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Madhavan Mukund

https://www.cmi.ac.in/~madhavan

Data Mining and Machine Learning
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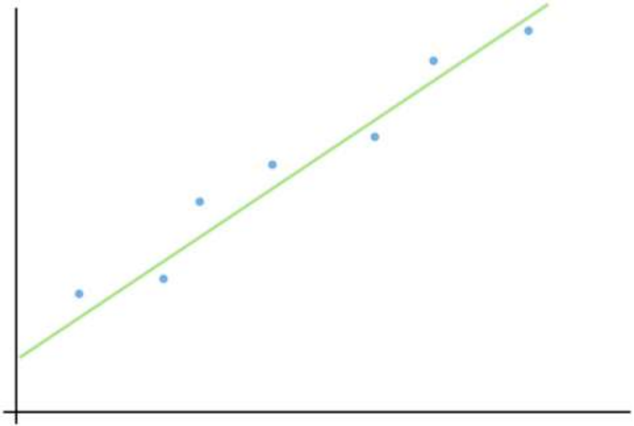
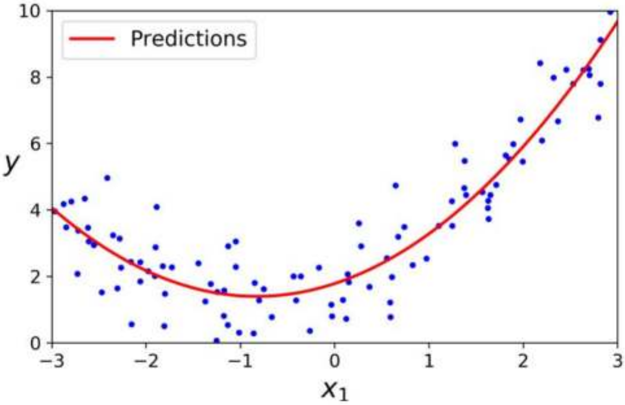
Linear regression

- Find the line that "fits" the data best
  - Normal equation
  - Gradient descent
- Linear: each parameter's contribution is independent
- Input $x : (x_1, x_2, \ldots, x_k)$
- $y = \theta_0 + \theta_1 x_1 + \cdots + \theta_k x_k$



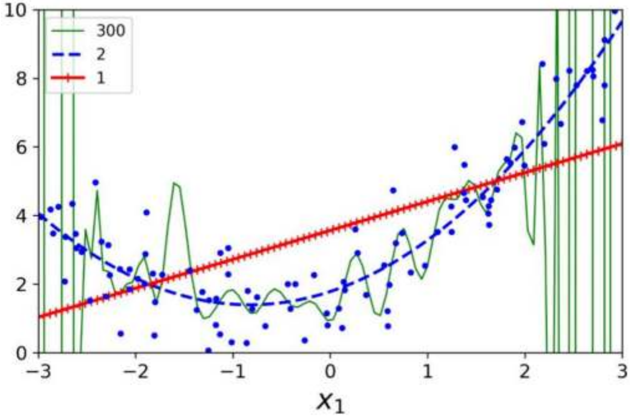
The non-linear case

- What if the relationship is not linear?
- Here the best possible explanation seems to be a quadratic
- Non-linear : cross dependencies
- Input $x_i : (x_{i_1}, x_{i_2})$
- Quadratic dependencies:
  $y = \theta_0 + \theta_1 x_{i_1} + \theta_2 x_{i_2} + \theta_{11} x_{i_1}^2 + \theta_{22} x_{i_2}^2 + \theta_{12} x_{i_1} x_{i_2}$



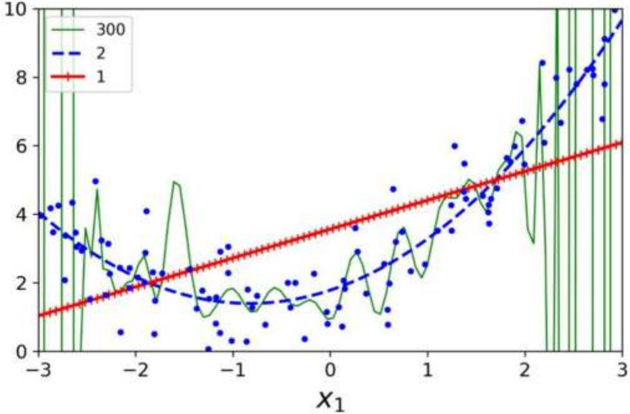
Higher degree polynomials

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



Overfitting

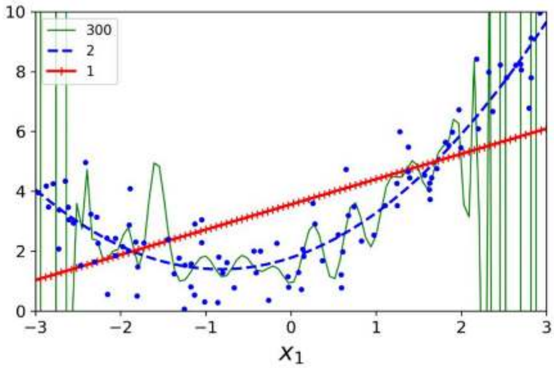
- Need to be careful about adding higher degree terms
- For n training points,can always fit polynomial of degree $(n-1)$ exactly
- However, such a curve would not generalize well to new data points
- Overfitting — model fits training data well, performs poorly on unseen data



