Interpretable Machine Learning

The Basics

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NUNI IT Online Seminar

Outline

Outline

Introduction

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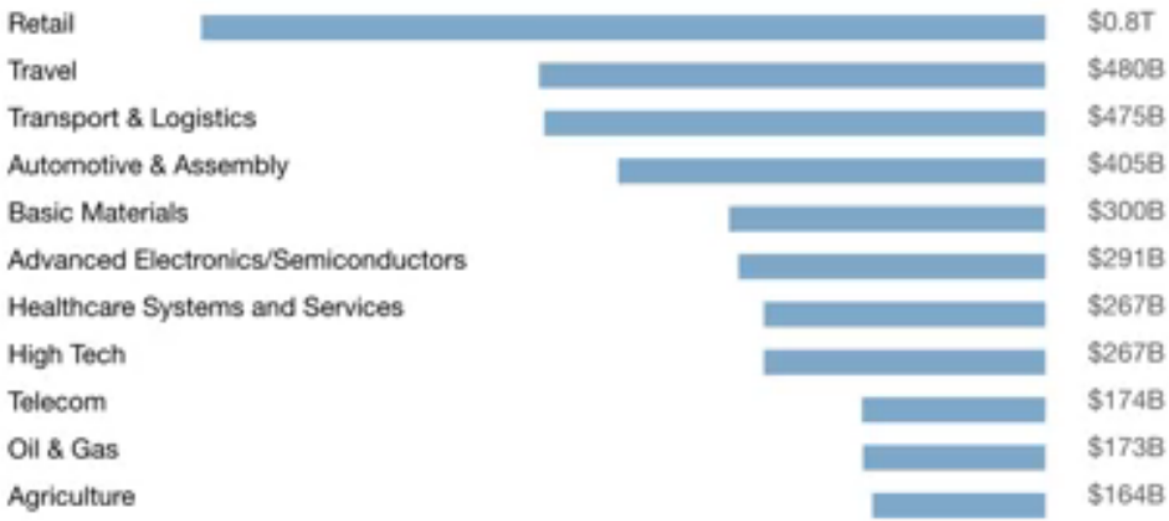
AI value creation by 2030

$13 trillion



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

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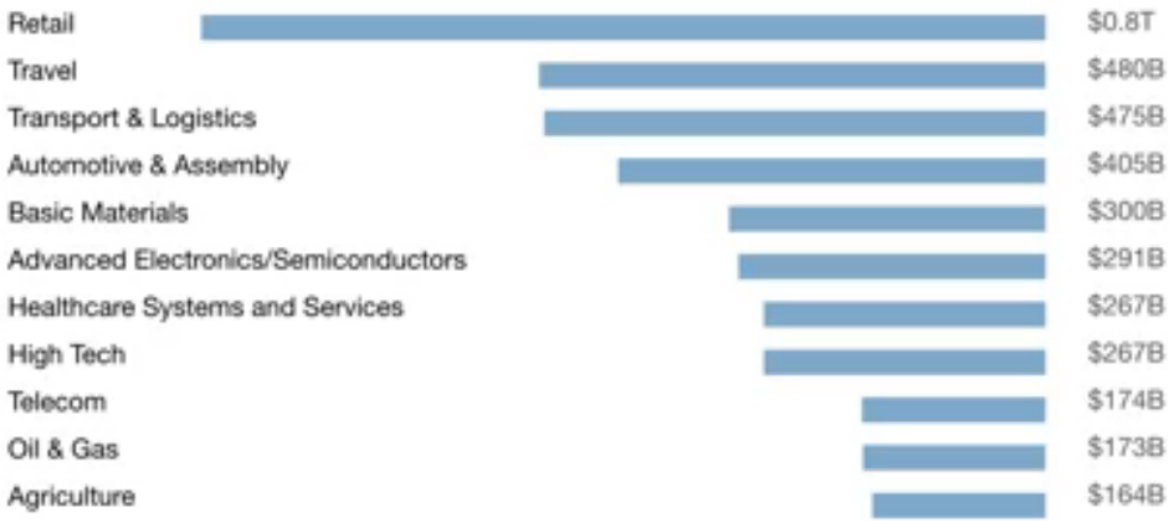

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$$\$13 \text{ trillion} = \$13 \times 10^{12} = \text{Rp}183.000.000.000.000.000,-$$

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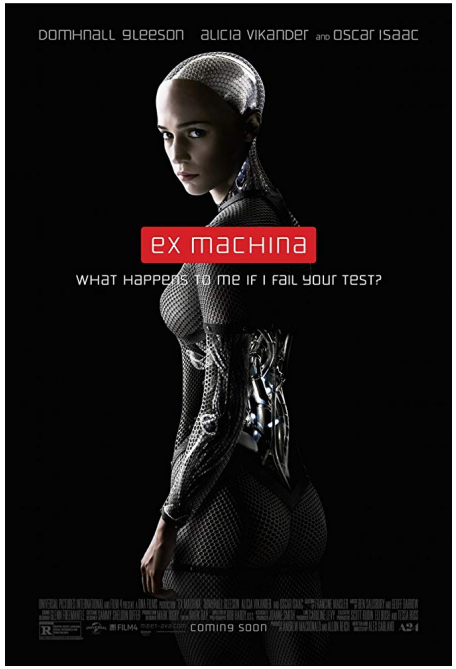

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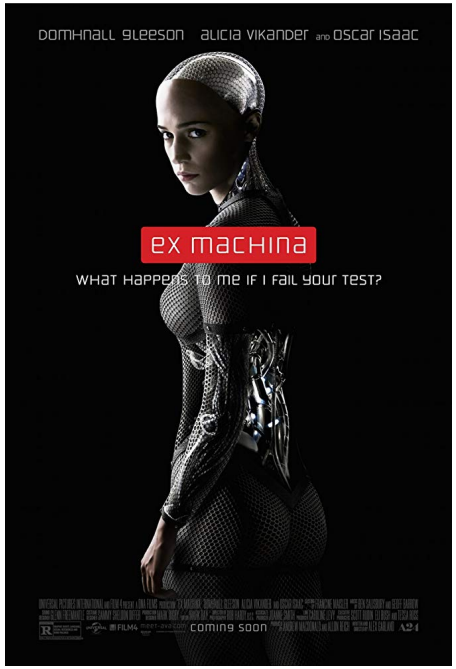

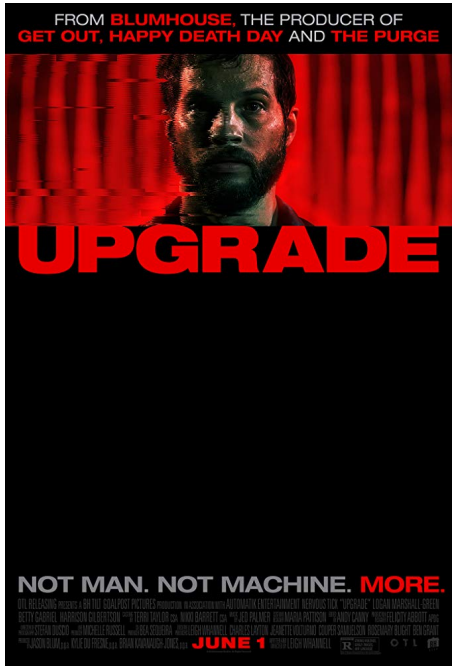

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Diagram Venn tentang AI, ML, DL, Data Science

