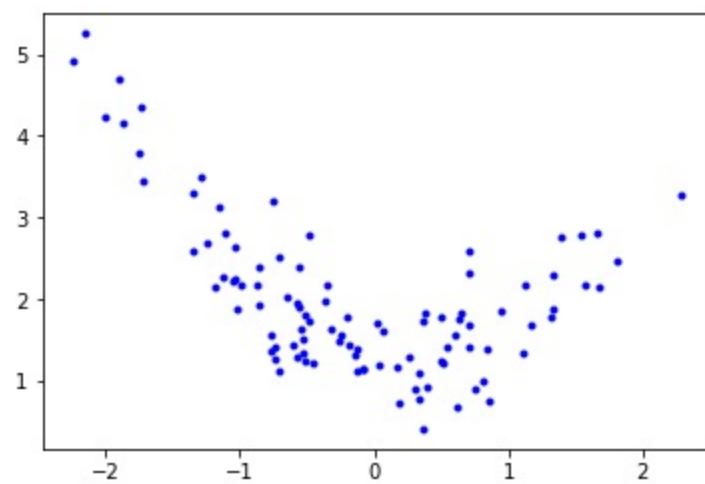


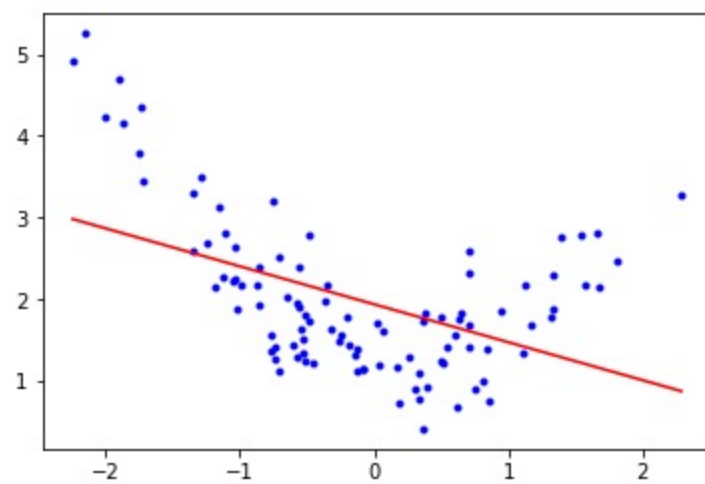
Polynomial Regression & Overfitting

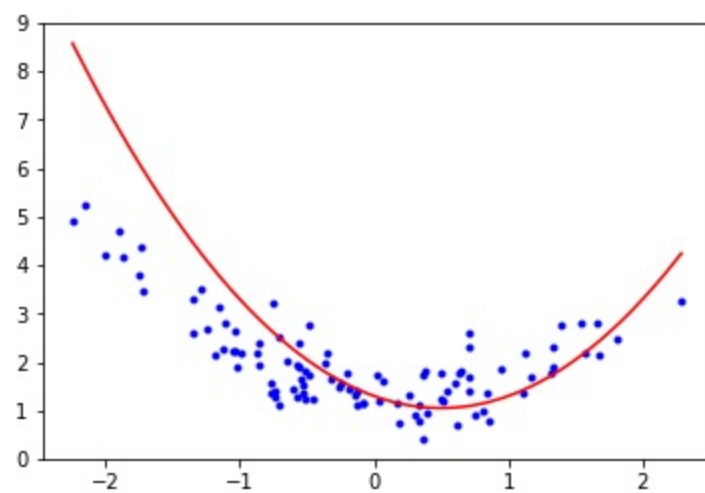
Outline

1. Recall **Linear Regression**
2. **Polynomial Regression**: What is it and how is it different (or not so different)?
3. Caution! **Dangers** of polynomial regression!