Regularization

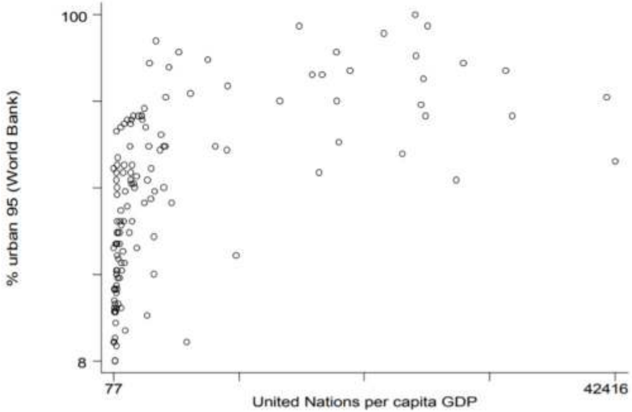
$$\frac{1}{2}\sum_{i=1}^{n}(z_i - y_i)^2 + \sum_{j=1}^{k}\theta_j^2$$

- 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: $\sum_{j=1}^{k}\lambda_1|\theta_j| + \lambda_2\theta_j^2$



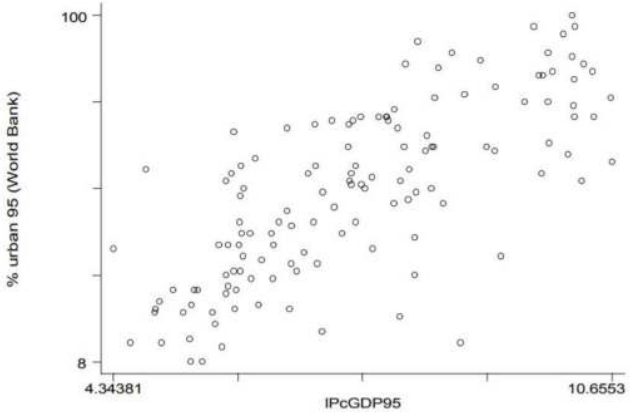
The non-polynomial case

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



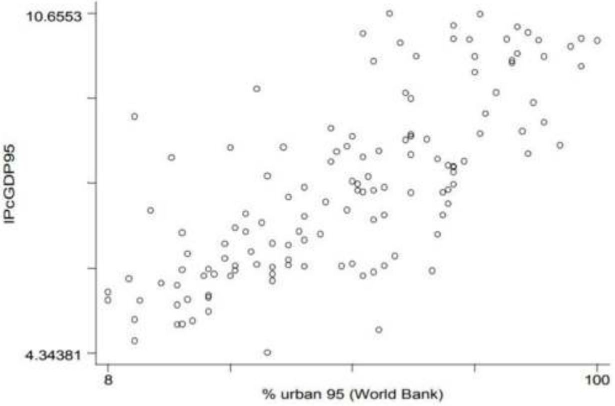
The non-polynomial case

- 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



Regression for classification

- Regression line
- Set a threshold
- Classifier
  - Output below threshold : 0 (No)
  - Output above threshold : 1 (Yes)

Regression for classification

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  - Output below threshold : 0 (No)
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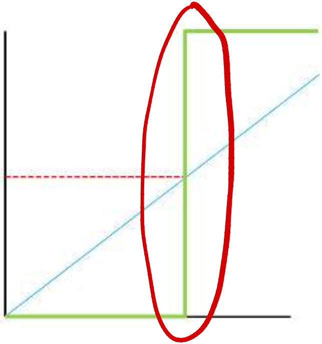
- Classifier output is a step function

$$\begin{bmatrix} x_1^1 \cdots x_k^1 \\ x_1^2 \quad x_k^2 \\ \vdots \\ x_1^n \quad x_2^n \end{bmatrix} \begin{matrix} y^1 \\ y^2 \\ \\ y^n \end{matrix} \begin{bmatrix} v^1 = 0/1 \\ v^2 = 0/1 \\ \\ v^n = 0/1 \end{bmatrix}$$



Loss per input is 0 or 1

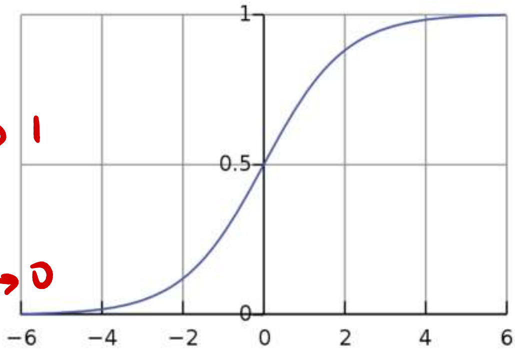
$$(x^T\theta - y)^2$$

- Sigmoid function

$$\sigma(z) = \frac{1}{1+e^{-z}}$$

$z \to \infty \quad e^{-z} \to 0 \quad \frac{1}{1+e^{-z}} \to 1$

$z \to -\infty \quad e^{-z} = \infty \quad \frac{1}{1+e^{-z}} \to 0$



1

0

tend to 0

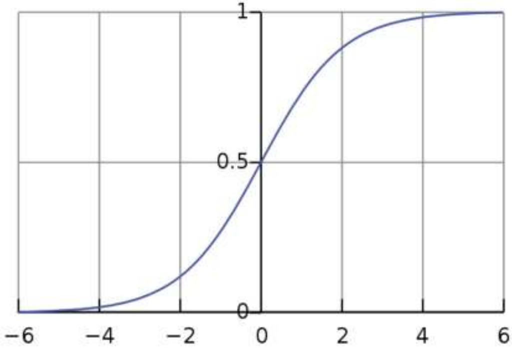
tend to 1

- Sigmoid function

$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

- Input z is output of our regression

$$\sigma(z) = \frac{1}{1 + e^{-(\theta_0 + \theta_1 x_1 + \cdots + \theta_k x_k)}}$$



