INTRODUCTION TO DATA ANALYTICS

# Linear Regression

หลักเริ่มของ โมเดล predictive


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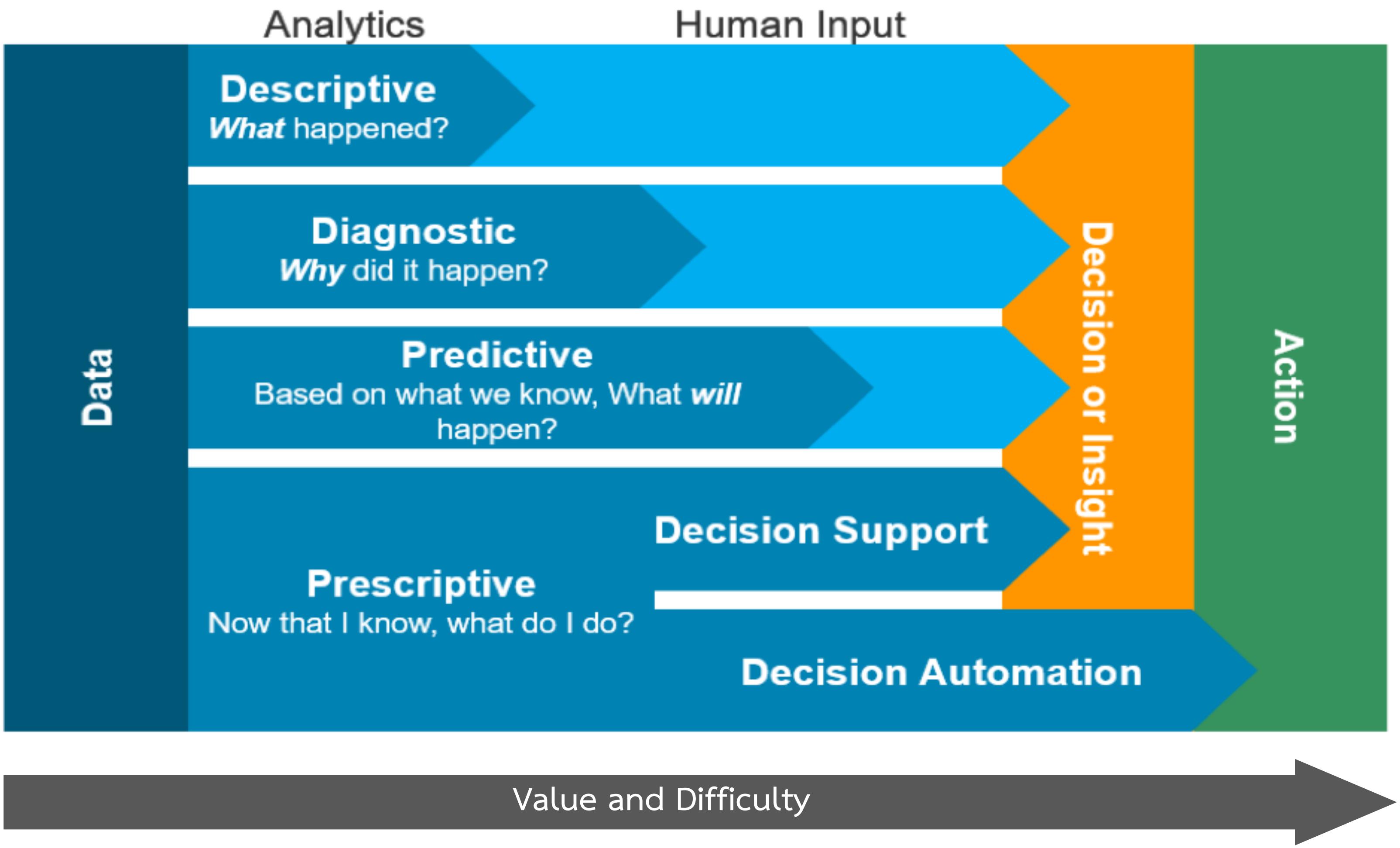
# Agenda

- Linear Regression
- Evaluation Methods
- Feature Extraction
- Cross Validation
- Feature Scaling

# Data Analytics




**Ref:**
- Four types of analytics capability (Gartner, 2014)
- (image) https://www.healthcatalyst.com/closed-loop-analytics-method-healthcare-data-insights

ทำให้โมเดลเรียนรู้ได้

# Machine Learning

รู้ทั้ง x, y

## Supervised Learning

Develop predictive model based on both input and output data

รู้ x หาการจัดกลุ่มเอง

## Unsupervised Learning

Develop predictive model based on both input and output data

ค่าcontinuousแบบnumber

### Regression

- Linear Regression
- Polynomial Regression

ค่าแยกกลุ่ม

### Classification

- Decision Tree
- Logistic Regression
- Neural Network
- etc.

### Clustering

- K-Means
- DB-SCAN
- etc.

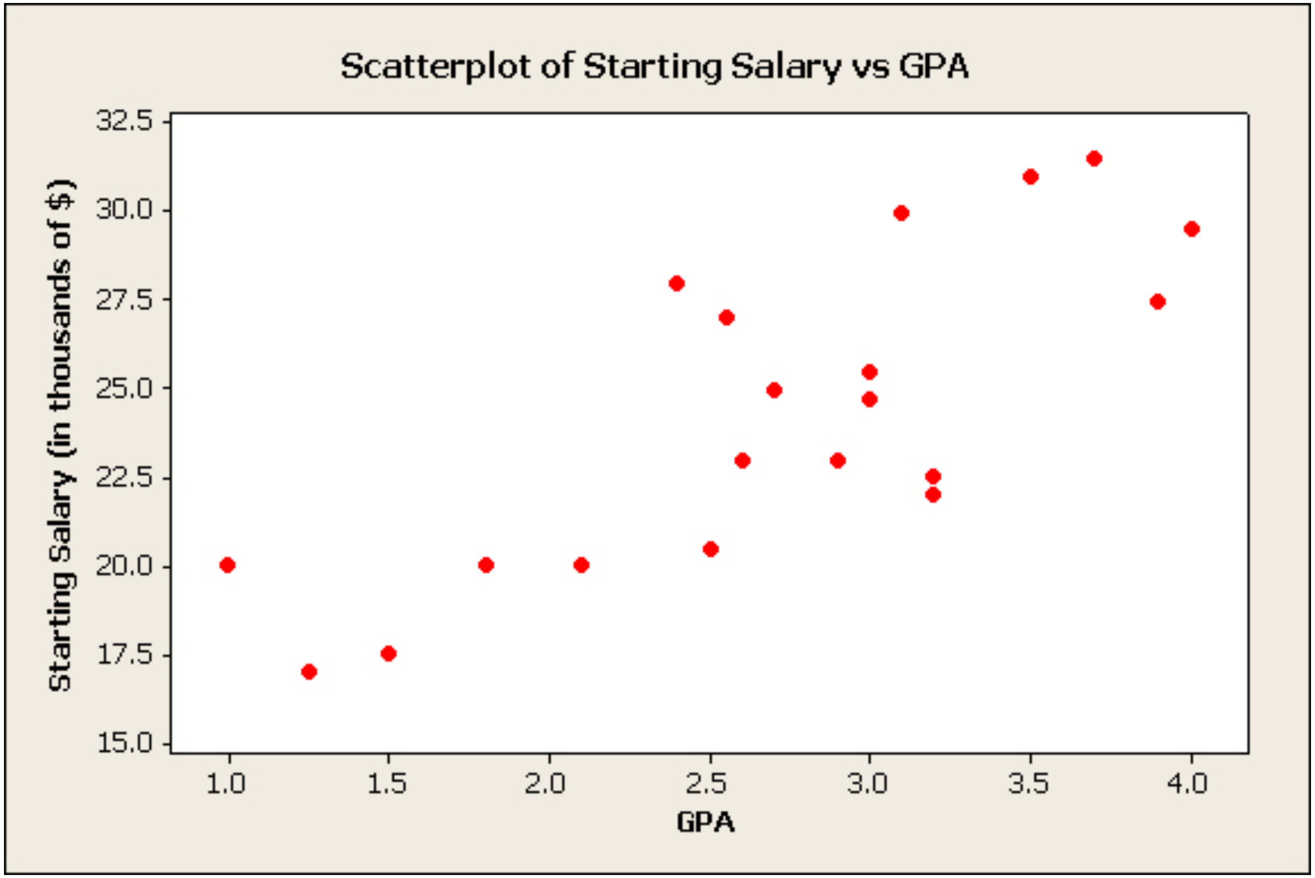
# Linear Regression

# Your Salary?

| GPA | Salary |
|---|---|
| 1.07 | 15,400 |
| 2.32 | 20,500 |
| 2.75 | 23,300 |
| 3.02 | 28,200 |
| 3.25 | 27,900 |
| 3.63 | 32,100 |
| 3.98 | 30,200 |

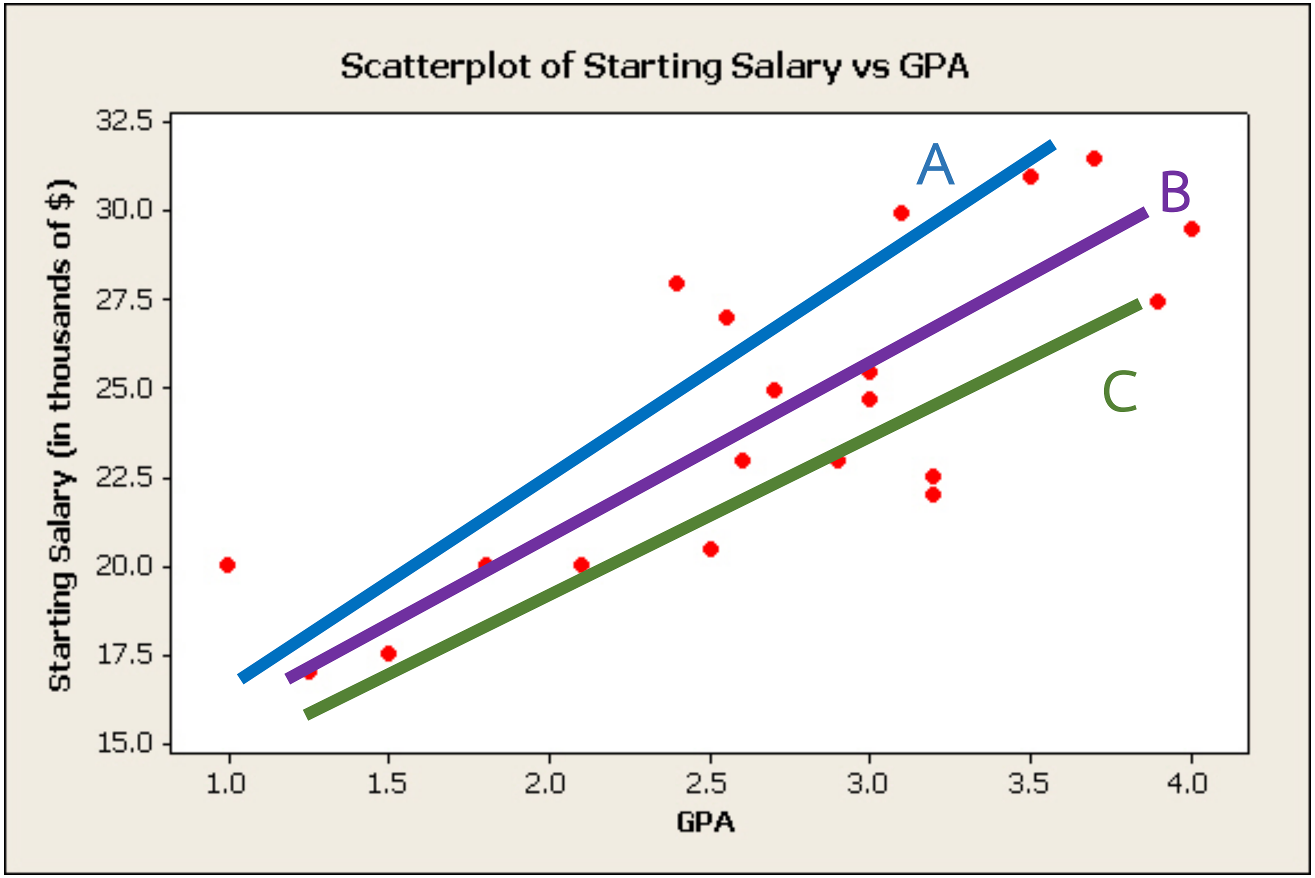
(assumed data)

# Prediction !




Ref: • (image) http://www.chegg.com/homework-help/questions-and-answers/orientation-meeting-new-students-college-president-wants-emphasize-importance-getting-good-q12615281

# Prediction !

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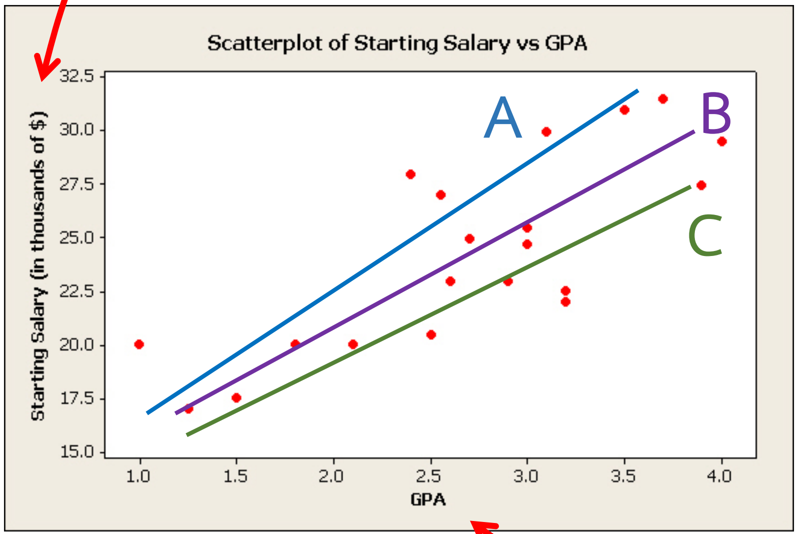
# Linear Equation




หาค่าใกล้
ของธรรมมากที่สุด

? ?

$$y = ax + c$$

Ref: • (image) http://www.chegg.com/homework-help/questions-and-answers/orientation-meeting-new-students-college-president-wants-emphasize-importance-getting-good-q12615281

# Simple Linear Regression

$$\hat{Y}_i = b_0 + b_1 X_i$$

# Simple Linear Regression

$$\hat{Y}_i = b_0 + b_1 X_i$$

| Salary |
|---|
| *15,400* |
| *20,500* |
| *23,300* |
| *26,200* |
| *27,900* |
| *32,100* |
| *30,200* |

| GPA |
|---|
| 1.07 |
| 2.32 |
| 2.75 |
| 3.02 |
| 3.25 |
| 3.63 |
| 3.98 |

# Your Salary?

| GPA | U. Ranking | Salary |
|---|---|---|
| 1.07 | 6 | 15,400 |
| 2.32 | 7 | 20,500 |
| 2.75 | 8 | 23,300 |
| 3.02 | 9 | 28,200 |
| 3.25 | 7 | 27,900 |
| 3.63 | 10 | 32,100 |
| 3.98 | 5 | 30,200 |

(assumed data)

