

Ridge and LASSO regression

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Outline

- Polynomial regression
- Power of model
- Overfitting
- Ridge regression
- LASSO regression
- LASSO for feature selection

Recall

$$Y = f(X)$$

Linear regression: $f(X) = aX + b$

Loss function (error): $\sum_i (\hat{y}_i - y_i)^2$ $=$
 $\sum_i (f(x_i) - y_i)^2$

Polynomial regression

$$Y = f(X)$$

$$f(X) = w_0 + w_1X + w_2X^2 + \dots + w_kX^k$$

Loss function: $\mathcal{L} = \sum_i (f(x_i) - y_i)^2$
p.s. X is random variable , x_i is data

Power of model

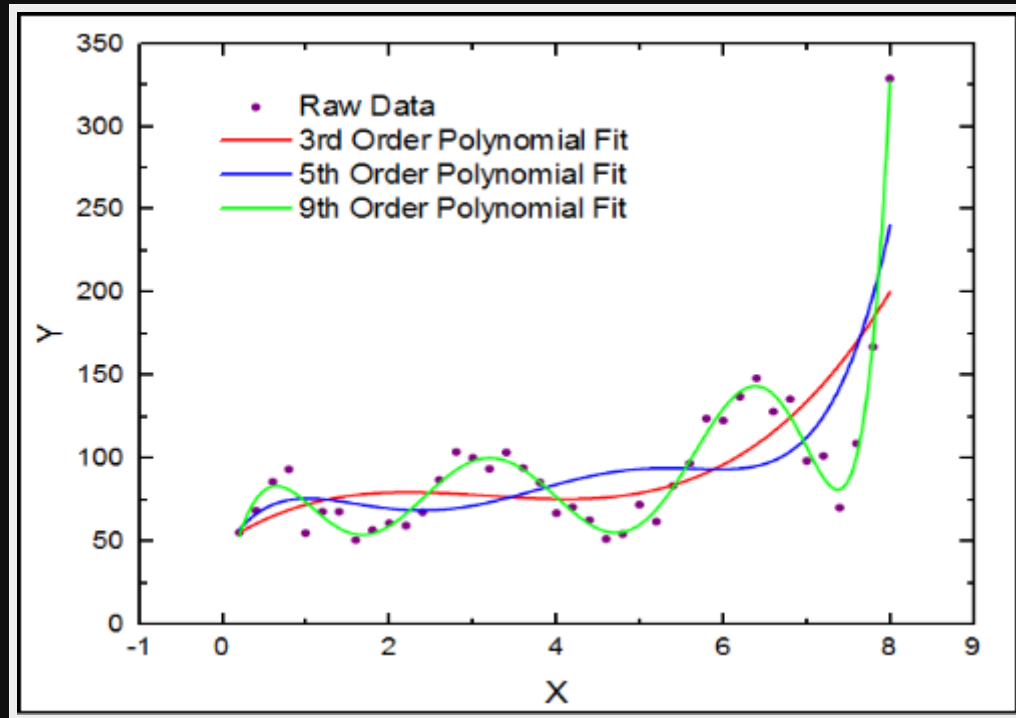