Smoothen the step

- Sigmoid function

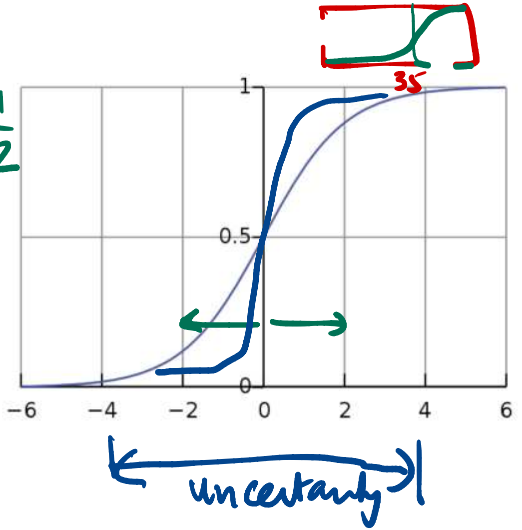
$$\sigma(z) = \frac{1}{1 + e^{-z}}$$

$$\frac{1}{1+e^0} = \frac{1}{2}$$

- Input z is output of our regression

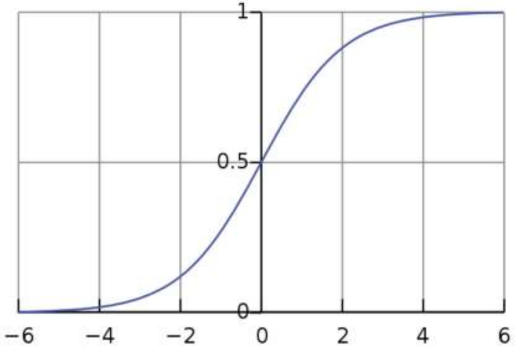
$$\sigma(z) = \frac{1}{1 + e^{-(\theta_0 + \theta_1 x_1 + \cdots + \theta_k x_k)}}$$

- Adjust parameters to fix horizontal position and steepness of step



Logistic regression

- Compute the coefficients?
- Solve by gradient descent



Logistic regression

- Compute the coefficients?
- Solve by gradient descent
- Need derivatives to exist
  - Hence smooth sigmoid, not step function
  - $\sigma'(z) = \sigma(z)(1 - \sigma(z))$

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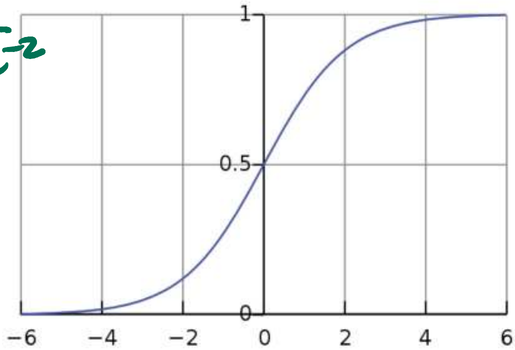
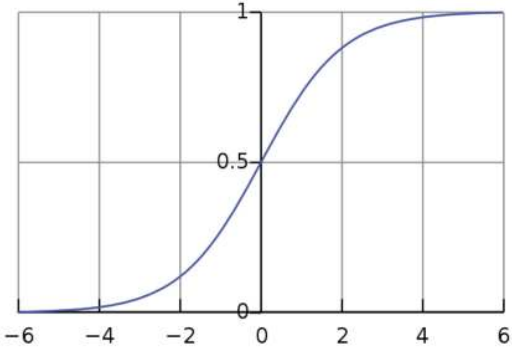


Logistic regression

- Compute the coefficients?
- Solve by gradient descent
- Need derivatives to exist
  - Hence smooth sigmoid, not step function
  - $\sigma'(z) = \sigma(z)(1 - \sigma(z))$
- Need a cost function to minimize



Loss function for logistic regression

- Goal is to maximize log likelihood

Loss function for logistic regression

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- Let $h_\theta(x_i) = \sigma(z_i)$.

final output

input

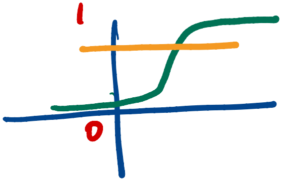
Loss function for logistic regression

- Goal is to maximize log likelihood

$x_i^T\theta$

- Let $h_\theta(x_i) = \sigma(z_i)$. So, $P(y_i = 1 \mid x_i; \theta) = h_\theta(x_i)$,
  $P(y_i = 0 \mid x_i; \theta) = 1 - h_\theta(x_i)$

- Combine as $P(y_i \mid x_i; \theta) = \underline{h_\theta(x_i)^{y_i}} \cdot \underline{(1 - h_\theta(x_i))^{1-y_i}}$



