

Interpretable Machine Learning

The Basics

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9 April 2021
NUNI IT Online Seminar



Outline

- 1 Introduction
- 2 Machine Learning
- 3 Example: Predicting Profits of Food Trucks
- 4 A Machine Learning Component: Data
- 5 A Machine Learning Component: Model/Hypothesis
- 6 A Machine Learning Component: Cost/Loss Function
- 7 A Machine Learning Component: Optimization Algorithm
- 8 Demo from Stanford Machine Learning
- 9 Interpretability
- 10 Interpretable Models
- 11 Example of an Interpretable Model
- 12 Example: How to Interpret the Model
- 13 Conclusion

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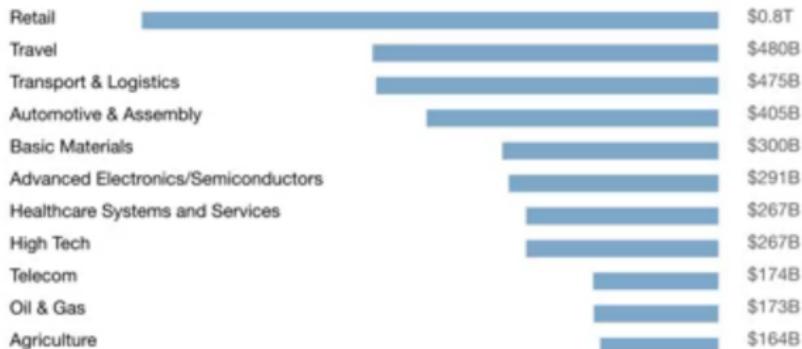
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Introduction

Introduction

AI value creation
by 2030

\$13
trillion

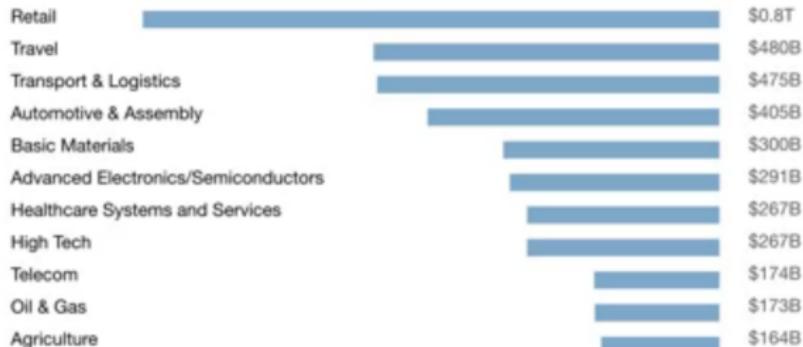


Source: McKinsey Global Institute (Ng, 2019)

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

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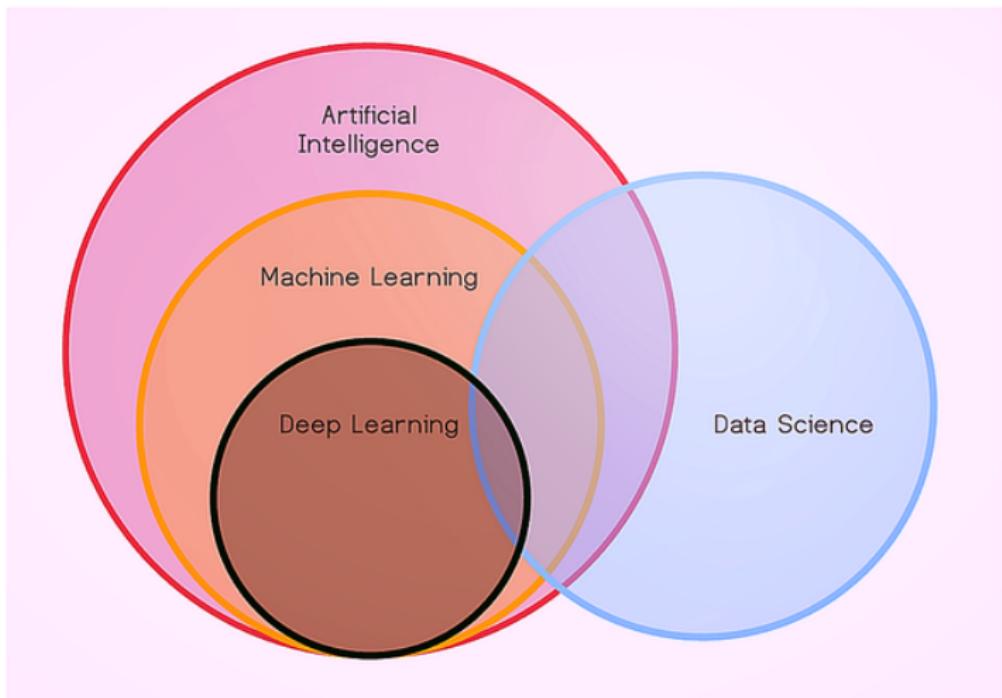


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Diagram Venn tentang AI, ML, DL, Data Science

