Interpretable Machine Learning

The Basics

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Outline

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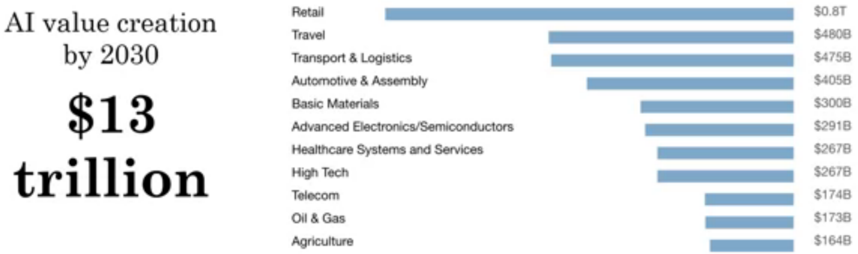
Introduction



Source: McKinsey Global Institute (**?**)

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$13 trillion = $13 $\times$ 10^{12} $=$ Rp183.000.000.000.000.000, $-$

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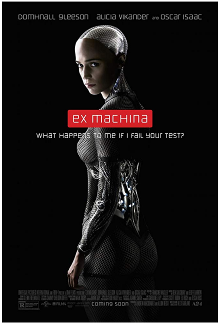

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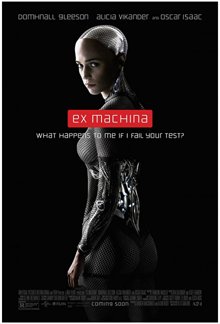

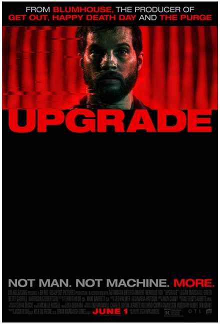

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Diagram Venn tentang AI, ML, DL, Data Science

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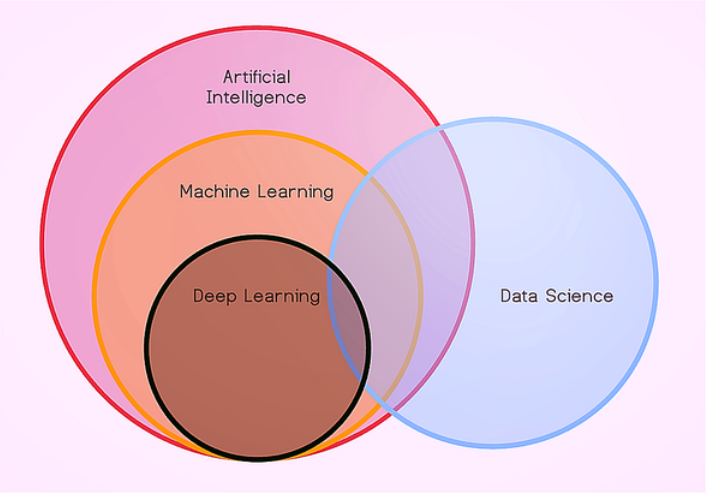

Relationship among AI, ML, DL, and DS (**?**)

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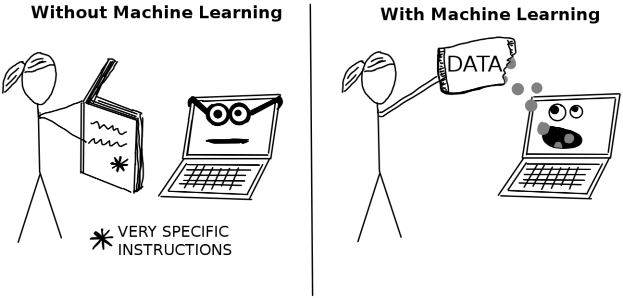

A paradigm shift from "normal programming" to "indirect programming"

Machine Learning: Supervised Learning (1/2)

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- A **Machine Learning Algorithm** is *the program* used to learn a ML model from data (**?**).

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image of phone	$\longrightarrow$	defect? (0/1)	visual inspection

Why Now?