Fixed θ

Fixes $\frac{1}{1+e^{-x^T\theta}}$

Loss function for logistic regression

- Goal is to maximize log likelihood
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- Combine as $P(y_i \mid x_i; \theta) = h_\theta(x_i)^{y_i} \cdot (1 - h_\theta(x_i))^{1-y_i}$
- Likelihood: $\mathcal{L}(\theta) = \prod_{i=1}^{n} h_\theta(x_i)^{y_i} \cdot (1 - h_\theta(x_i))^{1-y_i}$

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Loss function for logistic regression

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- Log-likelihood: $\ell(\theta) = \sum_{i=1}^{n} y_i \log h_\theta(x_i) + (1 - y_i) \log(1 - h_\theta(x_i))$
- Minimize cross entropy: $-\sum_{i=1}^{n} y_i \log h_\theta(x_i) + (1 - y_i) \log(1 - h_\theta(x_i))$

MSE for logistic regression and gradient descent

- Suppose we take mean sum-squared error as the loss function.
- Consider two inputs $x = (x_1, x_2)$

$$C = \frac{1}{n}\sum_{i=1}^{n}(y_i - \sigma(z_i))^2, \text{ where } z_i = \theta_0 + \theta_1 x_{i_1} + \theta_2 x_{i_2}$$

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- For gradient descent, we compute $\frac{\partial C}{\partial \theta_1}, \frac{\partial C}{\partial \theta_2}, \frac{\partial C}{\partial \theta_0}$

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  - For $j = 1, 2$,
    $$\frac{\partial C}{\partial \theta_j} = \frac{2}{n}\sum_{i=1}^{n}(y_i - \sigma(z_i)) \cdot -\frac{\partial \sigma(z_i)}{\partial \theta_j}$$

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$g(f(x))$

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  - For $j = 1, 2,$

$\frac{dg}{dx}\quad \frac{dg}{df}\cdot\frac{df}{dx}$

$$\frac{\partial C}{\partial \theta_j} = \frac{2}{n}\sum_{i=1}^{n}(y_i - \sigma(z_i)) \cdot -\frac{\partial \sigma(z_i)}{\partial \theta_j} = \frac{2}{n}\sum_{i=1}^{n}(\sigma(z_i) - y_i)\ \underline{\frac{\partial \sigma(z_i)}{\partial z_i}\frac{\partial z_i}{\partial \theta_j}}$$

CHAIN RULE

MSE for logistic regression and gradient descent

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0, 1

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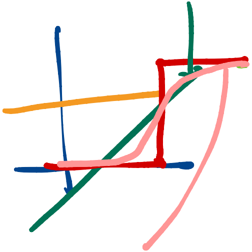
$$\frac{\partial C}{\partial \theta_j} = \frac{2}{n}\sum_{i=1}^{n}(y_i - \sigma(z_i)) \cdot -\frac{\partial \sigma(z_i)}{\partial \theta_j} = \frac{2}{n}\sum_{i=1}^{n} (\sigma(z_i) - y_i)\, \frac{\partial \sigma(z_i)}{\partial z_i}\frac{\partial z_i}{\partial \theta_j}$$

$$= \frac{2}{n}\sum_{i=1}^{n}(\sigma(z_i) - y_i)\sigma'(z_i)x_{i_j}$$

$z = x^T\theta$



$\sigma(z)$

MSE for logistic regression and gradient descent

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$$\frac{\partial C}{\partial \theta_j} = \frac{2}{n}\sum_{i=1}^{n}(y_i - \sigma(z_i)) \cdot -\frac{\partial \sigma(z_i)}{\partial \theta_j} = \frac{2}{n}\sum_{i=1}^{n}(\sigma(z_i) - y_i)\frac{\partial \sigma(z_i)}{\partial z_i}\frac{\partial z_i}{\partial \theta_j}$$

$$= \frac{2}{n}\sum_{i=1}^{n}(\sigma(z_i) - y_i)\sigma'(z_i)x_{i_j}$$

  - $\dfrac{\partial C}{\partial \theta_0} = \dfrac{2}{n}\sum_{i=1}^{n}(\sigma(z_i) - y_i)\dfrac{\partial \sigma(z_i)}{\partial z_i}\dfrac{\partial z_i}{\partial \theta_0} = \dfrac{2}{n}\sum_{i=1}^{n}(\sigma(z_i) - y_i)\sigma'(z_i)$

MSE for logistic regression and gradient descent ...

- For $j = 1, 2$, $\dfrac{\partial C}{\partial \theta_j} = \dfrac{2}{n} \sum_{i=1}^{n} (\sigma(z_i) - y_i)\sigma'(z_i)x_j^i$, and $\dfrac{\partial C}{\partial \theta_0} = \dfrac{2}{n} \sum_{i=1}^{n} (\sigma(z_i) - y_i)\sigma'(z_i)$

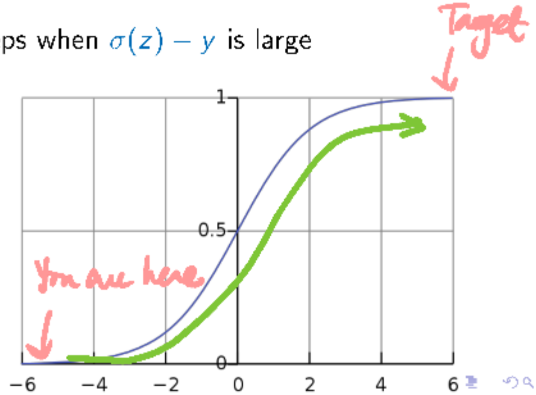
- Each term in $\dfrac{\partial C}{\partial \theta_1}$, $\dfrac{\partial C}{\partial \theta_2}$, $\dfrac{\partial C}{\partial \theta_0}$ is proportional to $\sigma'(z_i)$

MSE for logistic regression and gradient descent ...