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Relationship among AI, ML, DL, and DS (Kharkovyba, 2019)

Machine Learning

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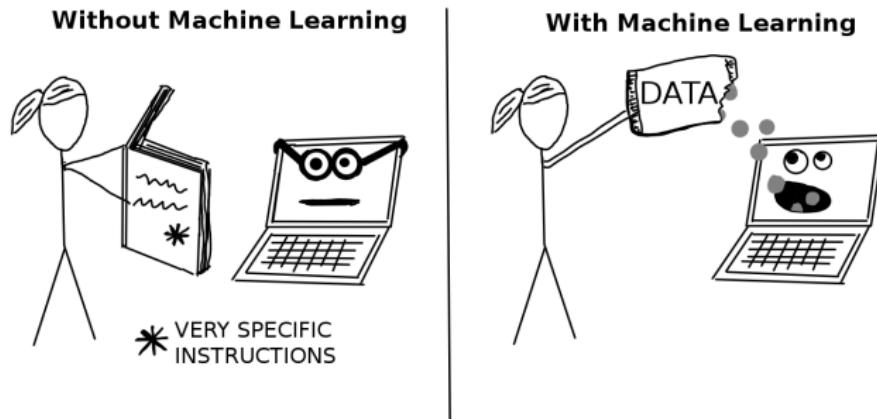
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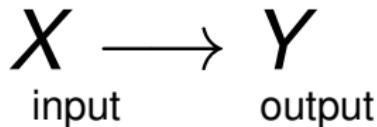


A paradigm shift from "normal programming" to "indirect programming"

Machine Learning: Supervised Learning (1/2)

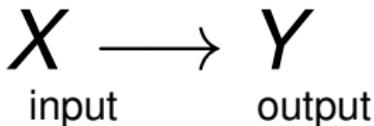
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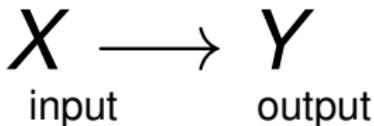


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- A **Machine Learning Algorithm** is *the program* used to learn a ML model from data (Molnar, 2019).



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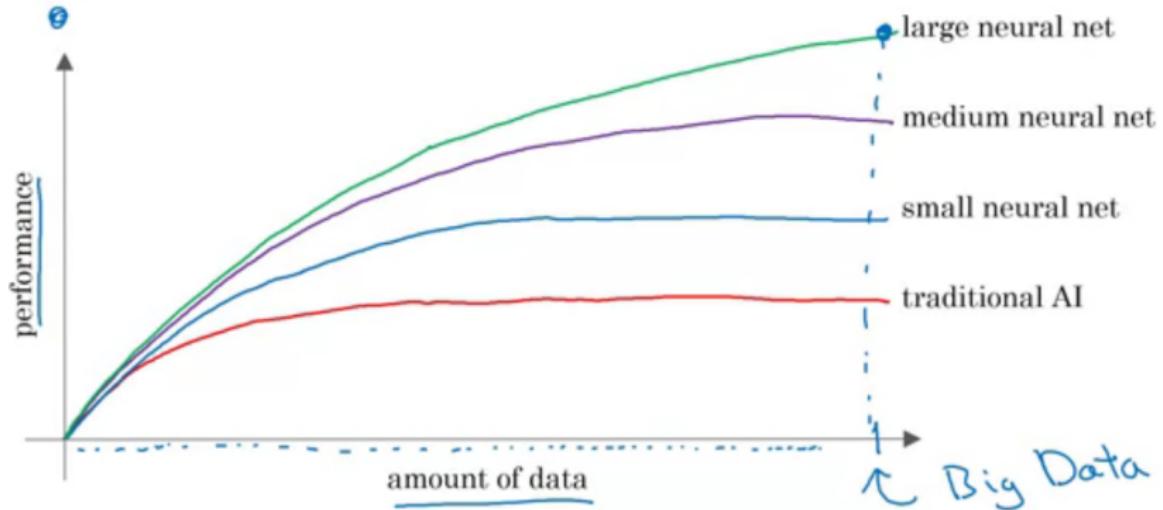
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image of phone	→ defect? (0/1)	visual inspection

