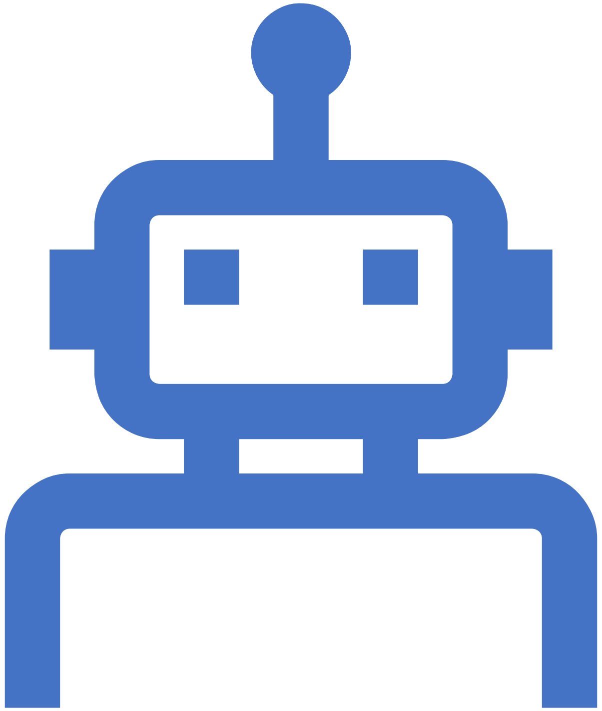


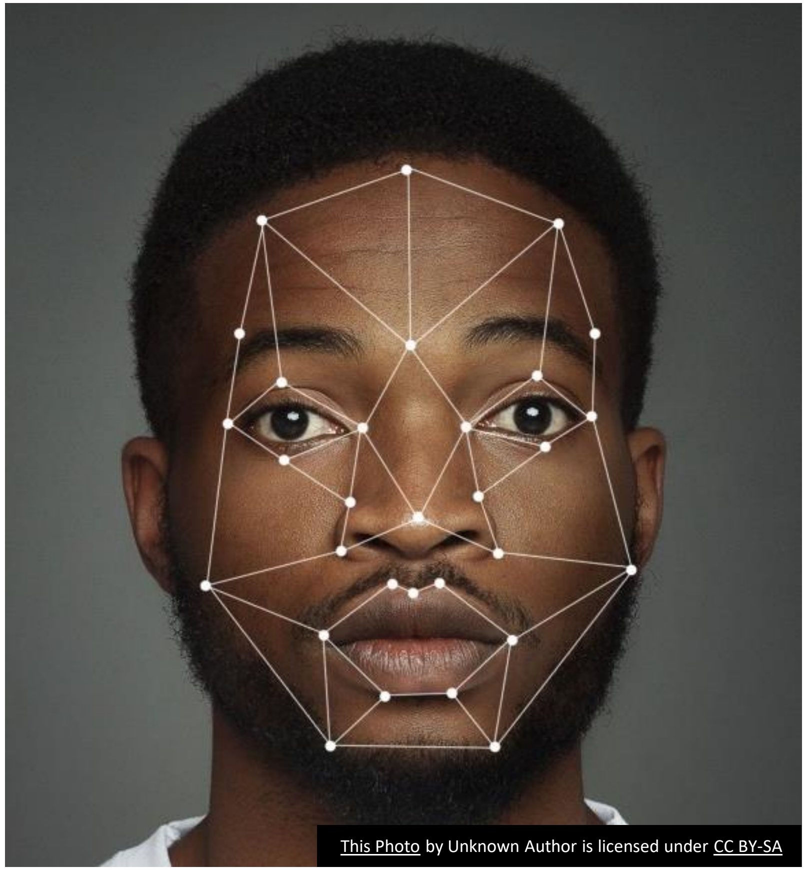
SOC 121D: People Analytics

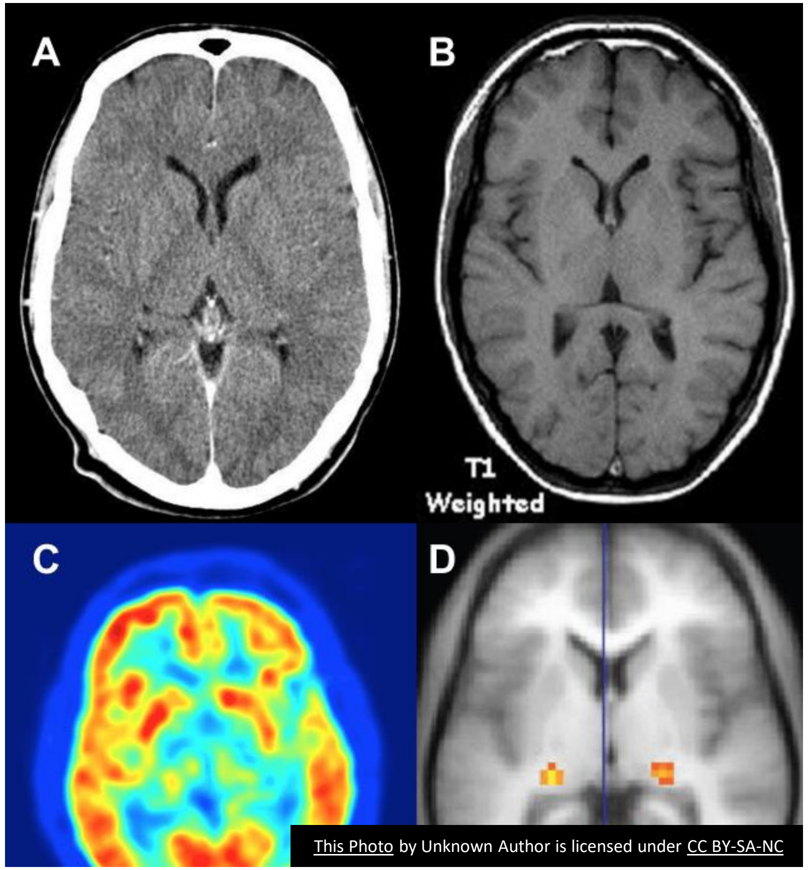
Austin van Loon

Machine Learning 1

Overview for this week

- Today – Machine learning 1
  - What is machine learning?
  - Machine learning basics and terminology
  - Introduce three families of algorithms
- Thursday – Machine Learning 2
  - Sources of bias in machine learning
  - Conceptualizing/Measuring Fairness
  - Predictive algorithms and inequality
  - In-class exercise (hopefully)
- Methods Module 1
  - Available now on Canvas
  - Provides more technical walk-through of methods and hands-on examples
  - Coding requirements are minimal (mostly copy and pasting)
  - Turn in before start of class next Tuesday, 7/5