# Multiple Linear Regression

$$\hat{Y}_i = b_0 + b_1 X_{1i} + b_2 X_{2i} + \cdots$$

# Multiple Linear Regression

$$\hat{Y}_i = b_0 + b_1 X_{1i} + b_2 X_{2i} + \cdots$$

| Salary |
|---|
| 15,400 |
| 20,500 |
| 23,300 |
| 28,200 |
| 27,900 |
| 32,100 |
| 30,200 |

| GPA |
|---|
| 1.07 |
| 2.32 |
| 2.75 |
| 3.02 |
| 3.25 |
| 3.63 |
| 3.98 |

| U. Ranking |
|---|
| 6 |
| 7 |
| 8 |
| 9 |
| 7 |
| 10 |
| 5 |

**Ref:**

# Coefficients

$$\hat{Y}_i = 4006 + 5655 * GPA + 698 * URank$$

# Python

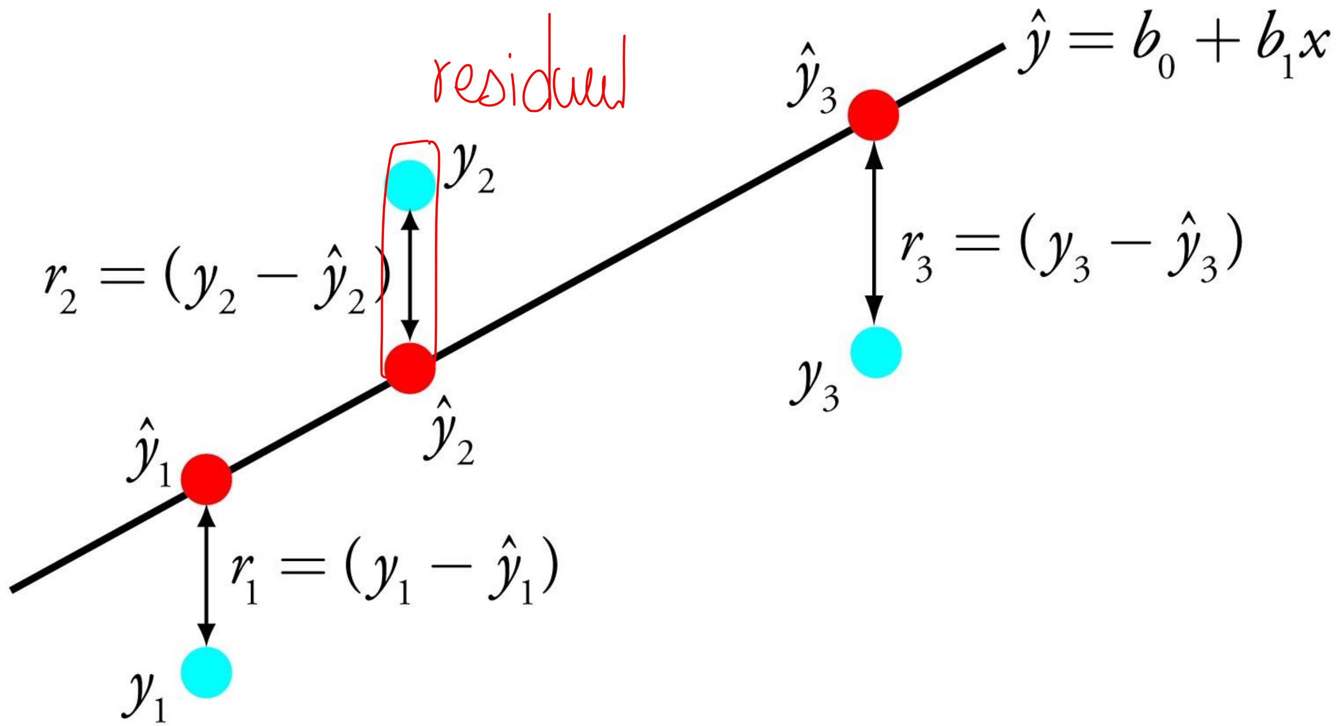
1. from sklearn import linear_model
2. X = df[“GPA”, “Urank”]
3. y = df[“Salary”]
4. lm = linear_model.LinearRegression()
5. lm.fit (X,y)
6. lm.coef_

   array([ 406,  565, 698])

การกำหนดขอบเขตเป็นเส้นไหม?

# Evaluation Methods

# Residual




**Ref:** • (image) https://towardsdatascience.com/simple-linear-regression-2421076a5892

# Root Mean Squared Error (RMSE)

predicted

actual

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(\hat{y}_i - y_i)^2}{N}}$$

number of samples

# RMSE

$$\hat{Y}_i = ? + ??* \, GPA + ???* \, URank$$

| GPA | U. Ranking | Actual Salary |
|---|---|---|
| 1.07 | 6 | 15,400 |
| 2.32 | 7 | 20,500 |
| 2.75 | 8 | 23,300 |
| 3.02 | 9 | 28,200 |
| 3.25 | 7 | 27,900 |
| 3.63 | 10 | 32,100 |
| 3.98 | 5 | 30,200 |

# RMSE

$$\hat{Y}_i = 4006 + 5655 * GPA + 698 * URank$$

| GPA | U. Ranking | Actual Salary |
|---|---|---|
| 1.07 | 6 | 15,400 |
| 2.32 | 7 | 20,500 |
| 2.75 | 8 | 23,300 |
| 3.02 | 9 | 28,200 |
| 3.25 | 7 | 27,900 |
| 3.63 | 10 | 32,100 |
| 3.98 | 5 | 30,200 |

# RMSE

$$\hat{Y}_i = 4006 + 5655 * GPA + 698 * URank$$

| GPA | U. Ranking | Actual Salary | Predicted Salary |
|---|---|---|---|
| 1.07 | 6 | 15,400 | 16,350 |
| 2.32 | 7 | 20,500 | 23,100 |
| 2.75 | 8 | 23,300 | 25,750 |
| 3.02 | 9 | 28,200 | 27,600 |
| 3.25 | 7 | 27,900 | 27,750 |
| 3.63 | 10 | 32,100 | 31,150 |
| 3.98 | 5 | 30,200 | 30,400 |

# RMSE

$$\hat{Y}_i = 4006 + 5655 * GPA + 698 * URank$$

| GPA | U. Ranking | Actual Salary | Predicted Salary | $\hat{y}_i - y_i$ | $(\hat{y}_i - y_i)^2$ |
|---|---|---|---|---|---|
| 1.07 | 6 | 15,400 | 16,350 | 1,155.15 | 1,334,371.52 |
| 2.32 | 7 | 20,500 | 23,100 | -1,511.60 | 2,284,934.56 |
| 2.75 | 8 | 23,300 | 25,750 | -1,841.25 | 3,390,201.56 |
| 3.02 | 9 | 28,200 | 27,600 | 833.90 | 695,389.21 |
| 3.25 | 7 | 27,900 | 27,750 | 629.25 | 395,955.56 |
| 3.63 | 10 | 32,100 | 31,150 | 586.35 | 343,806.32 |
| 3.98 | 5 | 30,200 | 30,400 | 197.10 | 38,848.41 |
| | | | | SUM | **8,483,507.15** |
| | | | | MEAN | **1,211,929.59** |
| | | | | RMSE | **1,100.88** |

# Other Evaluation Methods

ตัววัดอื่นๆ

| | |
|---|---|
| Mean squared error | $\text{MSE} = \frac{1}{n}\sum_{t=1}^{n} e_t^2$ |
| Root mean squared error | $\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n} e_t^2}$ |
| Mean absolute error | $\text{MAE} = \frac{1}{n}\sum_{t=1}^{n} \lvert e_t \rvert$ |
| Mean absolute percentage error | $\text{MAPE} = \frac{100\%}{n}\sum_{t=1}^{n} \left\lvert \frac{e_t}{y_t} \right\rvert$ |

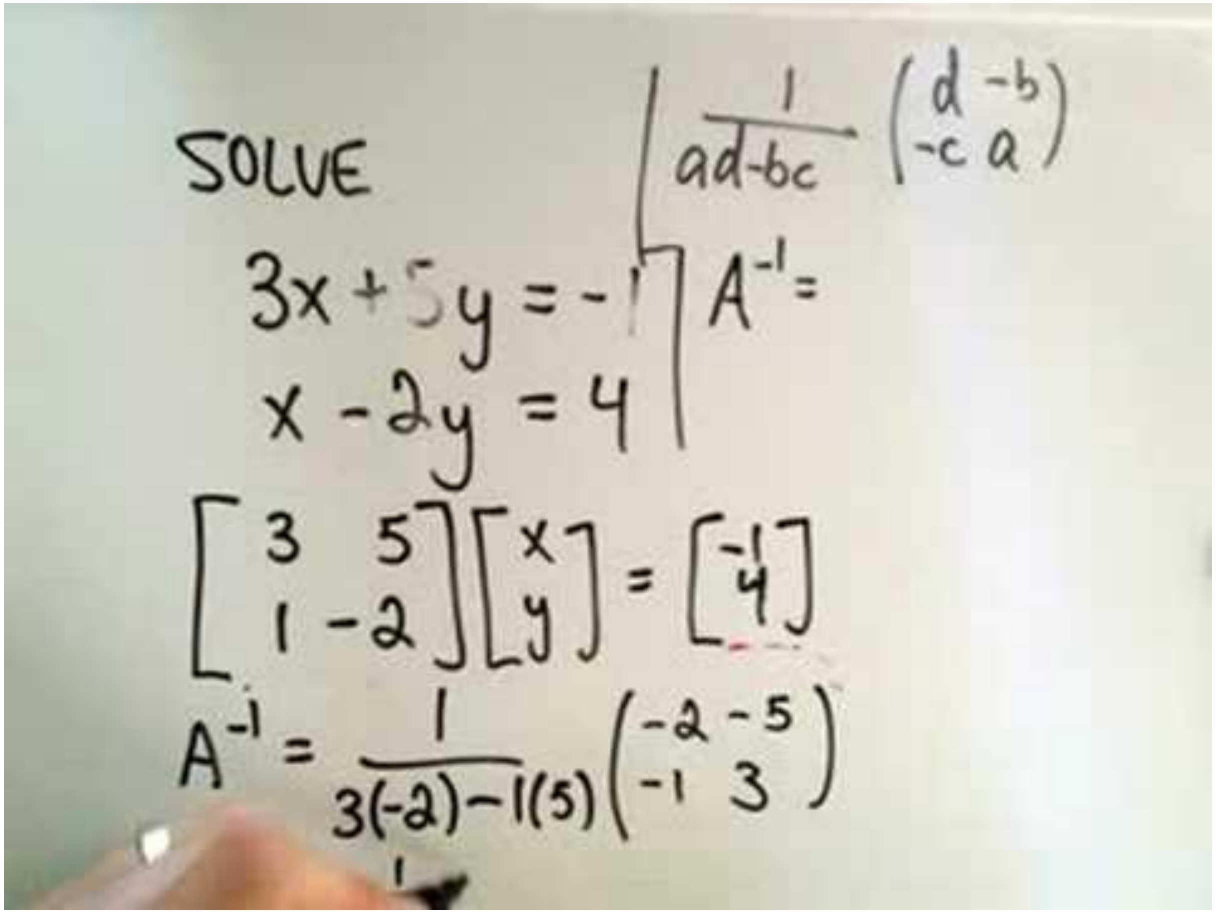
**Ref:** • (image) https://tex.stackexchange.com/questions/170372/increase-vertical-space-in-table

# Python

- from sklearn import linear_model
- from sklearn.metrics import mean_squared_error
- from math import sqrt
- X = df[“GPA”, “Urank”]
- y = df[“Salary”]
- lm = linear_model.LinearRegression()
- lm.fit (X,y)
- y_predicted = lm.predict(X)
- rmse = sqrt(mean_squared_error(y, y_predicted))

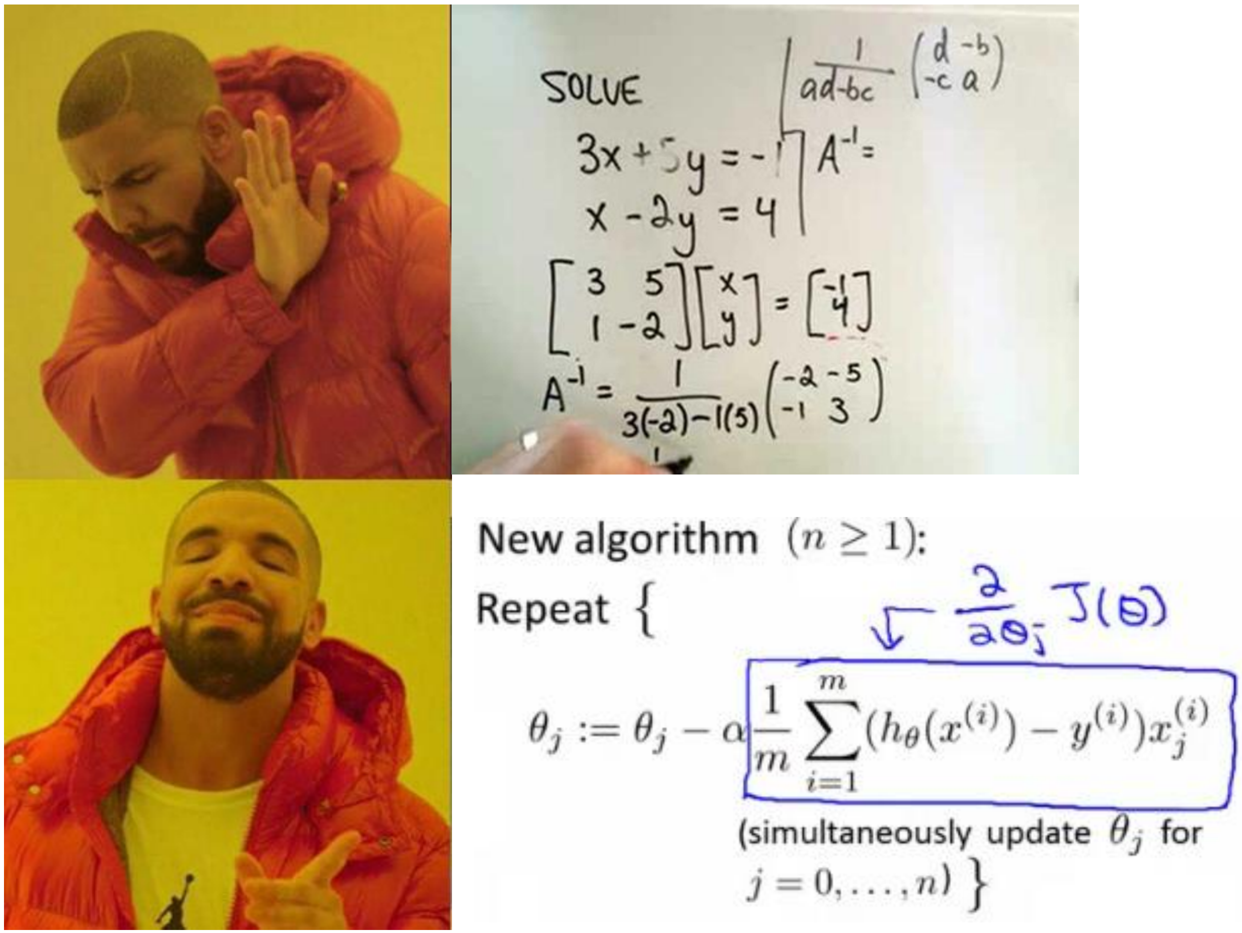
# Learning

# Solve by Matrix




**Ref:** • https://www.youtube.com/watch?v=PTN8rganLWo

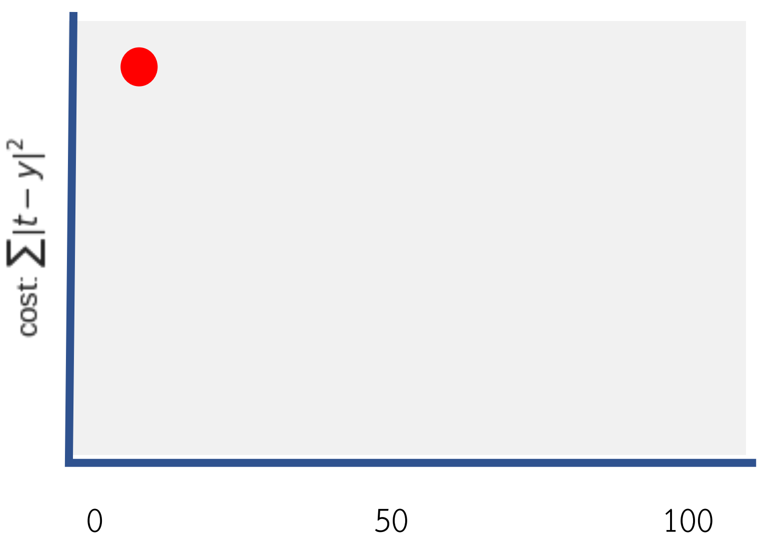
# Solve by ........