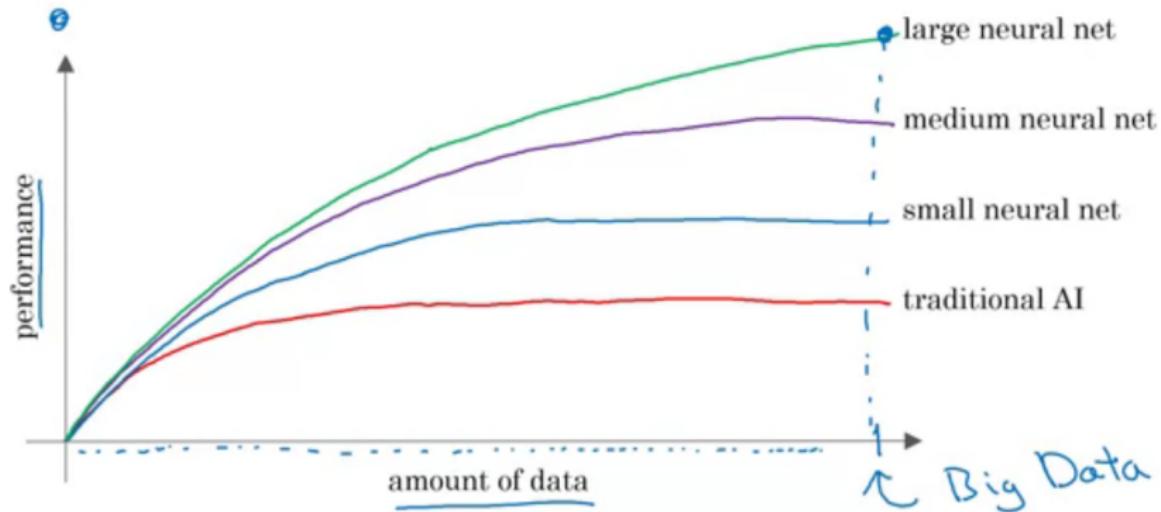


Why Now?

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Large neural net + Big Data = High Performance (Ng, 2019)

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



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A food truck serving Chinese food (Louis, 2011)

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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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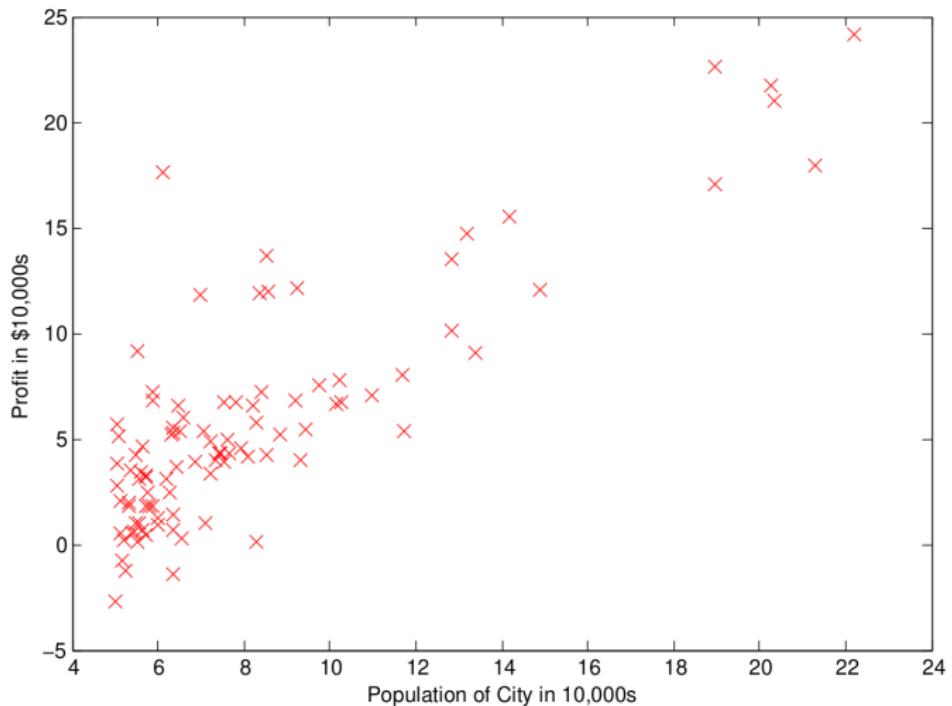
$$x_1^{(3)} = 8.5186 \text{ and } y^{(3)} = 13.662, \text{ and}$$

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Machine Learning Component: Data (2/2)

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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 \implies improve computing efficiency.



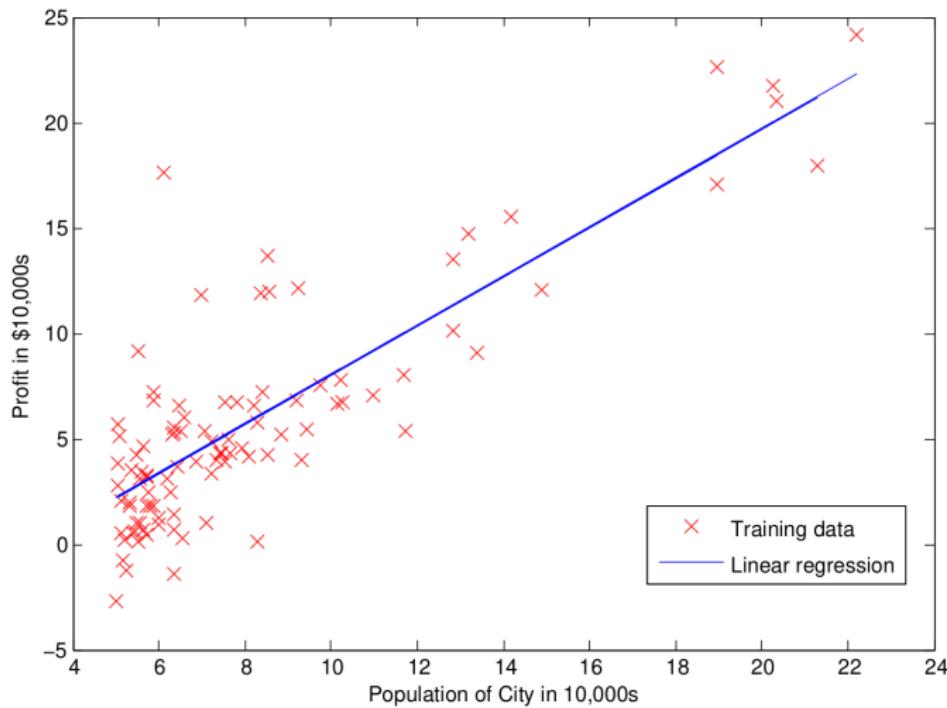
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Assuming that we have θ , we can compute and plot our regression line as follows:



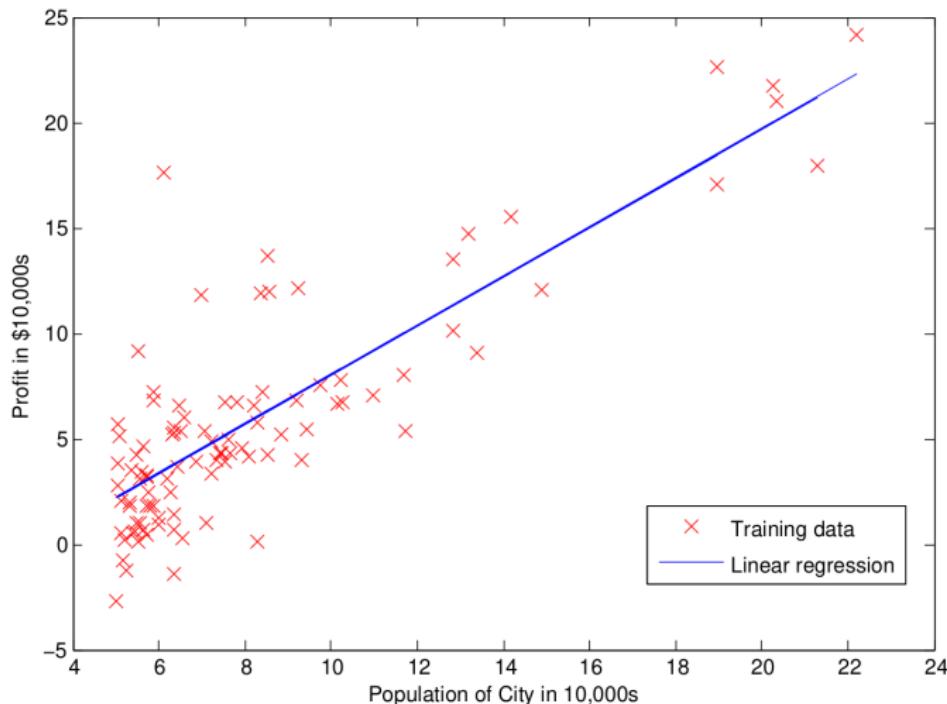
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The regression line; however, how do we find θ_0 and θ_1 ?

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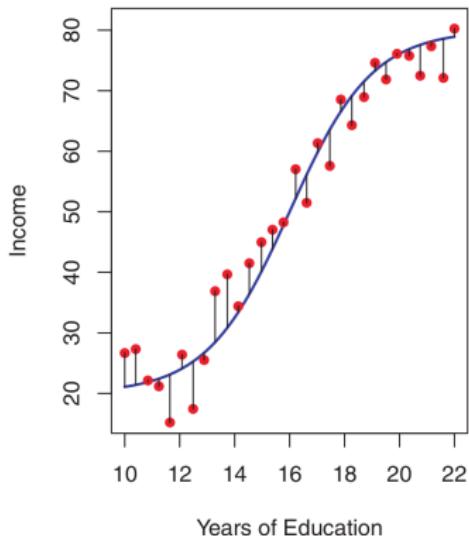
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An example of errors; Specifically the black lines represent the error associated with each instance (James et al., 2013)

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

$$J(\theta) =$$

=

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The Goal: How do we minimize **the cost function?**

We need **Calculus.**

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

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



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



Machine Learning Component: Cost Function (3/3)

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

$$\arg \min_{\theta_0, \theta_1} \left\{ \frac{1}{2 \times 97} \sum_{i=1}^{97} \left(\theta_0 + \theta_1 x_1^{(i)} - y^{(i)} \right)^2 \right\}.$$

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

We need an **Optimization Algorithm**.