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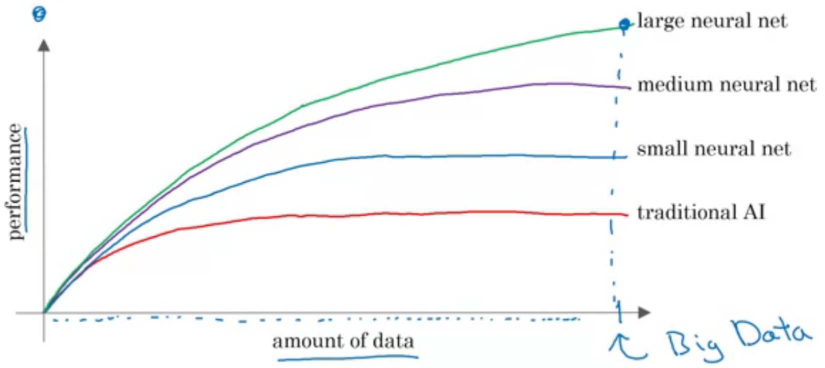

large neural net
medium neural net
small neural net
traditional AI
performance
amount of data
Big Data

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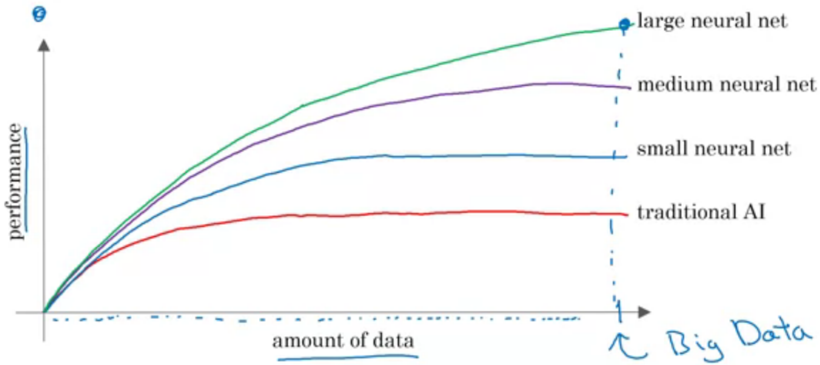

Large neural net + Big Data = High Performance (**?**)

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Let's walk through all these components in a concrete example!

Outline

Predicting Profits for Food Trucks

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A food truck serving chinese food(**?**)

Outline

Machine Learning Component: Data (1/2)

Population (***X***)	**Profit** (***Y***)
6.1101	17.592
5.5277	9.130
8.5186	13.662
⋮	⋮
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Population of city is in 10,000s while **Profit** is in $10,000s

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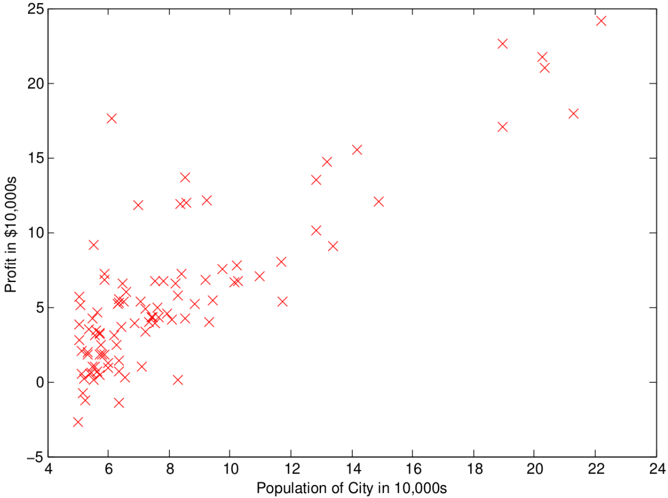

Scatter plot of food trucks data

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X is also called a *design matrix*.

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Utilizing a product of two matrices $\Longrightarrow$ improve computing efficiency.

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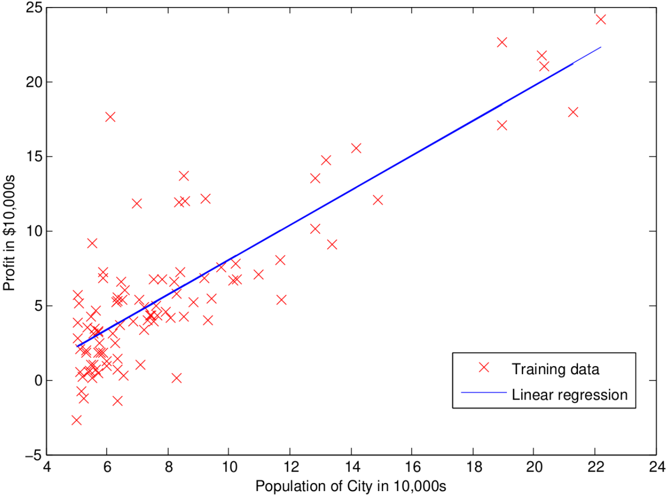

