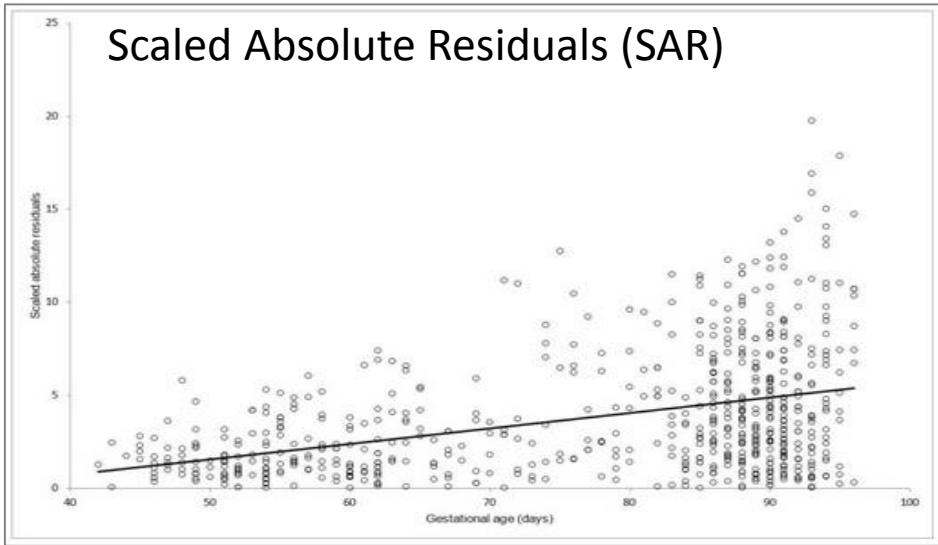


# Gradient Descent

A few fine points

# Recall this slide



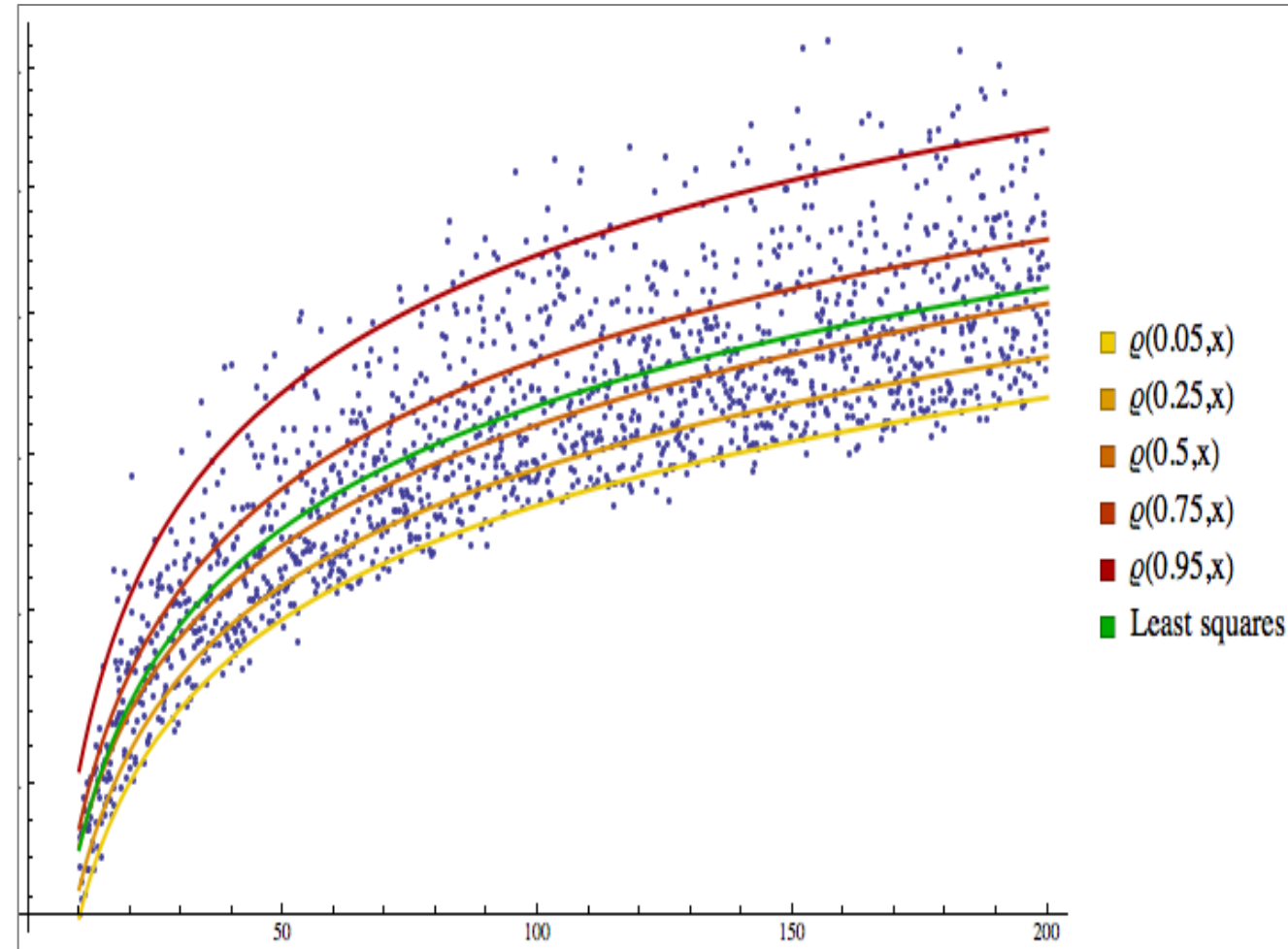
## And a little bit more math

$$y(\mathbf{a} | \mathbf{p}, x_{\text{train}}) = \mathbf{a}_0 + \mathbf{a}_1 * x_1 + \mathbf{a}_2 * x_2 + \dots + \mathbf{a}_n * x_n$$

$$\varepsilon_p[i] = y_{p,\text{model}}[i] - y_{p,\text{observed}}[i]$$

$$\mathbf{a} = \text{argmin} \{E[|\varepsilon_p|]\}$$

$$E[|\varepsilon_p|] = \sum_{i=1}^N p * |\varepsilon_p[i]| (\varepsilon_p[i] > 0) + \sum_{i=1}^N (1 - p) * |\varepsilon_p[i]| (\varepsilon_p[i] < 0)$$



## Advantages:

- Accurate representation of each quantile.
- In-depth understanding of underlying behavior.

## Disadvantages:

- No closed-form solution.