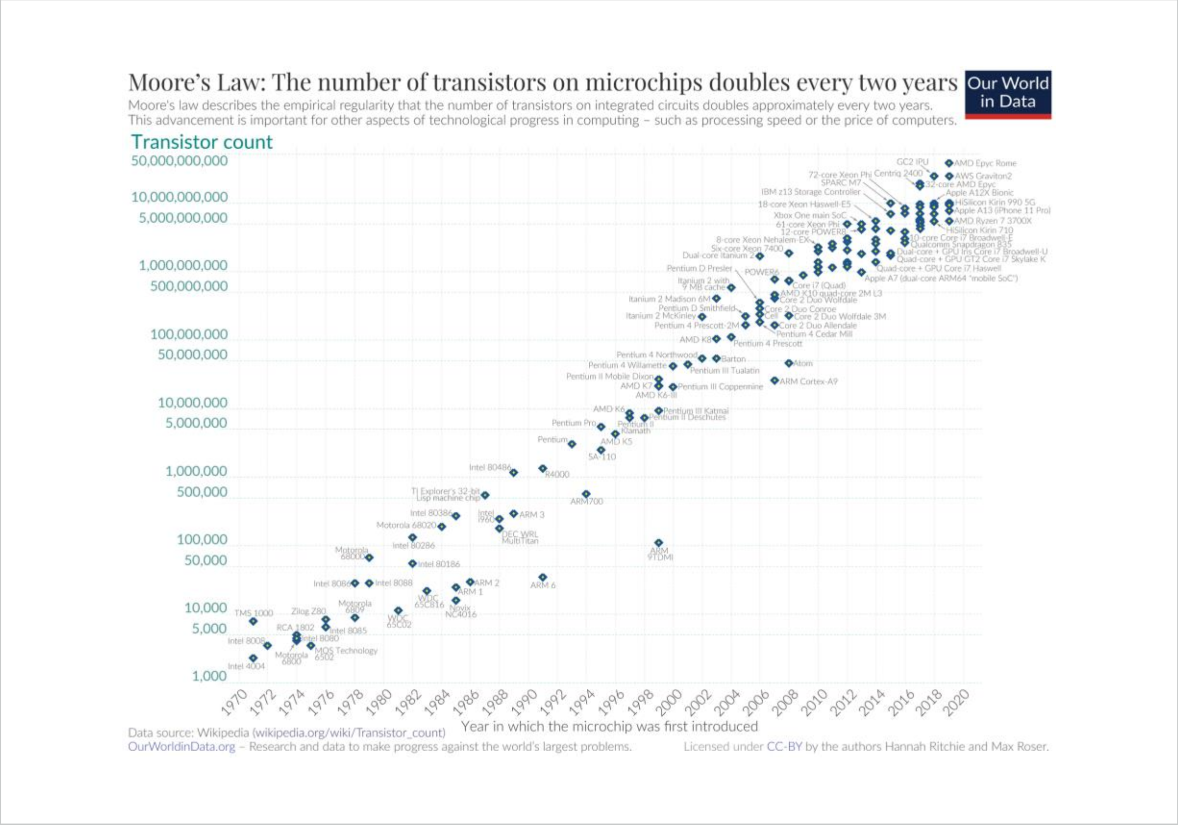


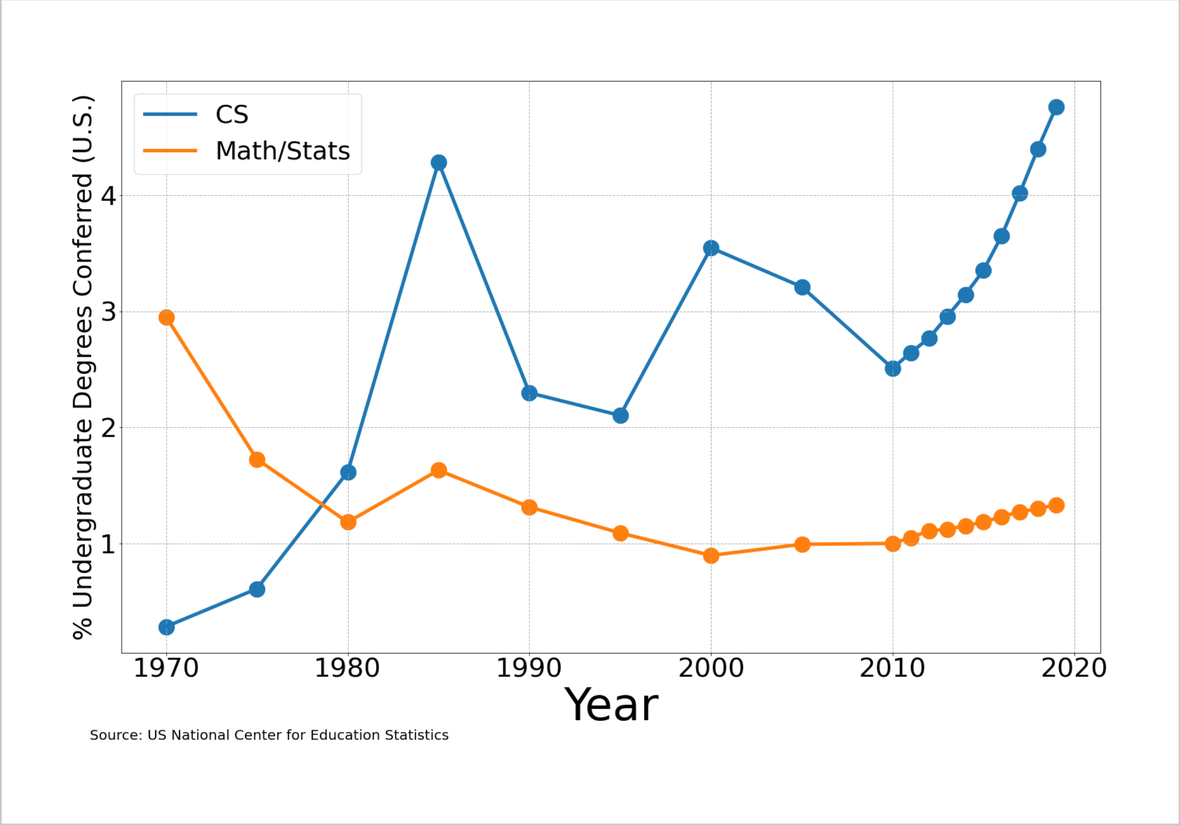


What is machine learning (ML)?

Why the rise of machine learning?

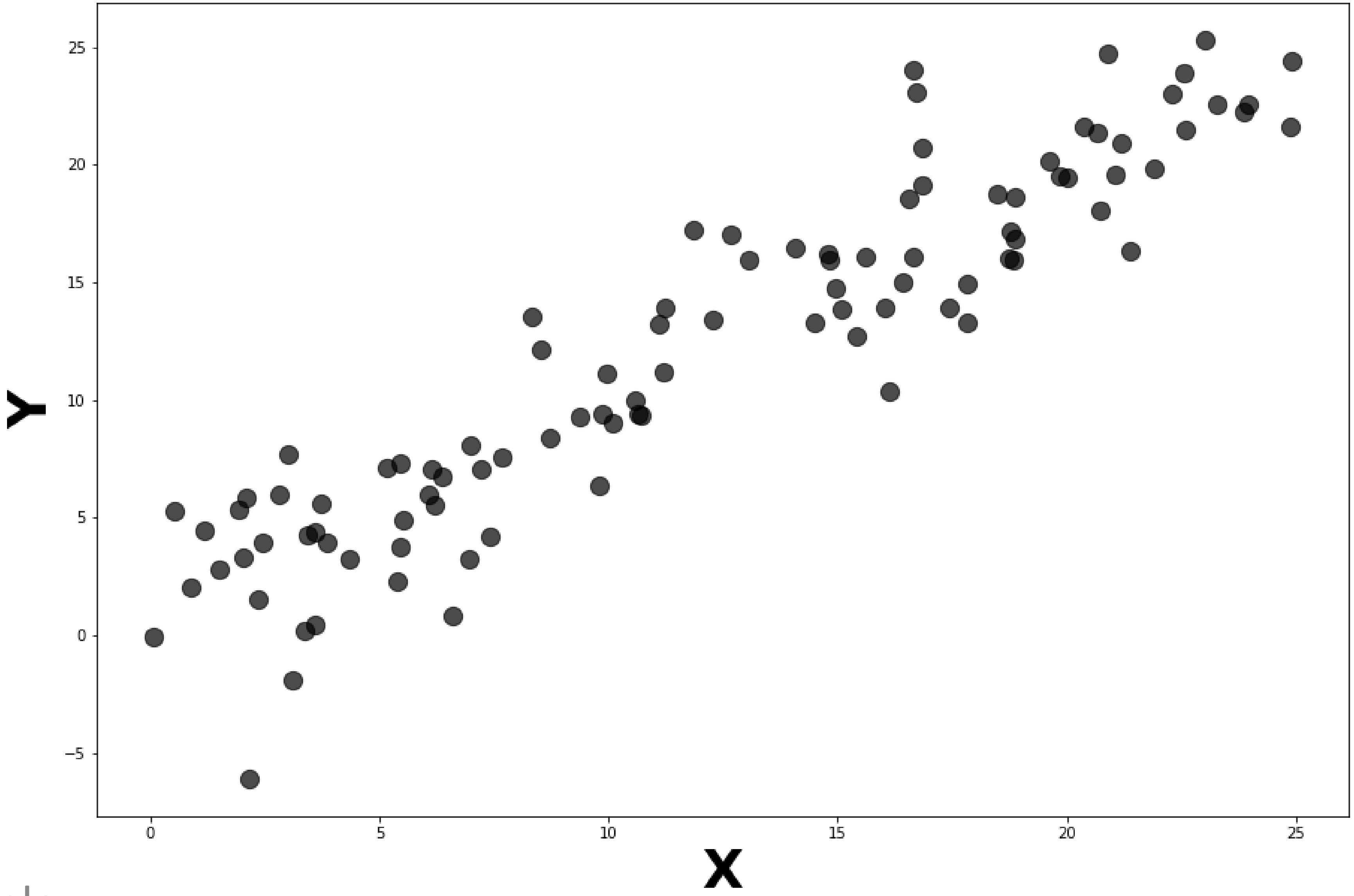
- Increased computational resources (Moore's Law)
- Prevalence of specialized knowledge (CS departments, YouTube)
- Strong economic incentives
- Highly legitimate (maybe too legitimate…)