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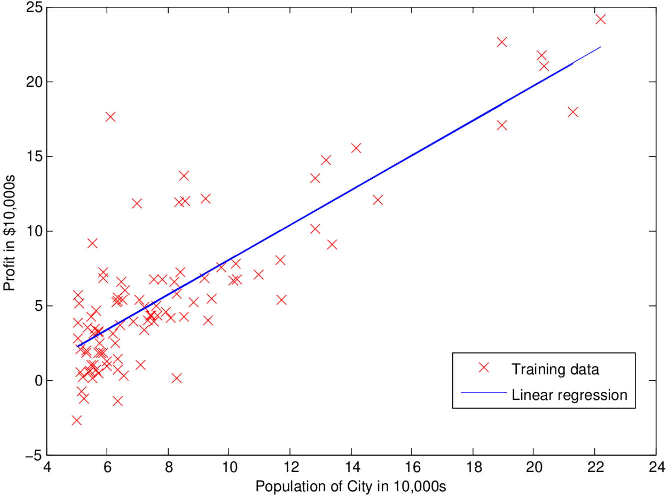

The regression line; however, how do we find θ_0 and θ_1?

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Machine Learning Component: Cost Function (1/3)

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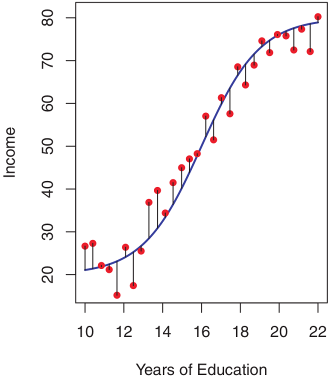

An example of errors; Specifically *the black lines* represent the error associated with each instance (**?**)

Machine Learning Component: Cost Function (2/3)

The Cost/Loss Function is usually denoted as J; moreover, in case of linear regression:

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We need **Calculus**.

We need to find θ_0 and θ_1 which minimize $J(\theta)$, that is

$$\arg\min_{\theta_0,\theta_1} \qquad .$$

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ML Component: Optimization Algorithm (1/7)

A famous optimization algorithm:

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A famous optimization algorithm: **Gradient Descent**

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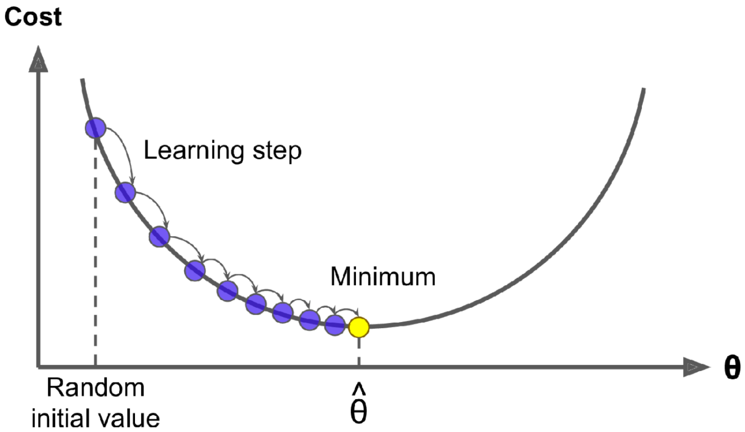

Gradient descent in action (**?**)

ML Component: Optimization Algorithm (2/7)

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The *gradient* is the **partial derivative** of J
(We need **Calculus** to calculate this one).

ML Component: Optimization Algorithm (3/7)

Our cost/loss function for linear regression:

$$J(\theta) = \frac{1}{2 \times 97} \times \sum_{i=1}^{97} \left(\theta_0 + \theta_1 x_1^{(i)} - y^{(i)} \right)^2$$

With the help of **Calculus**, we have

$$\frac{\partial J}{\partial \theta_0} =$$

$$=$$

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ML Component: Optimization Algorithm (6/7)

Learning rate (α) is the size of the steps.