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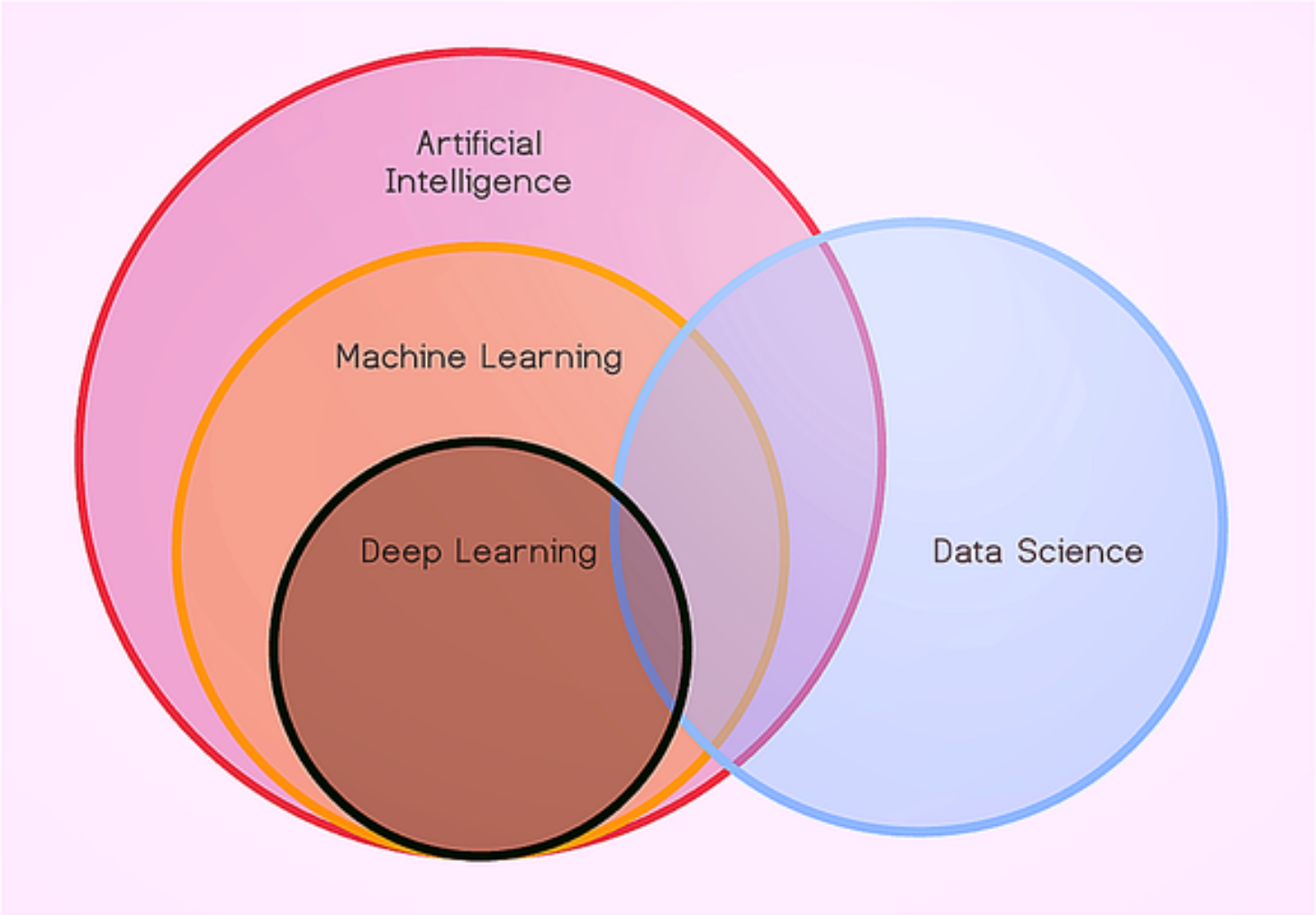

Relationship among AI, ML, DL, and DS (**?**)

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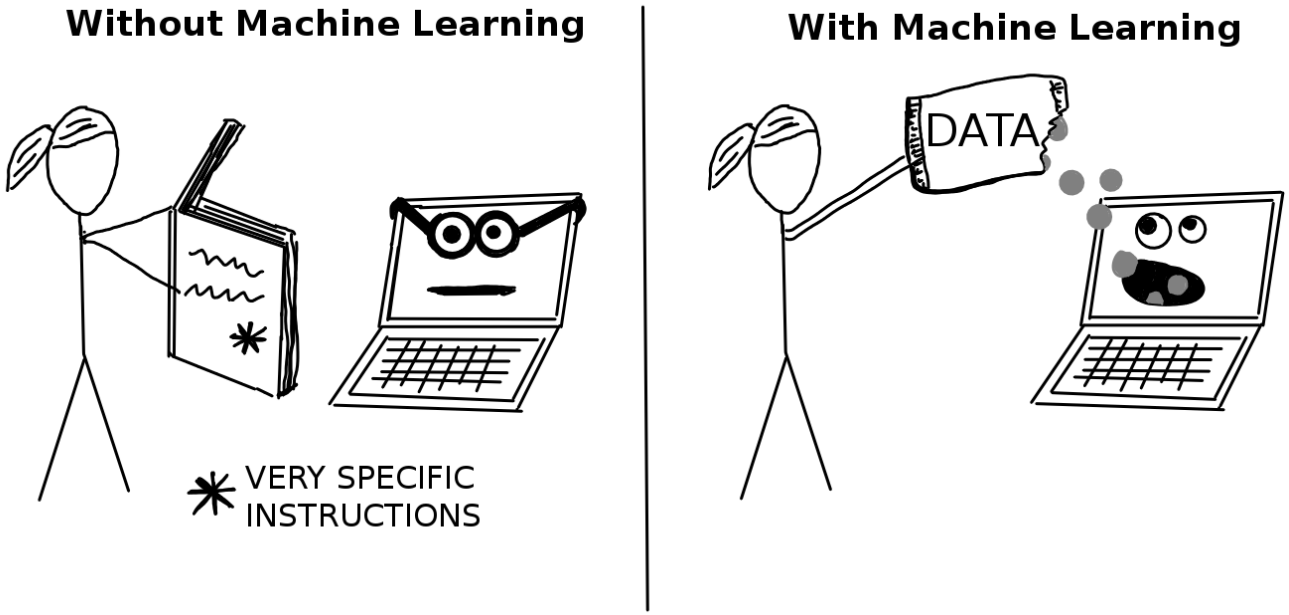

A paradigm shift from "normal programming" to "indirect programming"

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

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Why Now?

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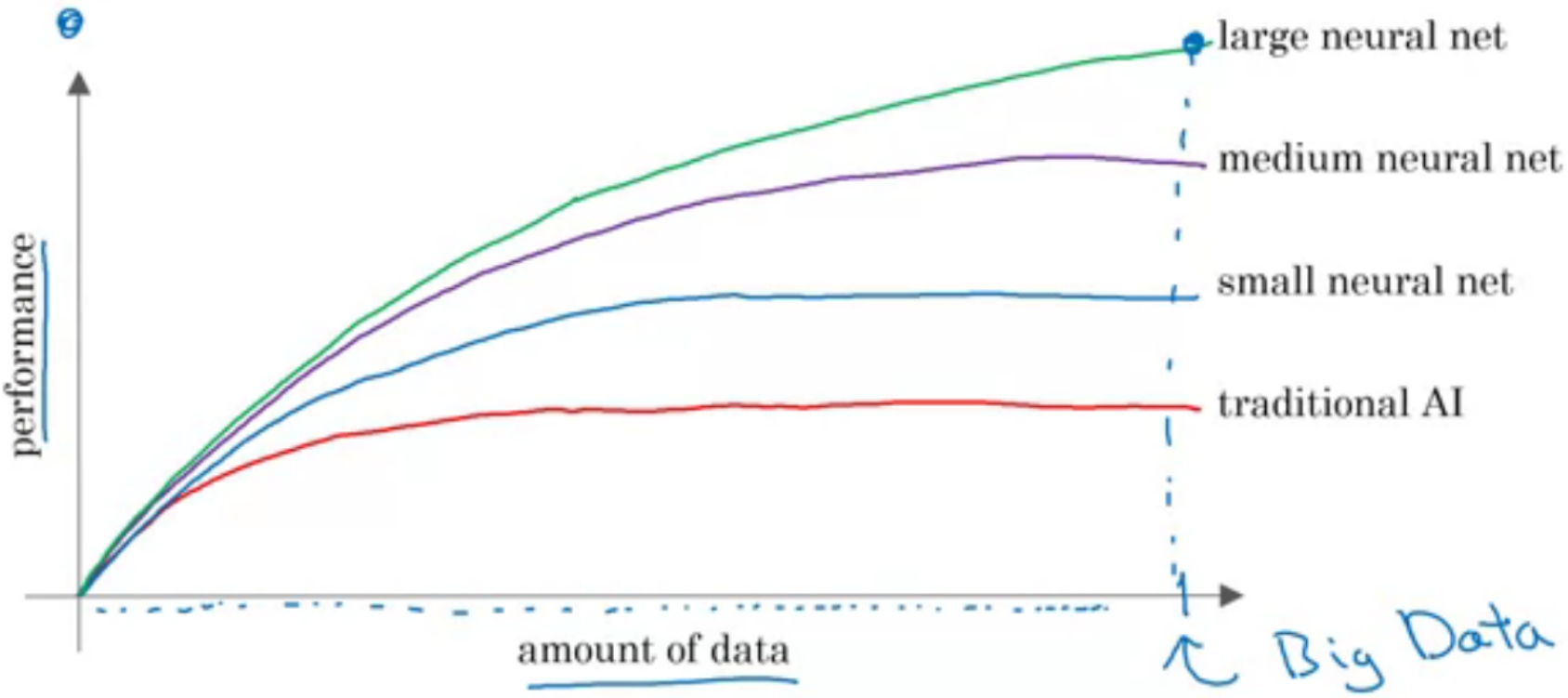
large neural net
medium neural net
small neural net
traditional AI
performance
amount of data
Big Data