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A famous optimization algorithm:

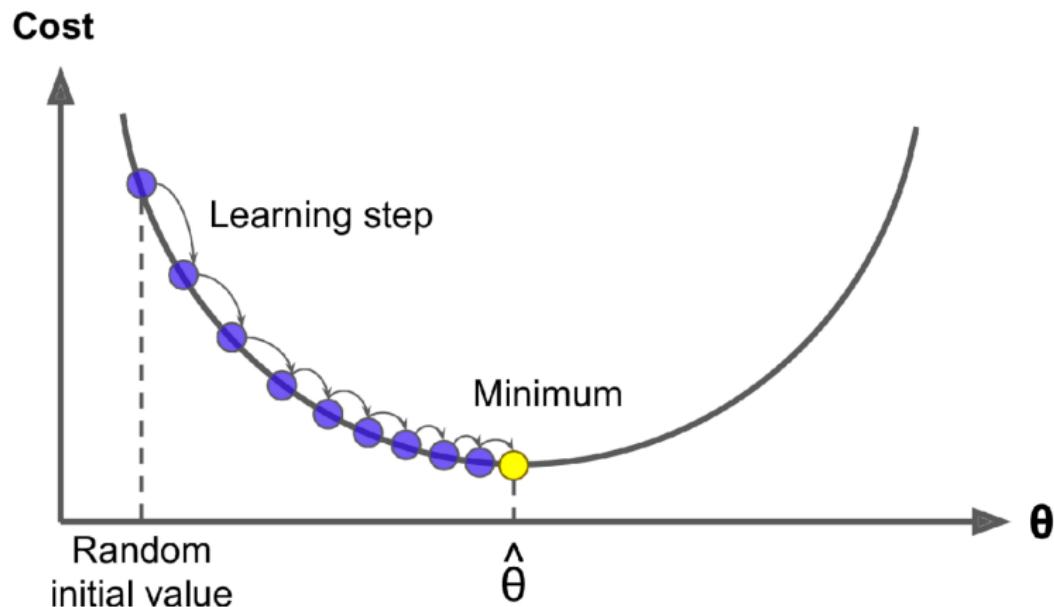


A famous optimization algorithm: **Gradient Descent**



ML Component: Optimization Algorithm (1/7)

A famous optimization algorithm: **Gradient Descent**



Gradient descent in action (Géron, 2019)

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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:

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

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

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

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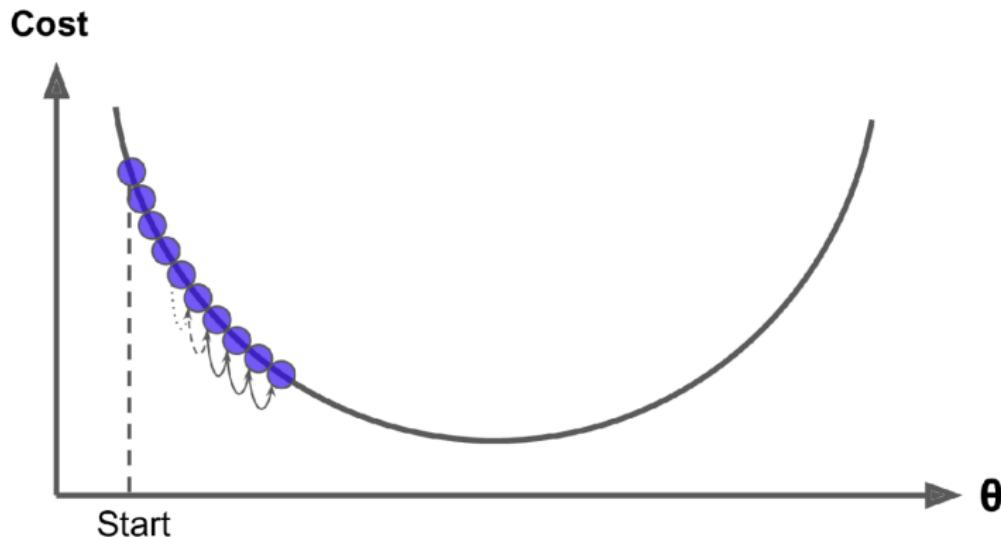
ML Component: Optimization Algorithm (6/7)

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



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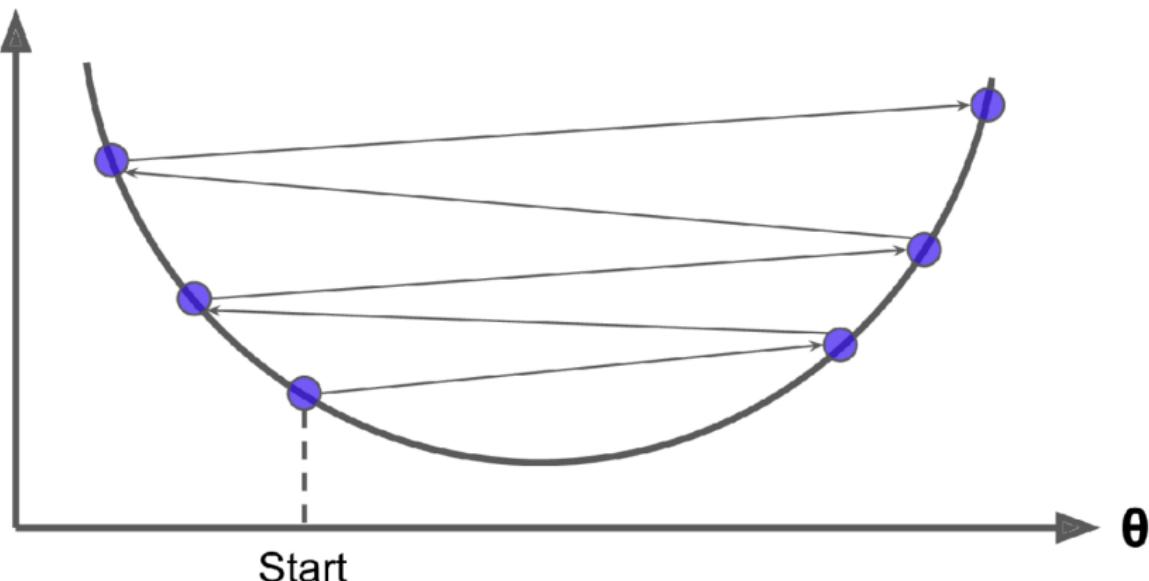
This will happen when the α is too small (Géron, 2019)

