Lecture 6: 25 January, 2024

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Data Mining and Machine Learning
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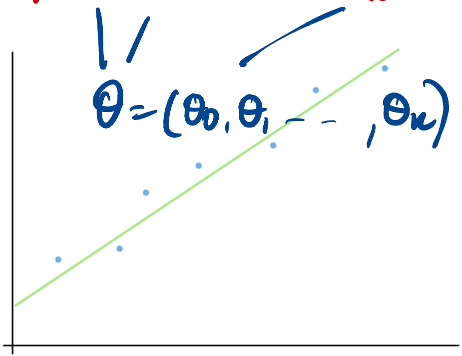
Finding the best fit line

$h_\theta(x_1, x_2, \ldots, x_k) = \theta_0 + \theta_1 x_1 + \ldots + \theta_k x_k$

- Training input is $\{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$
  - Each input x_i is a vector $(x_i^1, \ldots, x_i^k)$
  - Add $x_i^0 = 1$ by convention
  - y_i is actual output
- How far away is our prediction $h_\theta(x_i)$ from the true answer y_i?
- Define a cost (loss) function

$$J(\theta) = \frac{1}{2}\sum_{i=1}^{n}(h_\theta(x_i) - y_i)^2$$

- Essentially, the sum squared error (SSE)
- Divide by n, mean squared error (MSE)



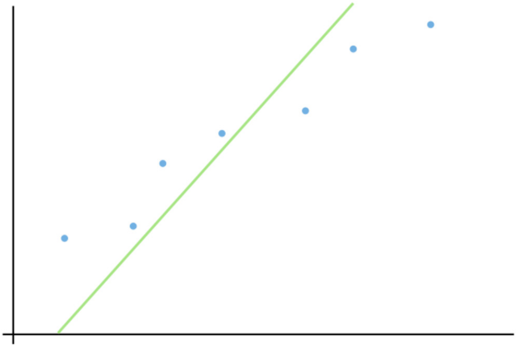
Minimizing SSE

- Write x_i as row vector $\begin{bmatrix} 1 & x_i^1 & \cdots & x_i^k \end{bmatrix}$
- $X = \begin{bmatrix} 1 & x_1^1 & \cdots & x_1^k \\ 1 & x_2^1 & \cdots & x_2^k \\ & & \cdots & \\ 1 & x_i^1 & \cdots & x_i^k \\ & & \cdots & \\ 1 & x_n^1 & \cdots & x_n^k \end{bmatrix}$, $y = \begin{bmatrix} y_1 \\ y_2 \\ \cdots \\ y_i \\ \cdots \\ y_n \end{bmatrix}$
- Write θ as column vector, $\theta^T = \begin{bmatrix} \theta_0 & \theta_1 & \cdots & \theta_k \end{bmatrix}$
- $J(\theta) = \frac{1}{2}\sum_{i=1}^{n}(h_\theta(x_i) - y_i)^2 = \frac{1}{2}(X\theta - y)^T(X\theta - y)$
- Minimize $J(\theta)$ — set $\nabla_\theta\ J(\theta) = 0$

$X\theta$ $\quad$ y

Minimizing SSE iteratively

- Normal equation $\theta = (X^T X)^{-1} X^T y$ is a closed form solution
- Computational challenges
  - Matrix inversion $(X^T X)^{-1}$ is expensive, also need invertibility
- Iterative approach, make an initial guess



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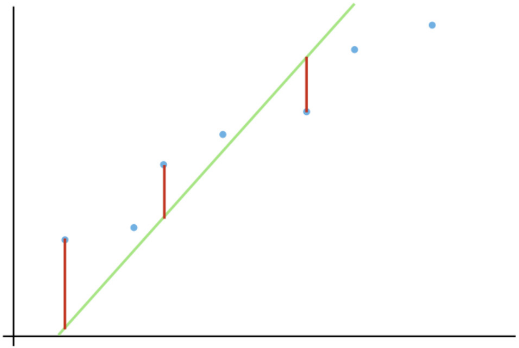
- Adjust each parameter against gradient
  - $\theta_i = \theta_i - \alpha \frac{\partial}{\partial \theta_i} J(\theta)$



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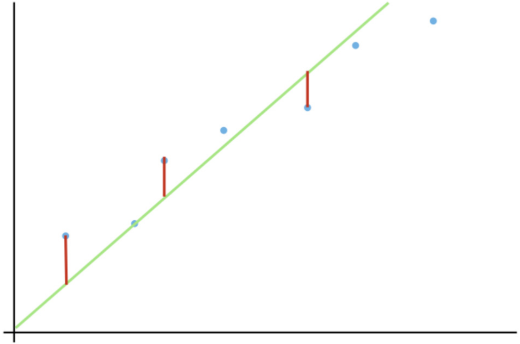