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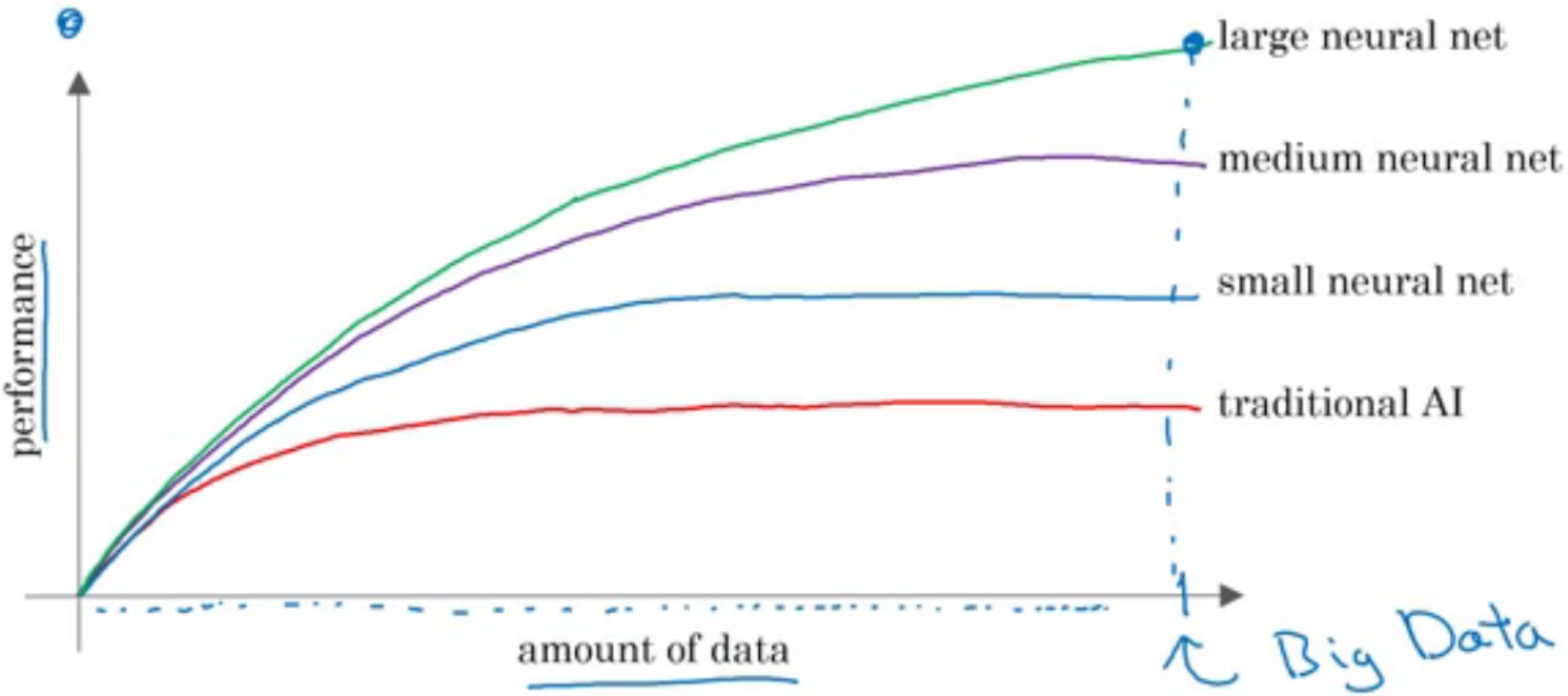

Large neural net + Big Data = High Performance (**?**)

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

Outline

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

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Population (X)	**Profit** (Y)
6.1101	17.592
5.5277	9.130
8.5186	13.662
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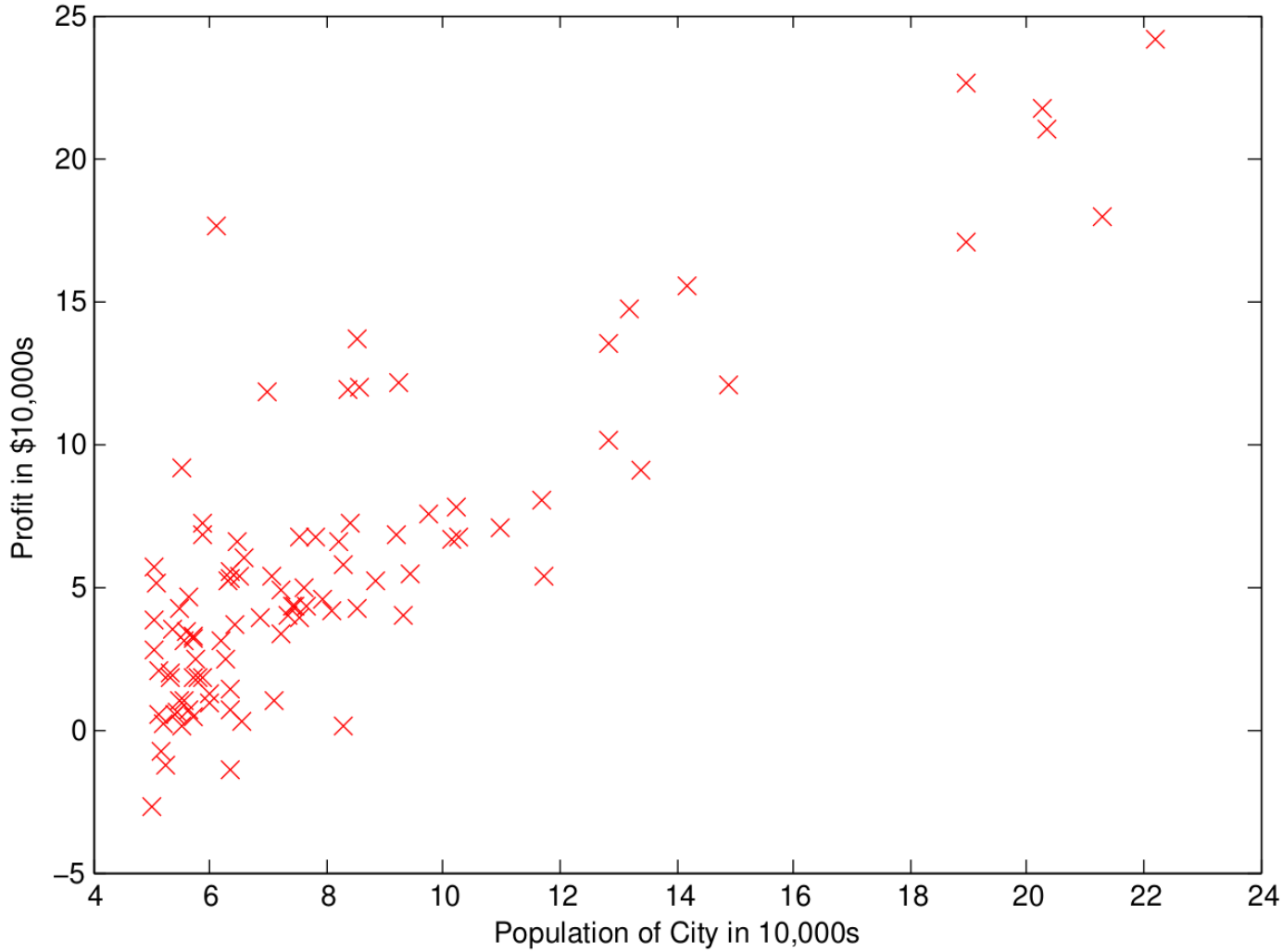

Scatter plot of food trucks data

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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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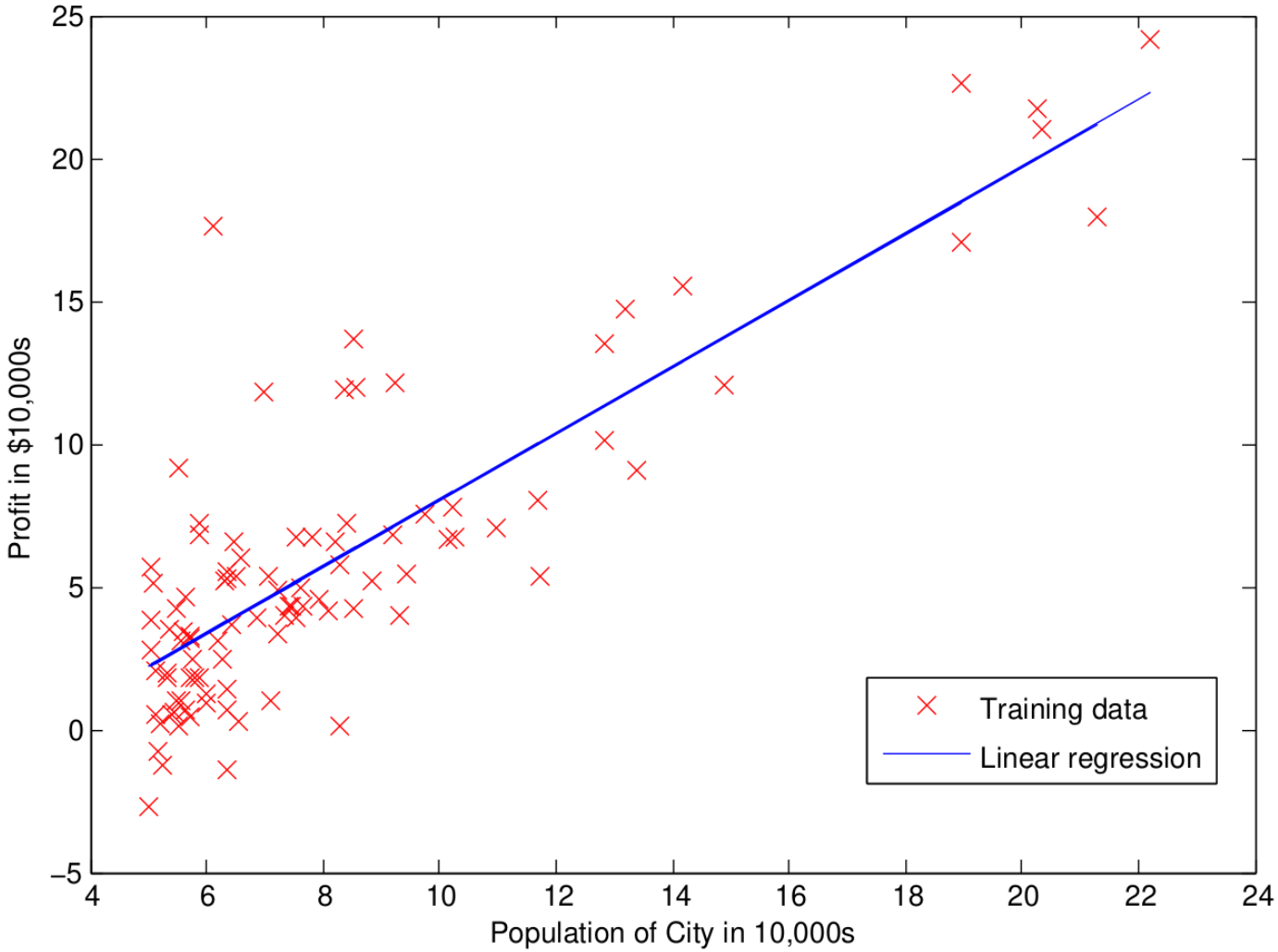