1st order: $Y = w_0 + w_1X$

2nd order: $Y = w_0 + w_1X + w_2X^2$

3rd order: $Y = w_0 + w_1X + w_2X^2 + w_3X^3$

Power: 1st < 2nd < 3rd < ... < k-th

Use of over-powered model

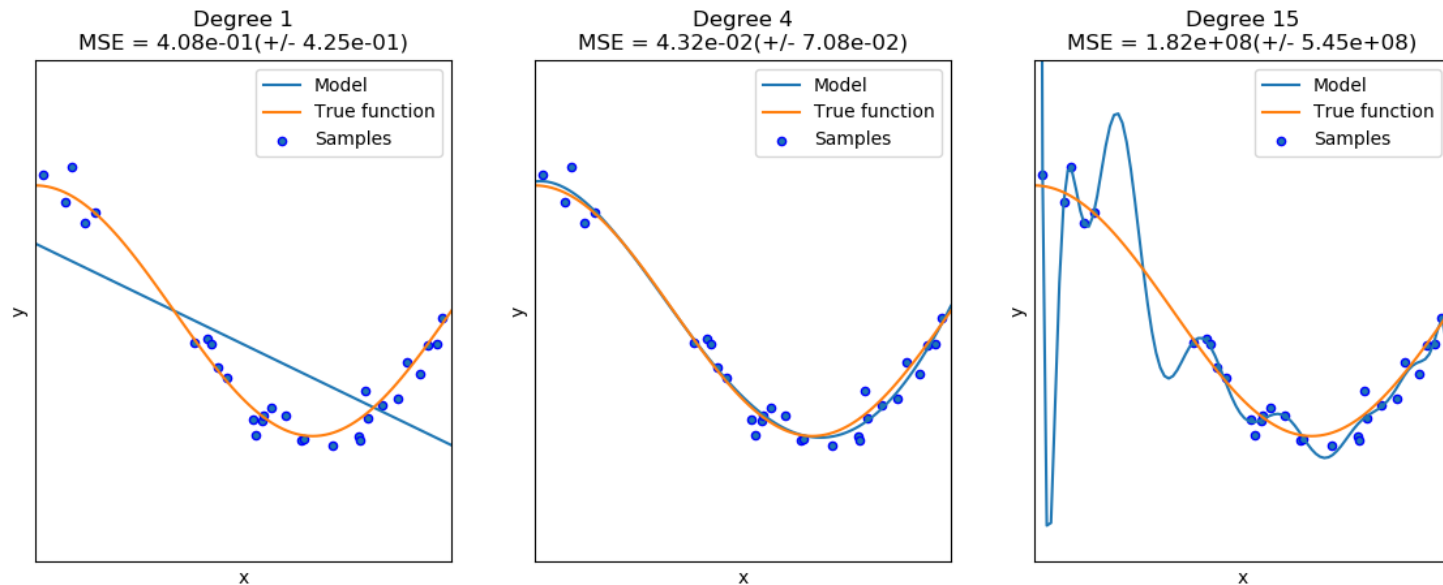


Use of over-powered model

那我們是不是拿全宇宙最強大的模型就可以 fit 任何的資料了？

事情沒有你想像的單純！

Overfitting



那怎麼辦？

Regularization

Add penalty!

Loss function: $\mathcal{L} = \sum_i (f(x_i) - y_i)^2 + \{\text{Large } \Omega\}$

Regularization

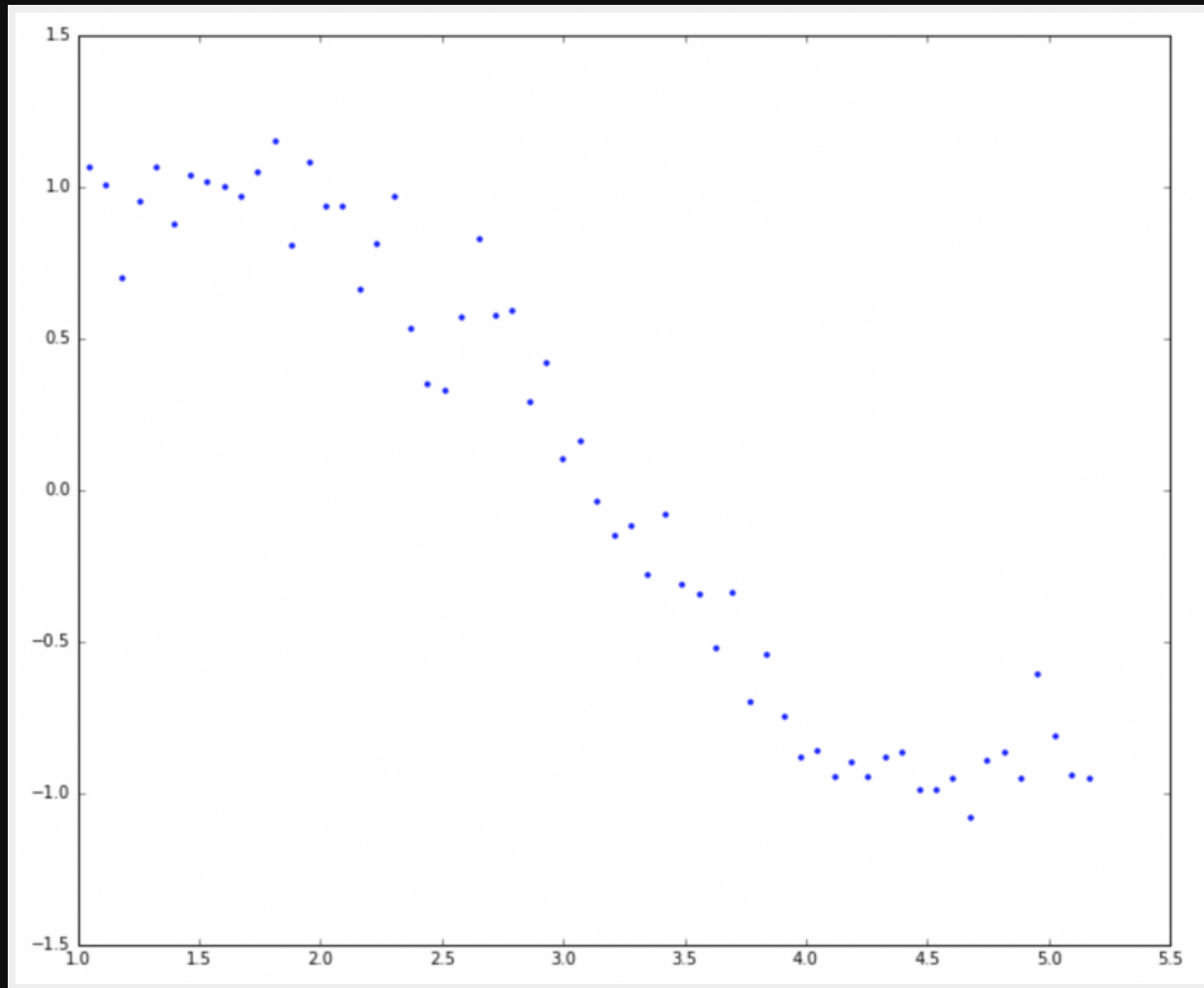
$$\mathcal{L} = \sum_i (w_0 + w_1 x_i + \dots + w_k x_i^k - y_i)^2 + \{\text{Large } \Omega\}$$