Minimizing SSE iteratively

- Normal equation $\theta = (X^T X)^{-1} X^T y$ is a closed form solution

$\nabla_\theta J = 0$

- Computational challenges
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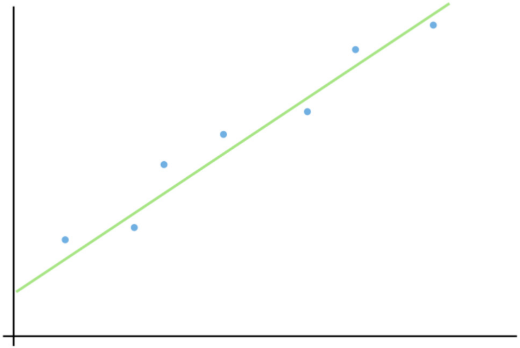
- Iterative approach, make an initial guess
- Adjust each parameter against gradient
  - $\theta_i = \theta_i - \alpha \frac{\partial}{\partial \theta_i} J(\theta)$
- Stop when we converge
- Gradient descent



Regression and SSE loss

- Training input is $\{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$
  - Outputs are noisy samples from a linear function
  - $y_i = \theta^T x_i + \epsilon$

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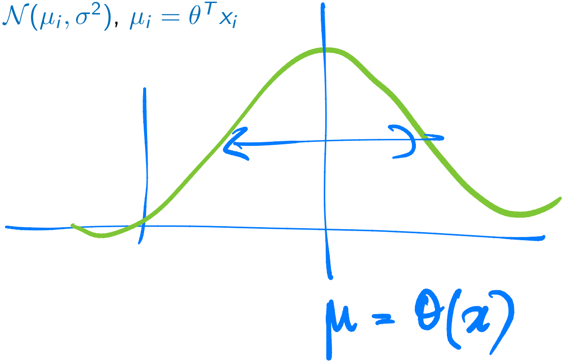
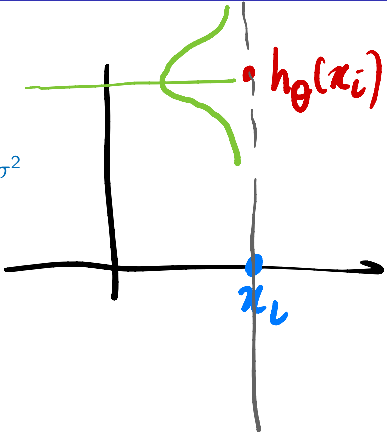
  - $\epsilon \sim \mathcal{N}(0, \sigma^2)$: Gaussian noise, mean 0, fixed variance σ^2
  - $y_i \sim \mathcal{N}(\mu_i, \sigma^2)$, $\mu_i = \theta^T x_i$





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- How good is our estimate?

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- Model gives us an estimate for θ, so regression learns μ_i for each x_i
- How good is our estimate?
- Likelihood — probability of current observation given θ

$$\mathcal{L}(\theta) = \prod_{i=1}^{n} P(y_i \mid x_i; \theta)$$

Likelihood

- How good is our estimate?

Likelihood

- How good is our estimate?
- Want Maximum Likelihood Estimator (MLE)
  - Find θ that maximizes $\mathcal{L}(\theta) = \prod_{i=1}^{n} P(y_i \mid x_i; \theta)$

Coin toss

7 heads out of 10

heads probability p

tails " $(1-p)$

$\max_p \binom{10}{7} p^7 (1-p)^3$

$\prod \text{toss}_i$

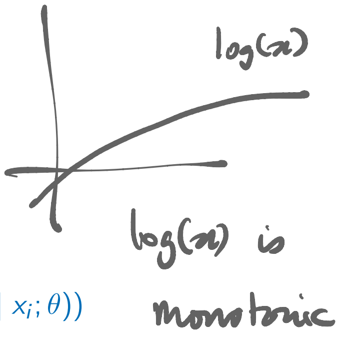
$p = 0.7$

Likelihood

- How good is our estimate?
- Want Maximum Likelihood Estimator (MLE)
  - Find θ that maximizes $\mathcal{L}(\theta) = \prod_{i=1}^{n} P(y_i \mid x_i; \theta)$
- Equivalently, maximize log likelihood

$$\ell(\theta) = \log\left(\prod_{i=1}^{n} P(y_i \mid x_i; \theta)\right) = \sum_{i=1}^{n} \log(P(y_i \mid x_i; \theta))$$

  - Easier to work with summation than product



Log likelihood and SSE loss

- $y_i = \mathcal{N}(\mu_i, \sigma^2)$, so $P(y_i \mid x_i; \theta) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y-\mu_i)^2}{2\sigma^2}}$

$y_i \in \mathcal{N}(\mu_i, \sigma^2)$

$\mu_i = \theta^T x_i$

Log likelihood and SSE loss

- $y_i = \mathcal{N}(\mu_i, \sigma^2)$, so $P(y_i \mid x_i; \theta) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y_i - \mu_i)^2}{2\sigma^2}} = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y_i - \theta^T x_i)^2}{2\sigma^2}}$

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- Log likelihood

$$\ell(\theta) = \sum_{i=1}^{n} \log\left(\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y_i-\theta^T x_i)^2}{2\sigma^2}}\right)$$