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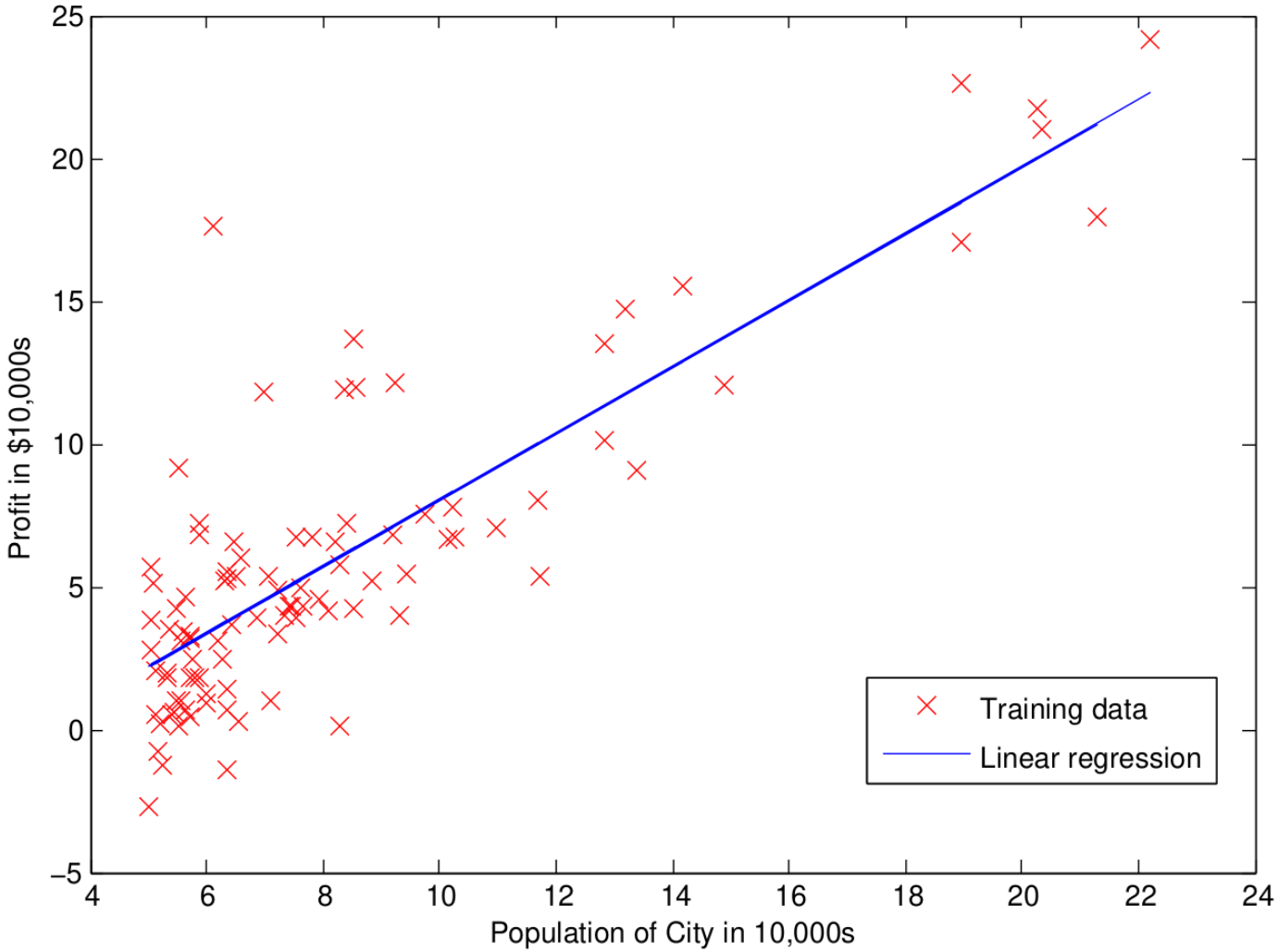

The regression line; however, how do we find θ_0 and θ_1?

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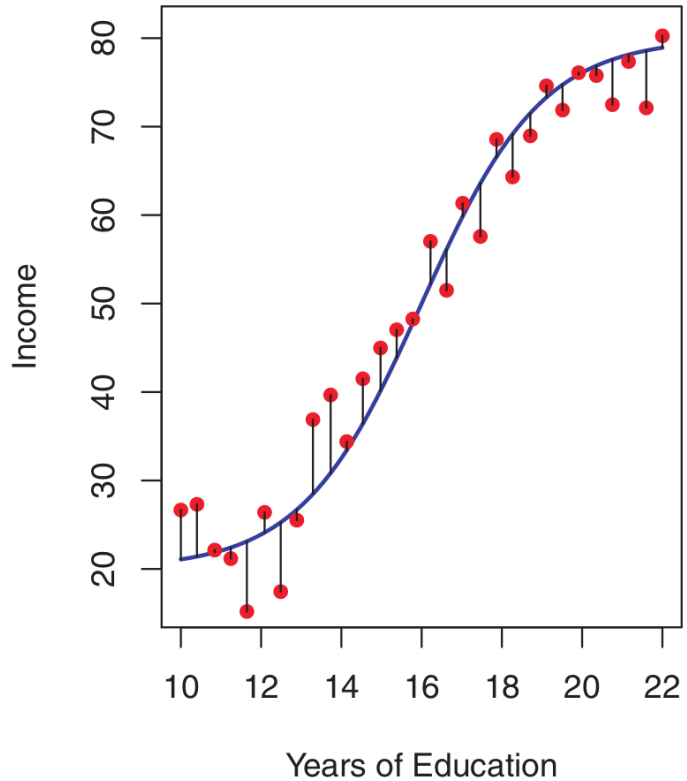

An example of errors; Specifically *the black lines* represent the error associated with each instance (**?**)

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We need **Calculus**.

Machine Learning Component: Cost Function (3/3)

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How do we find θ_0 and θ_1 that minimize the **cost function**?

We need an **Optimization Algorithm**.

Outline

ML Component: Optimization Algorithm (1/7)

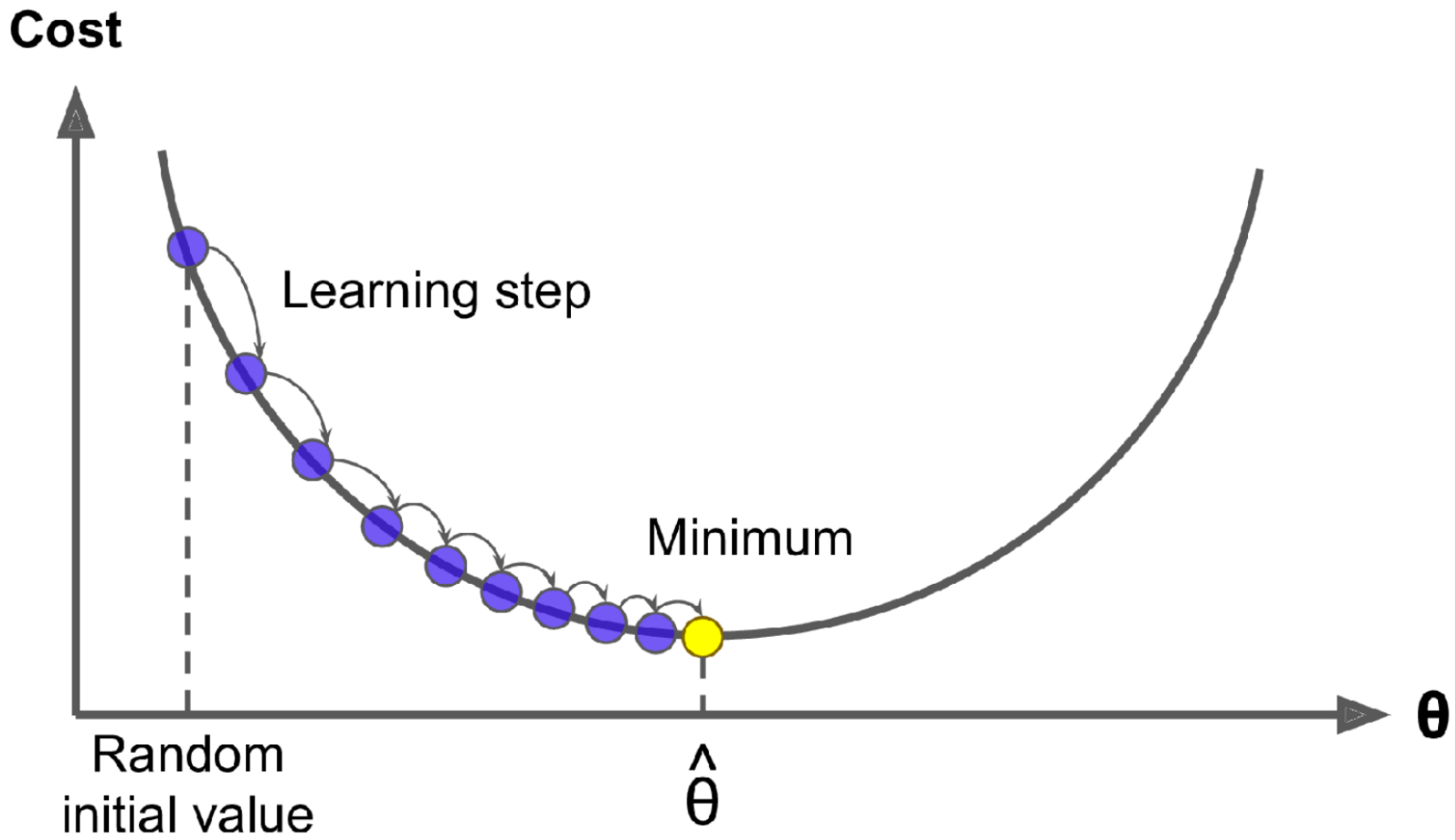
A famous optimization algorithm:

ML Component: Optimization Algorithm (1/7)

A famous optimization algorithm: **Gradient Descent**

ML Component: Optimization Algorithm (1/7)

A famous optimization algorithm: **Gradient Descent**



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:

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

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

$$=$$

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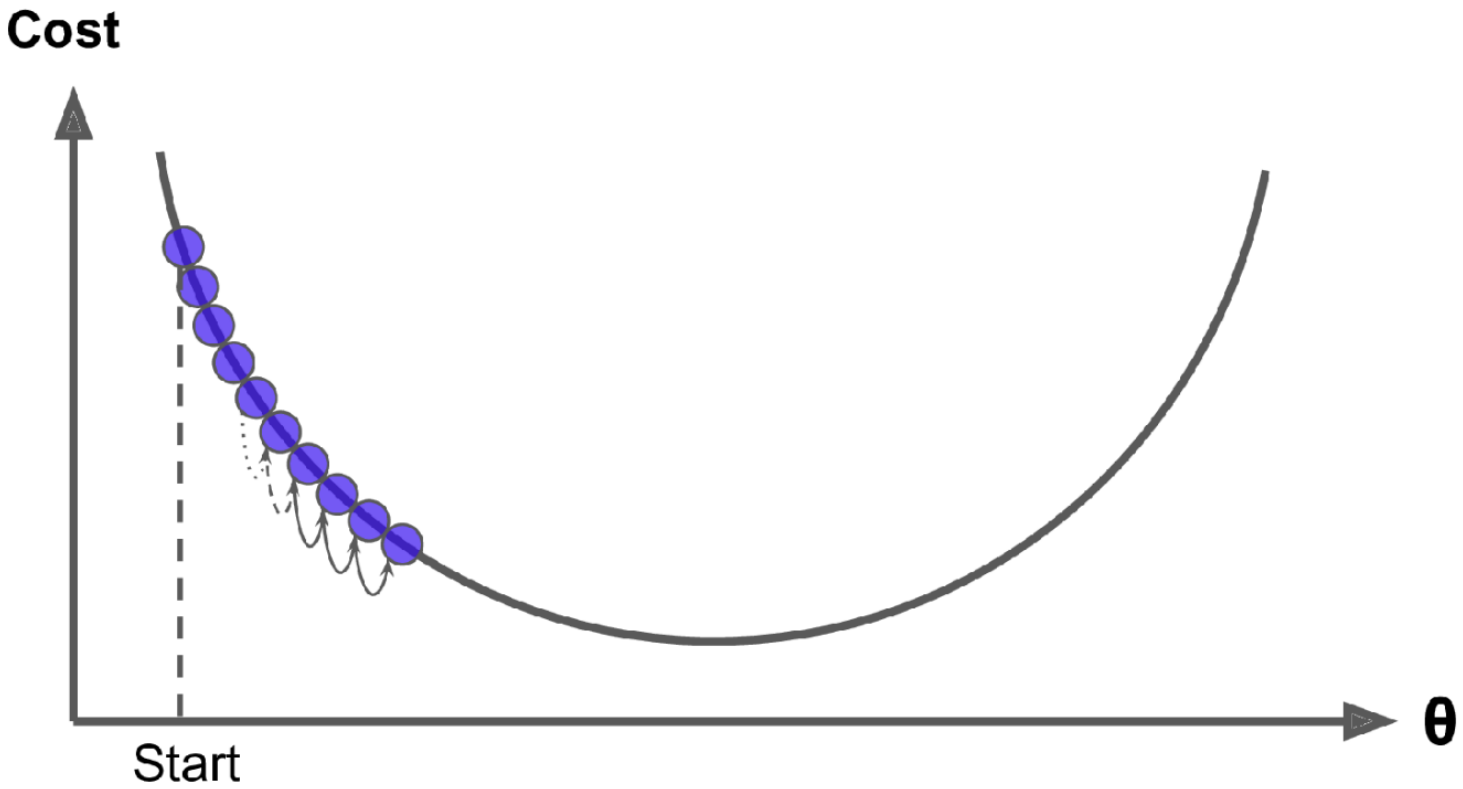

This will happen when the α is too small (**?**)

ML Component: Optimization Algorithm (7/7)

What happens when α is too large?

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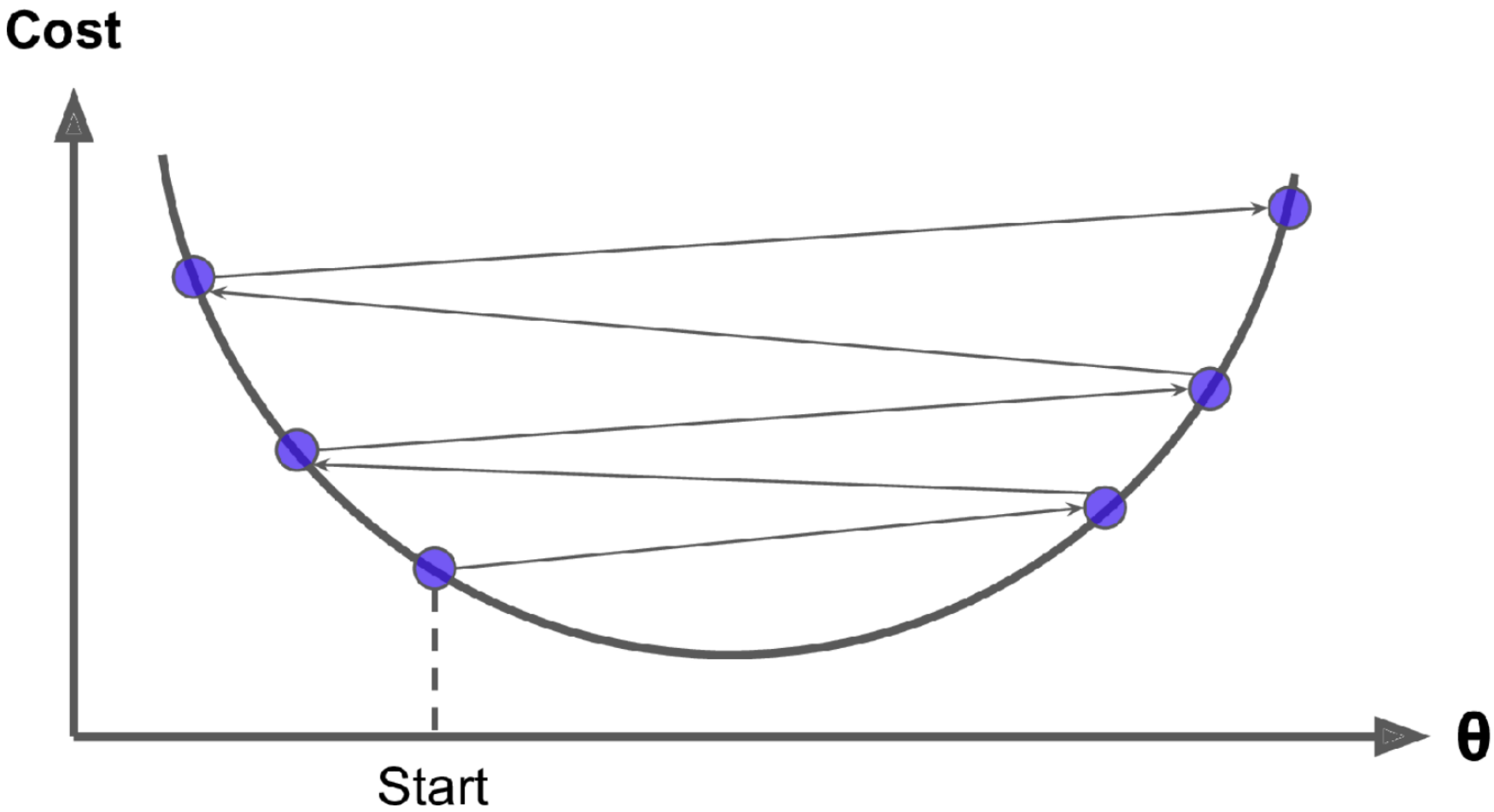