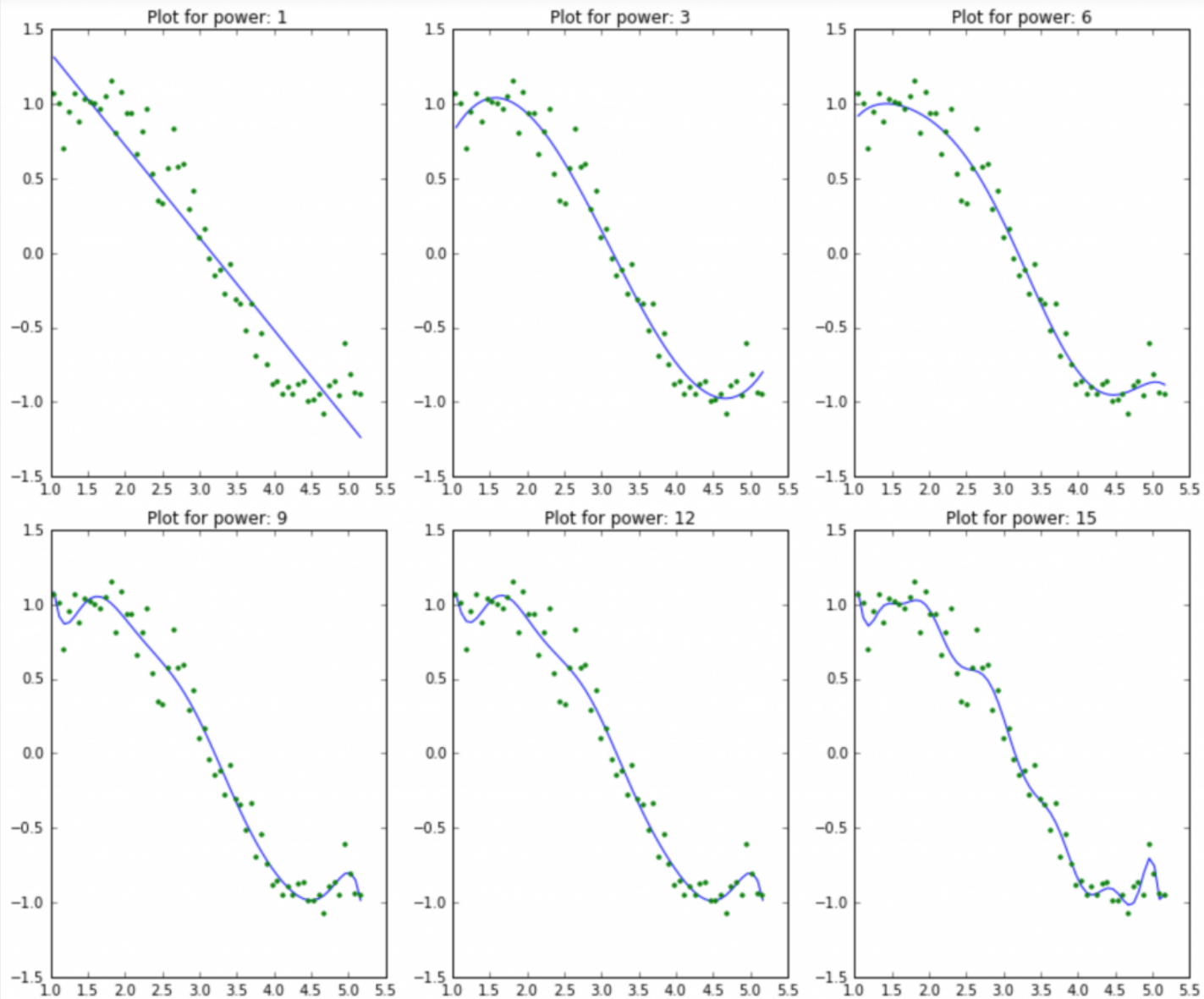
$$\mathcal{L} = \sum_i (\sum_j w_j x_i^j - y_i)^2 + \{\text{Large } \lambda \sum_j (w_j)^2\}$$