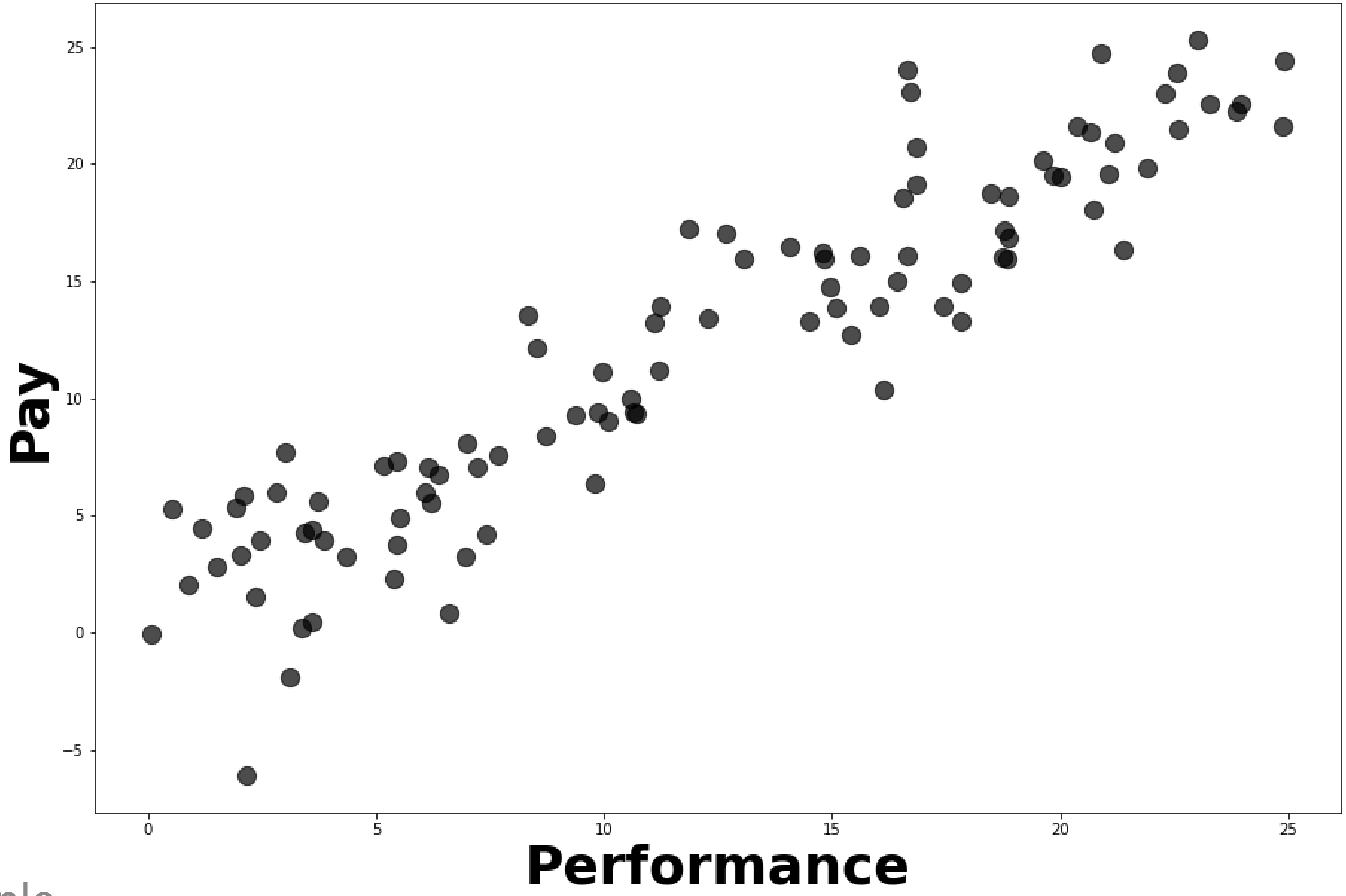


Philosophy of ML

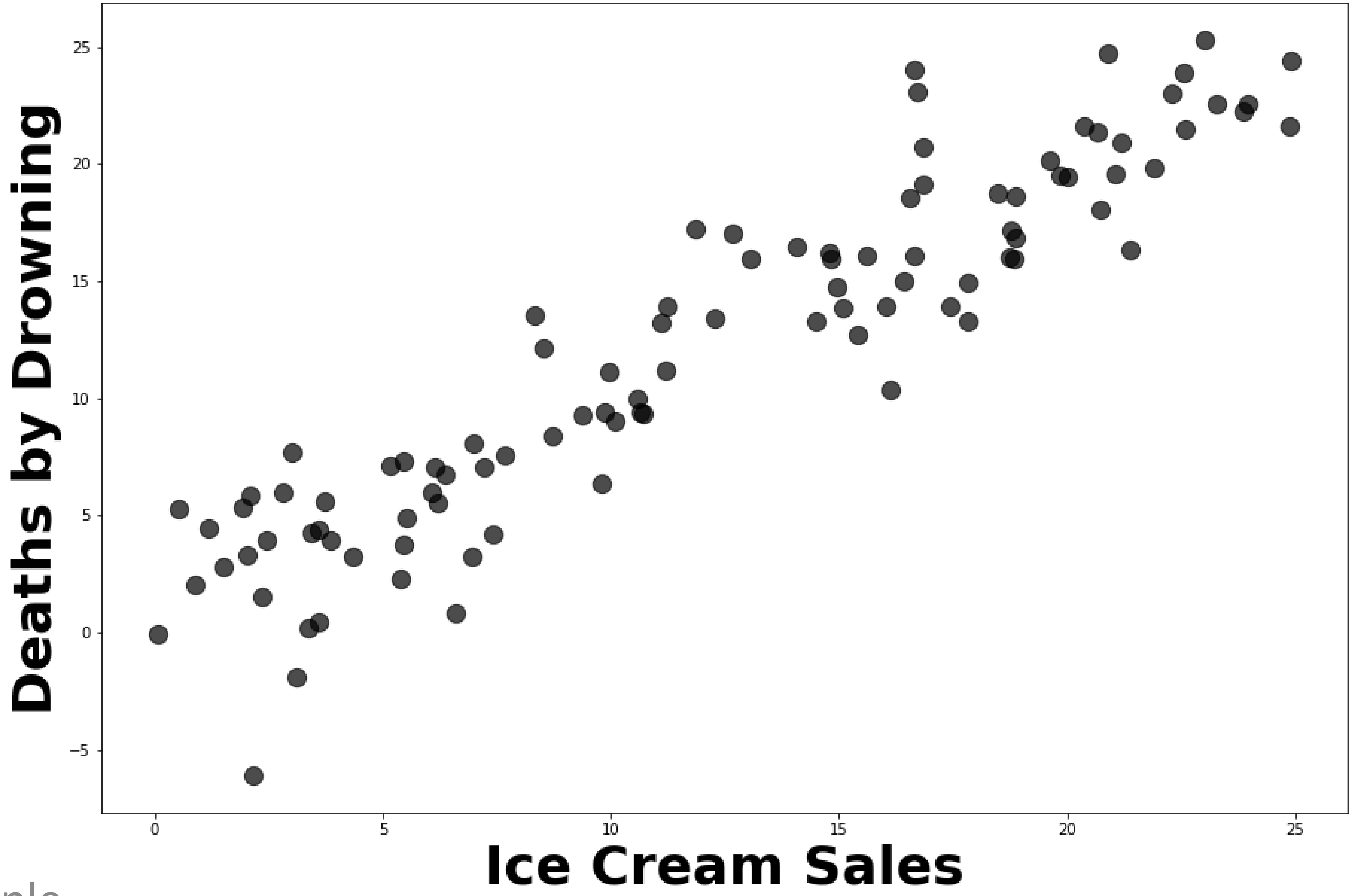
- **Correlation** is the empirical tendency for two or more variables to "move together" in a specific way
- **Causation** is the relationship between two variables that changing one will change the other.
- **Prediction** is the ability to reliably estimate the value of one variable from another (better than chance).