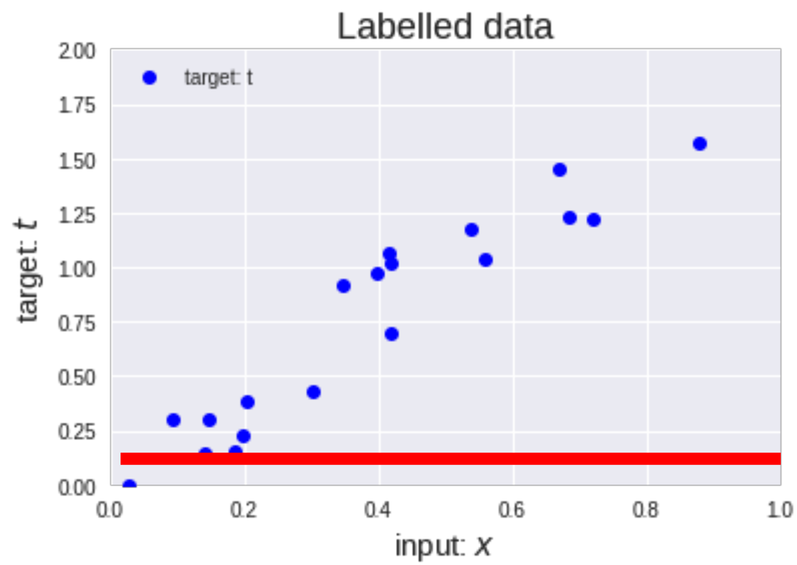
SOLVE
$3x + 5y = -1$
$x - 2y = 4$
$A^{-1} = \frac{1}{ad-bc}\begin{pmatrix} d & -b \\ -c & a \end{pmatrix}$
$\begin{bmatrix} 3 & 5 \\ 1 & -2 \end{bmatrix}\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} -1 \\ 4 \end{bmatrix}$
$A^{-1} = \frac{1}{3(-2)-1(5)}\begin{pmatrix} -2 & -5 \\ -1 & 3 \end{pmatrix}$
New algorithm $(n \geq 1)$:
Repeat {
$\frac{\partial}{\partial \theta_j} J(\theta)$
$\theta_j := \theta_j - \alpha \boxed{\frac{1}{m}\sum_{i=1}^{m}(h_\theta(x^{(i)}) - y^{(i)})x_j^{(i)}}$
(simultaneously update $\theta_j$ for $j = 0, \ldots, n$) }

# Learning based on Gradient Descent

y = ax + c



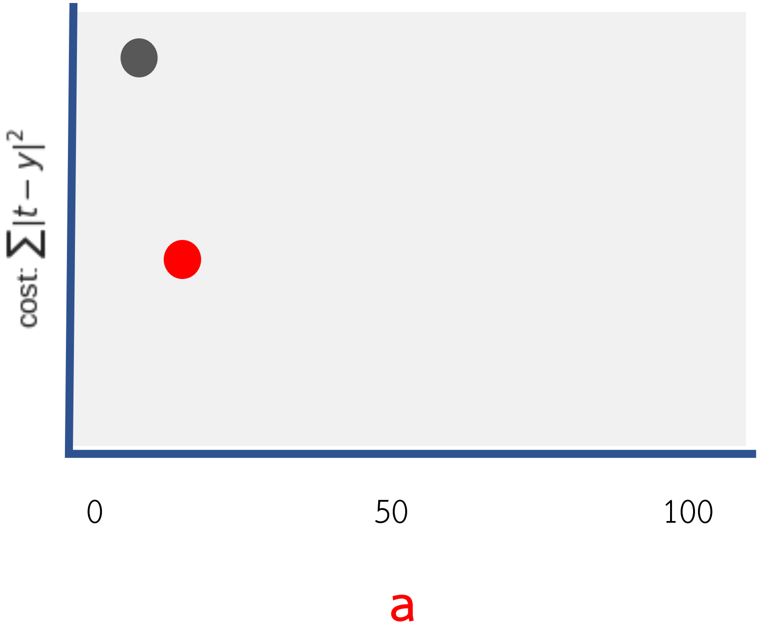

a

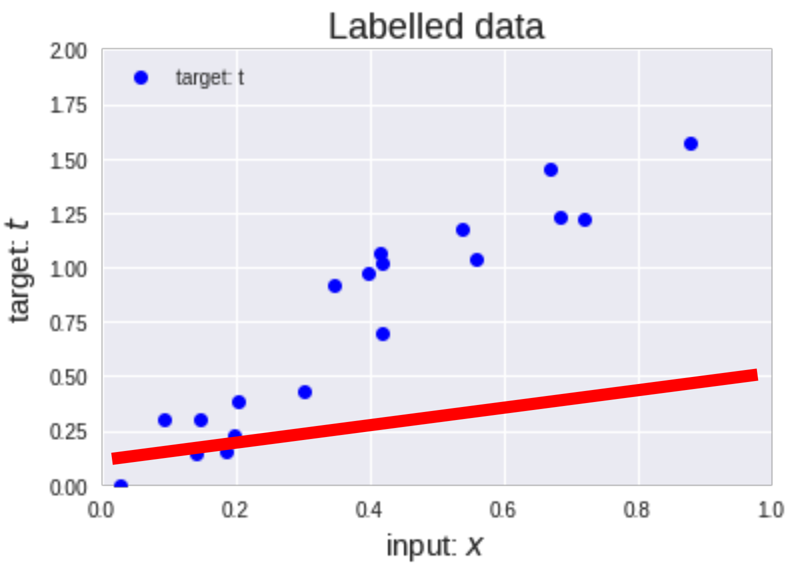



Ref: • (image) https://medium.com/onfido-tech/machine-learning-101-be2e0a86c96a

# Learning

$y = ax + c$



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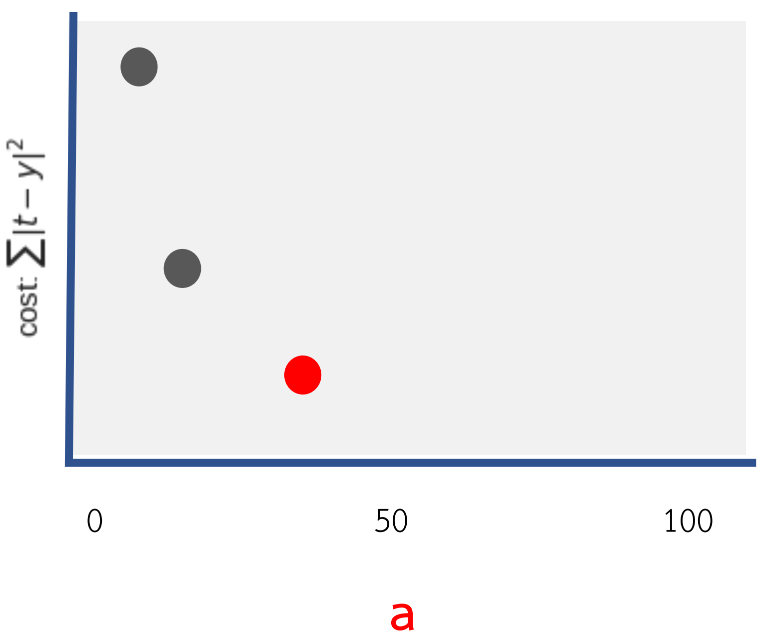
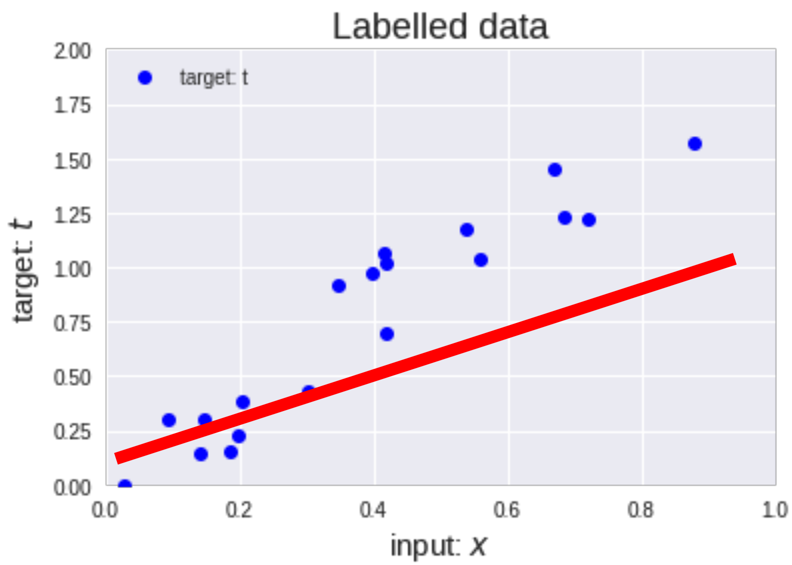
$y = ax + c$



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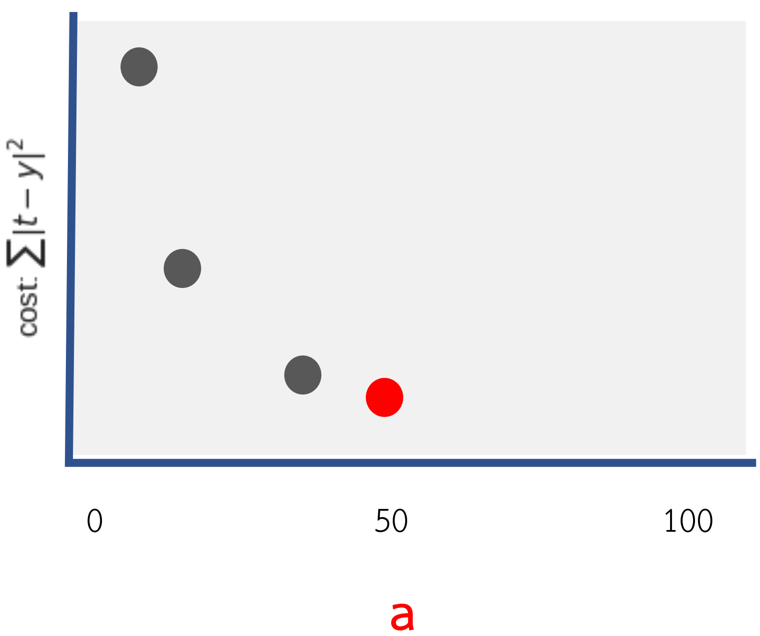
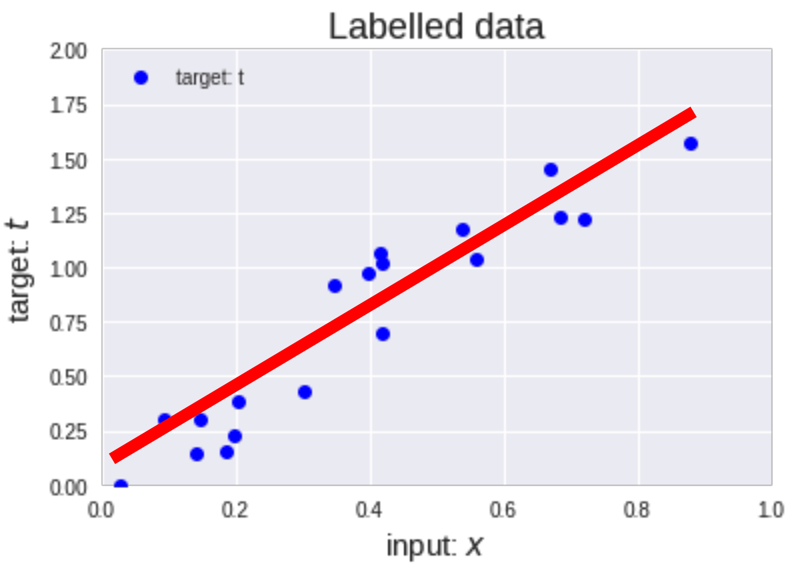
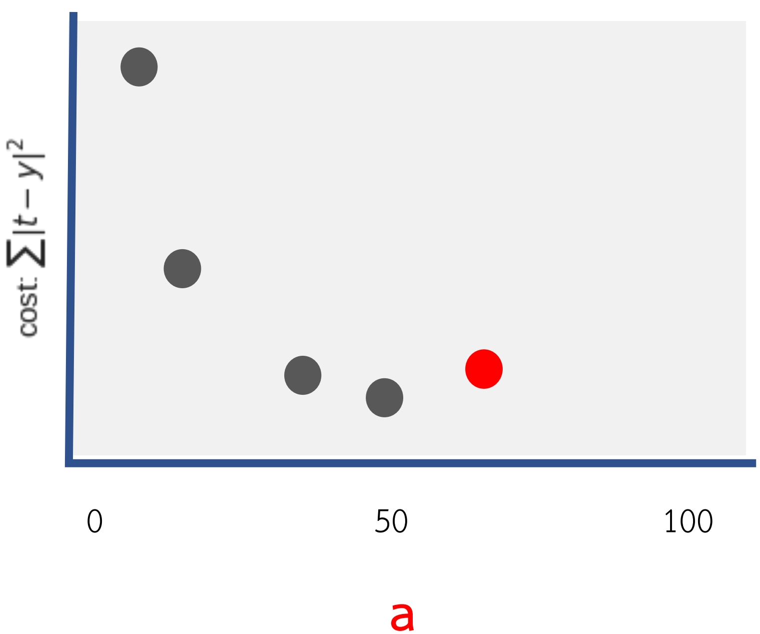
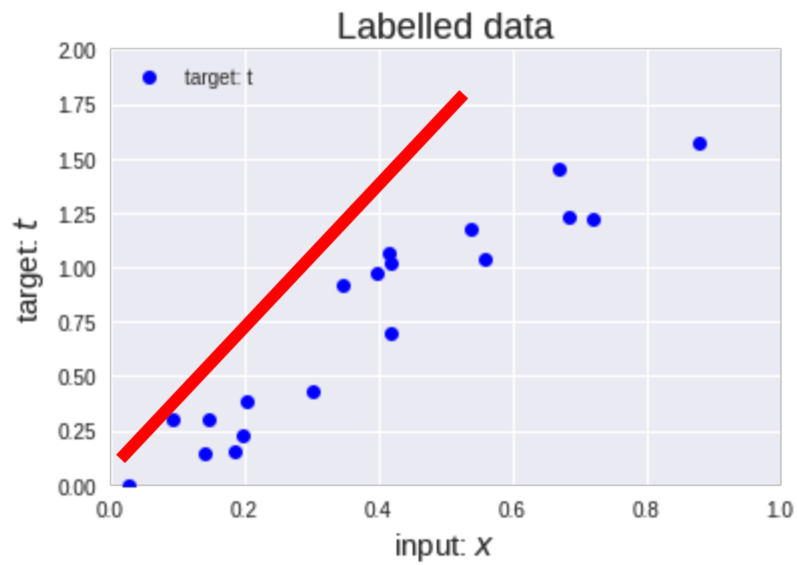