- For $j = 1, 2$, $\dfrac{\partial C}{\partial \theta_j} = \dfrac{2}{n}\displaystyle\sum_{i=1}^{n}(\sigma(z_i) - y_i)\sigma'(z_i)x_j^i$, and $\dfrac{\partial C}{\partial \theta_0} = \dfrac{2}{n}\displaystyle\sum_{i=1}^{n}(\sigma(z_i) - y_i)\sigma'(z_i)$
- Each term in $\dfrac{\partial C}{\partial \theta_1}, \dfrac{\partial C}{\partial \theta_2}, \dfrac{\partial C}{\partial \theta_0}$ is proportional to $\sigma'(z_i)$
- Ideally, gradient descent should take large steps when $\sigma(z) - y$ is large

MSE for logistic regression and gradient descent ...

- For $j = 1, 2$, $\dfrac{\partial C}{\partial \theta_j} = \dfrac{2}{n}\sum_{i=1}^{n}(\sigma(z_i) - y_i)\sigma'(z_i)x_i^j$, and $\dfrac{\partial C}{\partial \theta_0} = \dfrac{2}{n}\sum_{i=1}^{n}(\sigma(z_i) - y_i)\sigma'(z_i)$
- Each term in $\dfrac{\partial C}{\partial \theta_1}, \dfrac{\partial C}{\partial \theta_2}, \dfrac{\partial C}{\partial \theta_0}$ is proportional to $\sigma'(z_i)$
- Ideally, gradient descent should take large steps when $\sigma(z) - y$ is large
- $\sigma(z)$ is flat at both extremes
- If $\sigma(z)$ is completely wrong, $\sigma(z) \approx (1 - y)$, we still have $\sigma'(z) \approx 0$
- Learning is slow even when current model is far from optimal



Cross entropy and gradient descent

- $C = -[y \ln(\sigma(z)) + (1-y)\ln(1-\sigma(z))]$

Cross entropy and gradient descent

- $C = -[y \ln(\sigma(z)) + (1-y)\ln(1-\sigma(z))]$

- $\dfrac{\partial C}{\partial \theta_j} = \dfrac{\partial C}{\partial \sigma}\dfrac{\partial \sigma}{\partial \theta_j}$

Cross entropy and gradient descent

- $C = -[y \ln(\sigma(z)) + (1-y)\ln(1-\sigma(z))]$
- $\dfrac{\partial C}{\partial \theta_j} = \dfrac{\partial C}{\partial \sigma}\dfrac{\partial \sigma}{\partial \theta_j} = -\left[\dfrac{y}{\sigma(z)} - \dfrac{1-y}{1-\sigma(z)}\right]\dfrac{\partial \sigma}{\partial \theta_j}$

$\dfrac{d\ \ln(x)}{x} = \dfrac{1}{\ln(x)}$

Cross entropy and gradient descent

- $C = -[y \ln(\sigma(z)) + (1-y)\ln(1-\sigma(z))]$

- $$\frac{\partial C}{\partial \theta_j} = \frac{\partial C}{\partial \sigma}\frac{\partial \sigma}{\partial \theta_j} = -\left[\frac{y}{\sigma(z)} - \frac{1-y}{1-\sigma(z)}\right]\frac{\partial \sigma}{\partial \theta_j}$$
$$= -\left[\frac{y}{\sigma(z)} - \frac{1-y}{1-\sigma(z)}\right]\frac{\partial \sigma}{\partial z}\frac{\partial z}{\partial \theta_j}$$

Cross entropy and gradient descent

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$$= -\left[\frac{y}{\sigma(z)} - \frac{1-y}{1-\sigma(z)}\right]\frac{\partial \sigma}{\partial z}\frac{\partial z}{\partial \theta_j}$$
$$= -\underbrace{\left[\frac{y}{\sigma(z)} - \frac{1-y}{1-\sigma(z)}\right]}_{\text{different}}\underbrace{\sigma'(z)x_j}_{\text{same}}$$

Cross entropy and gradient descent

- $C = -[y \ln(\sigma(z)) + (1-y)\ln(1-\sigma(z))]$

- $$\begin{aligned}
\frac{\partial C}{\partial \theta_j} = \frac{\partial C}{\partial \sigma}\frac{\partial \sigma}{\partial \theta_j} &= -\left[\frac{y}{\sigma(z)} - \frac{1-y}{1-\sigma(z)}\right]\frac{\partial \sigma}{\partial \theta_j} \\
&= -\left[\frac{y}{\sigma(z)} - \frac{1-y}{1-\sigma(z)}\right]\frac{\partial \sigma}{\partial z}\frac{\partial z}{\partial \theta_j} \\
&= -\left[\frac{y}{\sigma(z)} - \frac{1-y}{1-\sigma(z)}\right]\sigma'(z)x_j \\
&= -\left[\frac{y(1-\sigma(z)) - (1-y)\sigma(z)}{\sigma(z)(1-\sigma(z))}\right]\sigma'(z)x_j
\end{aligned}$$

Cross entropy and gradient descent . . .