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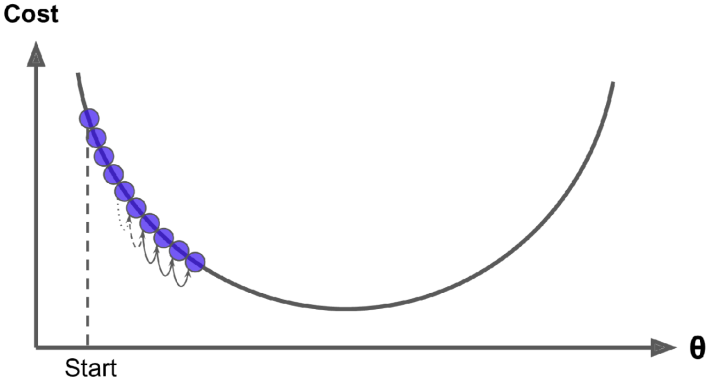

This will happen when the α is too small (**?**)

ML Component: Optimization Algorithm (7/7)

What happens when α is too large?

ML Component: Optimization Algorithm (7/7)

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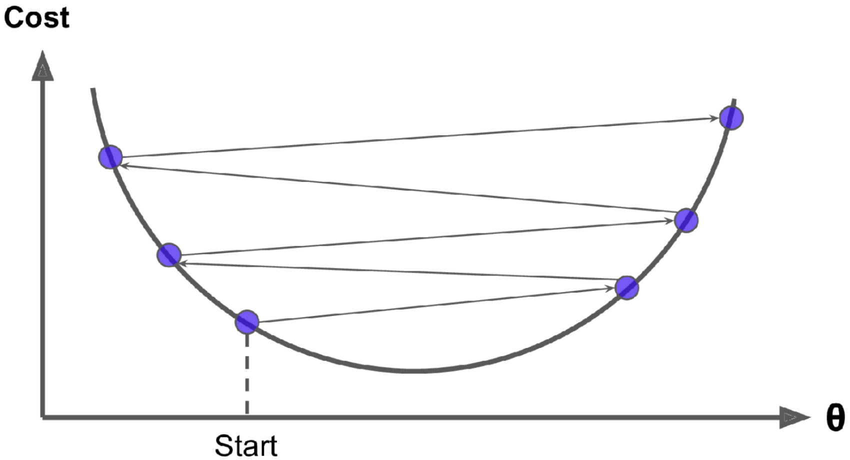

This will happen when α is too large (**?**)

Outline

Demo Time

We show a *Linear Regression* as our Machine Learning demo[1].

[1] https://www.coursera.org/learn/machine-learning

Outline

Importance of Interpretability

Why?

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That's why we need the **interpretability of machine learning**.

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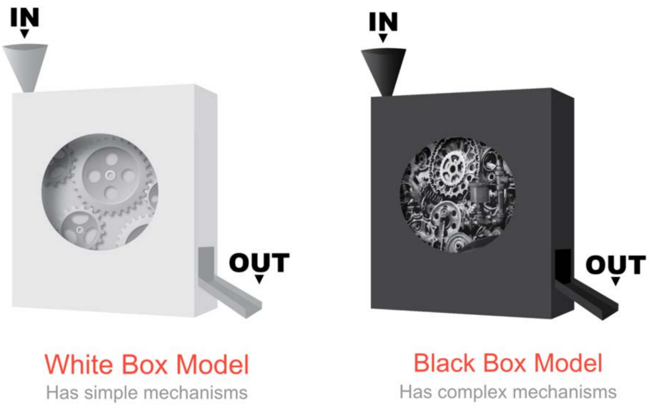
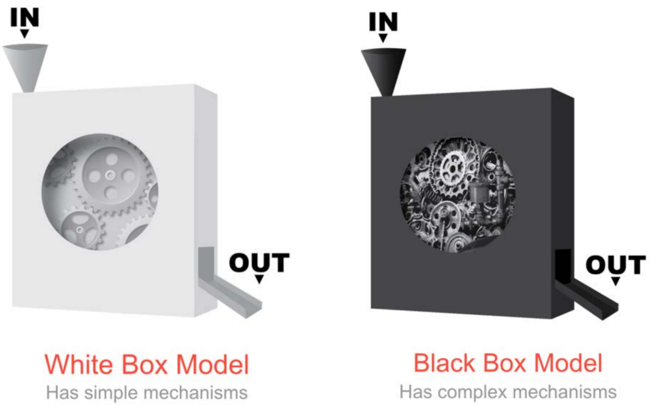
  Example: A machine learning model for OCR that processes images from envelopes and extracts addresses.