This will happen when α is too large (**?**)

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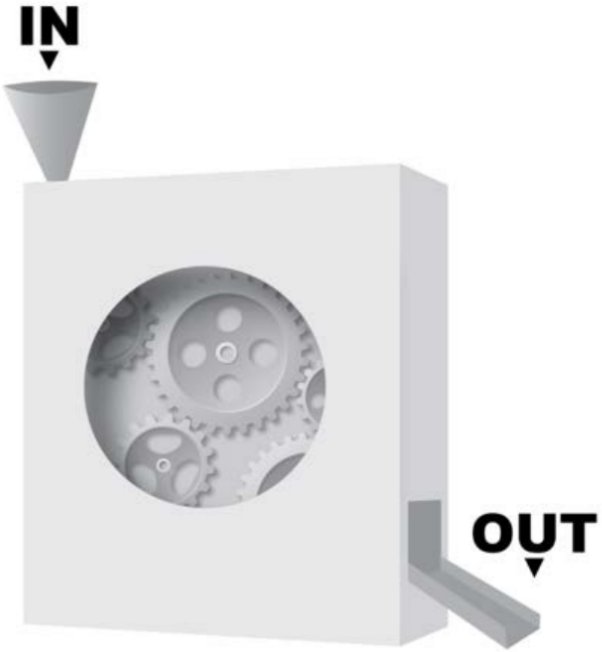
  Example: A machine learning model for OCR that processes images from envelopes and extracts addresses.

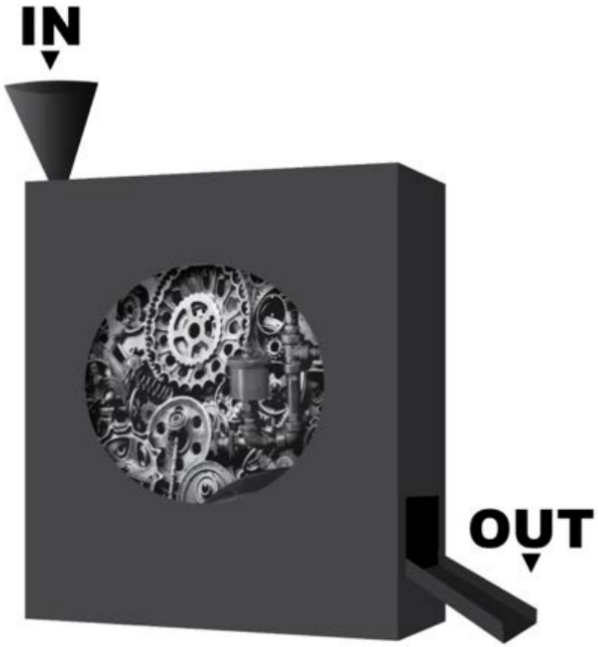
The Black Box of Machine Learning (?)

White Box vs Black Box (?)



White Box Model

Has simple mechanisms



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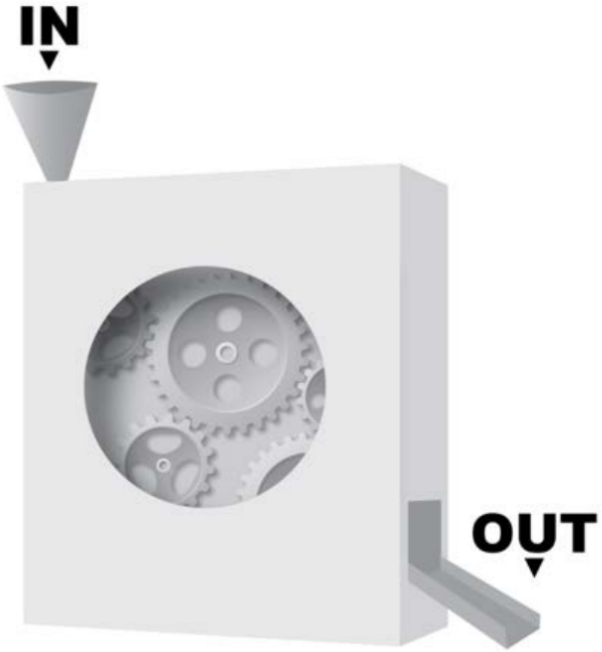
White Box vs Black Box (?)



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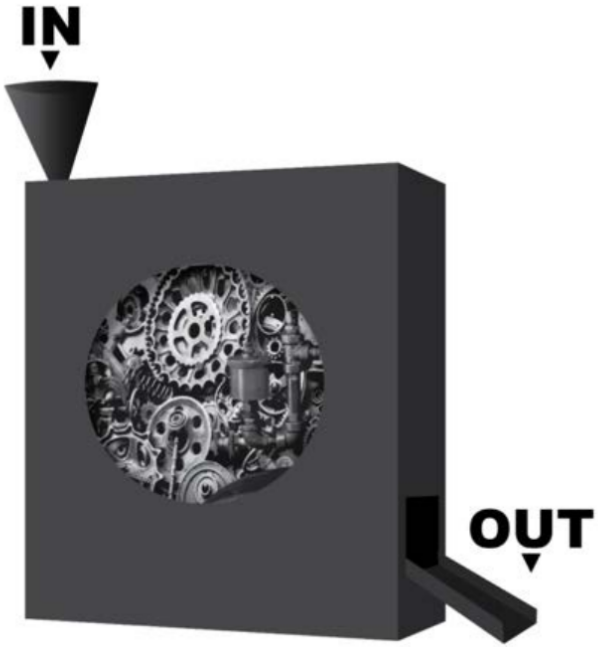

Black Box Model

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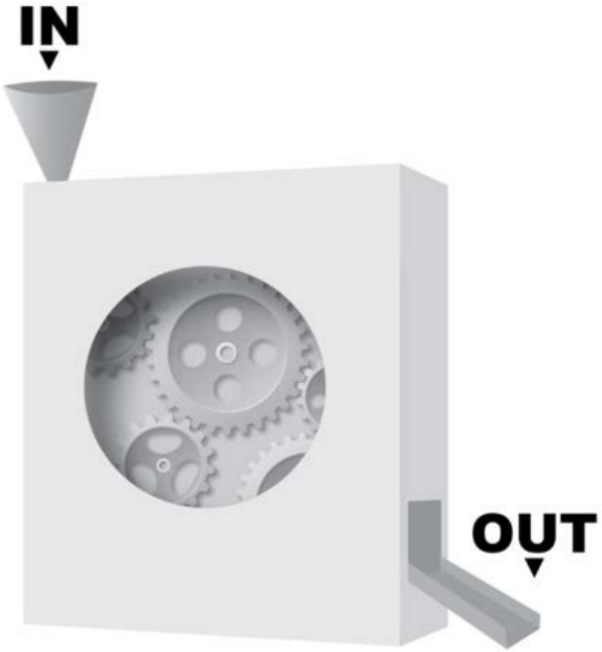

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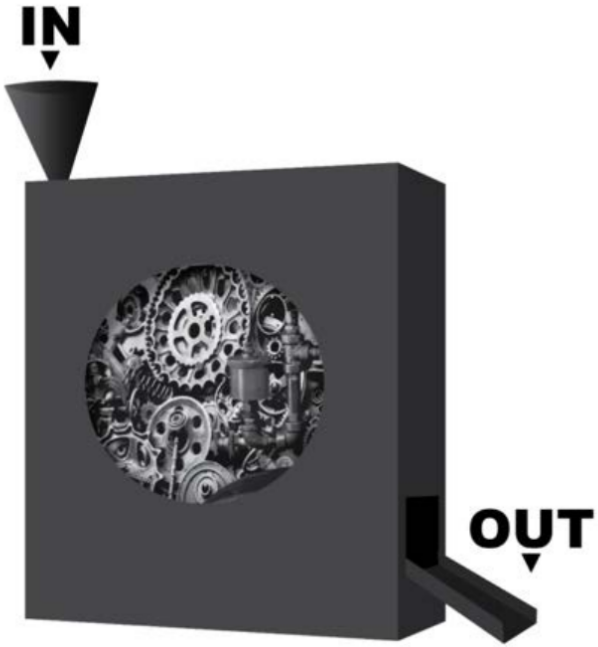

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They achieve *total* or *near-total interpretation transparency*