# Learning

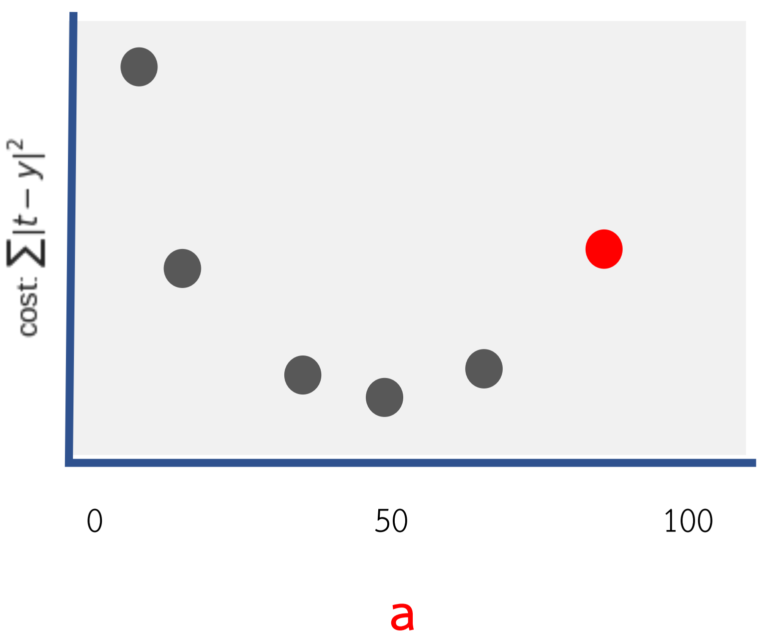
$y = ax + c$

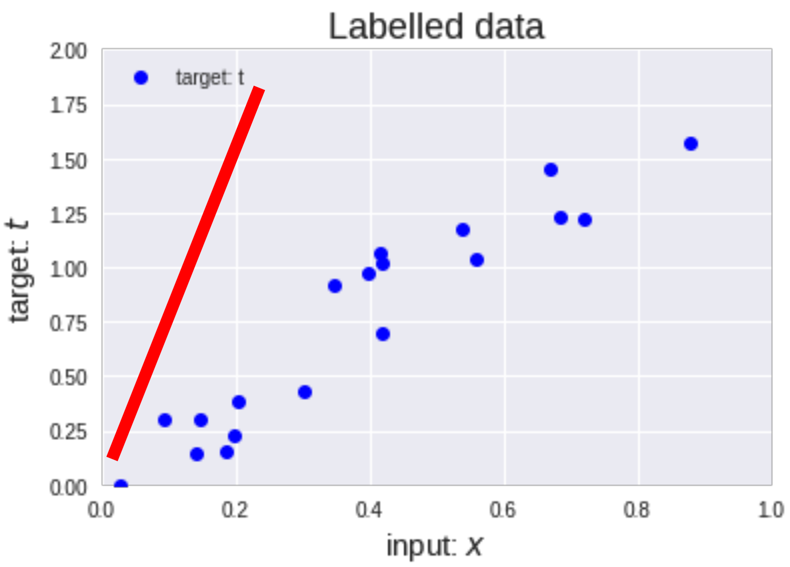


# Learning

$y = \color{red}{a}x + c$

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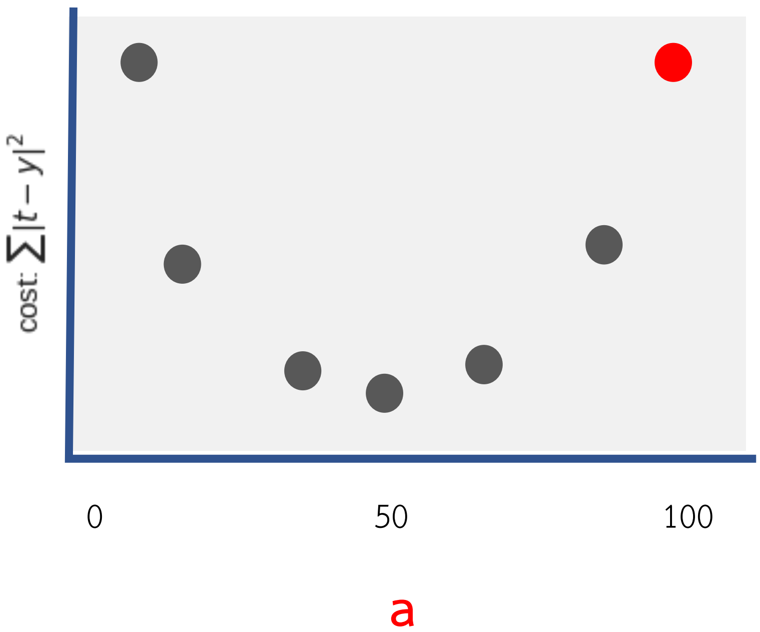
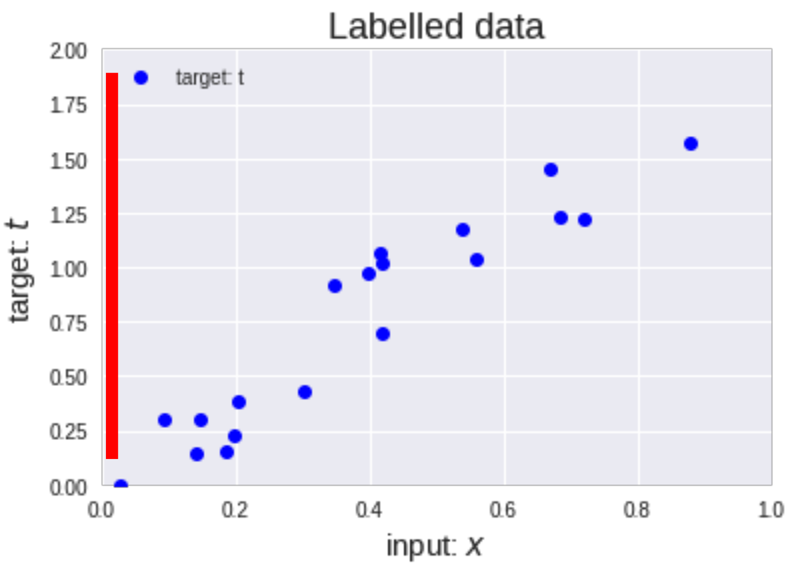
$y = ax + c$

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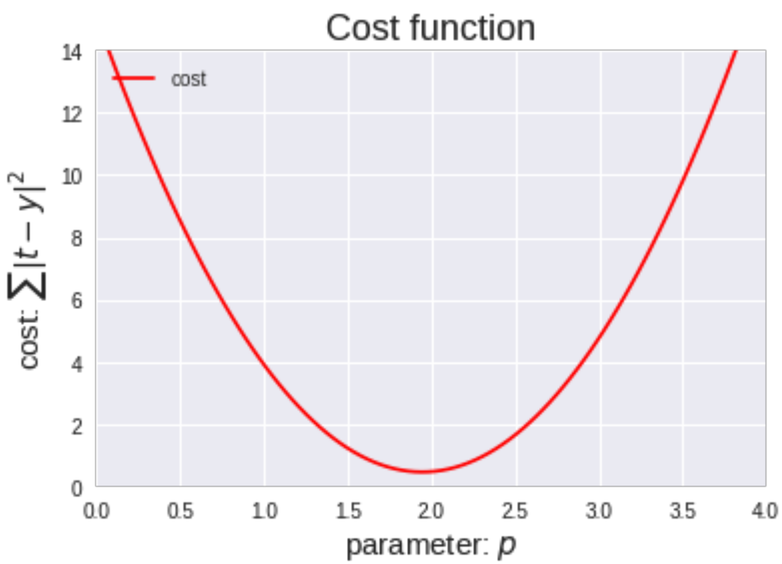


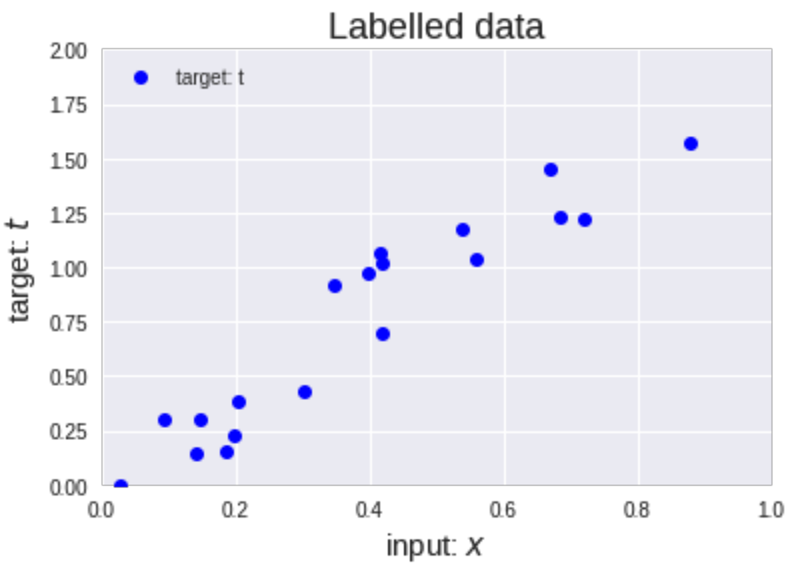


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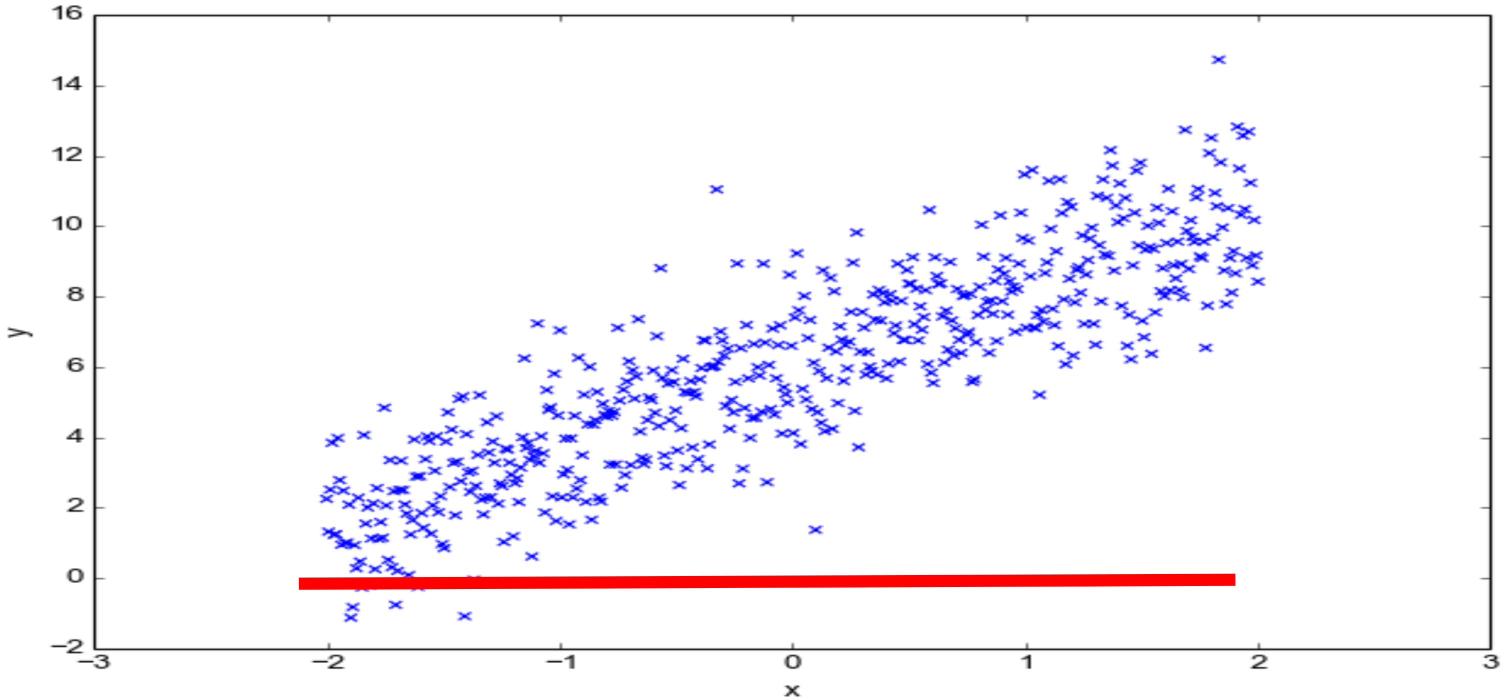



*n*-th round

Ref: • (image) https://medium.com/onfido-tech/machine-learning-101-be2e0a86c96a

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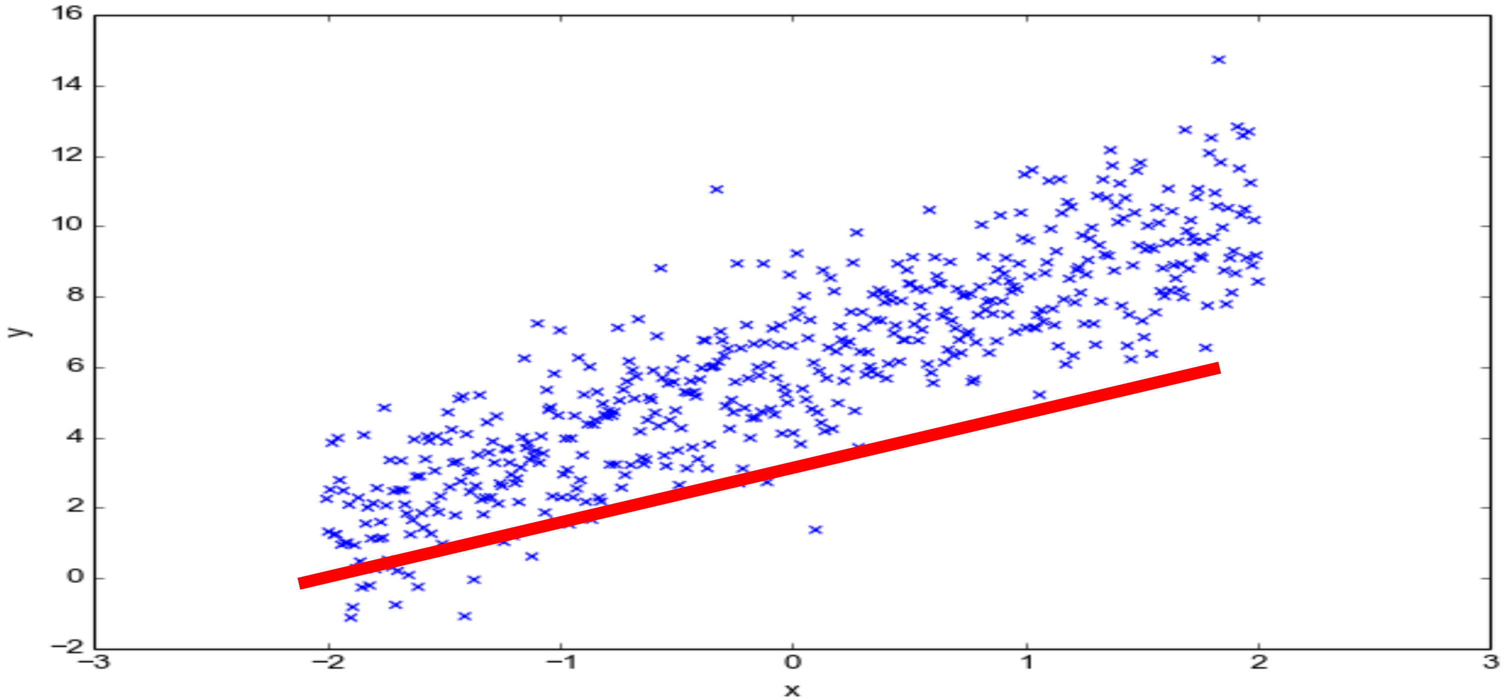



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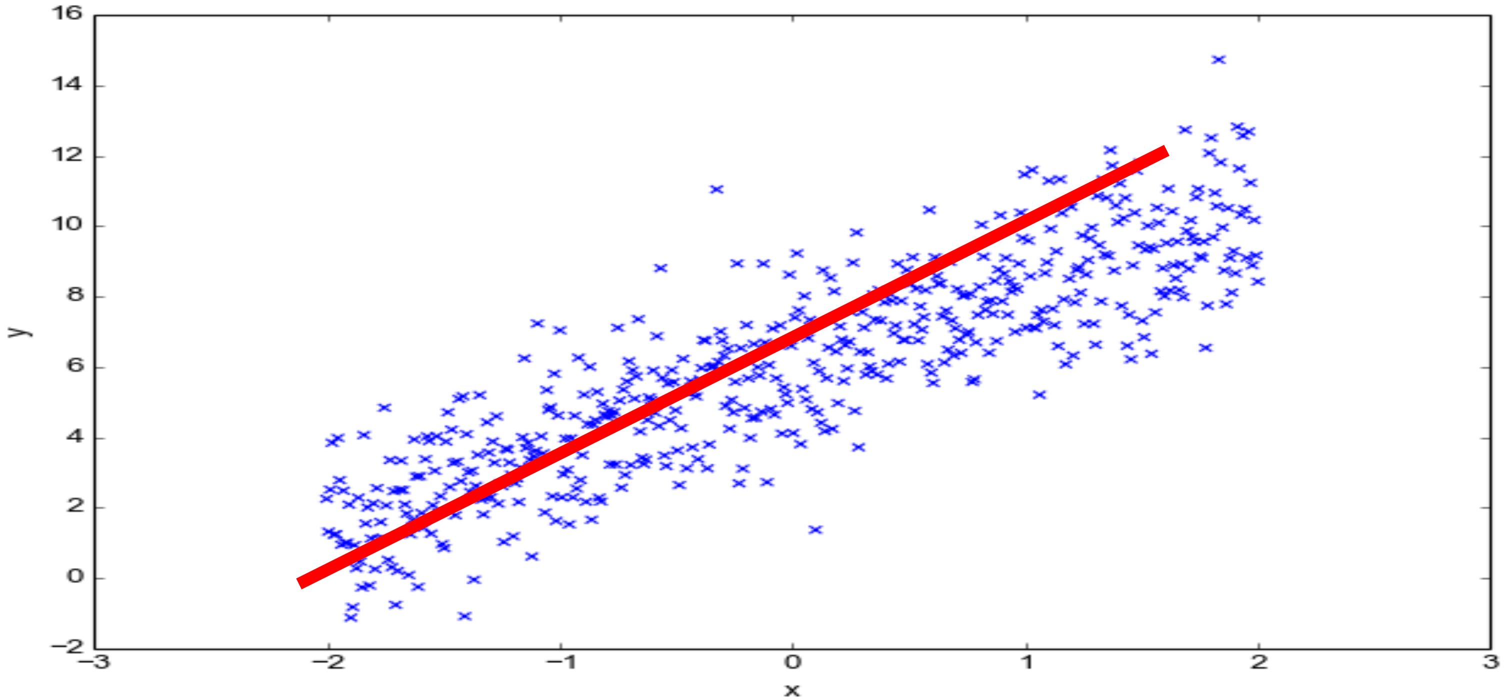