What happens when α is too large?

ML Component: Optimization Algorithm (7/7)

What happens when α is too large?

Cost



This will happen when α is too large (Géron, 2019)

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- 2 Machine Learning
- 3 Example: Predicting Profits of Food Trucks
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We show a *Linear Regression* as our Machine Learning demo¹.



¹<https://www.coursera.org/learn/machine-learning>

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Importance of Interpretability

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



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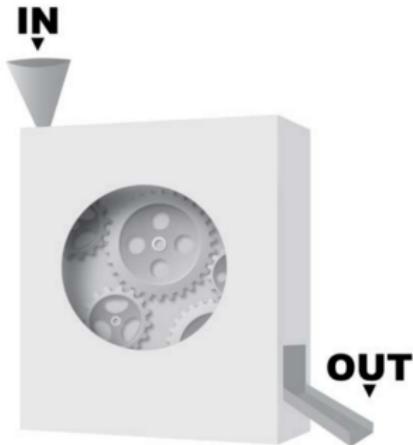
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Example: A machine learning model for OCR that processes images from envelopes and extracts addresses.



The Black Box of Machine Learning (Manpreet, 2019)



White Box vs Black Box (Masís, 2021)



White Box Model

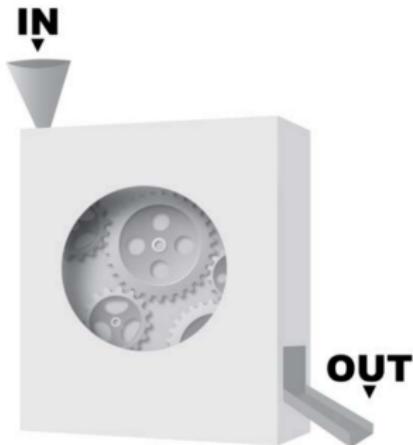
Has simple mechanisms



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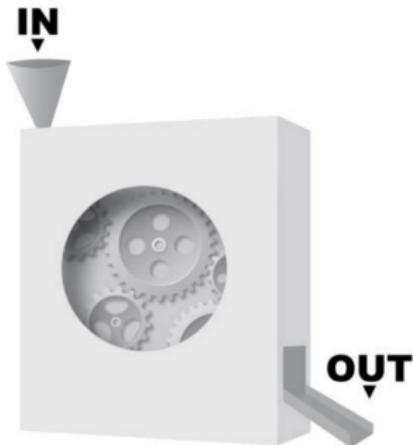


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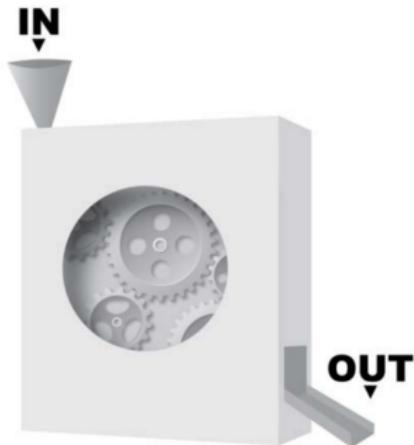


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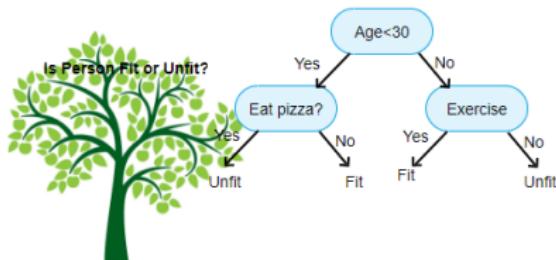
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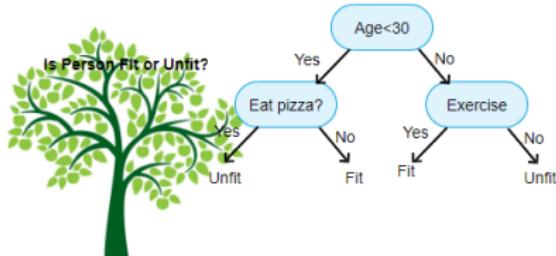
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An example of a decision tree (Chavan, 2019)

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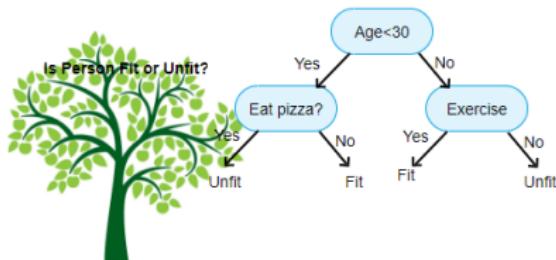
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A famous example comes from James et al. (2013).