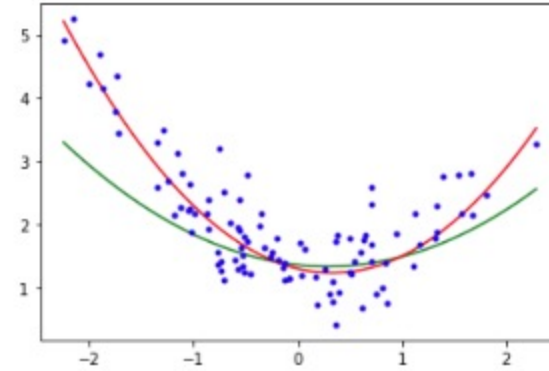


$$y = ax + b$$

$$y = ax^2 + bx + c$$

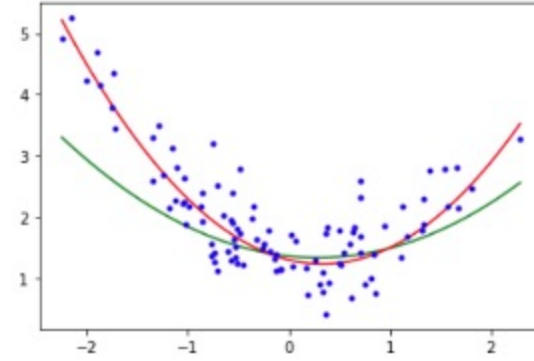
$$y = ax^3 + bx^2 + cx + d$$

$$y = ax^4 + bx^3 + cx^2 + dx + e$$



Which fit looks better?
Why?

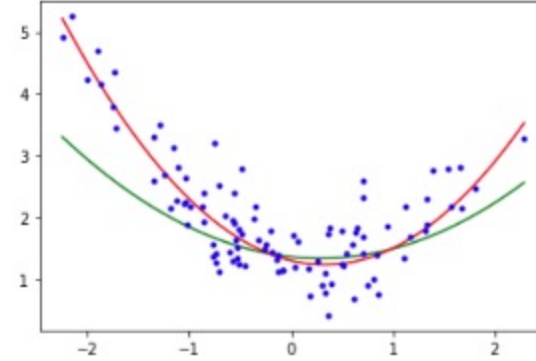
What degree
polynomial does this
appear to be?



Both are ***quadratics***

$$y = ax^2 + bx + c$$

They have different
polynomial
coefficients: a , b , & c




Polynomial Regression:

For a polynomial of a given degree find the coefficients that reduce the distance/error between the training data and the polynomial line.

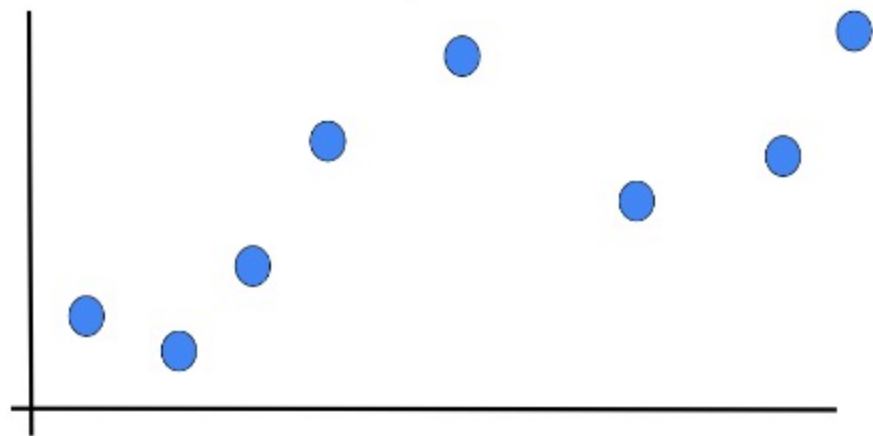
Polynomial Regression = Linear Regression