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- Log likelihood (assuming natural logarithm)

maximize

$$\ell(\theta) = \sum_{i=1}^{n} \log\left(\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y-\theta^T x_i)^2}{2\sigma^2}}\right) = n \log\left(\frac{1}{\sqrt{2\pi\sigma^2}}\right) - \sum_{i=1}^{n} \frac{(y-\theta^T x_i)^2}{2\sigma^2}$$

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- To maximize $\ell(\theta)$ with respect to θ, ignore all terms that do not depend on θ

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- Optimum value of θ is given by

$$\hat{\theta}_{\text{MSE}} = \arg\max_{\theta} \left[-\sum_{i=1}^{n} (y_i - \theta^T x_i)^2\right]$$

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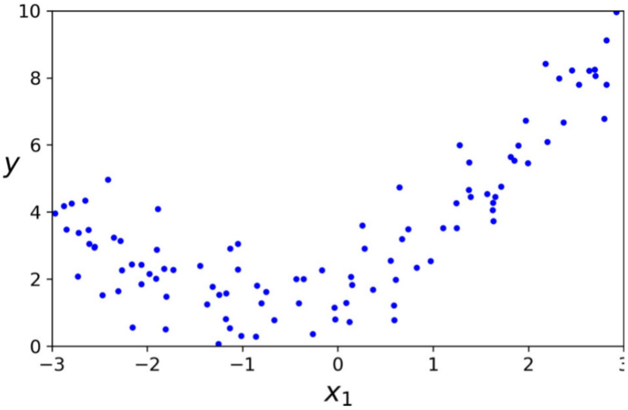
- Assuming data points are generated by linear function and then perturbed by Gaussian noise, SSE is the “correct” loss function to maximize likelihood

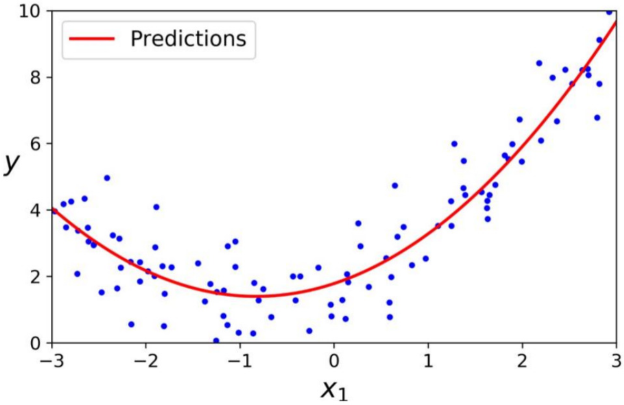
The non-linear case

- What if the relationship is not linear?



The non-linear case

- What if the relationship is not linear?
- Here the best possible explanation seems to be a quadratic



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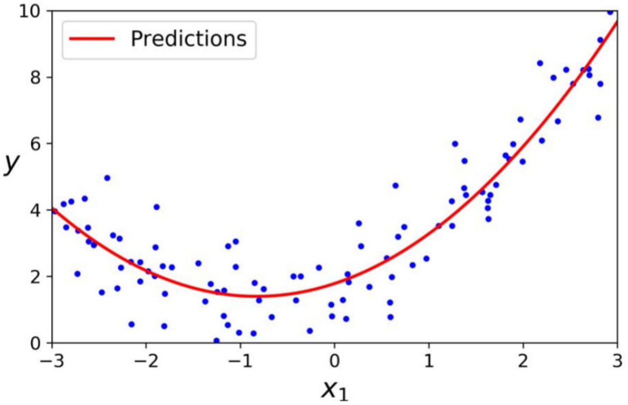

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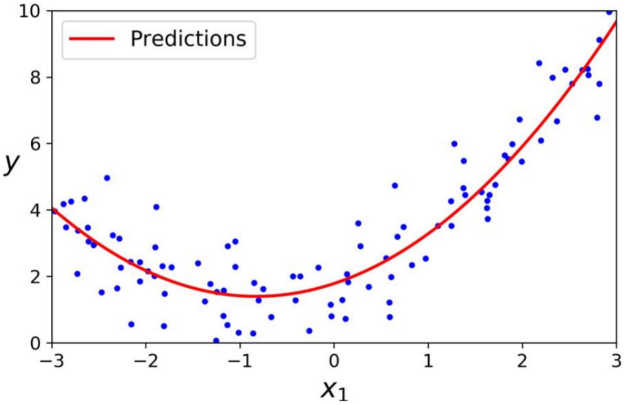
- Input $x_i : (x_{i_1}, x_{i_2})$