The Black Box of Machine Learning (?)

White Box vs Black Box (?)



White Box vs Black Box (?)



White box models are *transparent*.

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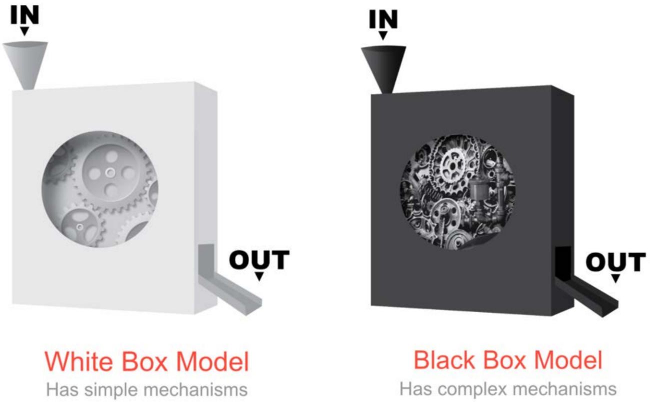

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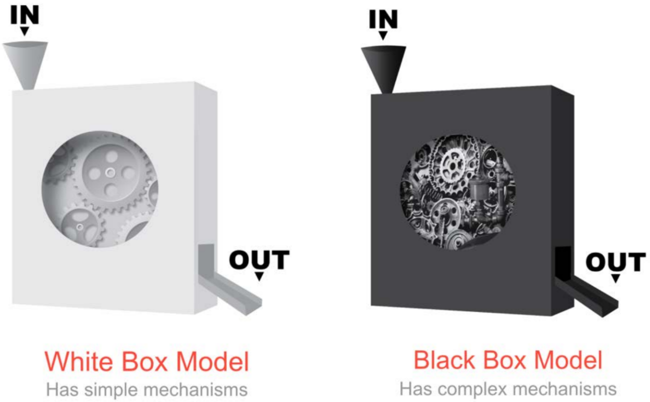

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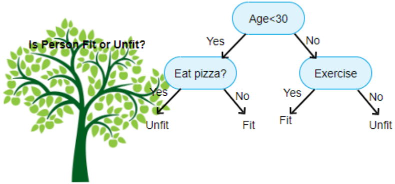

An example of a decision tree (**?**)

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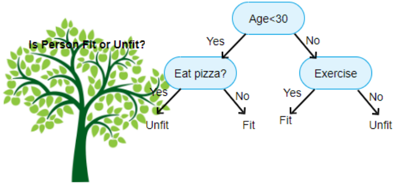

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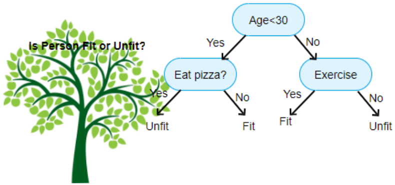

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  A famous example comes from **?**.

Interpretable Models (3/3)

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We shall explore a **linear regression algorithm** as an example of *interpretable model*.

Outline

Example of Interpretable Model: Dataset (1/3)

[2] https://www.capitalbikeshare.com

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- This dataset contains *daily counts of rented bicycles* from the bicycle rental company Capital-Bikeshare[2] in Washington D.C.
- The goal is to *predict how many bikes will be rented* depending on the weather and the day.

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- Temperature in degrees Celcius
- Relative humidity in percent (0 to 100)
- Wind speed in km per hour

Example of Interpretable Model: Dataset (3/3)

```
summary(bike_to_interpreted)
```

```
##       cnt            season          holiday       days_since_2011
##  Min.   :  22   SPRING:181   NO HOLIDAY:710   Min.   :  0.0
##  1st Qu.:3152   SUMMER:184   HOLIDAY   : 21   1st Qu.:182.5
##  Median :4548   FALL  :188                    Median :365.0
##  Mean   :4504   WINTER:178                    Mean   :365.0
##  3rd Qu.:5956                                 3rd Qu.:547.5
##  Max.   :8714                                 Max.   :730.0
##          workingday            weathersit       temp             hum
##  NO WORKING DAY:231   GOOD              :463   Min.   :-5.221   Min.   : 0.00
##  WORKING DAY   :500   MISTY             :247   1st Qu.: 7.843   1st Qu.:52.00
##                       RAIN/SNOW/STORM: 21   Median :15.422   Median :62.67
##                                                Mean   :15.283   Mean   :62.79
##                                                3rd Qu.:22.805   3rd Qu.:73.02
##                                                Max.   :32.498   Max.   :97.25
##    windspeed
##  Min.   : 1.500
##  1st Qu.: 9.042
##  Median :12.125
##  Mean   :12.763
##  3rd Qu.:15.625
##  Max.   :34.000
```