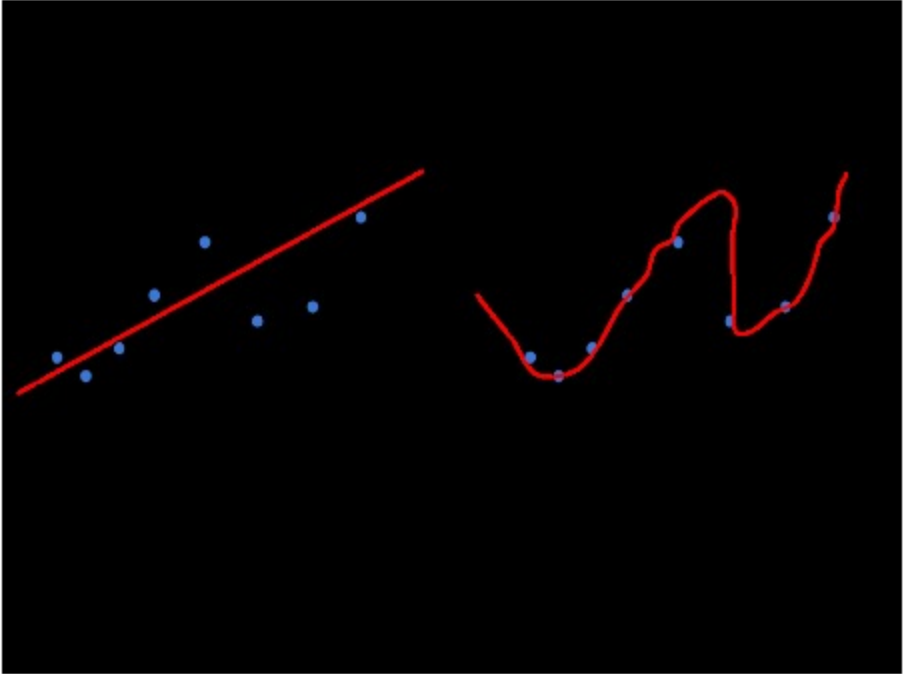
Turn the original polynomial regression problem into a polynomial regression problem with multiple features

Polynomial	$y = \theta_2 * x^2 + \theta_1 * x + \theta_0$
	
Linear	$y = \theta_2 * x_2 + \theta_1 * x_1 + \theta_0$

Overfitting

How would you fit this data?



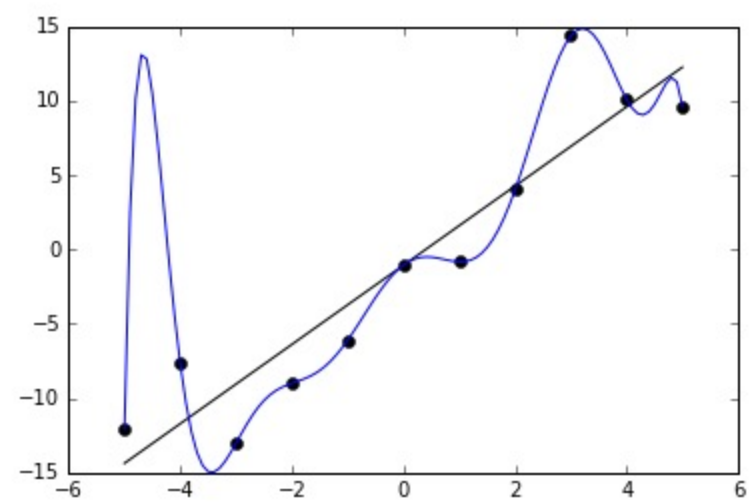












How Do We Avoid This?

Avoiding Overfitting

- Simpler polynomial
- More training data
- Dropping out some training data
- Overfitting penalties (regularization)

Regularization

Recall: Mean Squared Error

$$MSE(\theta) = \frac{1}{n} \sum_{i=1}^n (y_{true} - y_{pred})^2$$

$$= \frac{1}{n} \sum_{i=1}^n (y_{true} - \theta^T X)^2$$

$$= \frac{1}{n} \sum_{i=1}^n (y_{true} - (\theta_0 + \sum_{j=1}^p \theta_j x_i))^2$$

Lasso (L1)

$$MSE(\theta) + \lambda \sum_{j=1}^p |\theta_j|$$

Ridge (L2)

$$MSE(\theta) + \lambda \sum_{j=1}^p \theta_j^2$$

ElasticNet (L1 + L2)

Which Regularization Is Best?

Your Turn