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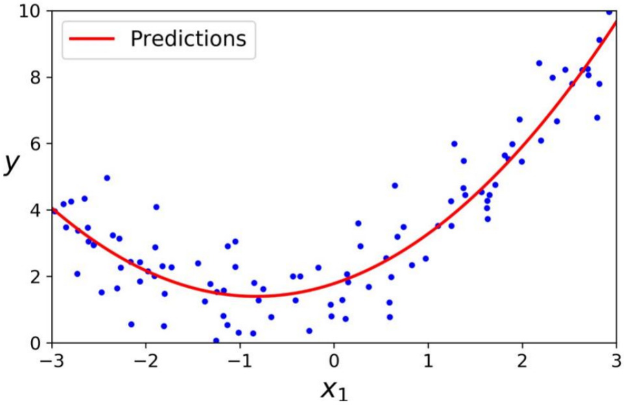
- Quadratic dependencies:

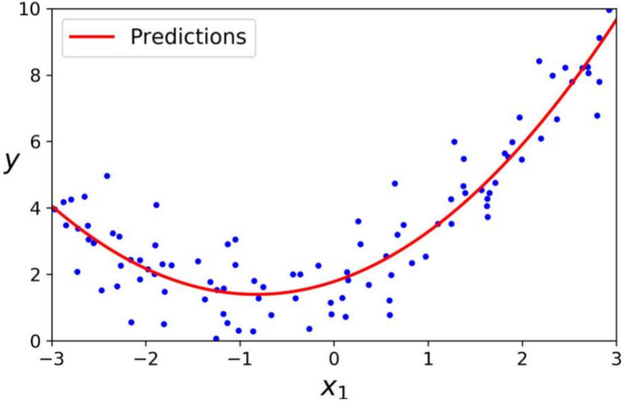


$$y = \theta_0 + \theta_1 x_{i_1} + \theta_2 x_{i_2} + \theta_{11} x_{i_1}^2 + \theta_{22} x_{i_2}^2 + \theta_{12} x_{i_1} x_{i_2}$$

The non-linear case

- Recall how we fit a line

$$\begin{bmatrix} 1 & x_i \end{bmatrix} \begin{bmatrix} \theta_0 \\ \theta_1 \end{bmatrix}$$



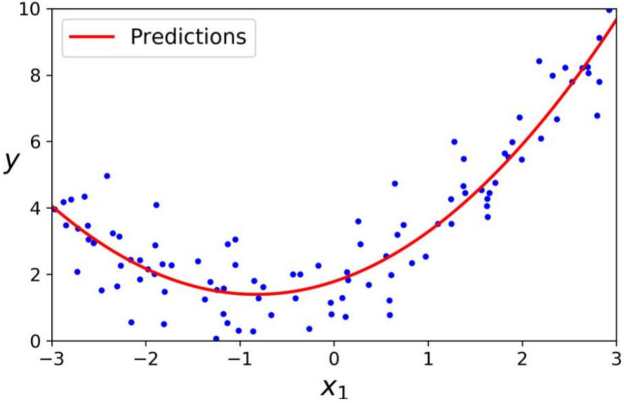
The non-linear case

- Recall how we fit a line

$$\begin{bmatrix} 1 & x_i \end{bmatrix} \begin{bmatrix} \theta_0 \\ \theta_1 \end{bmatrix}$$

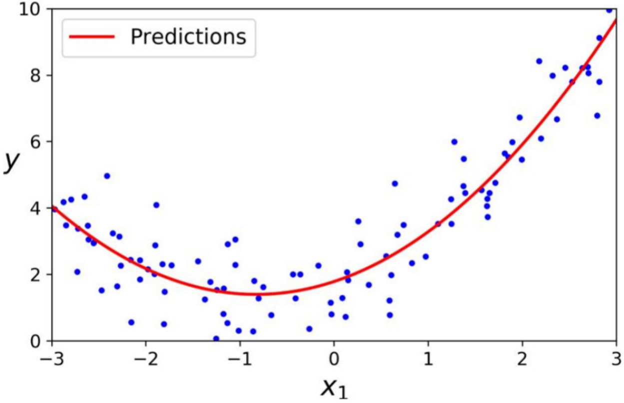
- For quadratic, add new coefficients and expand parameters

$$\begin{bmatrix} 1 & x_i & x_i^2 \end{bmatrix} \begin{bmatrix} \theta_0 \\ \theta_1 \\ \theta_2 \end{bmatrix}$$



The non-linear case

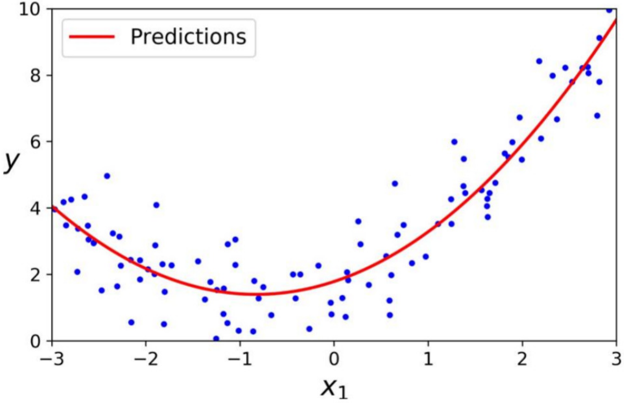
- Input (x_{i_1}, x_{i_2})