A summary of `bike_to_interpreted` dataset

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The epsilon (ϵ) is the **error** we still make, i.e. the difference between the prediction and the actual outcome.

Linear Regression Assumptions

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Outline

Example of Interpretable Model: How to Interpret (1/5)

The linear regression model:

$$y = \theta_0 + \theta_1 x_1 + \cdots + \theta_p x_p + \epsilon$$

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  An increase of feature x_k by one unit increases the prediction for y by θ_k units when *all other feature values remain fixed*.

- **Interpretation of a Categorical Feature**
  Changing feature x_k from the reference category to the other category increases the prediction for y by θ_k when *all other features remain fixed*.

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- ***R*-squared** tells us how much of the total variance of your target outcome is explained by the model.
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***R*-squared** tells us how much of our variance can be explained by the linear model ($0 \leq R$-squared ≤ 1).

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It is not meaningful to interpret a model with very low (**adjusted**) ***R*-squared**, because such a model basically does not explain much of the variance $\Longrightarrow$ any interpretation of the weights would not be meaningful.

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Bike Rentals: Interpretation (1/2)

In this example, we use linear regression to predict the **number of rented bikes** (cnt) on a particular day, given weather and calendar information.

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seasonFALL	138.2	161.7	0.9
seasonWINTER	425.6	110.8	3.8
holidayHOLIDAY	-686.1	203.3	3.4
workingdayWORKING DAY	124.9	73.3	1.7
weathersitMISTY	-379.4	87.6	4.3
weathersitRAIN/SNOW/STORM	-1901.5	223.6	8.5
temp	110.7	7.0	15.7
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windspeed	-42.5	6.9	6.2
days_since_2011	4.9	0.2	28.5

The estimated weight, the standard error of the estimate (*SE*), and the absolute value of *t*-statistic ($|t|$)

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- **Interpretation of a numerical feature ("temperature")**: An increase of the temperature by 1 degree Celcius increases the predicted number of bicycles by 110.7, *when all other features remain fixed*.
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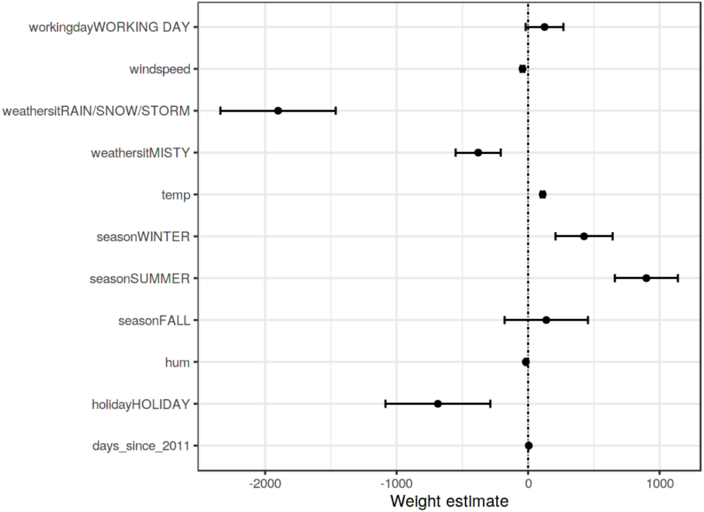
Visual Interpretation: Weight Plot (1/2)



Weights are displayed as points and the 95% confidence intervals as lines

Visual Interpretation: Weight Plot (2/2)

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- The weight of the working day feature is close to zero and zero is included in the 95% interval $\longrightarrow$ the effect is **not** statistically significant.

Visual Interpretation: Weight Plot (2/2)

- The figure shows that rainy/snowy/stormy weather has a **strong negative effect** on the predicted number of bikes.
- The weight of the working day feature is close to zero and zero is included in the 95% interval $\longrightarrow$ the effect is **not** statistically significant.
- Some *confidence intervals* are *very short* and the estimates are *close to zero*, yet the *feature effects were statistically significant* $\longrightarrow$ temperature.