- $\frac{\partial C}{\partial \theta_j} = -\left[\frac{y(1-\sigma(z)) - (1-y)\sigma(z)}{\sigma(z)(1-\sigma(z))}\right]\cancel{\sigma'}(z)x_j$

- Recall that $\sigma'(z) = \sigma(z)(1-\sigma(z))$

Cross entropy and gradient descent ...

- $\dfrac{\partial C}{\partial \theta_j} = -\left[\dfrac{y(1-\sigma(z)) - (1-y)\sigma(z)}{\sigma(z)(1-\sigma(z))}\right]\sigma'(z)x_j$

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- Therefore, $\dfrac{\partial C}{\partial \theta_j} = -[y(1-\sigma(z)) - (1-y)\sigma(z)]x_j$

Cross entropy and gradient descent . . .

- $\displaystyle \frac{\partial C}{\partial \theta_j} = -\left[\frac{y(1-\sigma(z)) - (1-y)\sigma(z)}{\sigma(z)(1-\sigma(z))}\right]\sigma'(z)x_j$

- Recall that $\sigma'(z) = \sigma(z)(1-\sigma(z))$

- Therefore, $\displaystyle \begin{aligned}\frac{\partial C}{\partial \theta_j} &= -[y(1-\sigma(z)) - (1-y)\sigma(z)]x_j \\ &= -[y - y\sigma(z) - \sigma(z) + y\sigma(z)]x_j\end{aligned}$

Cross entropy and gradient descent . . .

- $\dfrac{\partial C}{\partial \theta_j} = -\left[\dfrac{y(1-\sigma(z)) - (1-y)\sigma(z)}{\sigma(z)(1-\sigma(z))}\right]\sigma'(z)x_j$

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- Therefore, $\begin{aligned}\dfrac{\partial C}{\partial \theta_j} &= -[y(1-\sigma(z)) - (1-y)\sigma(z)]x_j \\ &= -[y - y\sigma(z) - \sigma(z) + y\sigma(z)]x_j \\ &= (\sigma(z) - y)x_j\end{aligned}$

Cross entropy and gradient descent ...

- $\dfrac{\partial C}{\partial \theta_j} = -\left[\dfrac{y(1-\sigma(z)) - (1-y)\sigma(z)}{\sigma(z)(1-\sigma(z))}\right] \sigma'(z) x_j$

- Recall that $\sigma'(z) = \sigma(z)(1-\sigma(z))$

- Therefore, $$\begin{aligned}\frac{\partial C}{\partial \theta_j} &= -[y(1-\sigma(z)) - (1-y)\sigma(z)]x_j \\ &= -[y - y\sigma(z) - \sigma(z) + y\sigma(z)]x_j \\ &= (\sigma(z) - y)x_j\end{aligned}$$

- Similarly, $\dfrac{\partial C}{\partial \theta_0} = (\sigma(z) - y)$

Cross entropy and gradient descent ...

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Cross entropy and gradient descent . . .

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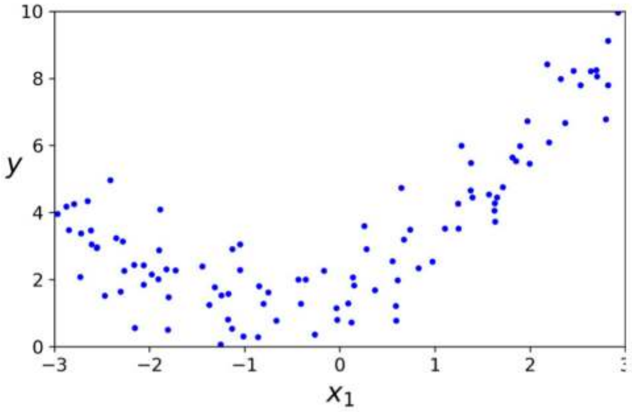
- Thus, as we wanted, the gradient is proportional to $\sigma(z) - y$

- The greater the error, the faster the learning rate

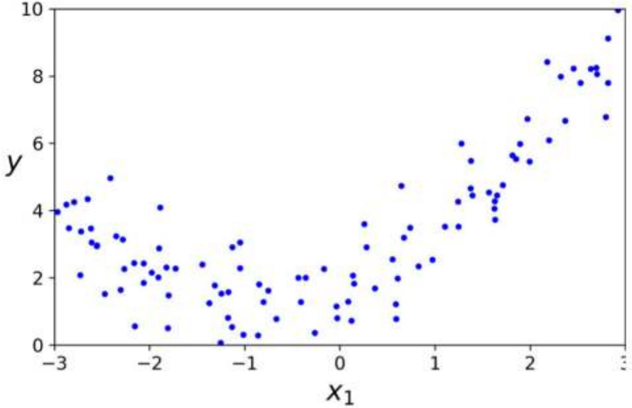
Decision trees for regression

- How do we use decision trees for regression?