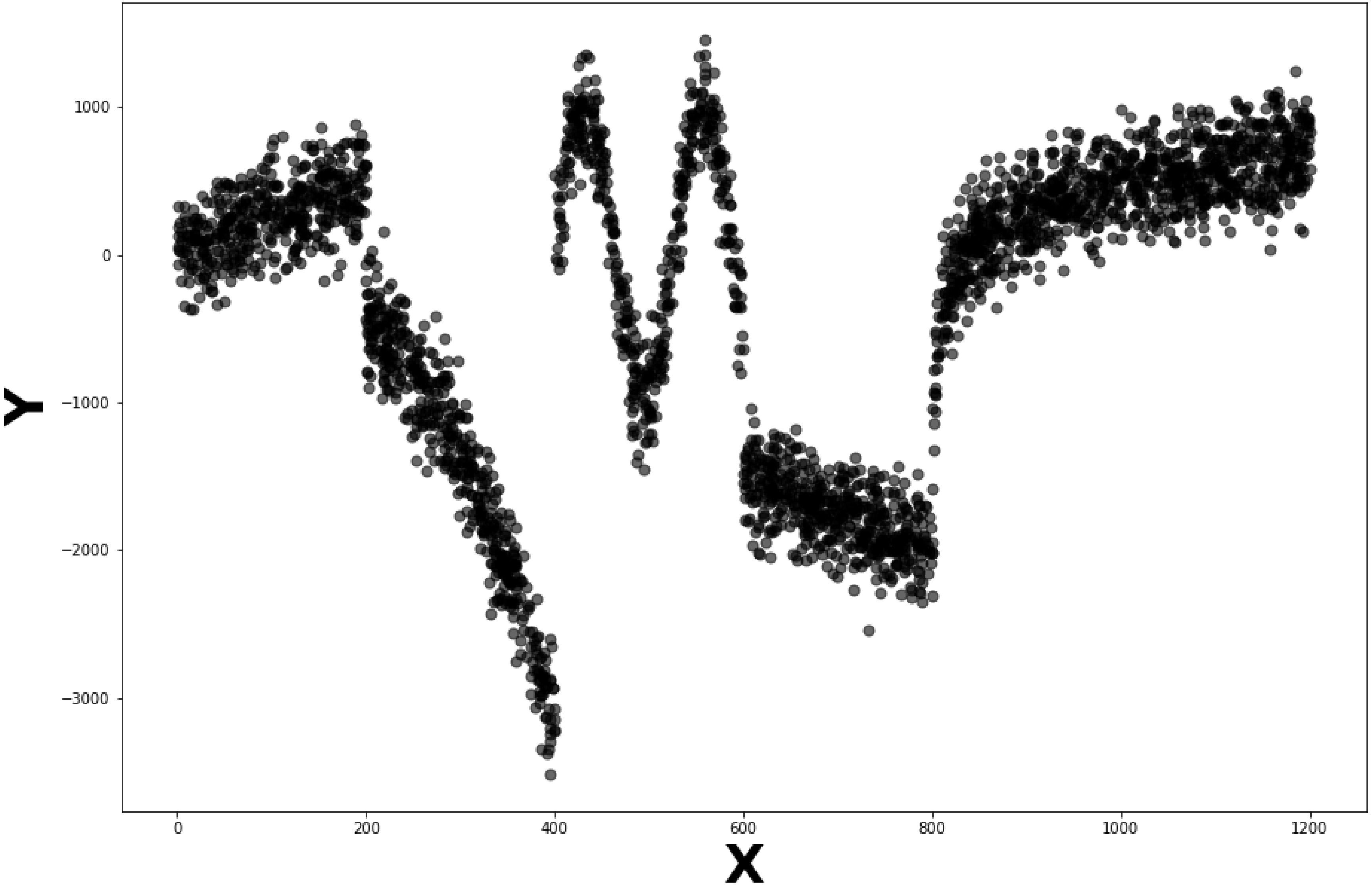
Correlation example



Correlation example



Correlation example



Prediction example

Statistical Science
2001, Vol. 16, No. 3, 199–231

Statistical Modeling: The Two Cultures

Leo Breiman

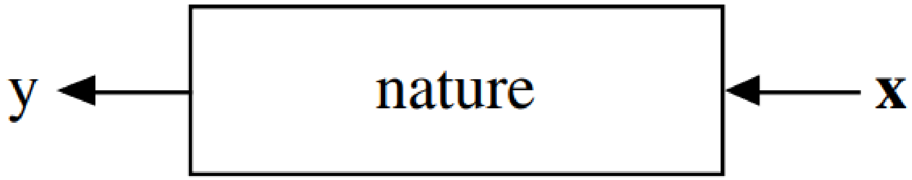
What we observe

Statistical Science
2001, Vol. 16, No. 3, 199–231

Statistical Modeling: The Two Cultures

Leo Breiman

What we observe



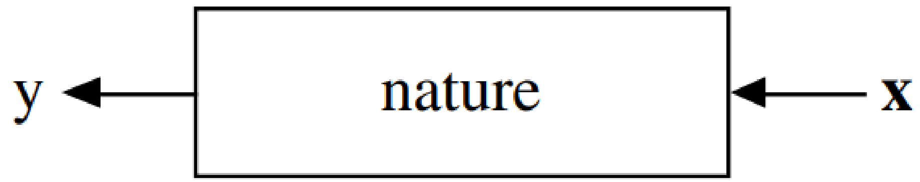
Data modeling culture

Statistical Science
2001, Vol. 16, No. 3, 199–231

Statistical Modeling: The Two Cultures

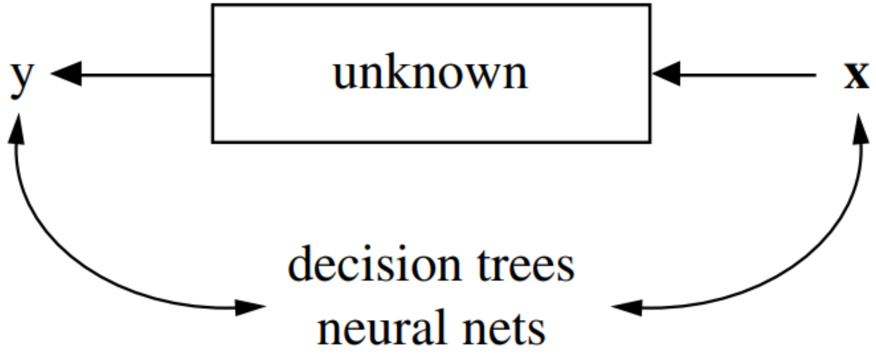
Leo Breiman

What we observe



Data modeling culture

Algorithmic modeling culture



Some ML vocabulary

- **Observation** – a record or datum (e.g., a single employee)
- **Dataset** – A collection of observations
- **Feature(s)** – the characteristic(s) of observations used to predict something
- **Outcome(s)** – the characteristic(s) of observations we want to predict

Some ML vocabulary

Name	Pay	Married?	Job	Age
Rachel	$32k	No	Server	24
Ross	$140k	No	Professor	26
Joey	$350k	No	Actor	25
Monica	$70k	Yes	Chef	24
Chandler	$120k	Yes	Data Specialist	26
Phoebe	$400k	No	Songwriter	26

Some ML vocabulary

Dataset

Name	Pay	Married?	Job	Age
Rachel	$32k	No	Server	24
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Monica	$70k	Yes	Chef	24
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Observations

Some ML vocabulary

Outcome

Features

Name	Pay	Married?	Job	Age
Rachel	$32k	No	Server	24
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Some ML vocabulary