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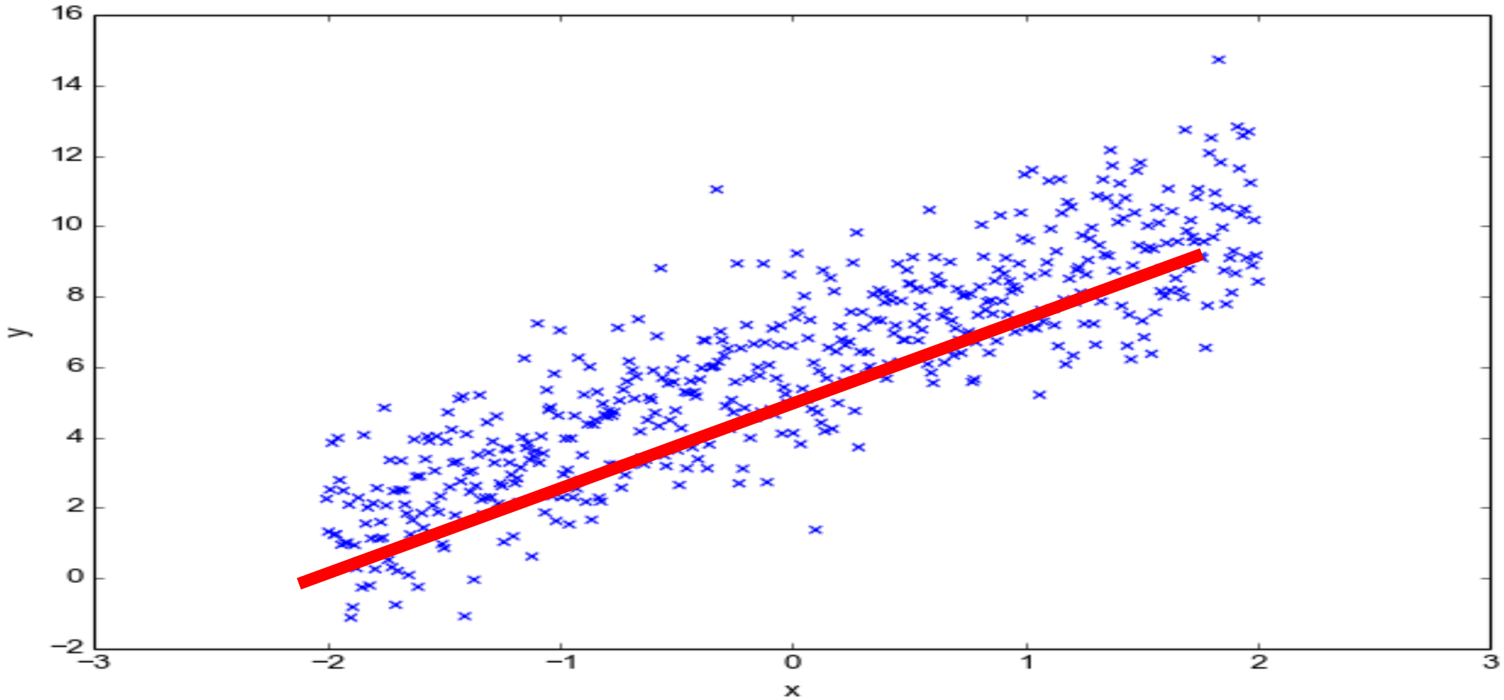


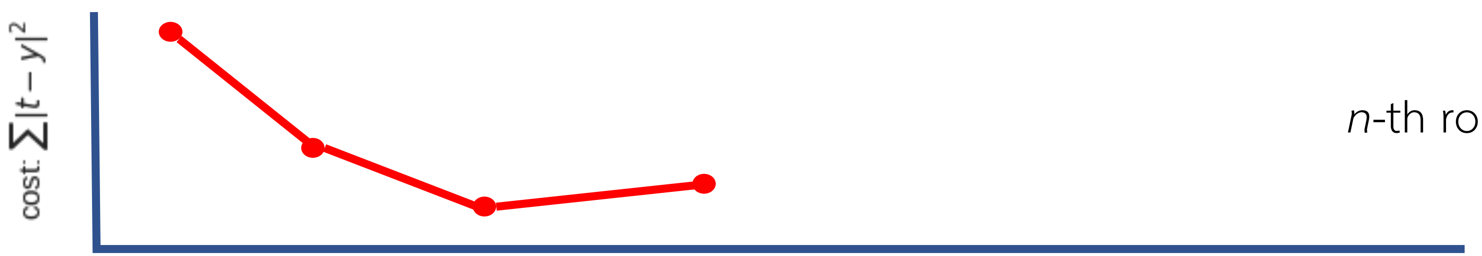


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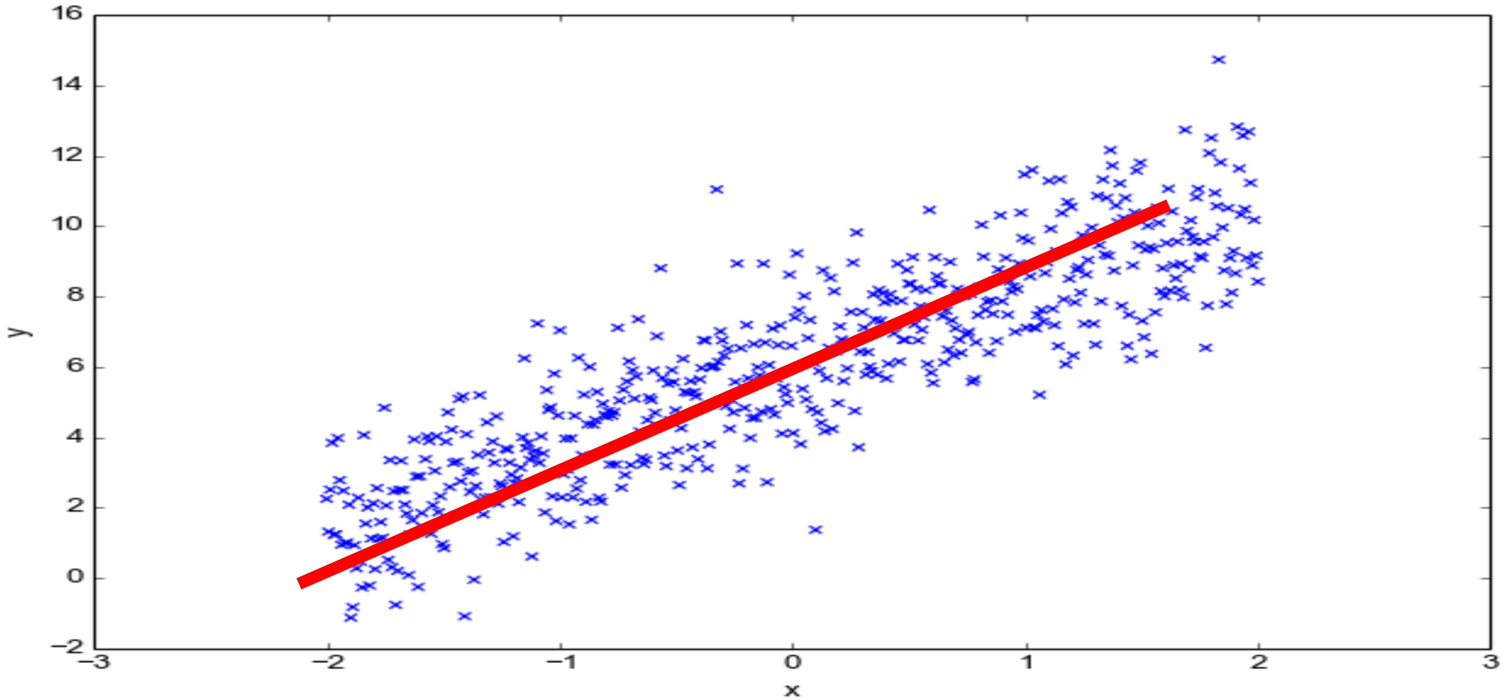


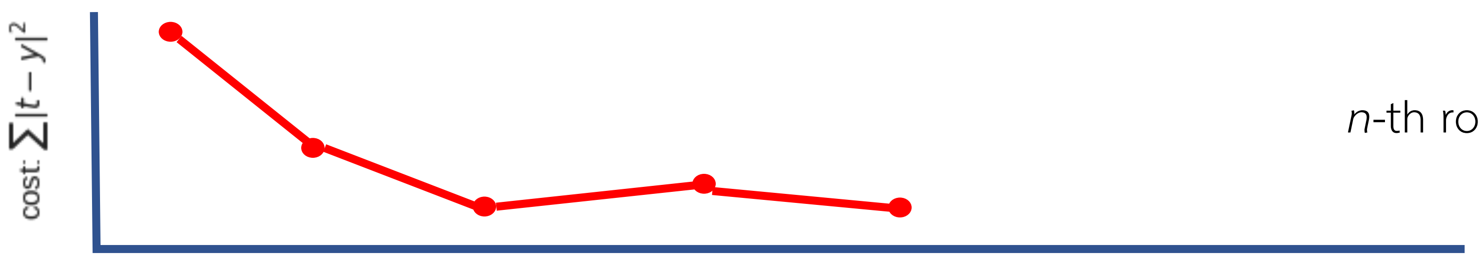


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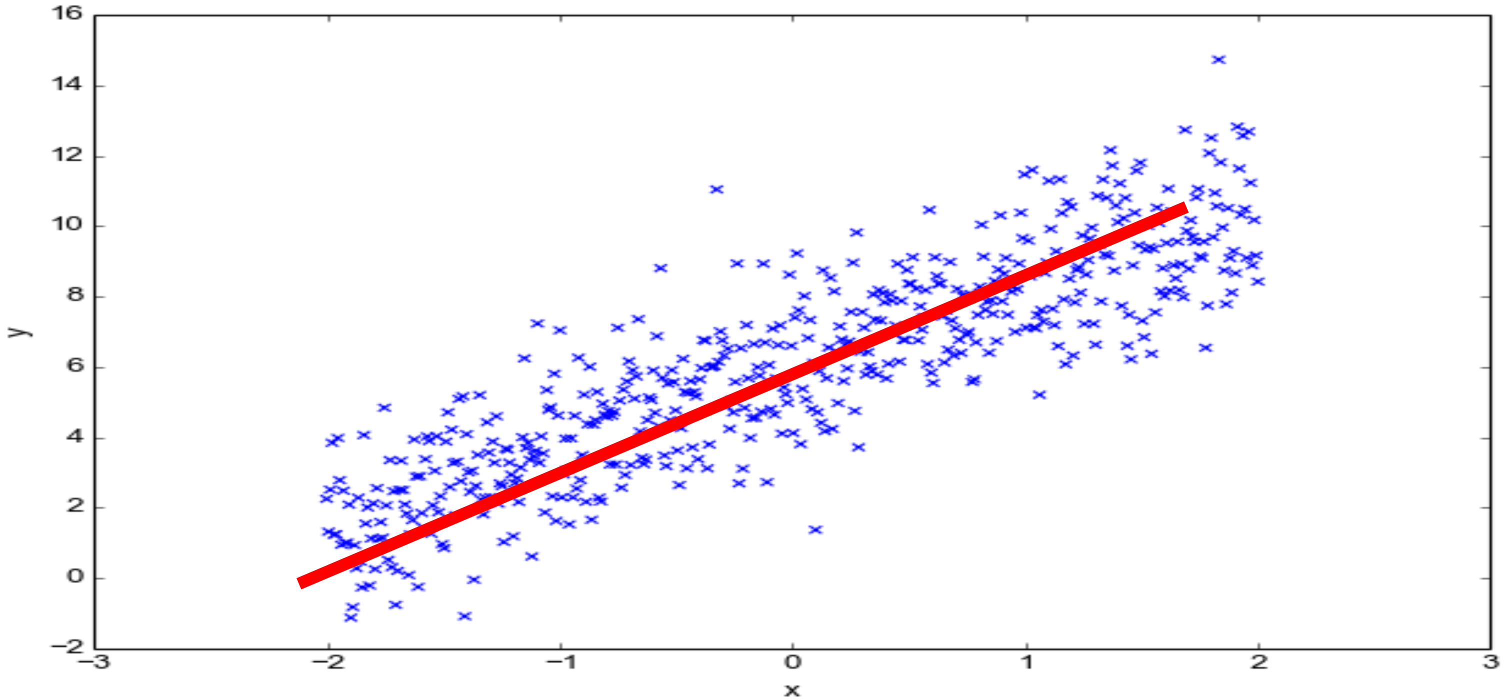


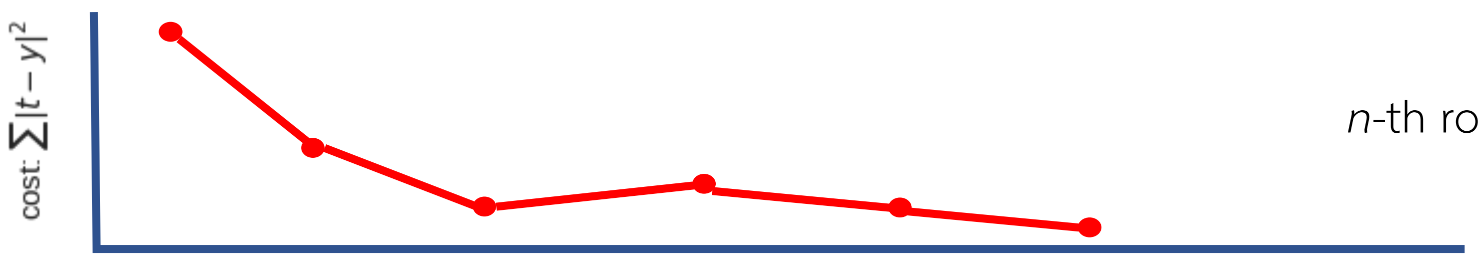


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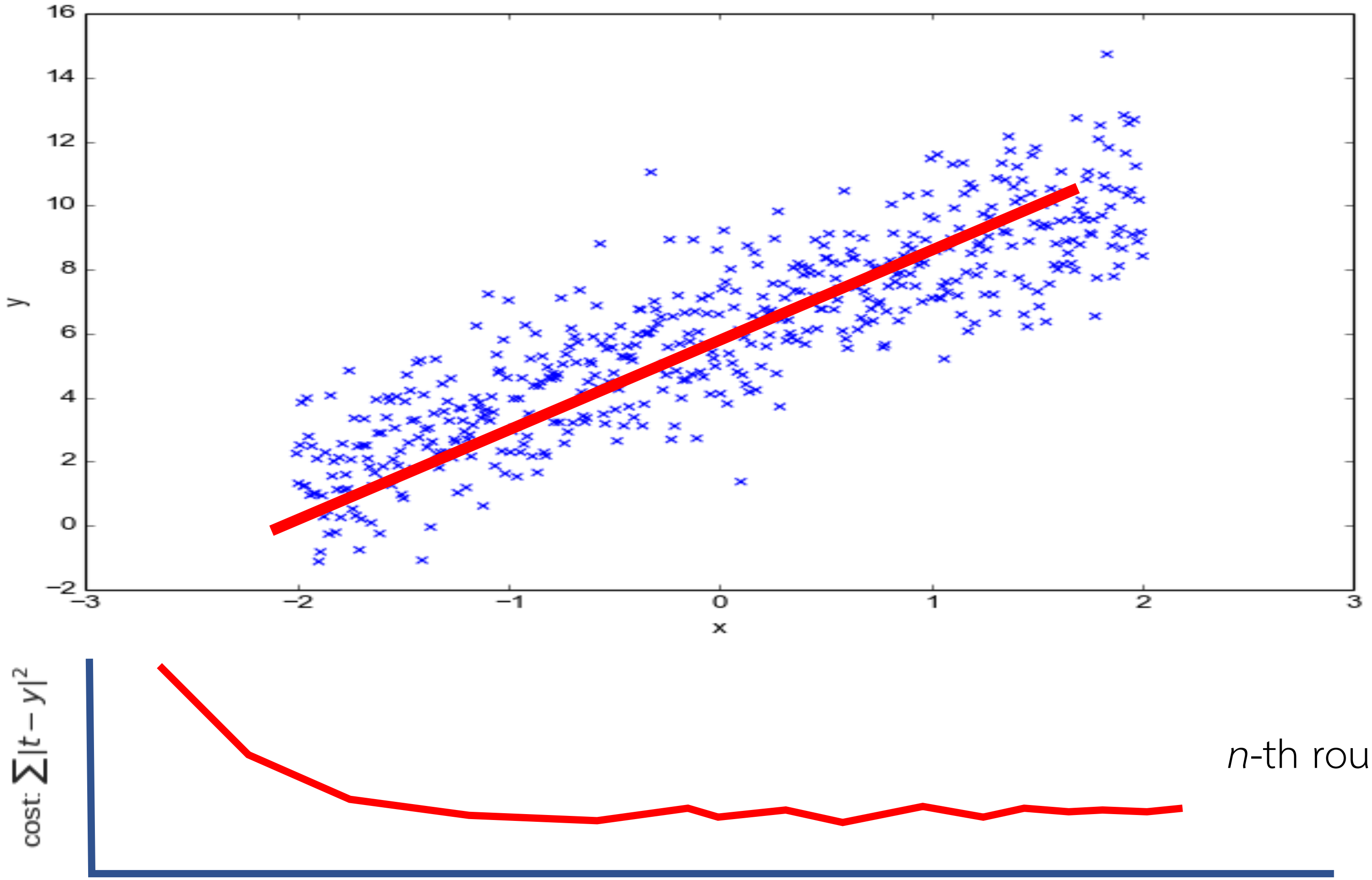