The non-linear case

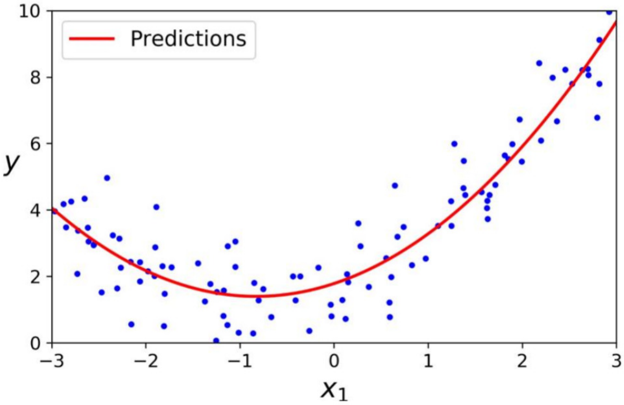
- Input (x_{i_1}, x_{i_2})
- For the general quadratic case, we add new derived "features"

$$x_{i_3} = x_{i_1}^2$$
$$x_{i_4} = x_{i_2}^2$$
$$x_{i_5} = x_{i_1} x_{i_2}$$



- Original input matrix

$$\begin{bmatrix} 1 & x_{1_1} & x_{1_2} \\ 1 & x_{2_1} & x_{2_2} \\ & \cdots & \\ 1 & x_{i_1} & x_{i_2} \\ & \cdots & \\ 1 & x_{n_1} & x_2 \end{bmatrix}$$

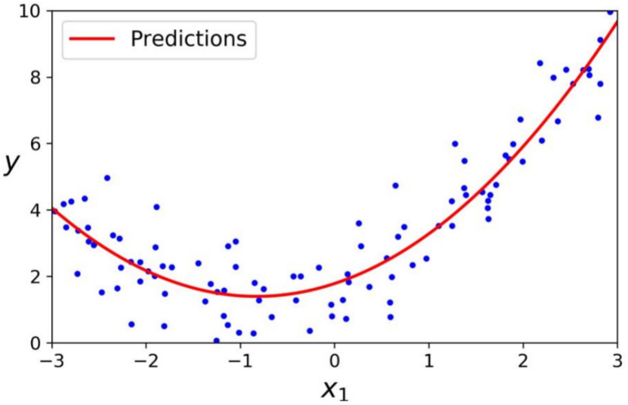


The non-linear case

- Expanded input matrix

x1 x2 x3 x4 x5

$$\begin{bmatrix} 1 & x_{1_1} & x_{1_2} & x_{1_1}^2 & x_{1_2}^2 & x_{1_1}x_{1_2} \\ 1 & x_{2_1} & x_{2_2} & x_{2_1}^2 & x_{2_2}^2 & x_{2_1}x_{2_2} \\ & \cdots \\ 1 & x_{i_1} & x_{i_2} & x_{i_1}^2 & x_{i_2}^2 & x_{i_1}x_{i_2} \\ & \cdots \\ 1 & x_{n_1} & x_{n_2} & x_{n_1}^2 & x_{n_2}^2 & x_{n_1}x_{n_2} \end{bmatrix}$$



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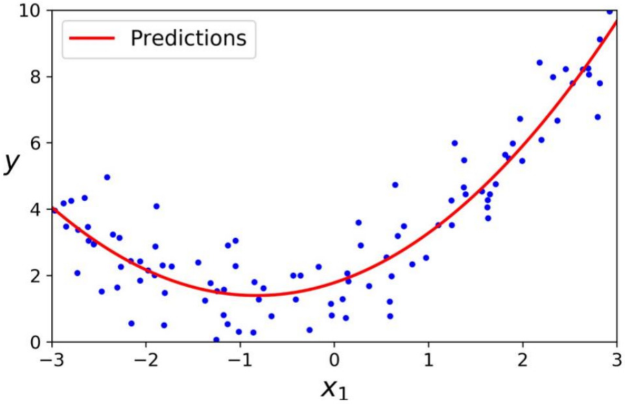
- New columns are computed and filled in from original inputs



Exponential parameter blow-up

- Cubic derived features

$x_{i_1}^3,\ x_{i_2}^3,\ x_{i_3}^3,$

$x_{i_1}^2 x_{i_2},\ x_{i_1}^2 x_{i_3},$

$x_{i_2}^2 x_{i_1},\ x_{i_2}^2 x_{i_3},$

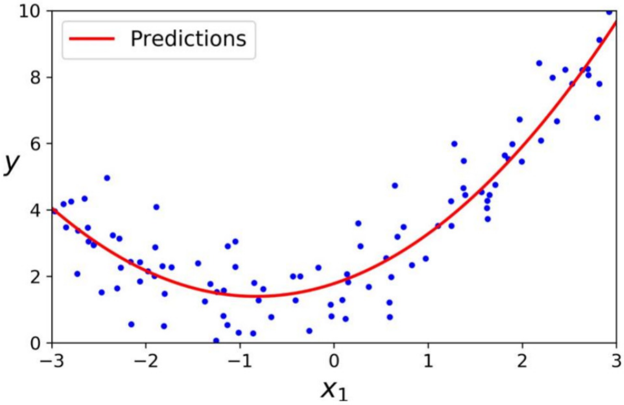
$x_{i_3}^2 x_{i_1},\ x_{i_3}^2 x_{i_2},$