Decision trees for regression

- How do we use decision trees for regression?
- Partition the input into intervals



Decision trees for regression

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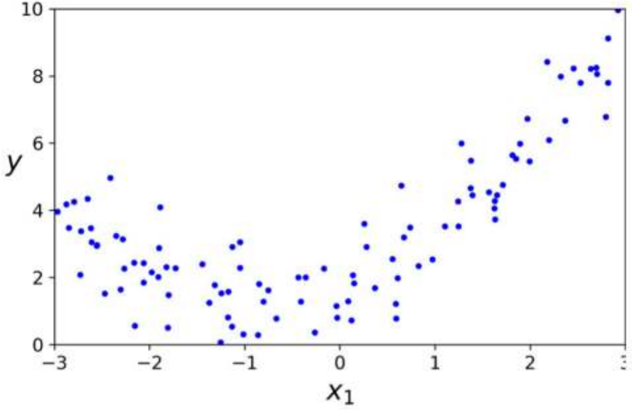
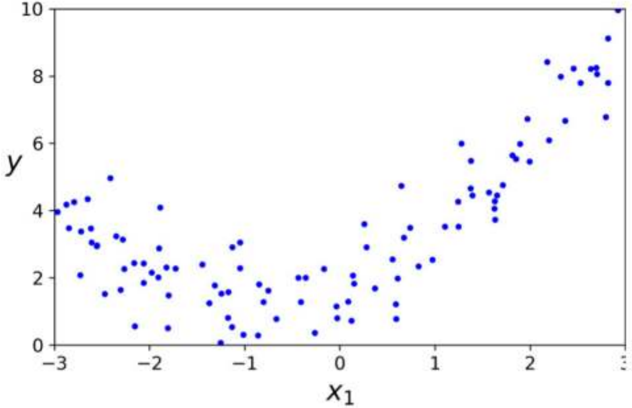
- Partition the input into intervals
- For each interval, predict mean value of output, instead of majority class



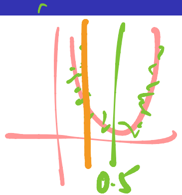
Decision trees for regression

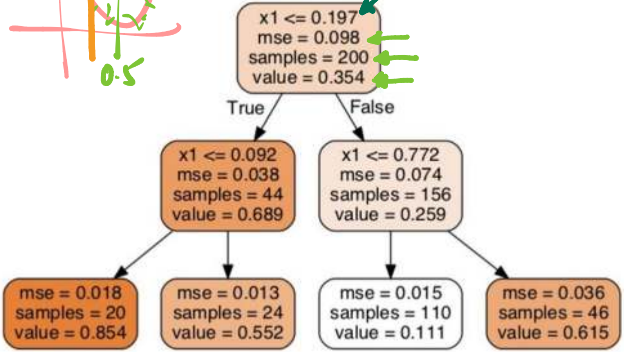
- How do we use decision trees for regression?
- Partition the input into intervals
- For each interval, predict mean value of output, instead of majority class
- Regression tree



Decision trees for regression

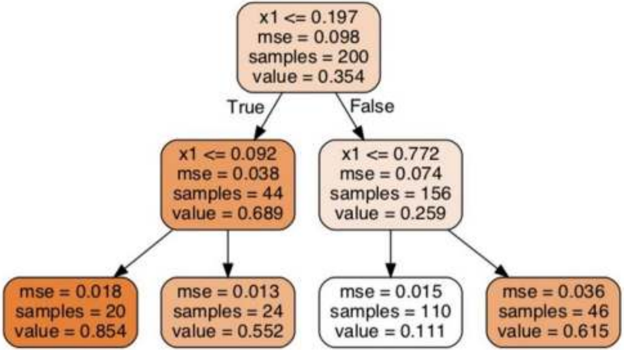
- Regression tree for noisy quadratic centered around $x_1 = 0.5$





Decision trees for regression

- Regression tree for noisy quadratic centered around $x_1 = 0.5$
- For each node, the output is the mean y value for the current set of points



Decision trees for regression

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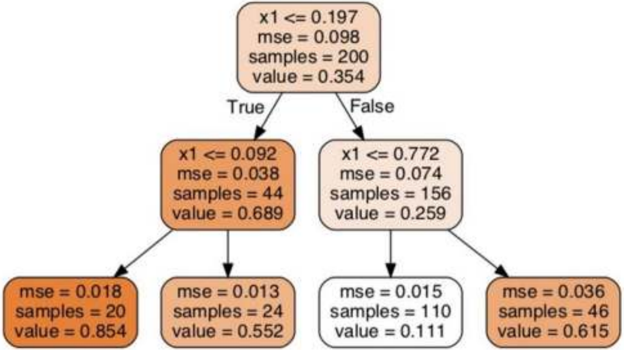
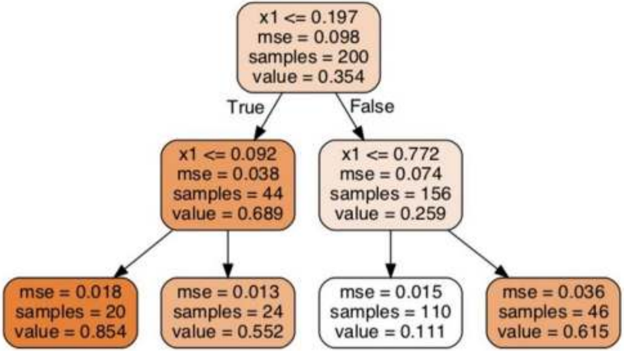
- Instead of impurity, use mean squared error (MSE) as cost function