Features

Outcome

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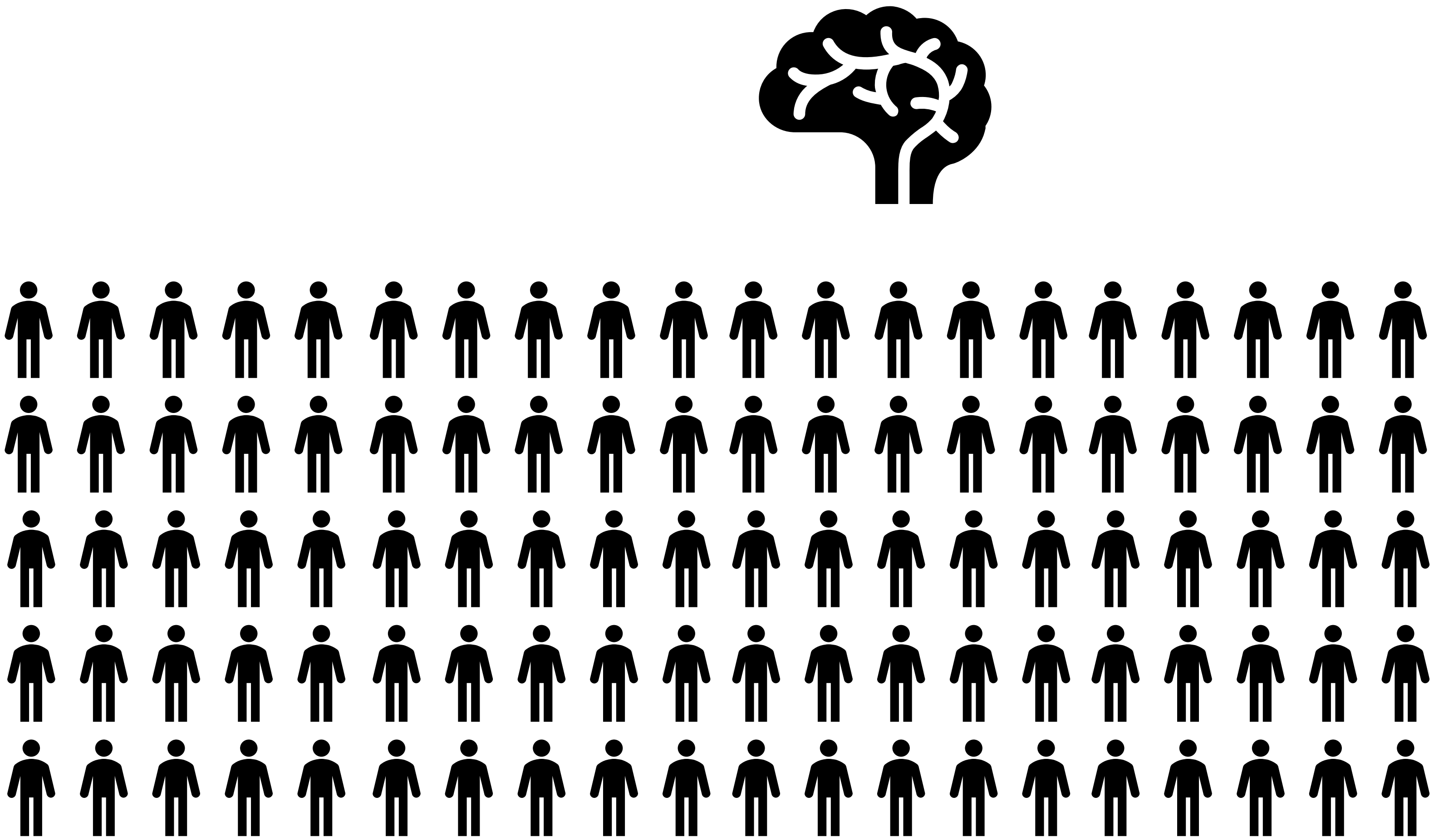
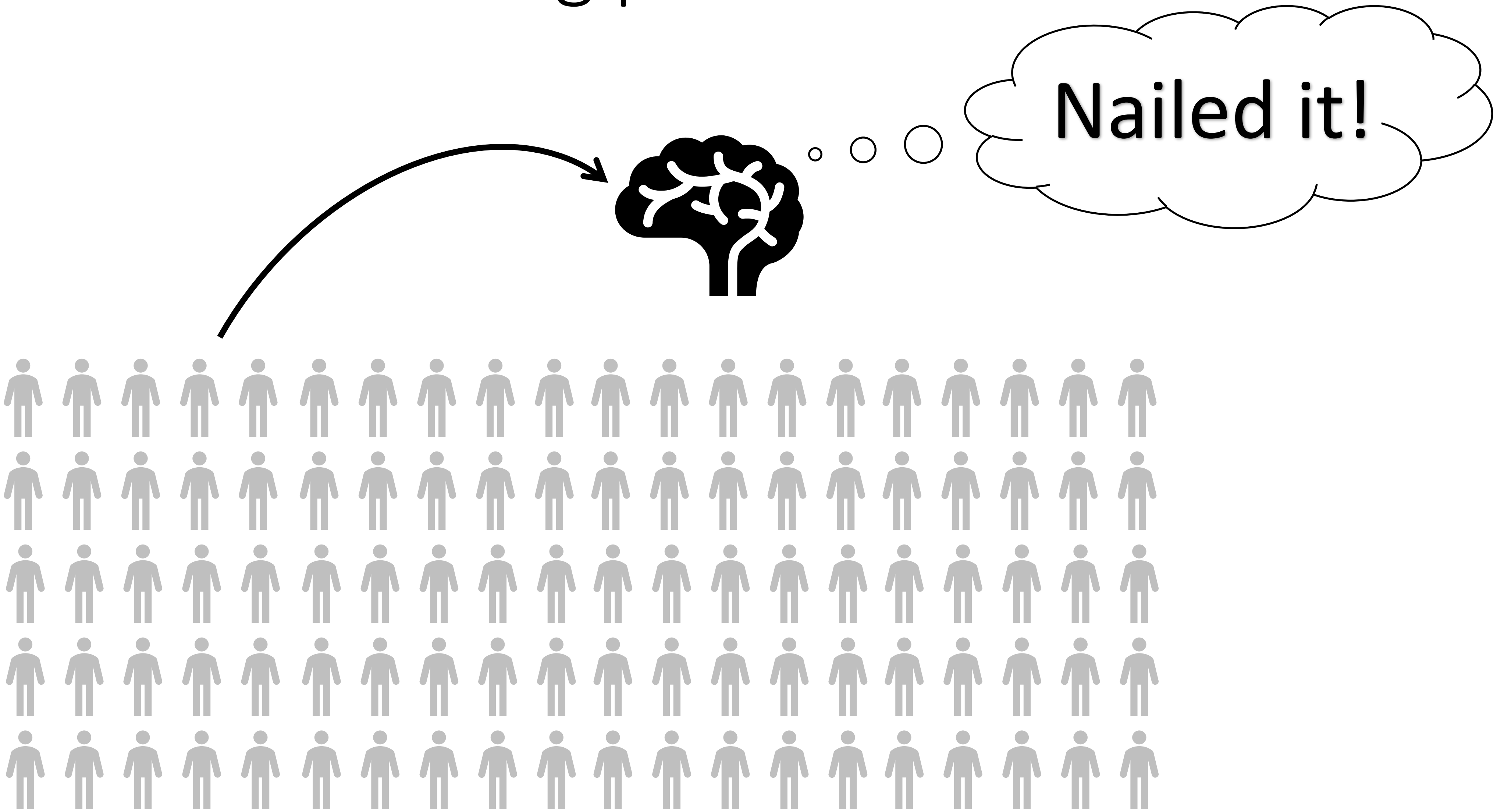
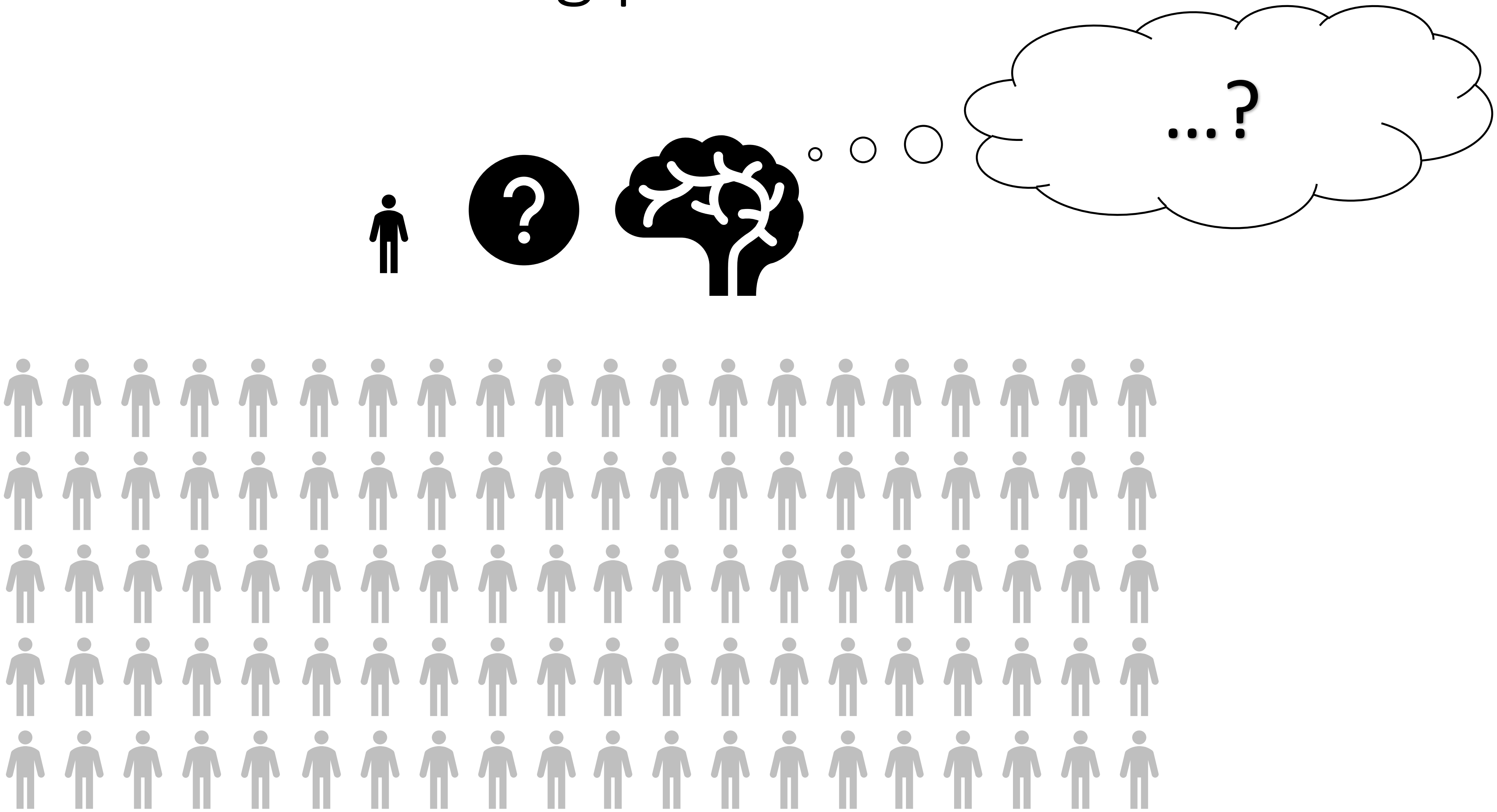
The practice: Assessing performance