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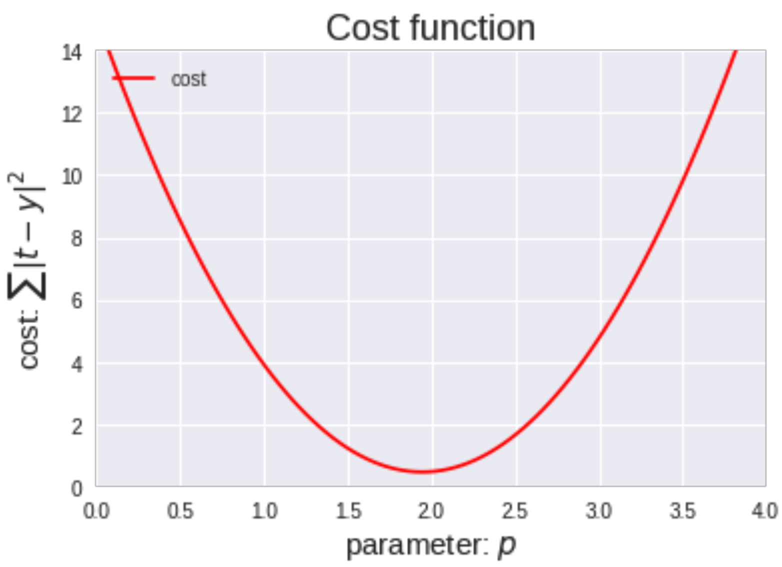


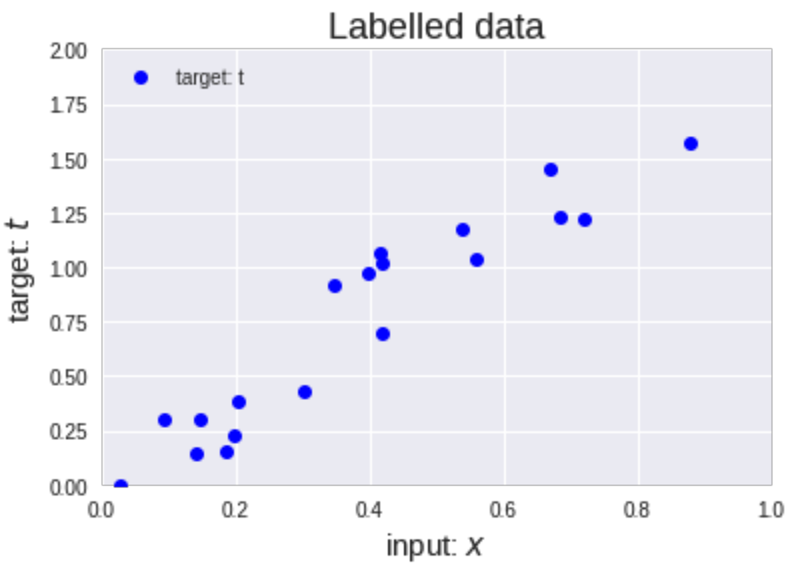


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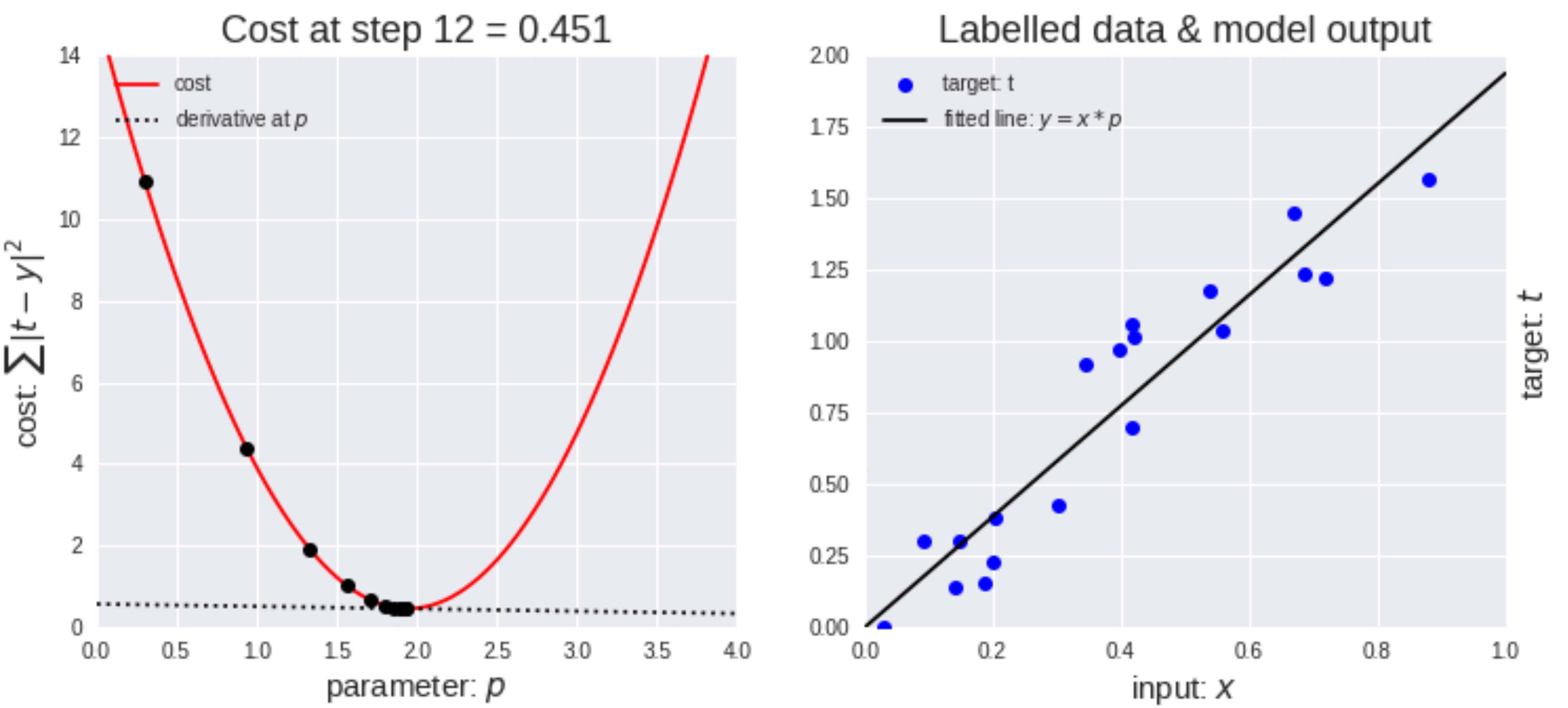
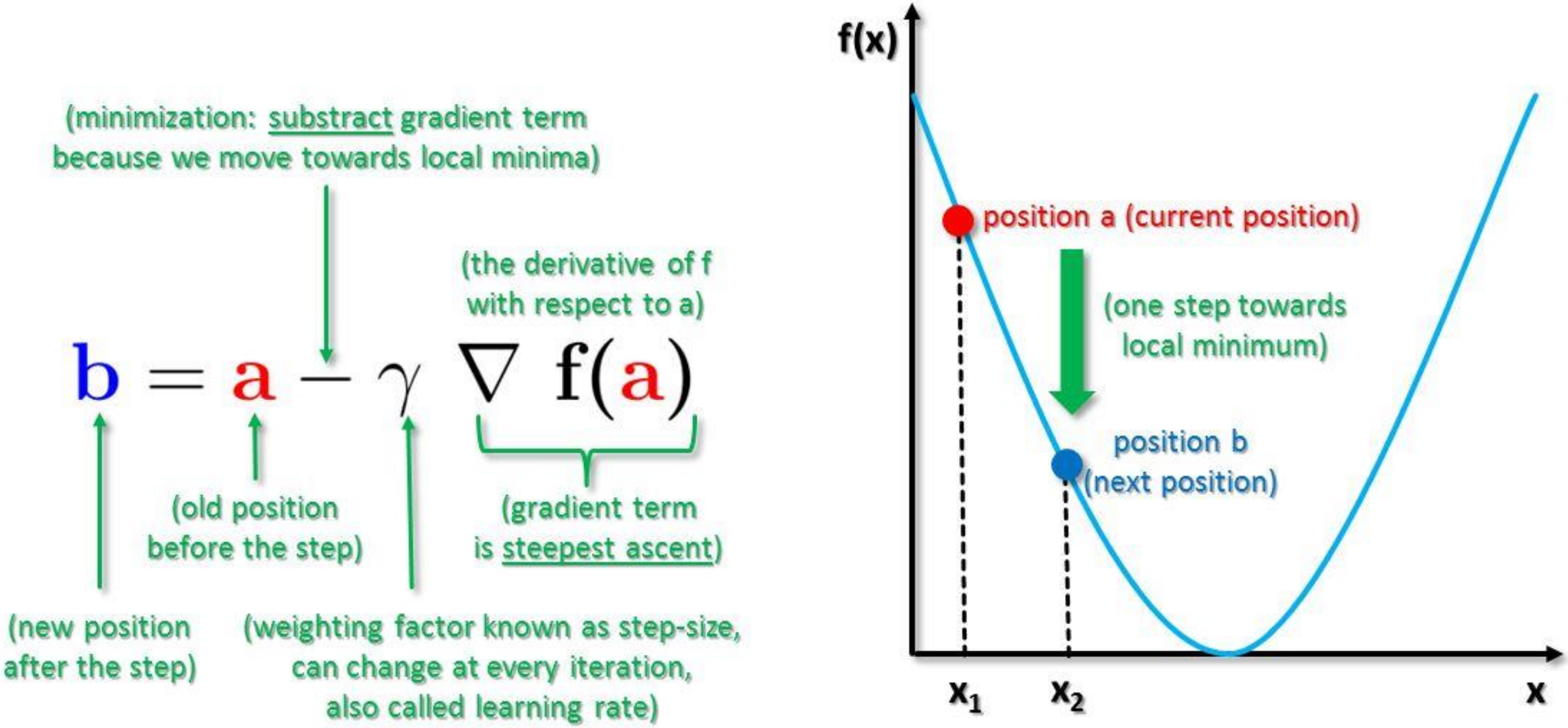
# Learning



Cost at step 12 = 0.451
cost
derivative at $p$
cost: $\sum|t-y|^2$
parameter: $p$
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
0
2
4
6
8
10
12
14
Labelled data & model output
target: t
fitted line: $y = x * p$
input: $x$
target: $t$
0.0
0.2
0.4
0.6
0.8
1.0
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00

# Gradient Descent for Linear Regression

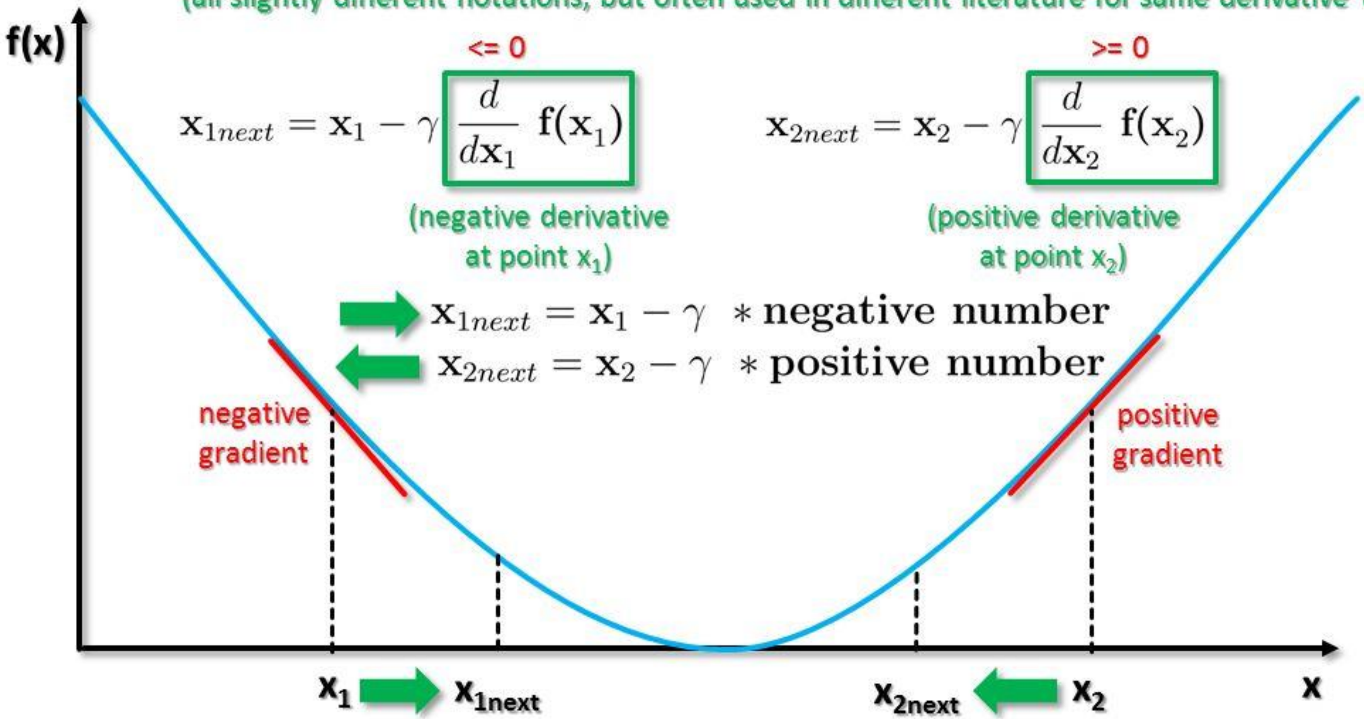



**Ref:** • http://www.big-data.tips/gradient-descent

# Gradient Descent for Linear Regression

$$\mathbf{b} = \mathbf{a} - \gamma\, \nabla\, \mathrm{f}(\mathbf{a}) \qquad \mathbf{b} = \mathbf{a} - \gamma\, \frac{\partial}{\partial \mathbf{a}}\, \mathrm{f}(\mathbf{a}) \qquad \mathbf{b} = \mathbf{a} - \gamma\, \frac{d}{d\mathbf{a}}\, \mathrm{f}(\mathbf{a})$$

(all slightly different notations, but often used in different literature for same derivative term)

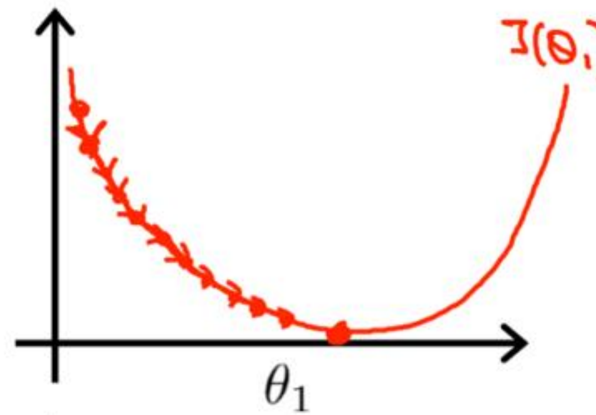


# Gradient Descent for Linear Regression

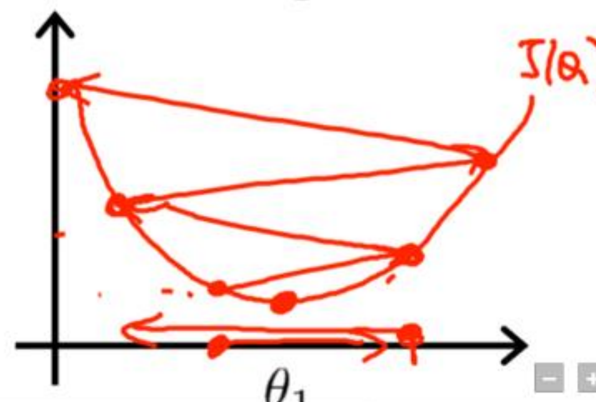
Andrew Ng

$$\theta_1 := \theta_1 - \alpha \frac{\partial}{\partial \theta_1} J(\theta_1)$$

If α is too small, gradient descent can be slow.