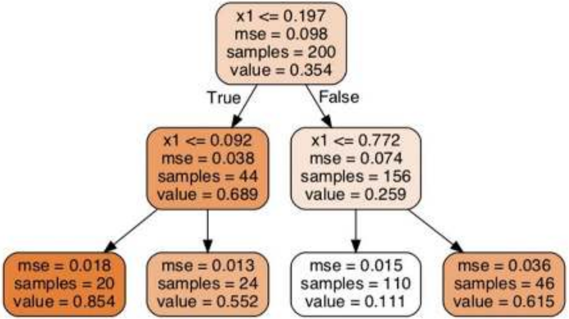
Decision trees for regression

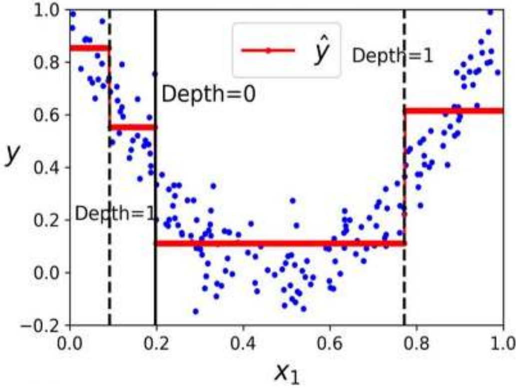
- Regression tree for noisy quadratic centered around $x_1 = 0.5$
- For each node, the output is the mean y value for the current set of points
- Instead of impurity, use mean squared error (MSE) as cost function
- Choose a split that minimizes MSE



Regression trees

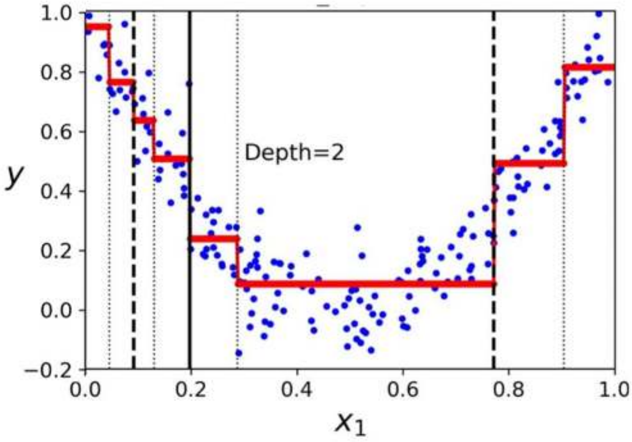
- Approximation using regression tree





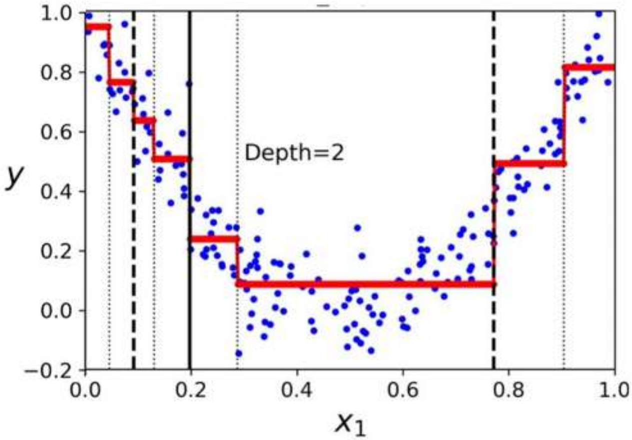
Regression trees

- Extend the regression tree one more level to get a finer approximation



Regression trees

- Extend the regression tree one more level to get a finer approximation
- Set a threshold on MSE to decide when to stop



Regression trees

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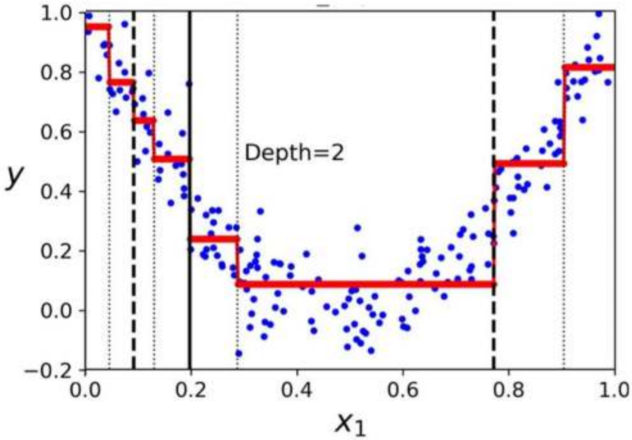
- Classification and Regression Trees (CART)



Regression trees

- Extend the regression tree one more level to get a finer approximation
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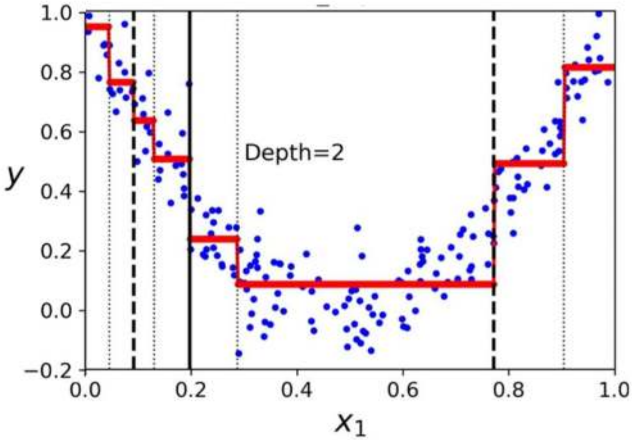
- Classification and Regression Trees (CART)
  - Combined algorithm for both use cases



Regression trees

- Extend the regression tree one more level to get a finer approximation
- Set a threshold on MSE to decide when to stop
- Classification and Regression Trees (CART)
  - Combined algorithm for both use cases
- Programming libraries typically provide CART implementation