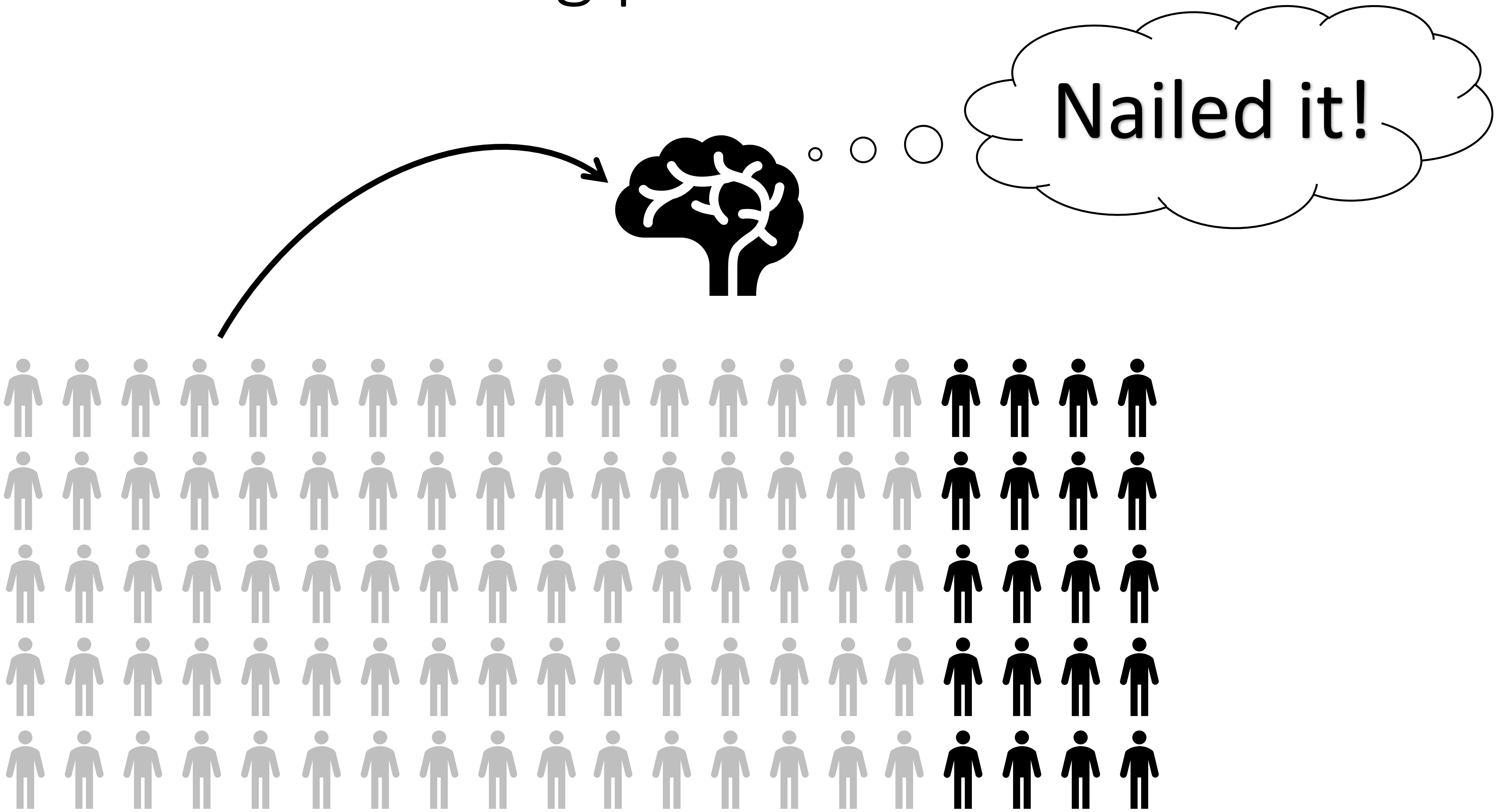
The practice: Assessing performance



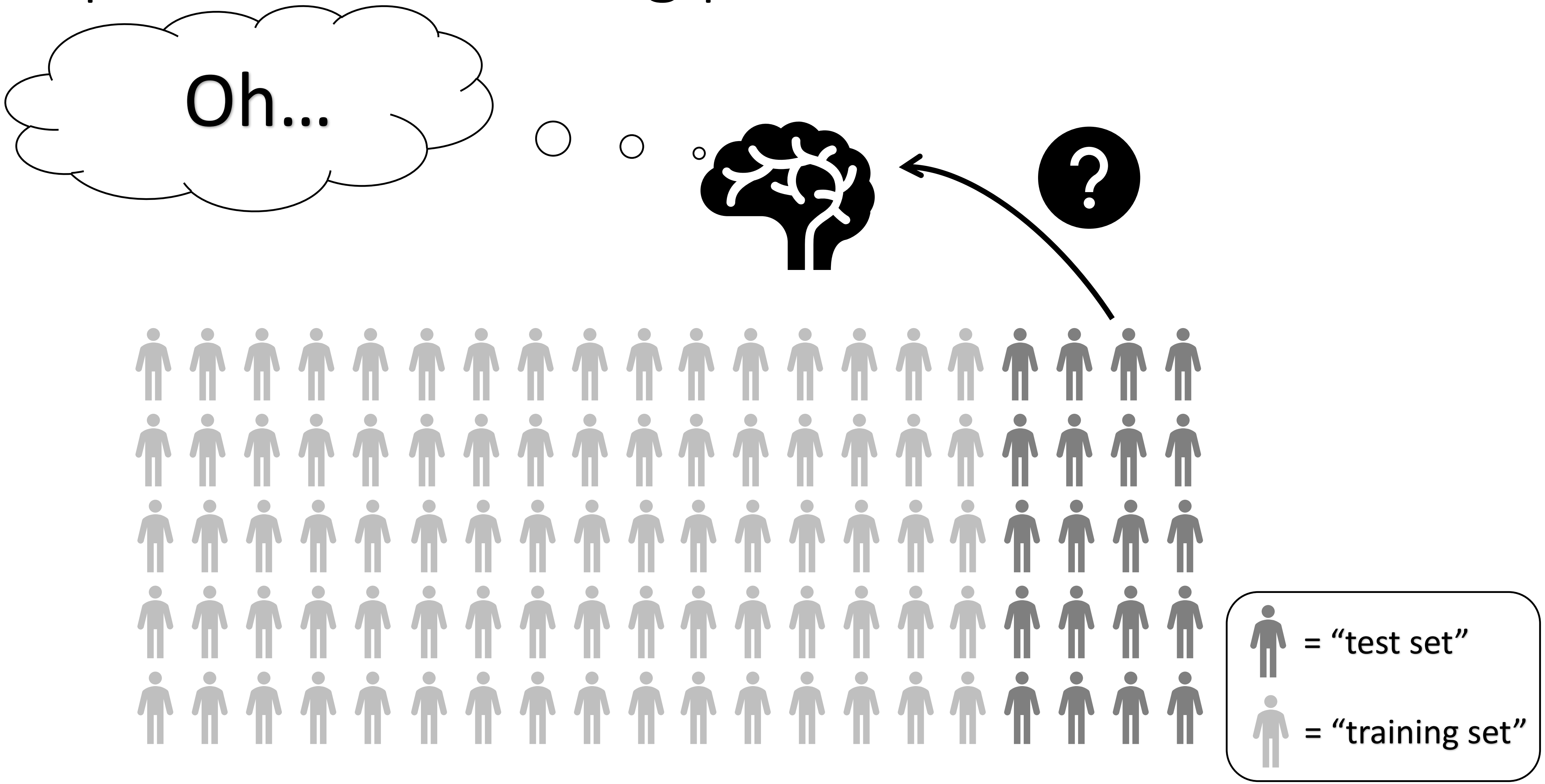
The practice: Assessing performance



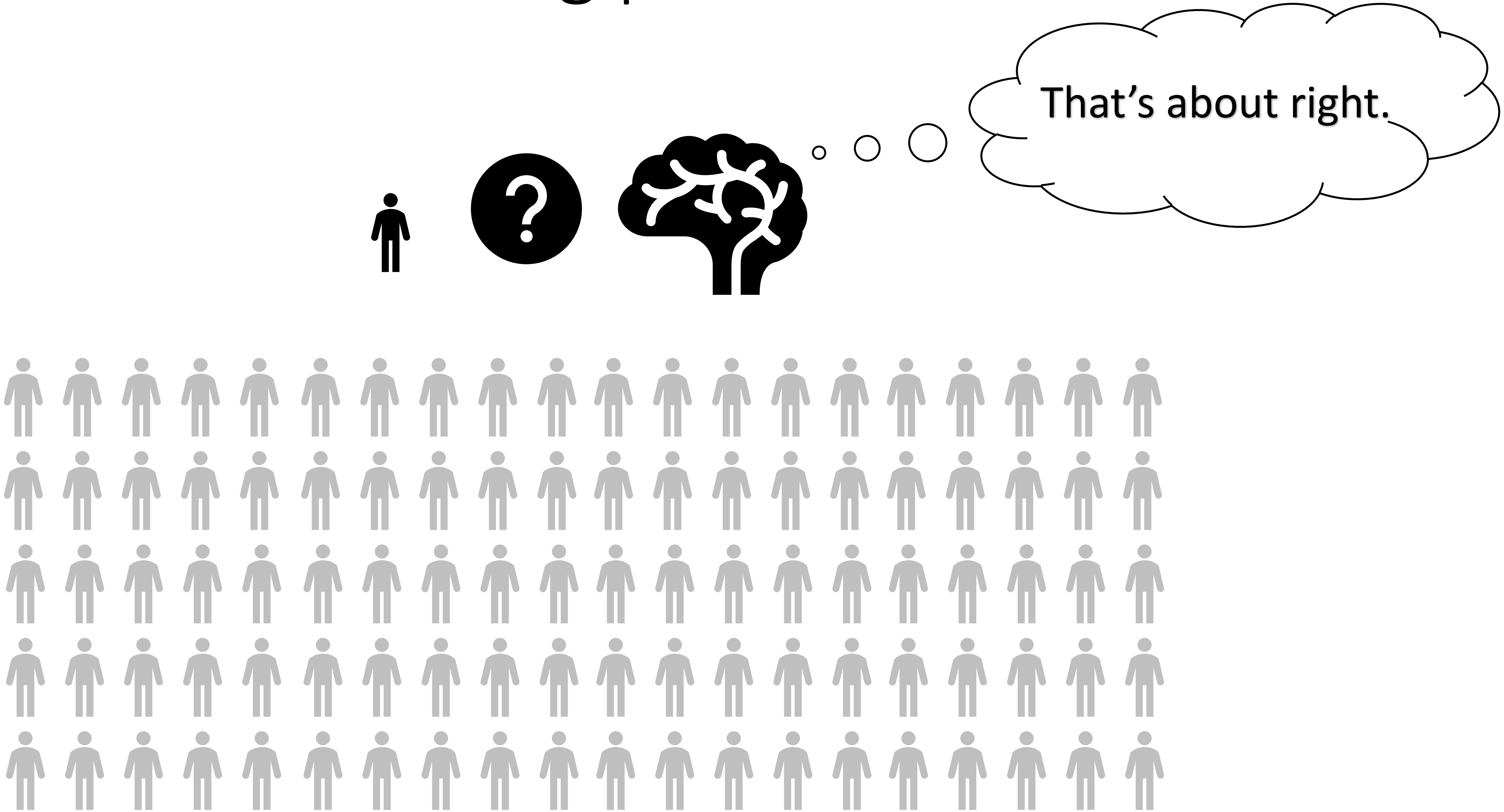
The practice: Assessing performance



The practice: Assessing performance



The practice: Assessing performance



The practice: Quantifying prediction

Binary outcomes

- Accuracy
- AUC scores

Continuous outcomes

- Mean absolute error
- Pearson correlation

The practice: Quantifying prediction

Binary outcomes

- Accuracy
- AUC scores

Continuous outcomes

- Mean absolute error and mean squared error
- Pearson correlation

	Actually Positive	**Actually Negative**
Predicted Positive		
Predicted Negative		

Accuracy

	Actually Positive	**Actually Negative**
Predicted Positive	True positive	False positive
Predicted Negative	False negative	True negative

Accuracy

	Actually Positive	Actually Negative
Predicted Positive	**True positive**	False positive
Predicted Negative	False negative	**True negative**

Accuracy

$$Accuracy = \frac{True\ positive + True\ negative}{Number\ of\ observations}$$

	Actually Positive	**Actually Negative**
Predicted Positive	200	50