Interpretable Models (3/3)

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



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Example of Interpretable Model: Dataset (1/3)

²<https://www.capitalbikeshare.com>

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- Temperature in degrees Celcius
- Relative humidity in percent (0 to 100)



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

Here are the *nine features* that are used:

- Count of bicycles $\Rightarrow y$
- The season, either spring, summer, fall, or winter
- Indicator whether the day was a holiday or not
- Number of days since the 01.01.2011 (the first day in the dataset)
- Indicator whether the day was a working day or weekend
- The weather situation on that day: good, misty, or rain/snow/storm
- 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
##  Max.   :8714

##      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 learned relationships between X and y are **linear** and can be written for a single instance i as follows:



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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** → each instance is *independent* of any other instance.



Outline

- 1 Introduction
- 2 Machine Learning
- 3 Example: Predicting Profits of Food Trucks
- 4 A Machine Learning Component: Data
- 5 A Machine Learning Component: Model/Hypothesis
- 6 A Machine Learning Component: Cost/Loss Function
- 7 A Machine Learning Component: Optimization Algorithm
- 8 Demo from Stanford Machine Learning
- 9 Interpretability
- 10 Interpretable Models
- 11 Example of an Interpretable Model
- 12 Example: How to Interpret the Model
- 13 Conclusion

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

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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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- 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 \implies any interpretation of the weights would not be meaningful.



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The importance of a feature (**feature importance**) in a linear regression model can be measured by



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The importance of a feature \uparrow , the weight also \uparrow .



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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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 ($|t|$)

Bike Rentals: Interpretation (2/2)

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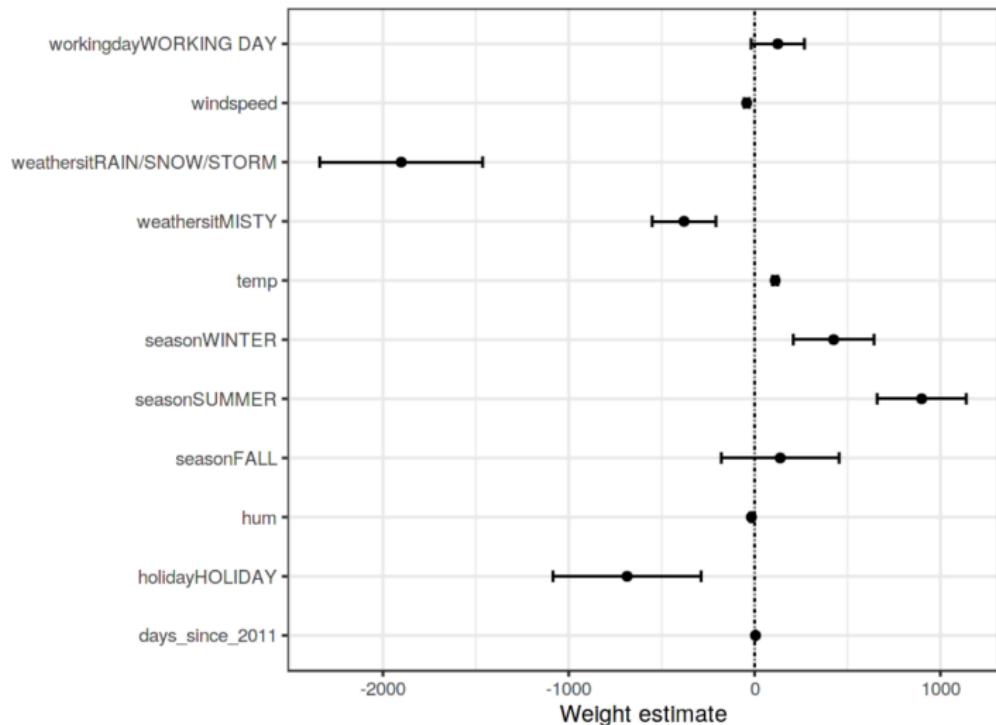


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- **Interpretation of a categorical feature ("weathersit"):** The estimated number of bicycles is -1901.5 lower when it is raining, snowing or stormy, compared to good weather—again *assuming that all other features do not change.*