# The main idea Behind Gradient Descent

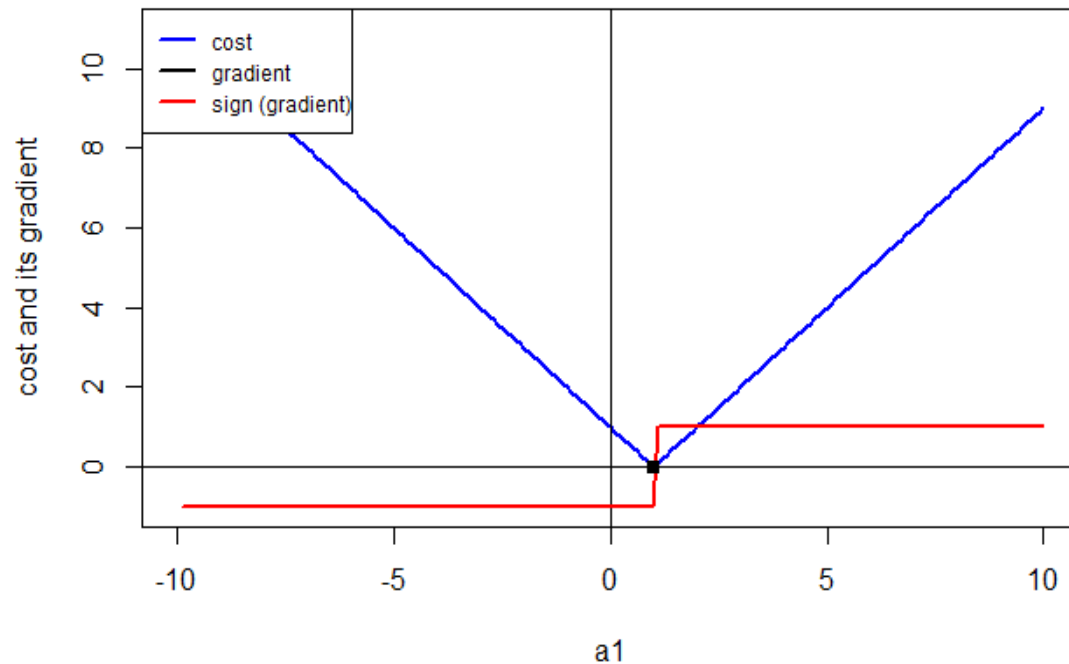
## Quantile Regression

$$y(\mathbf{a} | \mathbf{p}, x_{train}) = \mathbf{a}_0 + \mathbf{a}_1 * x_1 + \mathbf{a}_2 * x_2 + \dots + \mathbf{a}_n * x_n$$

$$\varepsilon_p[i] = y_{p,model}[i] - y_{p,observed}[i]$$

$$\mathbf{a} = \operatorname{argmin}\{cost\} = \operatorname{argmin}\{\mathbf{E}[|\varepsilon_p|]\}$$

$$y(\mathbf{a} | \mathbf{p}, x_{train}) = \mathbf{a}_1 * x_1$$



## OLS, GLM

$$y(\mathbf{a} | x_{train}) = \mathbf{a}_0 + \mathbf{a}_1 * x_1 + \mathbf{a}_2 * x_2 + \dots + \mathbf{a}_n * x_n$$

$$\varepsilon[i] = y_{model}[i] - y_{observed}[i]$$

$$\mathbf{a} = \operatorname{argmin}\{cost\} = \operatorname{argmin}\{\mathbf{E}[\varepsilon^2]\}$$

$$y(\mathbf{a} | x_{train}) = \mathbf{a}_1 * x_1$$