Visual Interpretation: Weight Plot (2/2)

- The figure shows that rainy/snowy/stormy weather has a **strong negative effect** on the predicted number of bikes.
- The weight of the working day feature is close to zero and zero is included in the 95% interval $\longrightarrow$ the effect is **not** statistically significant.
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- The problem: <u>the features are measured on different scales</u>.
- The solution: *scaling the features (zero mean and standard deviation of one) before fitting the linear model*.

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- The effects can be visualized with **boxplots**.

Visual Interpretation: Effect Plot (2/3)

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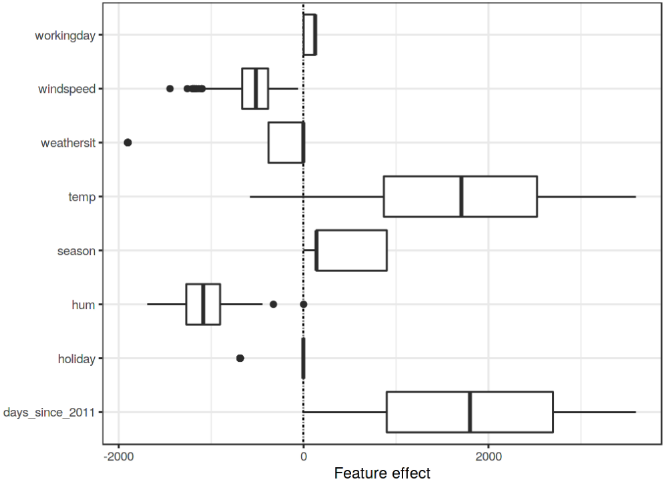

The *feature effect* plot shows the distribution of effects (= feature value $\times$ feature weight) across the data per feature

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Visual Interpretation: Effect Plot (3/3)

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  This means that the effect $\uparrow$ with each day and is highest for the *last day* in the dataset (31.12.2012).

Explain Individual Predictions (1/4)

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Feature	Value
season	SPRING
yr	2011
mnth	JAN
holiday	NO HOLIDAY
weekday	THU
workingday	WORKING DAY
weathersit	GOOD
temp	1.604356
hum	51.8261
windspeed	6.000868
cnt	1606
days_since_2011	5

The 6th instance from the bicycle dataset

Explain Individual Predictions (2/4)

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- For the value "WORKING DAY" of feature "workingday", the effect is 124.9 (124.9×1).
- For a temperature of 1.6 degrees Celcius, the effect is 177.6 (1.604356×110.7096).

Explain Individual Predictions (3/4)

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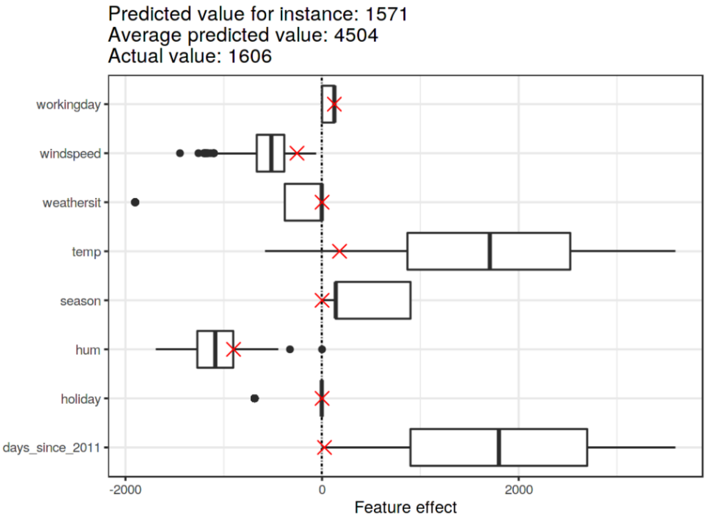

The effect plot for the 6-th instance is labeled cross $\times$

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  - The 6th instance has a *low temperature effect* because on this day the temperature was 2 degrees, which is low compared to most other days.
  - The effect of the *trend feature* "days_since_2011" is small compared to the other data instances because this instance is from early 2011 (5 days) and the *trend feature* also has a positive weight.

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- Lastly, Interpretability could boost **machine intelligence research**.

Daftar Pustaka I

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