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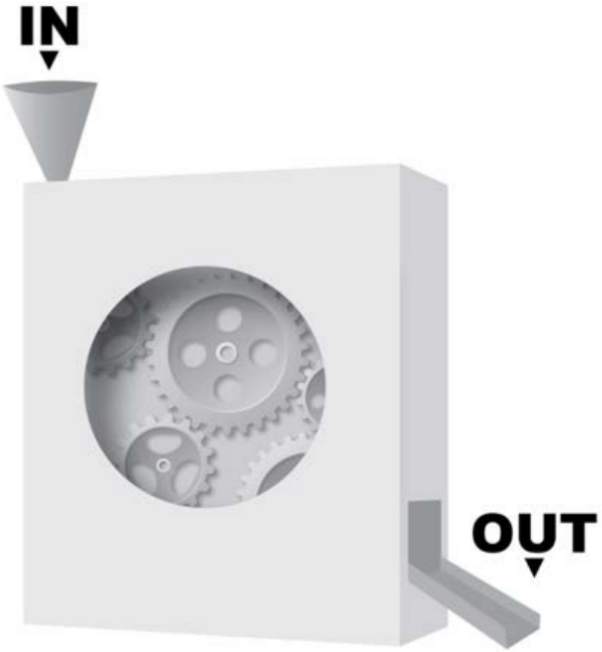

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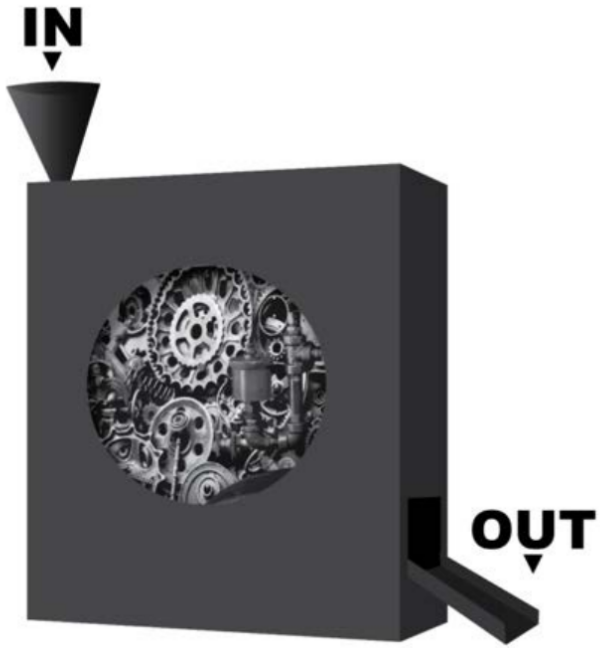

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$\Longrightarrow$ **interpretable**.

Outline

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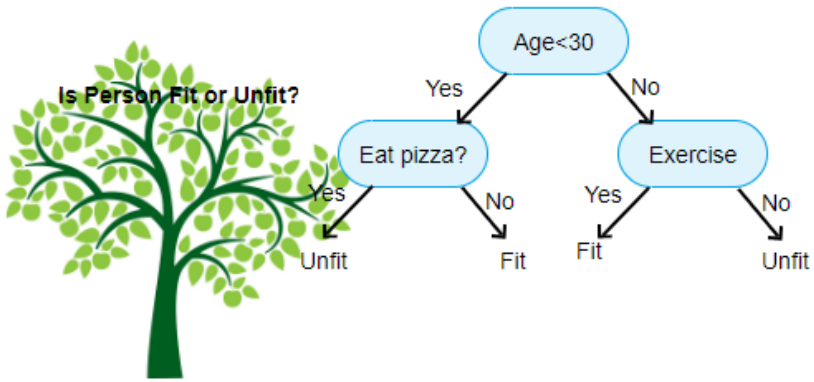

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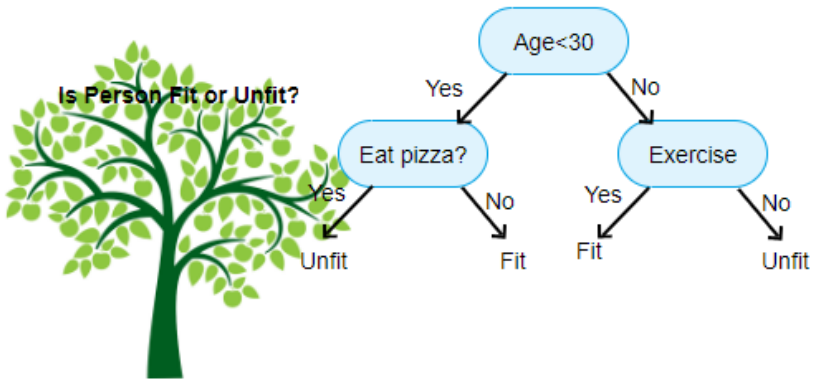

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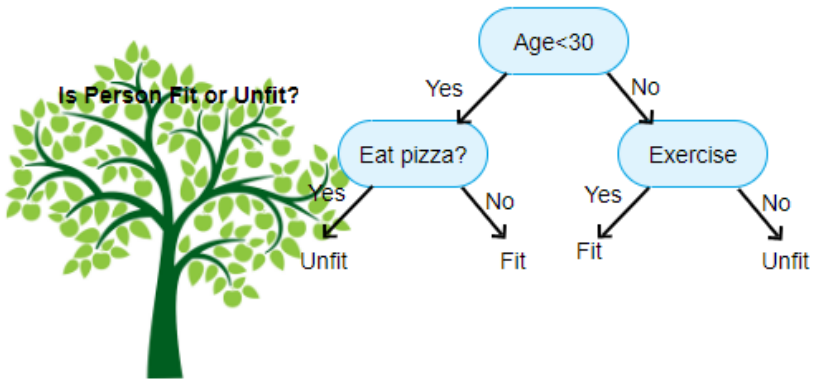

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  A famous example comes from **?**.

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k-nearest neighbors	✗	✗	✗	class, regr

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Interpretable Models (3/3)

Algorithm	Linear	Monotone	Interaction	Task
Linear regression	✓	✓	✗	regr
Logistic regression	✗	✓	✗	class
Decision trees	✗	?	✓	class, regr
RuleFit	✓	✗	✓	class, regr
Naïve-Bayes	✗	✓	✗	class
k-nearest neighbors	✗	✗	✗	class, regr

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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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Example of an Interpretable Model: Dataset (2/3)

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- 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

MARANATHA CHRISTIAN UNIVERSITY

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

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- **Independence of residuals error terms** $\rightarrow$ each instance is *independent* of any other instance.

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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- **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.
- The higher ***R*-squared**, the better our model explains the data.

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***R*-squared** tells us how much of our variance can be explained by the linear model ($0 \leq R\text{-squared} \leq 1$).

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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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	Weight	SE	t
(Intercept)	2399.4	238.3	10.1
seasonSUMMER	899.3	122.3	7.4
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
hum	-17.4	3.2	5.5
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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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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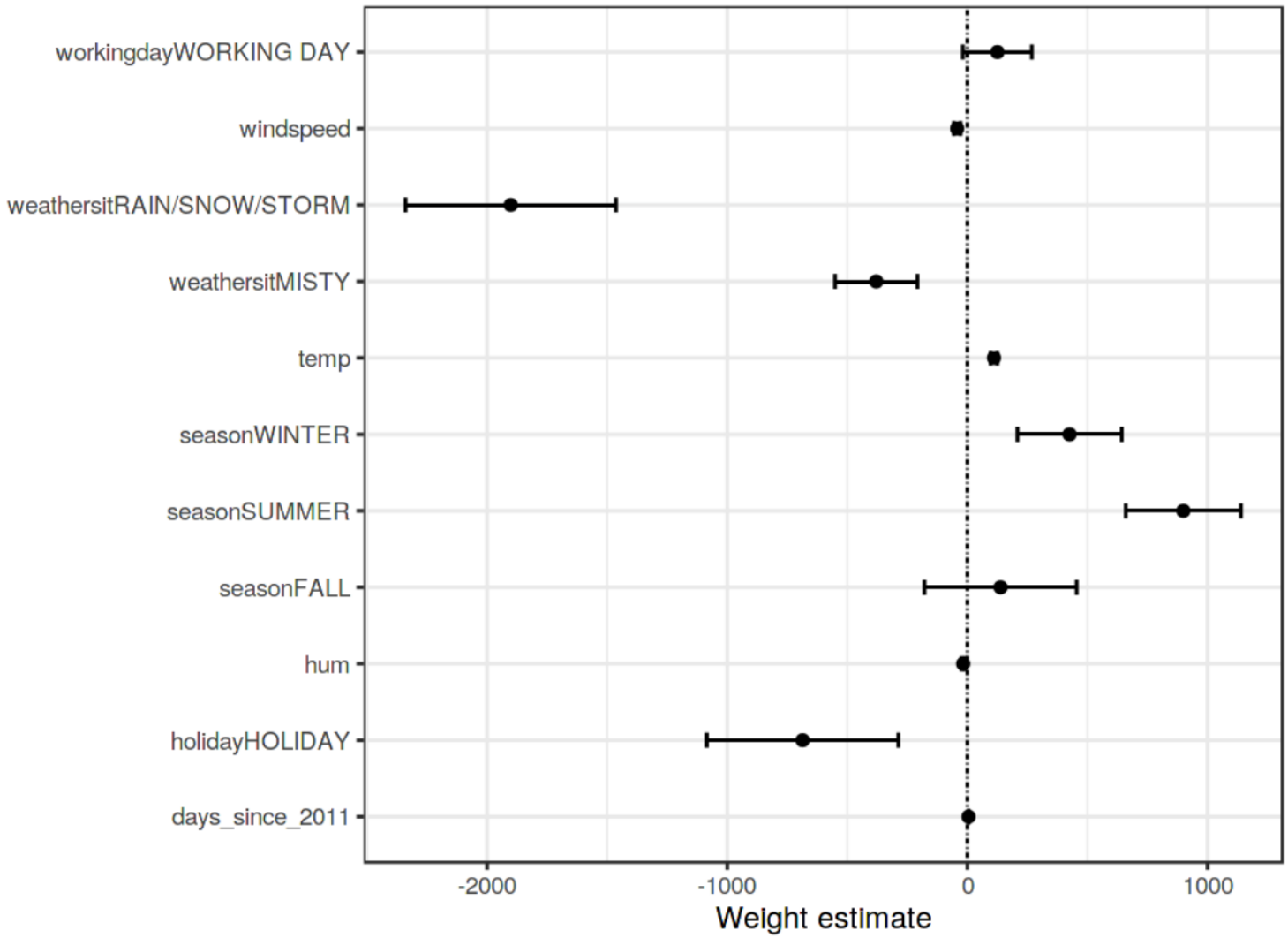
Visual Interpretation: Weight Plot (1/2)