$x_{i_1} x_{i_2} x_{i_3},$

$x_{i_1}^2,\ x_{i_2}^2,\ x_{i_3}^2,$

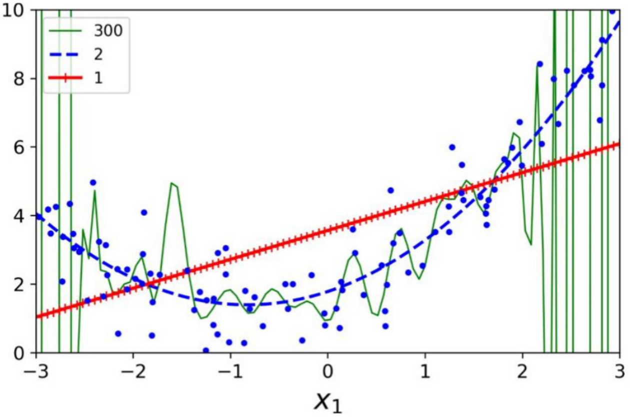
$x_{i_1} x_{i_2},\ x_{i_1} x_{i_3},\ x_{i_2} x_{i_3},$

$x_{i_1},\ x_{i_2},\ x_{i_3}.$



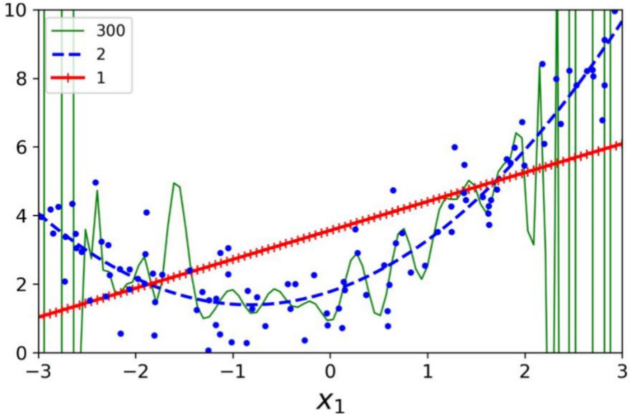
Higher degree polynomials

- How complex a polynomial should we try?



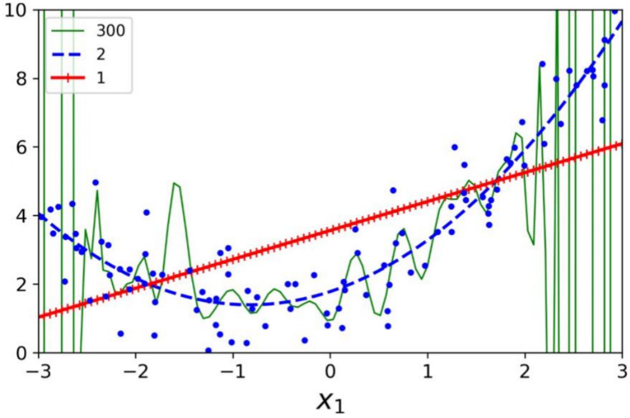
Higher degree polynomials

- How complex a polynomial should we try?
- Aim for degree that minimizes SSE



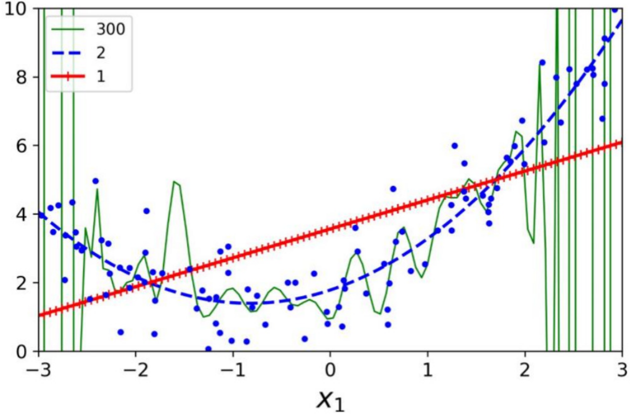
Higher degree polynomials

- How complex a polynomial should we try?
- Aim for degree that minimizes SSE
- As degree increases, features explode exponentially