Predicted Negative	50	200

Accuracy

$$Accuracy = ?$$

	Actually Positive	Actually Negative
Predicted Positive	**200**	50
Predicted Negative	50	**200**

Accuracy

$$Accuracy = \frac{TP + TN}{N} = \frac{200 + 200}{200 + 50 + 50 + 200} = \frac{400}{500} = \mathbf{0.8}$$

	Actually Positive	**Actually Negative**
Predicted Positive	0	0
Predicted Negative	100	400

Accuracy

$$Accuracy = ?$$

	Actually Positive	**Actually Negative**
Predicted Positive	**0**	0
Predicted Negative	100	**400**

Accuracy

$$Accuracy = \frac{TP + TN}{N} = \frac{400 + 0}{400 + 100} = \frac{400}{500} = \mathbf{0.8}$$

When Accuracy seems inaccurate

- If one outcome is very common, accuracy is easy to achieve
- This can be manually examined or tested
- Other metrics (F1 score, precision or recall, chi-square) can be more useful in these situations
- Alternatively, you can compare to a “baseline model”

The practice: Quantifying prediction

Binary outcomes

- Accuracy
- AUC

Continuous outcomes

- Mean absolute error
- Pearson correlation

Motivating AUC

1. Predicting who will fail the class (and ask them to come to office hours)
2. Predicting who will get COVID (and asking them to stay home from class)