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

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- The problem: the features are measured on different scales.
- 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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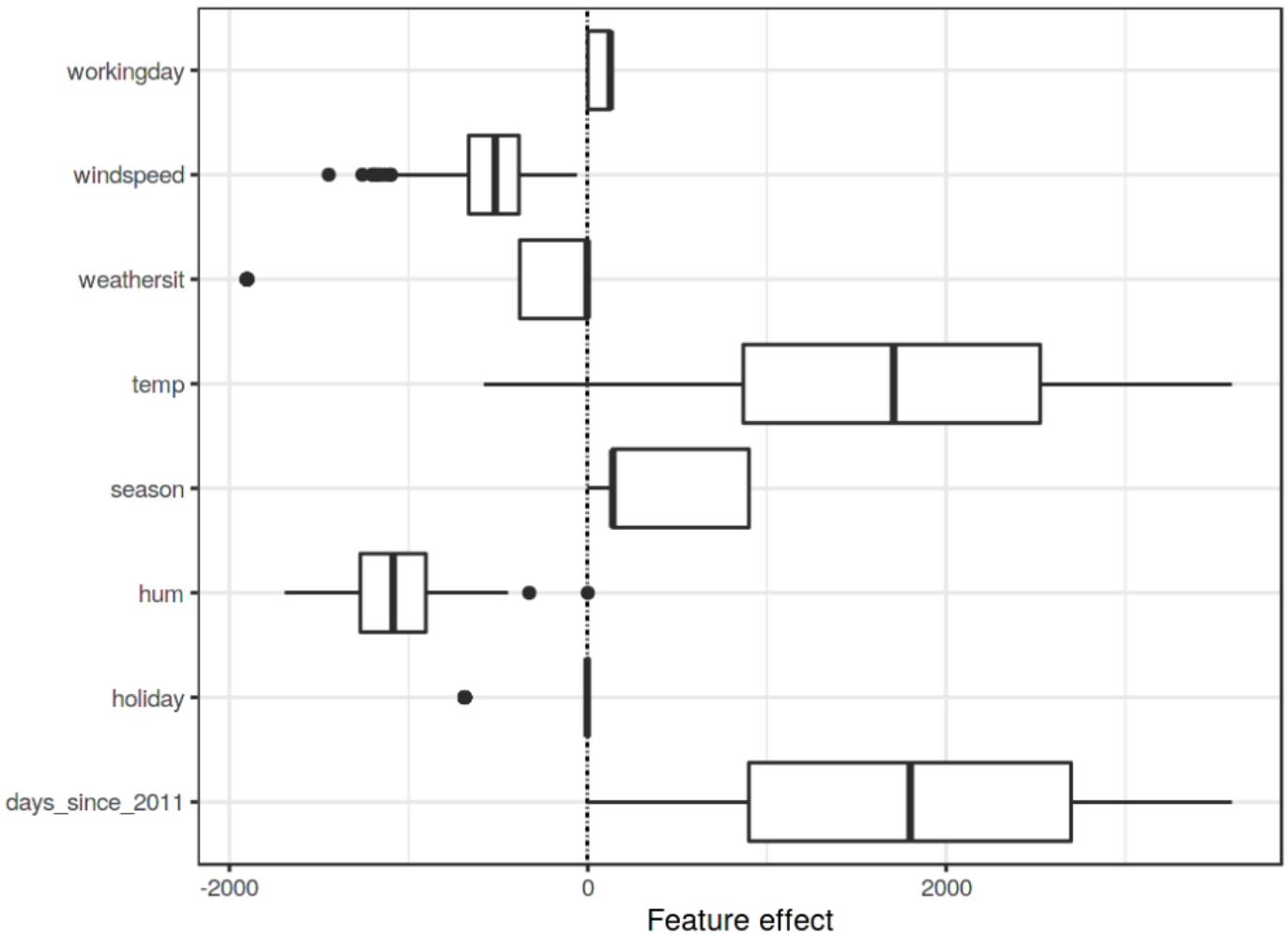

The *feature effect* plot shows the distribution of effects (= feature value $\times$ feature weight) across the data per feature

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- The **day trend** feature goes from *zero* to *large positive contributions*, because the first day in the dataset (01.01.2011) has a *very small trend effect* and the estimated weight for this feature is *positive* (4.93).
  This means that the effect ↑ with each day and is highest for the *last day* in the dataset (31.12.2012).

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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

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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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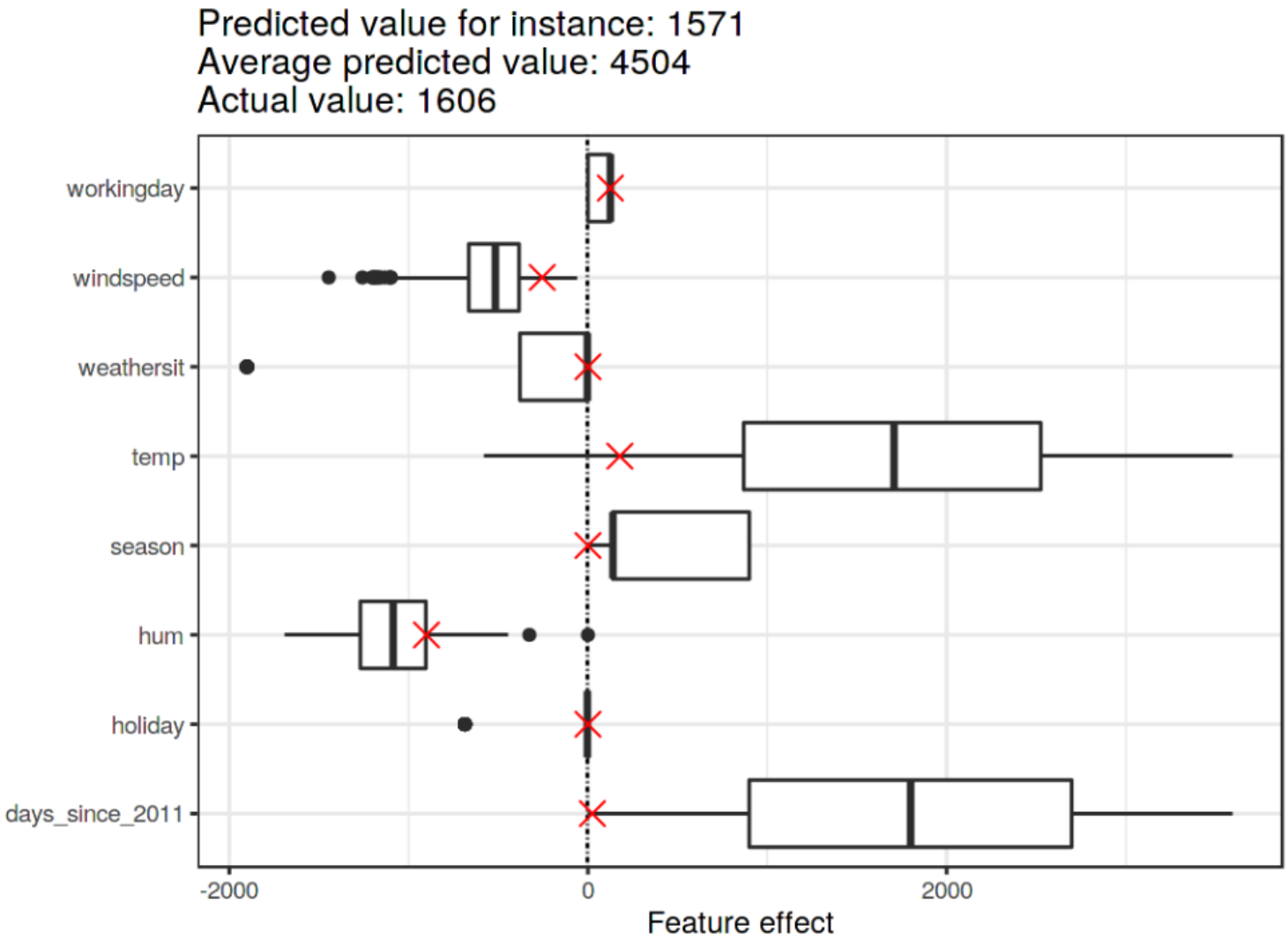

The effect plot for the 6-th instance is labeled cross $\times$

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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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