If α is too large, gradient descent can overshoot the minimum. It may fail to converge, or even diverge.




Andrew Ng

Ref: • screenshot from Andrew Ng video tutor

# Learning

$$y = \theta_0 + \theta_1 x_1$$

repeat until convergence: $\{$

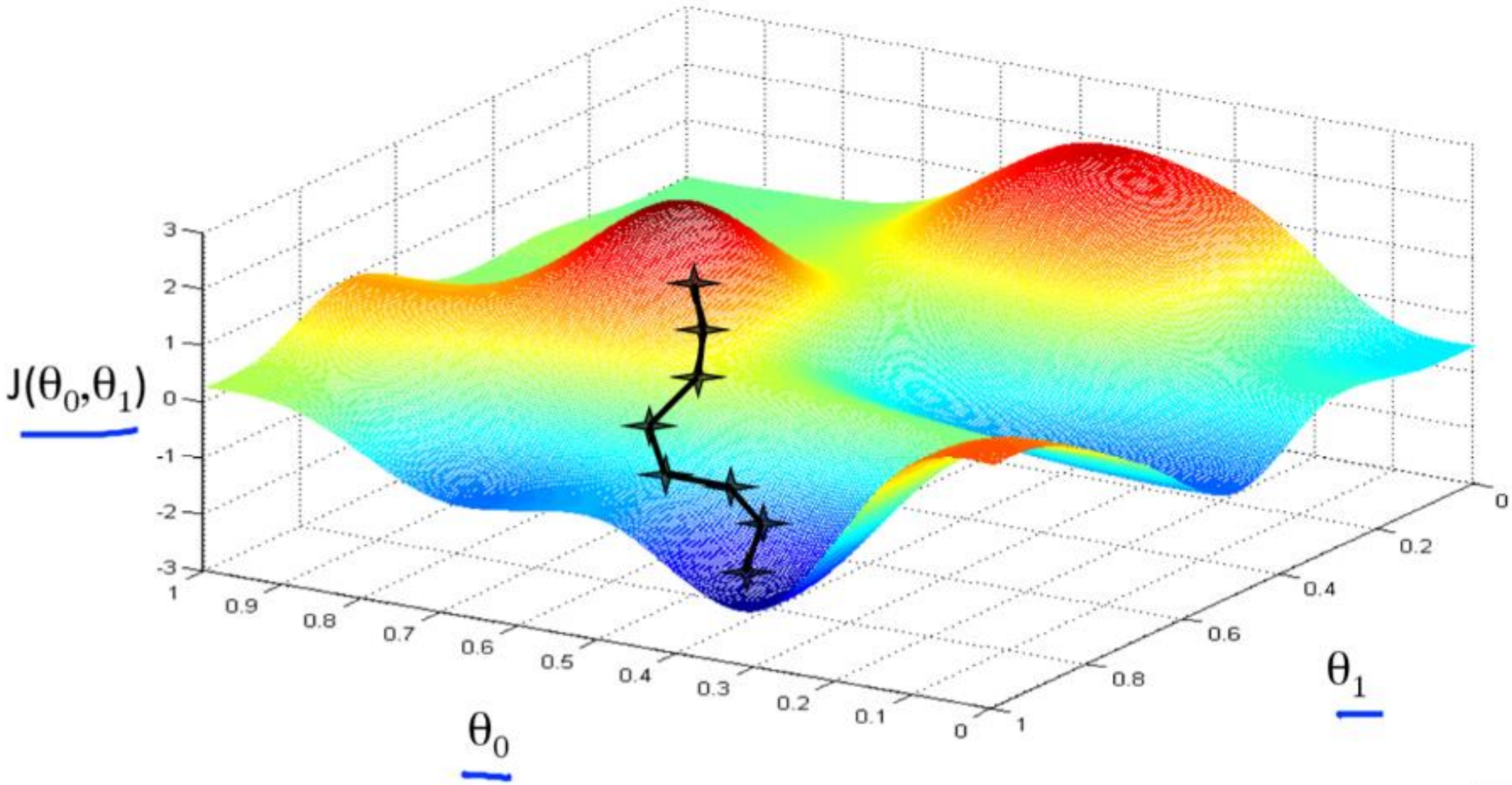
$$\theta_0 := \theta_0 - \alpha \frac{1}{m} \sum_{i=1}^{m} (h_\theta(x_i) - y_i)$$

$$\theta_1 := \theta_1 - \alpha \frac{1}{m} \sum_{i=1}^{m} ((h_\theta(x_i) - y_i) x_i)$$

$\}$

**Ref:** • screenshot from Andrew Ng video tutor

# Gradient Descent for Linear Regression




Ref: • screenshot from Andrew Ng video tutor

วันนี้ไล่เร็วกว่าทุกครั้งที่อาจารย์สอนมา

# Feature Extraction

# Boston Housing

| CRIM | ZN | INDUS | CHAS | NOX | RM | AGE | DIS | RAD | TAX | PTRATIO | B | LSTAT | MEDV | CAT. MEDV |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.00632 | 18 | 2.31 | 0 | 0.538 | 6.575 | 65.2 | 4.09 | 1 | 296 | 15.3 | 396.9 | 4.98 | 24 | 0 |
| 0.02731 | 0 | 7.07 | 0 | 0.469 | 6.421 | 78.9 | 4.9671 | 2 | 242 | 17.8 | 396.9 | 9.14 | 21.6 | 0 |
| 0.02729 | 0 | 7.07 | 0 | 0.469 | 7.185 | 61.1 | 4.9671 | 2 | 242 | 17.8 | 392.83 | 4.03 | 34.7 | 1 |
| 0.03237 | 0 | 2.18 | 0 | 0.458 | 6.998 | 45.8 | 6.0622 | 3 | 222 | 18.7 | 394.63 | 2.94 | 33.4 | 1 |
| 0.06905 | 0 | 2.18 | 0 | 0.458 | 7.147 | 54.2 | 6.0622 | 3 | 222 | 18.7 | 396.9 | 5.33 | 36.2 | 1 |
| 0.02985 | 0 | 2.18 | 0 | 0.458 | 6.43 | 58.7 | 6.0622 | 3 | 222 | 18.7 | 394.12 | 5.21 | 28.7 | 0 |
| 0.08829 | 12.5 | 7.87 | 0 | 0.524 | 6.012 | 66.6 | 5.5605 | 5 | 311 | 15.2 | 395.6 | 12.43 | 22.9 | 0 |
| 0.14455 | 12.5 | 7.87 | 0 | 0.524 | 6.172 | 96.1 | 5.9505 | 5 | 311 | 15.2 | 396.9 | 19.15 | 27.1 | 0 |
| 0.21124 | 12.5 | 7.87 | 0 | 0.524 | 5.631 | 100 | 6.0821 | 5 | 311 | 15.2 | 386.63 | 29.93 | 16.5 | 0 |
| 0.17004 | 12.5 | 7.87 | 0 | 0.524 | 6.004 | 85.9 | 6.5921 | 5 | 311 | 15.2 | 386.71 | 17.1 | 18.9 | 0 |
| 0.22489 | 12.5 | 7.87 | 0 | 0.524 | 6.377 | 94.3 | 6.3467 | 5 | 311 | 15.2 | 392.52 | 20.45 | 15 | 0 |
| 0.11747 | 12.5 | 7.87 | 0 | 0.524 | 6.009 | 82.9 | 6.2267 | 5 | 311 | 15.2 | 396.9 | 13.27 | 18.9 | 0 |
| 0.09378 | 12.5 | 7.87 | 0 | 0.524 | 5.889 | 39 | 5.4509 | 5 | 311 | 15.2 | 390.5 | 15.71 | 21.7 | 0 |
| 0.62976 | 0 | 8.14 | 0 | 0.538 | 5.949 | 61.8 | 4.7075 | 4 | 307 | 21 | 396.9 | 8.26 | 20.4 | 0 |
| 0.63796 | 0 | 8.14 | 0 | 0.538 | 6.096 | 84.5 | 4.4619 | 4 | 307 | 21 | 380.02 | 10.26 | 18.2 | 0 |

**Ref:** • https://www.solver.com/multiple-linear-regression-example

# Boston Housing

| | |
|---|---|
| CRIM | Per capita crime rate by town |
| ZN | Proportion of residential land zoned for lots over 25,000 sq.ft. |
| INDUS | Proportion of non-retail business acres per town |
| CHAS | Charles River dummy variable (= 1 if tract bounds river; 0 otherwise) |
| NOX | Nitric oxides concentration (parts per 10 million) |
| RM | Average number of rooms per dwelling |
| AGE | Proportion of owner-occupied units built prior to 1940 |
| DIS | Weighted distances to five Boston employment centers |
| RAD | Index of accessibility to radial highways |
| TAX | Full-value property-tax rate per $10,000 |
| PTRATIO | Pupil-teacher ratio by town |
| B | 1000(Bk - 0.63)^2 where Bk is the proportion of African-Americans by town |
| LSTAT | % Lower status of the population |
| MEDV | Median value of owner-occupied homes in $1000's |
| CAT.MEDV | Binary variable that indicates based on the MEDV variable. If MEDV > 30, CAT.MEDV = 1 |

X

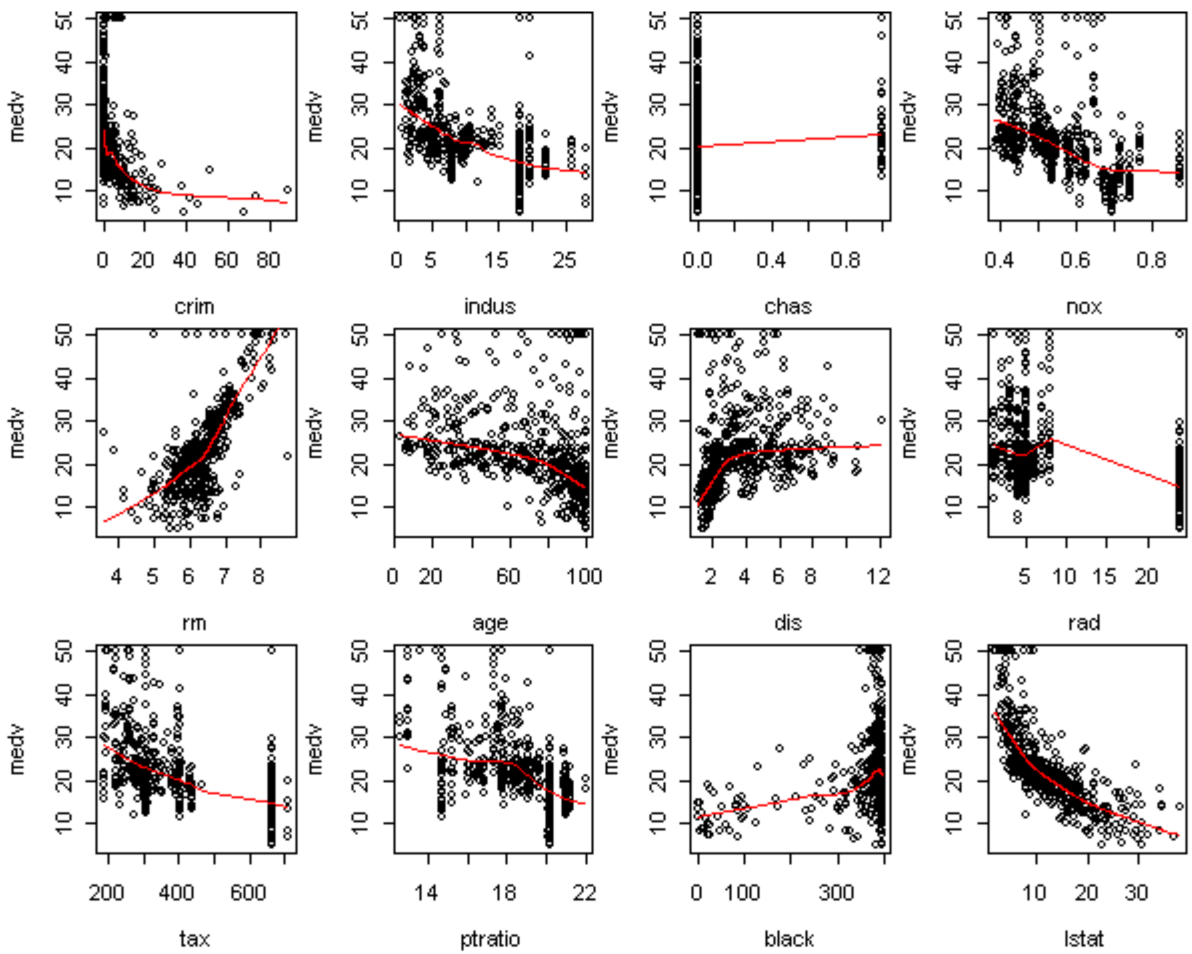
y

Ref: • https://www.solver.com/multiple-linear-regression-example

# Correlations

linear ตัวแปรที่เป็นเส้นตรง

- Content



# Correlations

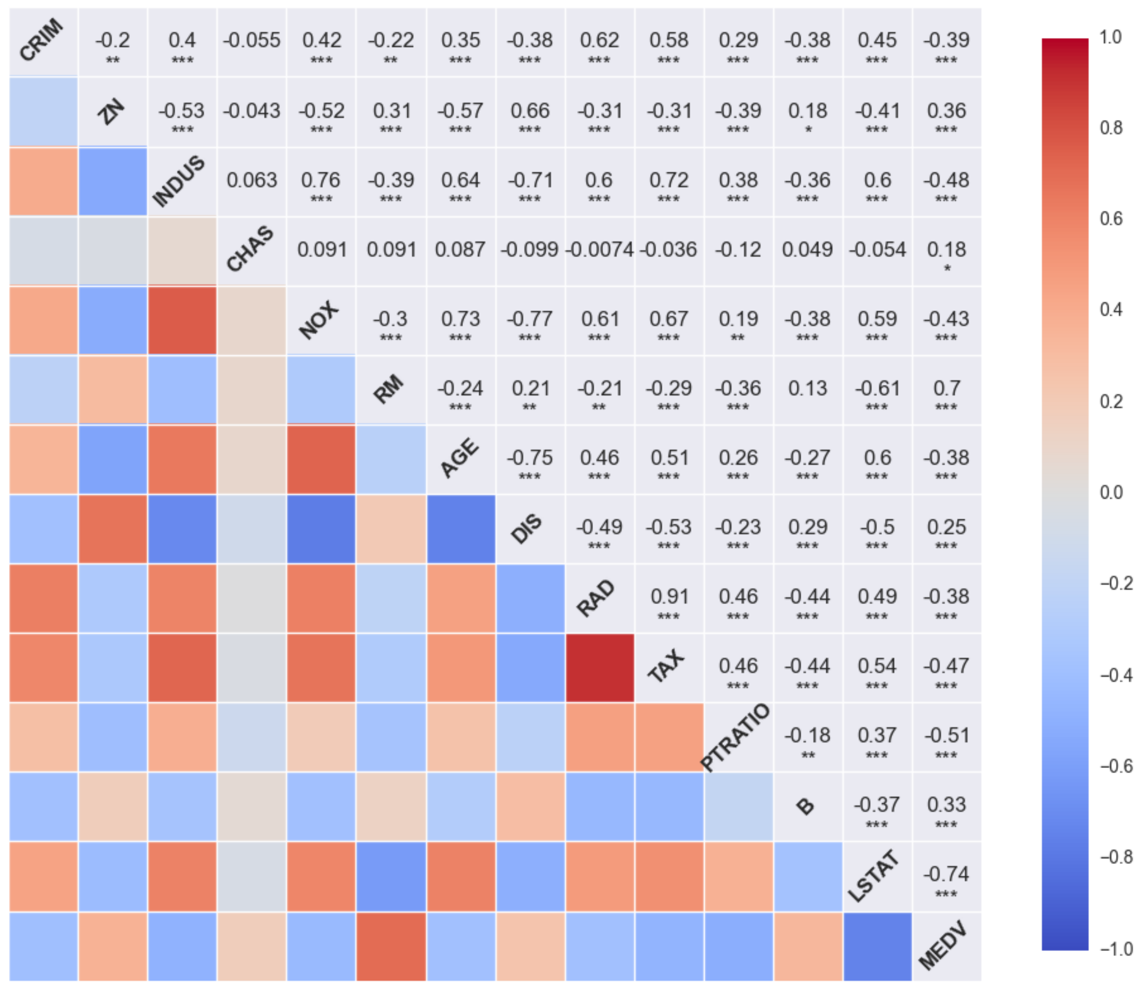
ที่บอกความสัมพันธ์กันของ x , y

regression

ใช้

pearson correlation

ก็ได้




เอาแต่ใกล้

≈ |x| > 0.7

แล้วแต่

Ref: • (image) http://www.neural.cz/dataset-exploration-boston-house-pricing.html