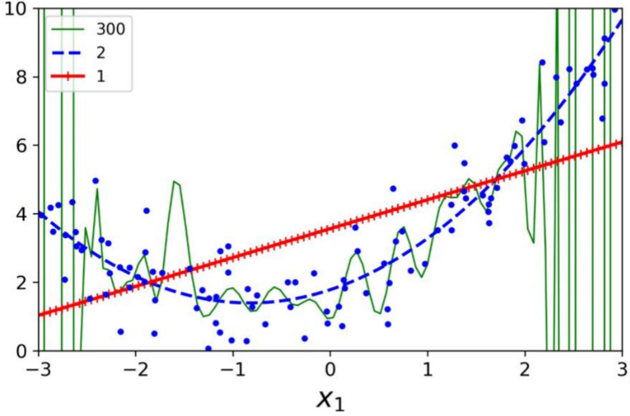
Overfitting

- Need to be careful about adding higher degree terms



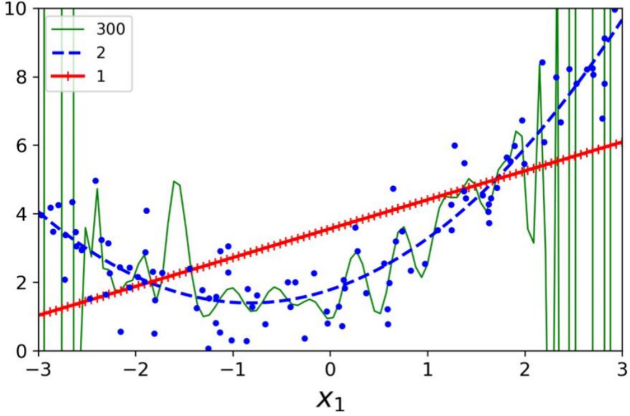
Overfitting

- Need to be careful about adding higher degree terms
- For n training points, can always fit polynomial of degree $(n-1)$ exactly
- However, such a curve would not generalize well to new data points



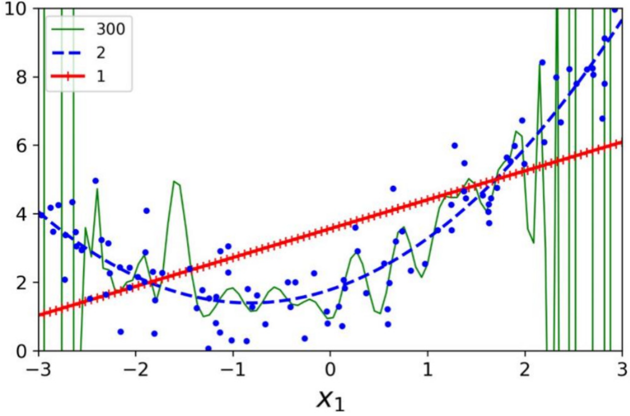
Overfitting

- Need to be careful about adding higher degree terms
- For n training points, can always fit polynomial of degree $(n-1)$ exactly
- However, such a curve would not generalize well to new data points
- Overfitting — model fits training data well, performs poorly on unseen data



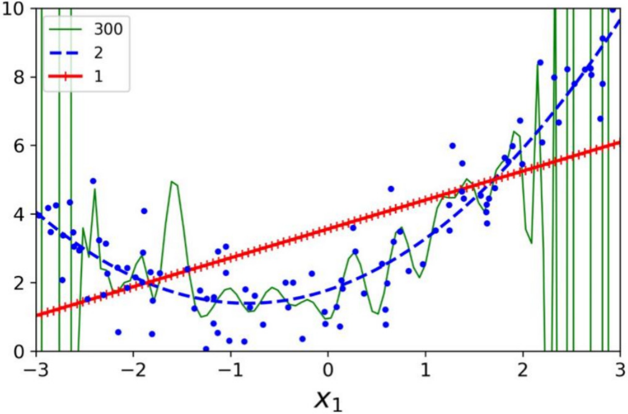
Regularization

- Need to trade off SSE against curve complexity



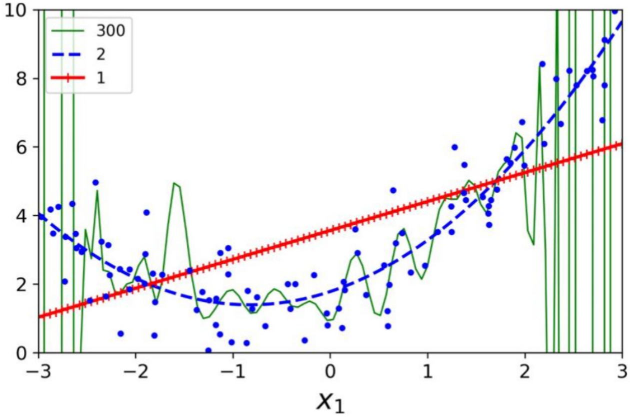
Regularization

- Need to trade off SSE against curve complexity
- So far, the only cost has been SSE



Regularization

- Need to trade off SSE against curve complexity
- So far, the only cost has been SSE
- Add a cost related to parameters $(\theta_0, \theta_1, \ldots, \theta_k)$