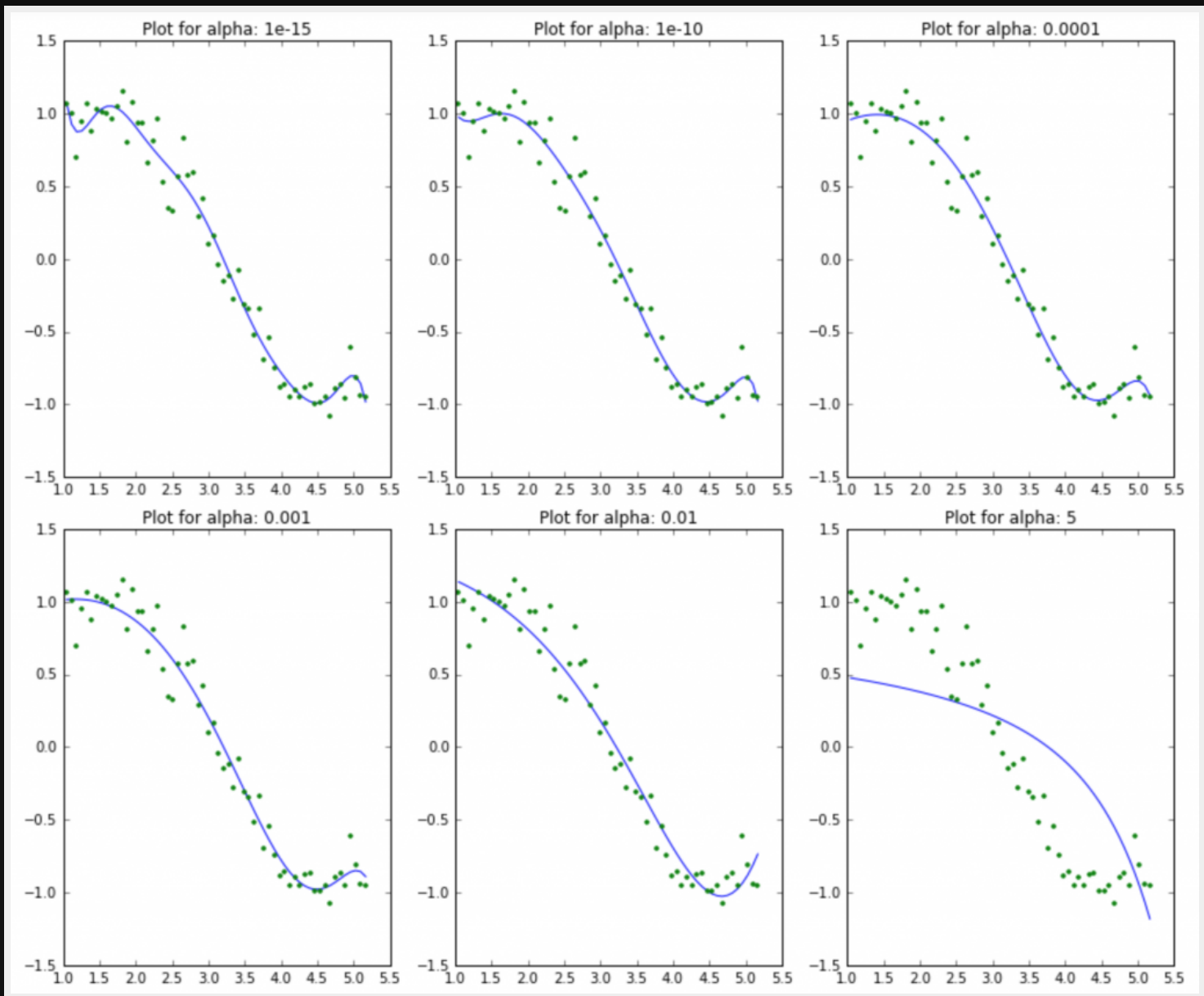
Ridge regression

$$\mathcal{L} = \sum_i (\sum_j w_j x_i^j - y_i)^2 + \lambda \sum_k (w_k)^2$$

ℓ^2 norm: $\sum_k (w_k)^2$
Purpose: reduce the complexity of model







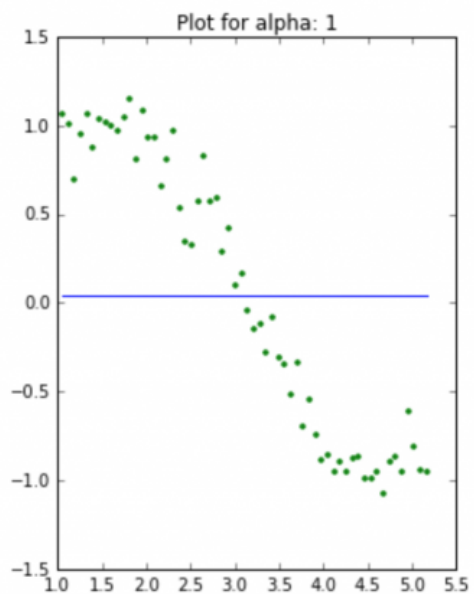
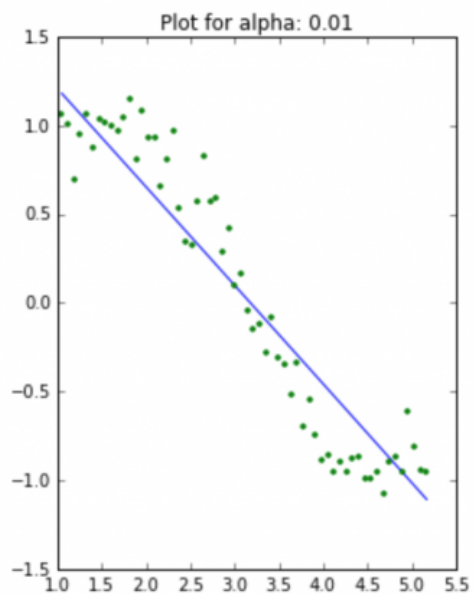
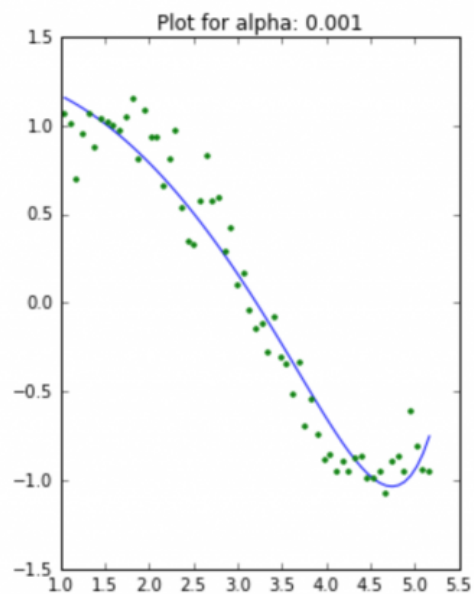
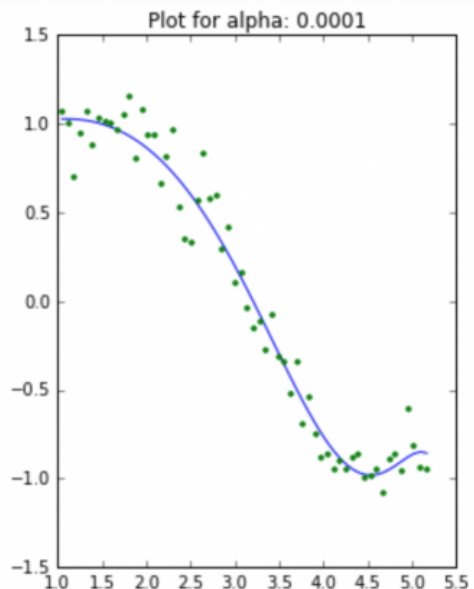
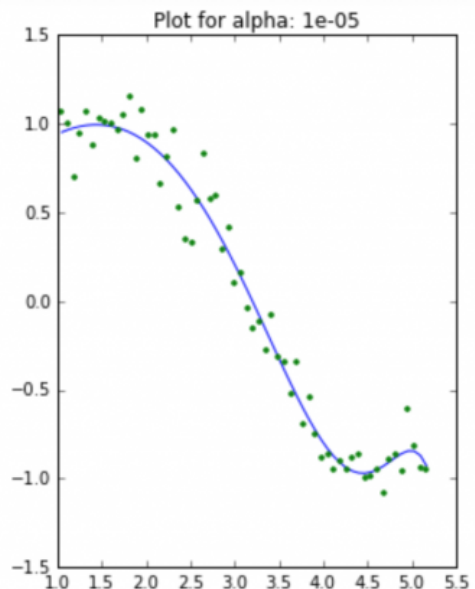