# Cross Validation

การวัดผล

# Rotation Estimation

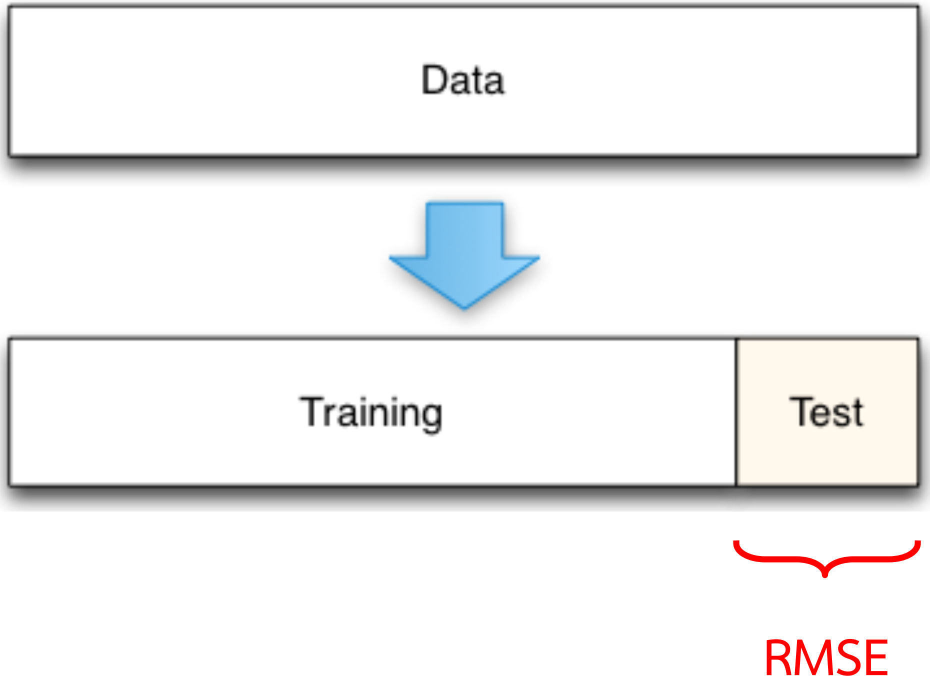
① train_test_split

## How accurately a predictive model will perform in practice?

- Cross-validation is a technique to evaluate predictive models by partitioning the original sample into a training set to train the model, and a test set to evaluate it.
- In k-fold cross-validation, the original sample is randomly partitioned into k equal size subsamples. Of the k subsamples, a single subsample is retained as the validation data for testing the model, and the remaining k-1 subsamples are used as training data. The cross-validation process is then repeated k times (the folds), with each of the k subsamples used exactly once as the validation data. The k results from the folds can then be averaged (or otherwise combined) to produce a single estimation. The advantage of this method is that all observations are used for both training and validation, and each observation is used for validation exactly once.

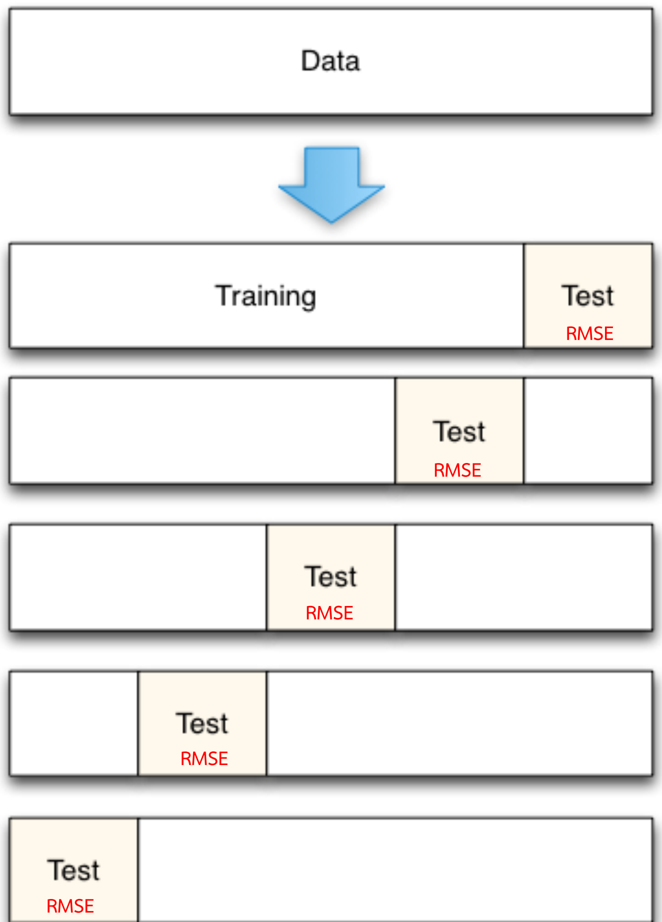
**Ref:** • (content) https://www.openml.org/a/estimation-procedures/1

# Cross-Validation




Ref: • (image) http://blog.kaggle.com/2015/06/29/scikit-learn-video-7-optimizing-your-model-with-cross-validation/

# K-Fold Cross-Validation




ทำหลายๆก้อน

แล้วค่อยหา mean

Average
RMSE

ยิ่งทำหลายรอบ → เสียเวลา

# Python Code

```
1. from sklearn import neighbors, datasets, preprocessing
2. from sklearn.model_selection import train_test_split
3. iris = datasets.load_iris()
4. X, y = iris.data[:, :2], iris.target
5. X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=33)
6. lm = linear_model.LinearRegression()
7. lm.fit (X_train, y_train)
8. y_predicted = lm.predict(X_test)
9. rmse = sqrt(mean_squared_error(y_test, y_predicted))
```

**Ref:** • https://www.datacamp.com/community/blog/scikit-learn-cheat-sheet

# Feature Scaling

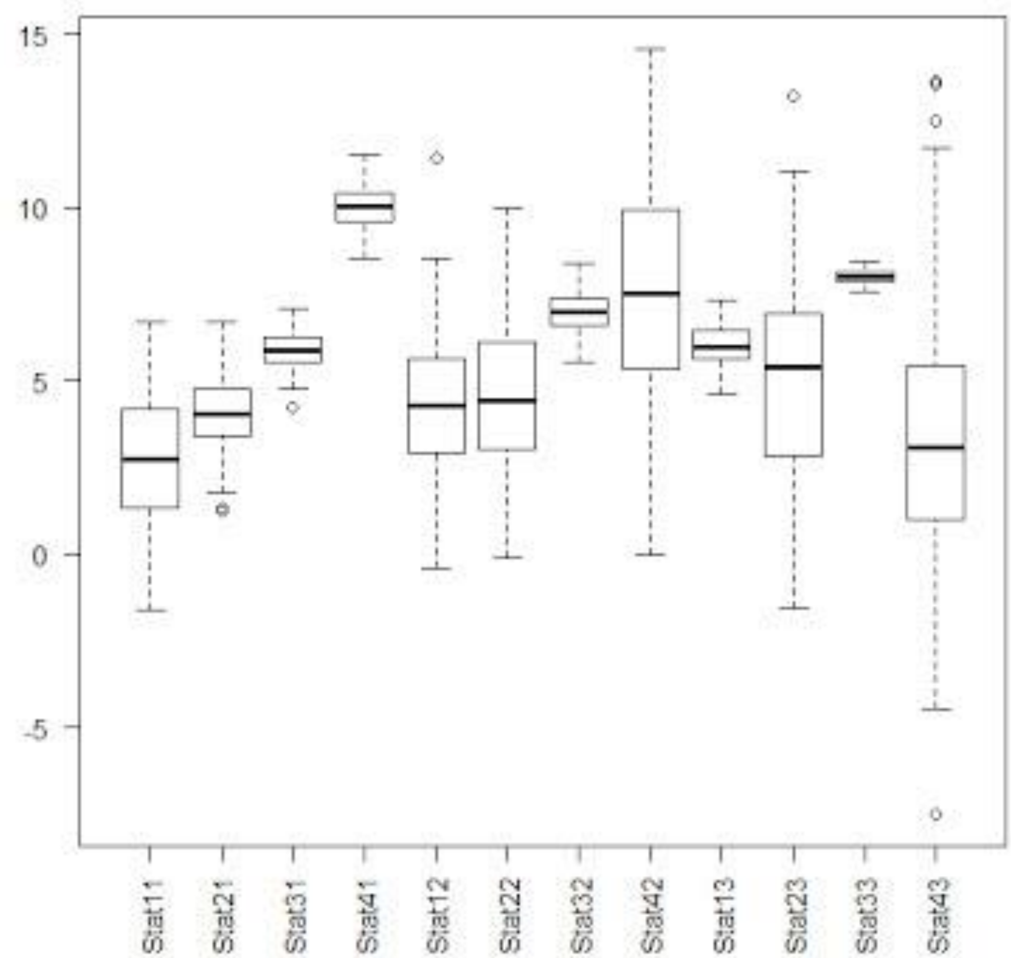
ขนาดspaceที่ต่างกัน

ประหยัดพลัง , ร้อง

การทำให้อยู่ใน space เดียวกัน

# Feature Scaling

- Feature scaling is a method used to standardize the range of independent variables or features of data. In data processing, it is also known as data normalization and is generally performed during the data preprocessing step.




**Ref:**
- (content) https://en.wikipedia.org/wiki/Feature_scaling
- (image) https://www.r-bloggers.com/box-plot-with-r-tutorial/

# Rescaling

- The simplest method is rescaling the range of features to scale the range in [0, 1] or [−1, 1]. Selecting the target range depends on the nature of the data. The general formula is given as:

ทำ min max norm(n)

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

- where x is an original value x' is the normalized value. For example, suppose that we have the students' weight data, and the students' weights span . To rescale this data, we first subtract 160 from each student's weight and divide the result by 40 (the difference between the maximum and minimum weights).

Ref: • https://en.wikipedia.org/wiki/Feature_scaling

# Mean Normalization

$$x' = \frac{x - \text{mean}(x)}{\max(x) - \min(x)}$$

- where x is an original value, x' is the normalized value.

Ref: • https://en.wikipedia.org/wiki/Feature_scaling

# Standardization

- In machine learning, we can handle various types of data, e.g. audio signals and pixel values for image data, and this data can include multiple dimensions. Feature standardization makes the values of each feature in the data have zero-mean (when subtracting the mean in the numerator) and unit-variance.

$$x' = \frac{x - \bar{x}}{\sigma}$$

- Where x is the original feature vector, x-bar is the mean of that feature vector, and sigma  is its standard deviation.

**Ref:** • https://en.wikipedia.org/wiki/Feature_scaling

# Scaling to unit length

- Another option that is widely used in machine-learning is to scale the components of a feature vector such that the complete vector has length one. This usually means dividing each component by the Euclidean length of the vector:

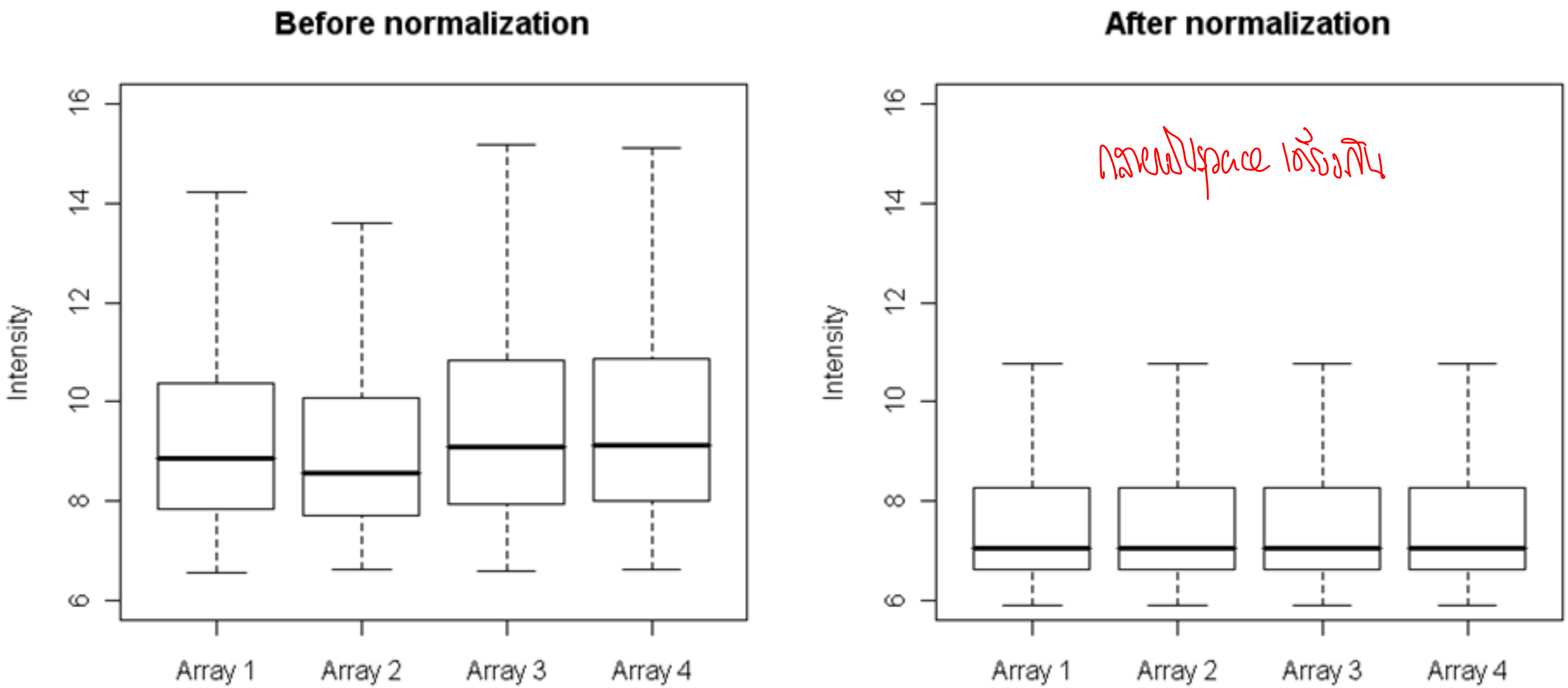
$$x' = \frac{x}{||x||}$$

$$\frac{\text{ข้อมูลของเรา}}{\text{ขนาดของเวกเตอร์}}$$

- In some applications (e.g. Histogram features) it can be more practical to use the L1 norm (i.e. Manhattan Distance, City-Block Length or Taxicab Geometry) of the feature vector. This is especially important if in the following learning steps the Scalar Metric is used as a distance measure.

Ref: • https://en.wikipedia.org/wiki/Feature_scaling

# Box Plot




**Ref:** • (image) http://telemedicina.med.muni.cz/genomic-proteomic-analysis/index-en.php?pg=E-learning--2-data-analysis--2-2-analysis-of-genomic-data--2-2-1-DNA-microarrays-1--2-2-1-6-normalization

# Python Code

```
1.    from sklearn import neighbors, datasets, preprocessing
2.    from sklearn.model_selection import train_test_split
3.    from sklearn.metrics import accuracy_score
4.    iris = datasets.load_iris()
5.    X, y = iris.data[:, :2], iris.target
6.    X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=33)
7.    scaler = preprocessing.StandardScaler().fit( X_train )
8.    X_train = scaler.transform(X_train)
9.    X_test = scaler.transform(X_test)
10.   # Do Prediction
```

ตัวที่เอาเอาไปค่าตัว scaler

> Data is a precious thing and will last longer than the systems themselves.

Tim Berners-Lee

つづく