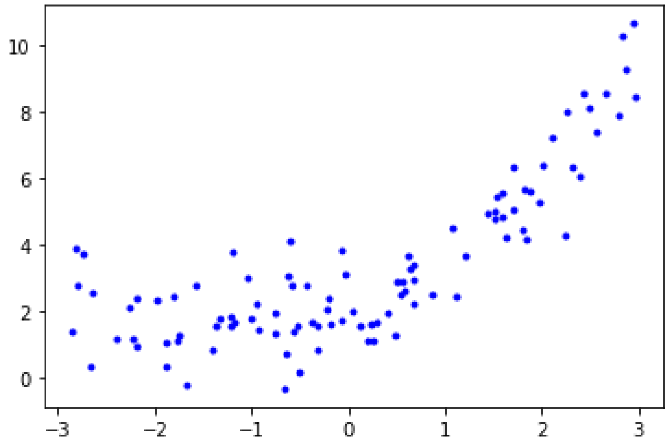
Polynomial Regression

It may happen that your data is too complex that you can't fit a straight line or use a linear regression for doing that, but Surprisingly,you can actually use a linear model to fit nonlinear data.



- **A simple way to do this is toadd powers of each feature as new features, then train a linear model on this extended set of features.**
- **This technique is called Polynomial Regression.**

Let's take an example,

- **firstly we will generate the linear cooking data which will be quadratic equation. y = ax^2 + bx + c**

In [1]:

```
### First we will generate the non - linear cooking data
import numpy as np
import matplotlib.pyplot as plt
m = 100
X = 6 * np.random.rand(m,1) - 3
y = 0.5 * X**2 + X + 2 + np.random.randn(m, 1)
```

In [2]:

```
from sklearn.preprocessing import PolynomialFeatures
polynomial_regression = PolynomialFeatures(degree=2, include_bias=False)
X_poly = polynomial_regression.fit_transform(X)
```

In [3]:

```
from sklearn.linear_model import LinearRegression
lr = LinearRegression()
lr.fit(X_poly, y)
```

Out[3]:

```
LinearRegression()
```

Regularized Linear Models

Let's recall the two famous known error, Overfitting, Underfitting. Overfitting Occurs when our model generalized well on our training data but fails to generalize well on new examples or testing data.

Underfitting Occurs when our model neither performs well on training data not on testing data.

The Best Solution of this problem is Regularization, we will now study regularization in detail.

Ridge Regression

Ridge Regression is a Regularization Technique that will regularize our parameters bu just adding regularization parameter which is:- $\alpha \frac{1}{2} \sum_{i=1}^{n} \Theta_i^2$

So, Now Our Cost function becomes which is often called Ridge Regression Cost Function:-

J(Θ) = $\frac{1}{m} + \sum_{i=1}^{m} (\Theta^T x^i - y^i)^2 + \alpha \frac{1}{2} \sum_{i=1}^{n} \Theta_i^2$

Something to Note:-

- **We will not regularize our bias term** Θ_0**, we will start regularizing our cost function from i = 1 to n leaving 0**

So, What we will do?

J(Θ) = $\frac{1}{m} + \sum_{i=0}^{m} (\Theta^T x^i - y^i)^2$

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If we put all the feature weights in 'w' vector, then the regularization term is simply a:-

J(Θ) = $\frac{1}{m} + \sum_{i=1}^{m} (\Theta^T x^i - y^i)^2 + \alpha \frac{1}{2} (||w||_2)^2$

Ridge Regression Gradient Descent

$\frac{\partial}{\partial \Theta_0} J(\Theta) = \frac{2}{m} + \sum_{i=0}^{m} (\Theta^T x^i - y^i)^2$
for $\Theta_j = 0$

$\nabla J(\Theta) = \frac{2}{m} + \sum_{i=1}^{m} (\Theta^T x^i - y^i)^2$
for $\Theta_j = 1 \ldots n$

Updating our theta :-

$\Theta_0 := \Theta_0 - \alpha J(\Theta)$

$\Theta_j := \Theta_j - \alpha \nabla J(\Theta)$

Now, we have developed our own Ridge Regression Model.

In [5]:

```
class Ridge():

    def __init__(self, alpha, iterations, l2_penalty):
        self.alpha = alpha
        self.iterations = iterations
        self.l2_penalty = l2_penalty
```

```python
    def fit(self, X,y):

        self.m, self.n = X.shape

        self.feature_weights = np.zeros(self.n)
        self.bias  = 0

        self.X = X
        self.y = y

        for i in range(iterations):
            self.update_params
        return self
    def update_params(self):

        y_pred = self.predict(X)
        dW = ( - ( 2 * ( self.X.T ).dot( self.Y - Y_pred ) ) +
               ( 2 * self.l2_penality * self.W ) ) / self.m
        db = - 2 * np.sum( self.Y - Y_pred ) / self.m

        self.W = self.W - self.learning_rate * dW
        self.b = self.b - self.learning_rate * db
        return self

    def predict(self, X):
        return  X.dot(self.feature_weights) + self.bias
```

In [6]:

```python
from sklearn.linear_model import SGDRegressor
reg = SGDRegressor(penalty="l2")
reg.fit(X,y)
```

```
C:\Users\welcome\anaconda3\lib\site-packages\sklearn\utils\validation.py:73: DataConversi
onWarning: A column-vector y was passed when a 1d array was expected. Please change the s
hape of y to (n_samples, ), for example using ravel().
  return f(**kwargs)
```

Out[6]:

```
SGDRegressor()
```

Technical Note On Using Ridge Regression

- **Before Using Any Regularized Models be sure to, Scale the data using scikit learn library "Standard Scaler".**

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