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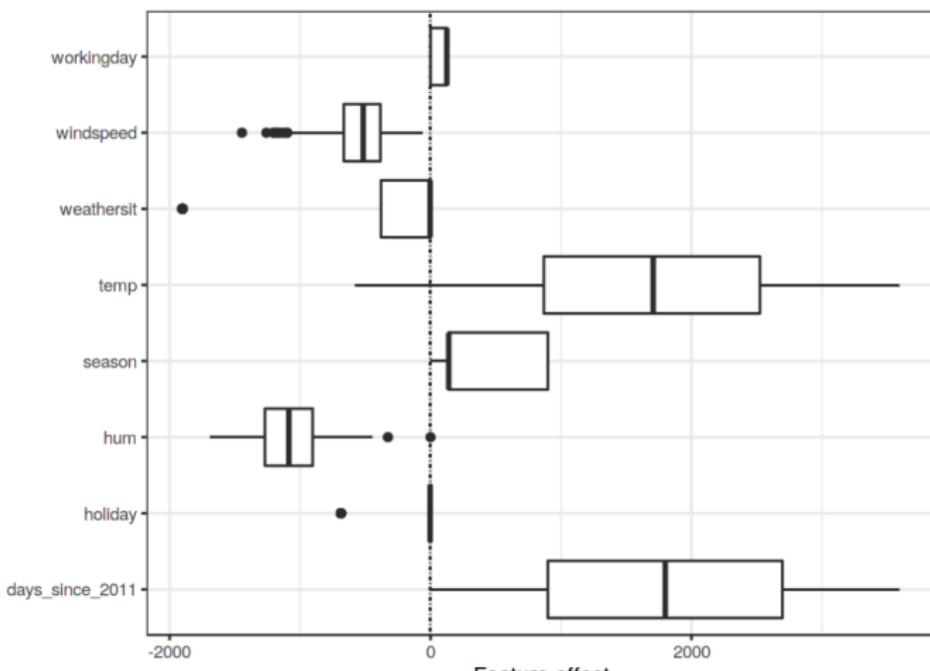
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- The effects can be visualized with **boxplots**.



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

Visual Interpretation: Effect Plot (3/3)

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Visual Interpretation: Effect Plot (3/3)

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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



Explain Individual Predictions (2/4)

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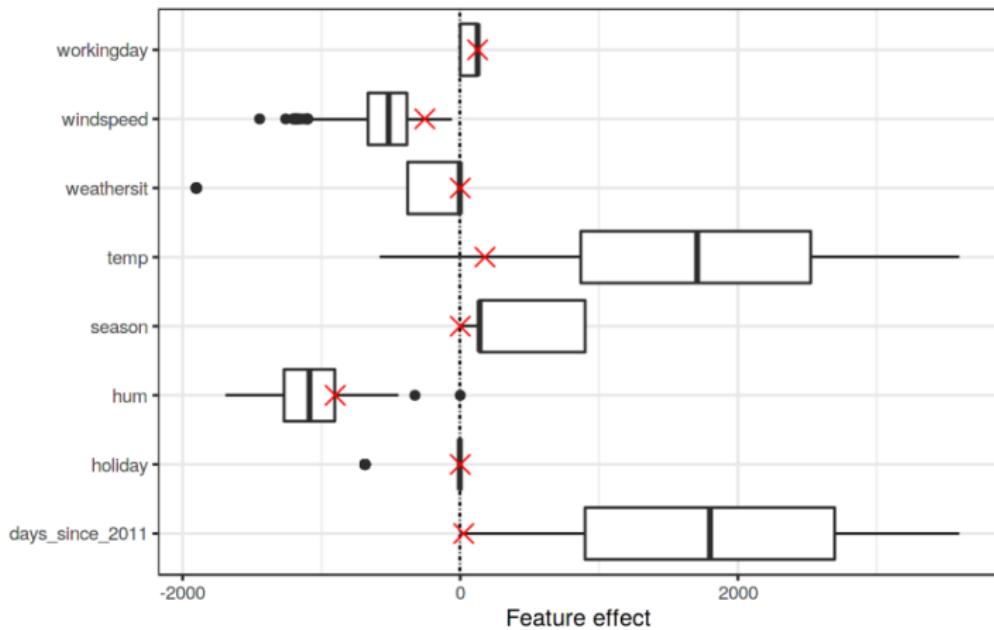
- For the value "WORKING DAY" of feature "workingday", the effect is 124.9 (124.9×1).
- For a temperature of 1.6 degrees Celcius, the effect is 177.6 (1.604356×110.7096).



Explain Individual Predictions (3/4)

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Predicted value for instance: 1571
Average predicted value: 4504
Actual value: 1606



The effect plot for the 6-th instance is labeled cross ×

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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.

Outline

- 1 Introduction
- 2 Machine Learning
- 3 Example: Predicting Profits of Food Trucks
- 4 A Machine Learning Component: Data
- 5 A Machine Learning Component: Model/Hypothesis
- 6 A Machine Learning Component: Cost/Loss Function
- 7 A Machine Learning Component: Optimization Algorithm
- 8 Demo from Stanford Machine Learning
- 9 Interpretability
- 10 Interpretable Models
- 11 Example of an Interpretable Model
- 12 Example: How to Interpret the Model
- 13 Conclusion

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

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*Thank
you*



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