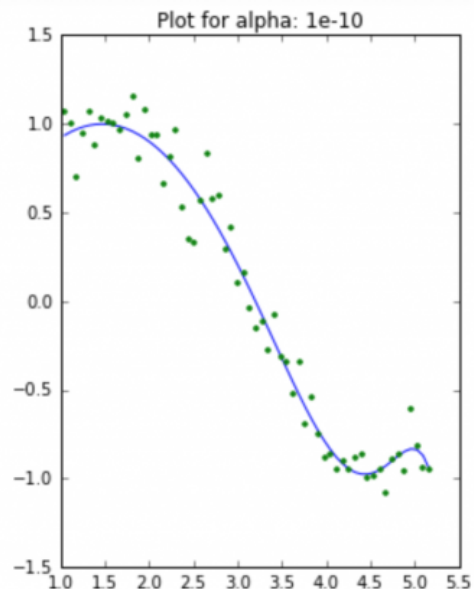
LASSO regression

Least Absolute Shrinkage and Selection Operator

$$\mathcal{L} = \sum_i (\sum_j w_j x_i^j - y_i)^2 + \lambda \sum_k |w_k|$$

$$\ell^1 \text{ norm: } \sum_k |w_k|$$

Purpose: reduce the effect of uncorrelated terms



LASSO on multiple regression

$$Y = f(X_1, X_2, \dots, X_k)$$

$$\hat{Y} = w_0 + w_1X_1 + w_2X_2 + \dots + w_kX_k$$

$$\hat{Y} = 0.001 + 7.5X_1 + 0.35X_2 + \dots + 7.2X_k$$

$$\hat{Y} = \dots + 7.5X_1 + \dots + 7.2X_k$$

LASSO for feature selection

Y

X_1

X_2

X_3

\vdots

\vdots

\vdots

\vdots

\checkmark

\checkmark

\times

\times

補充

$$\|\mathbf{w}\|_2^2 \text{ norm: } \sum_k (w_k)^2 = \|\mathbf{w}\|_2^2$$

$$\|\mathbf{w}\|_1 \text{ norm: } \sum_k |w_k| = \|\mathbf{w}\|_1$$

$$\|\mathbf{w}\|_p^p \text{ norm: } \sum_k |w_k|^p = \|\mathbf{w}\|_p^p$$

Q&A