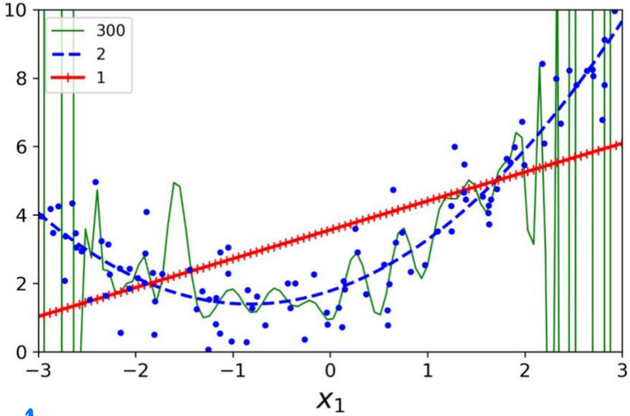


Regularization

- Need to trade off SSE against curve complexity
- So far, the only cost has been SSE
- Add a cost related to parameters $(\theta_0, \theta_1, \ldots, \theta_k)$
- Minimize, for instance

$$\frac{1}{2}\sum_{i=1}^{n}(z_i - y_i)^2 + \sum_{j=1}^{k}\theta_j^2$$

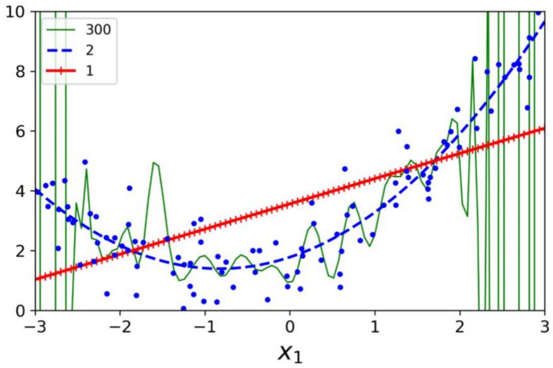
SSE   Coeff cost



Regularization

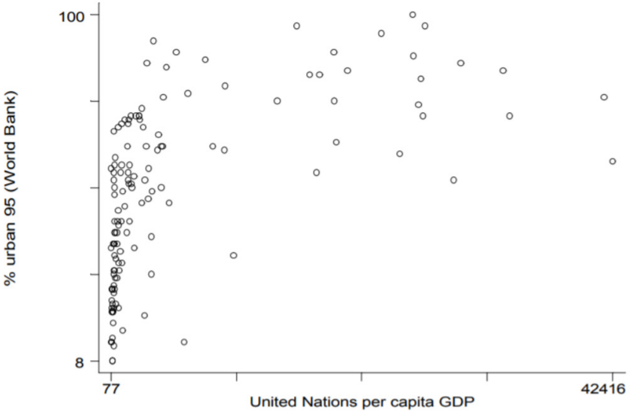
$$\frac{1}{2}\sum_{i=1}^{n}(z_i - y_i)^2 + \sum_{j=1}^{k}\theta_j^2$$

- Second term penalizes curve complexity
- Variations on regularatization
  - Ridge regression: $\sum_{j=1}^{k}\theta_j^2$
  - LASSO regression: $\sum_{j=1}^{k}|\theta_j|$
  - Elastic net regression: $\sum_{j=1}^{k}\lambda_1|\theta_j| + \lambda_2\theta_j^2$



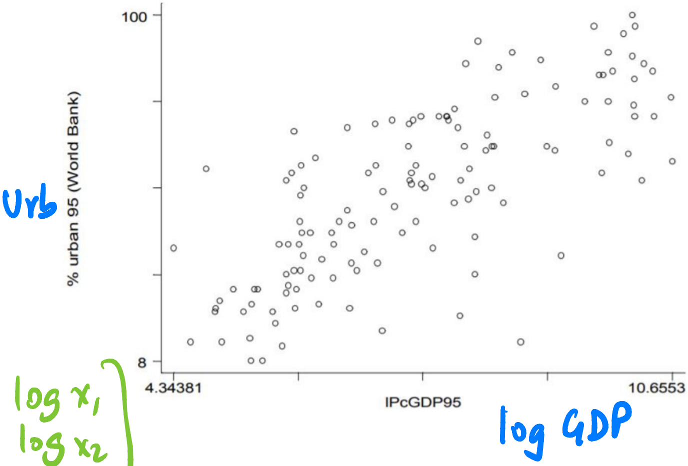
The non-polynomial case

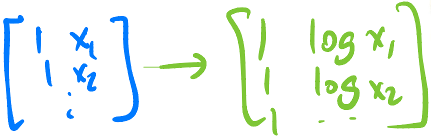
- Percentage of urban population as a function of per capita GDP
- Not clear what polynomial would be reasonable



The non-polynomial case

- Percentage of urban population as a function of per capita GDP
- Not clear what polynomial would be reasonable
- Take log of GDP
- Regression we are computing is $y = \theta_0 + \theta_1 \log x_1$





The non-polynomial case

- Reverse the relationship
- Plot per capita GDP in terms of percentage of urbanization
- Now we take log of the output variable $\log y = \theta_0 + \theta_1 x_1$
- Log-linear transformation
- Earlier was linear-log
- Can also use log-log