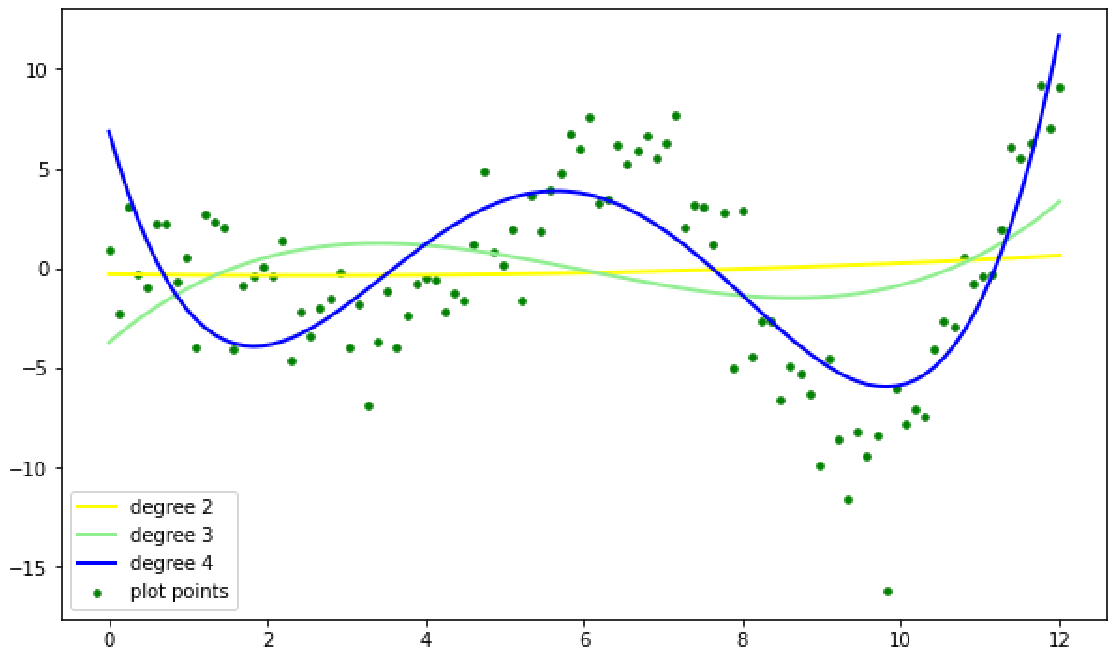
## 1.5 Build polynomial models

Now it's time to determine the optimal degree of polynomial features for a model that is fit to this data. For each of second, third and fourth degrees:

- Instantiate `PolynomialFeatures()` with the number of degrees
- Fit and transform the `X_train` features
- Instantiate and fit a linear regression model on the training data
- Transform the test data into polynomial features
- Use the model you built above to make predictions using the transformed test data
- Evaluate model performance on the test data using `r2_score()`
- In order to plot how well the model performs on the full dataset, transform `X` using `poly`
- Use the same model (`reg_poly`) to make predictions using `X_poly`

```
[14]: # Import relevant modules and functions
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score

colors = ['yellow', 'lightgreen', 'blue']
plt.figure(figsize=(10, 6))
plt.scatter(df['x'], df['y'], color='green', s=50, marker='.', label='plot␣
↪points')

# We'll fit 3 different polynomial regression models from degree 2 to degree 4
for index, degree in enumerate([2, 3, 4]):

    # Instantiate PolynomialFeatures
    poly = PolynomialFeatures(degree)

    # Fit and transform X_train
    X_poly_train = poly.fit_transform(X_train)

    # Instantiate and fit a linear regression model to the polynomial␣
↪transformed train features
    reg_poly = LinearRegression().fit(X_poly_train, y_train)

    # Transform the test data into polynomial features
    X_poly_test = poly.transform(X_test)

    # Get predicted values for transformed polynomial test data
    y_pred = reg_poly.predict(X_poly_test)

    # Evaluate model performance on test data
    print("degree %d" % degree, r2_score(y_test, y_pred))

    # Transform the full data
    X_poly = poly.transform(X)

    # Now, we want to see what the model predicts for the entire data
    y_poly = reg_poly.predict(X_poly)

    # Create plot of predicted values
    plt.plot(X, y_poly, color = colors[index], linewidth=2, label='degree %d' %␣
↪degree)
    plt.legend(loc='lower left')
```

```
degree 2 -0.14450360246115035
degree 3 0.01931659855734913
degree 4 0.5138362771623185
```




## 1.6 Summary

Great job! You now know how to include polynomials in your linear models.