Motivating AUC

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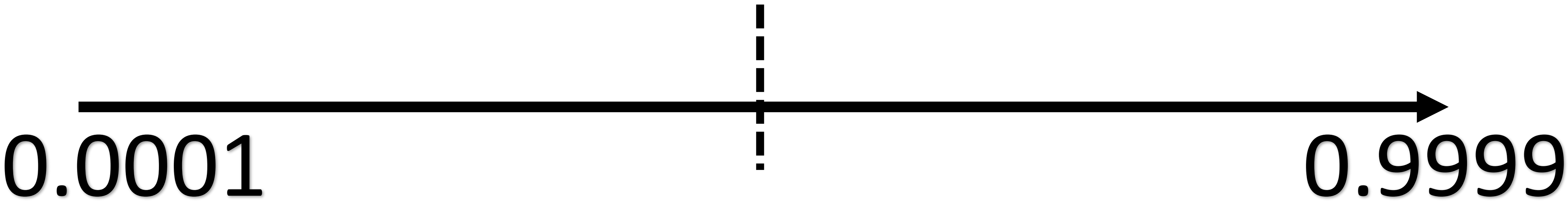
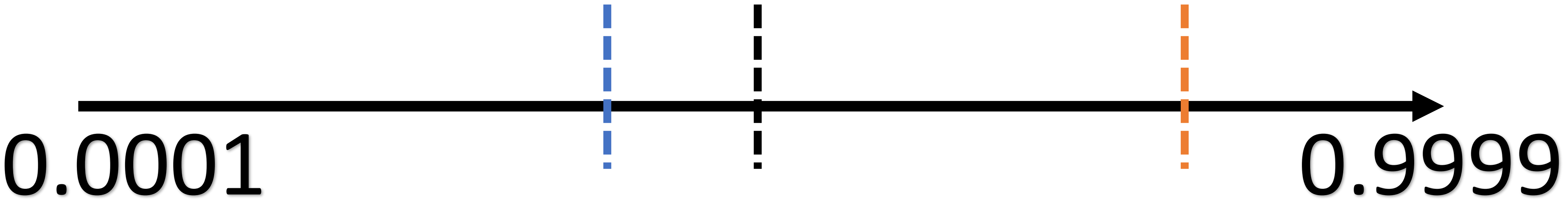


How sure are we that Y = 1?

Motivating AUC

1. Predicting who will fail the class (and ask them to come to office hours)
2. Predicting who will get COVID (and asking them to stay home from class)



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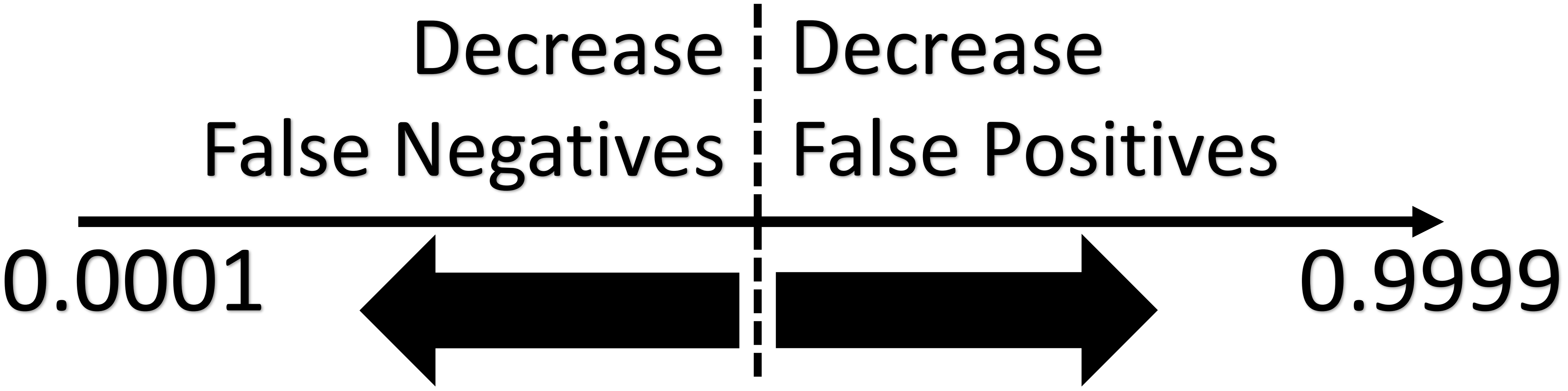
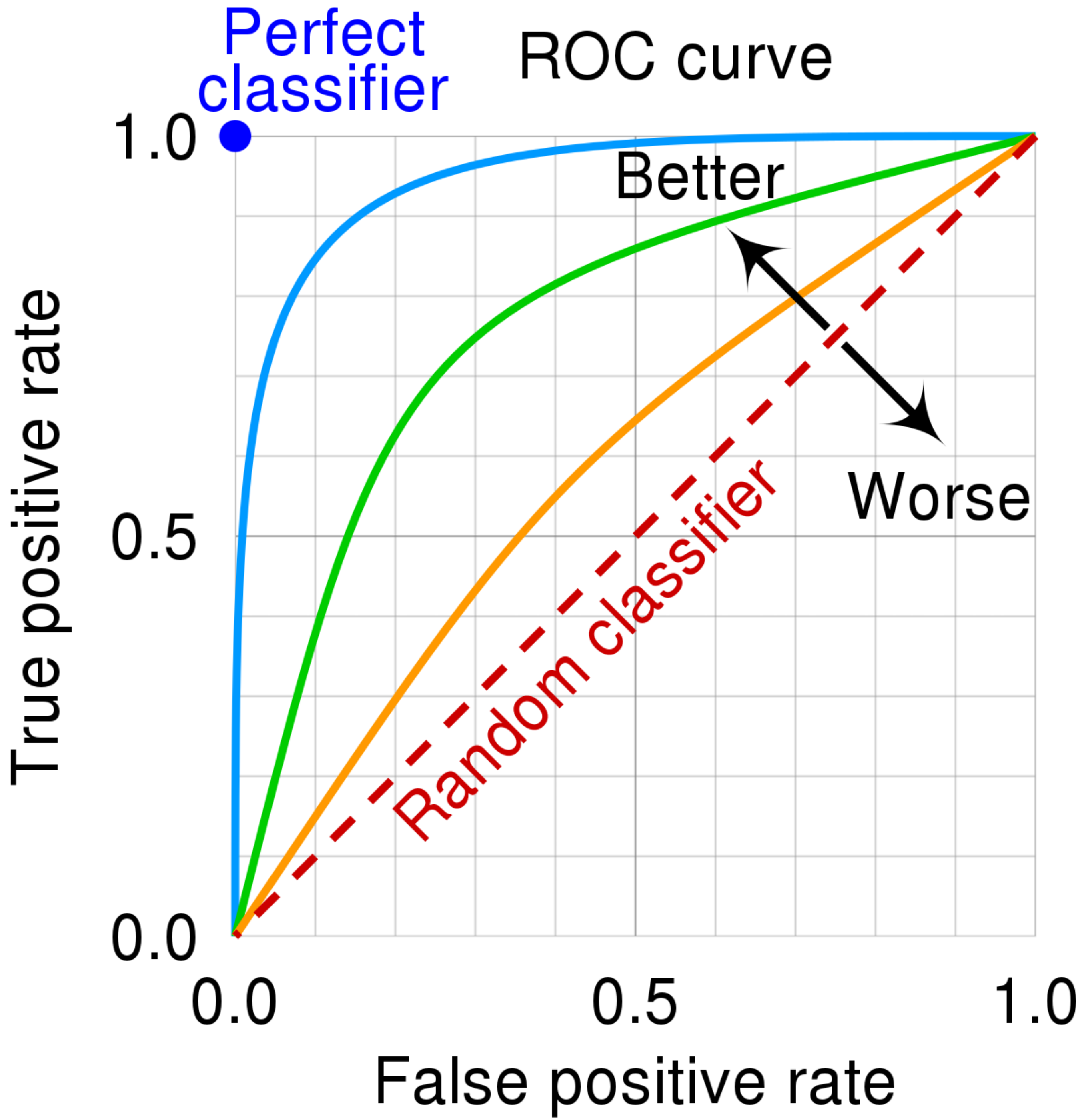
Motivating AUC



How sure are we that Y = 1?


Perfect classifier
ROC curve
1.0
Better
Worse
0.5
Random classifier
True positive rate
0.0
0.0
0.5
1.0
False positive rate

AUC

The practice: Quantifying prediction

Binary outcomes

- Accuracy
- AUC

Continuous outcomes

- Mean absolute error
- Pearson correlation

Mean absolute error

Pay	Age	Tenure (yrs)	Bachelors'?	Predicted Pay
$60k	35	2	Yes	$58k
$80k	45	27	No	$100k
$40k	19	1	No	$30k
$100k	53	20	No	$100k
$180k	52	3	Yes	$200k

Mean absolute error

Pay	Age	Tenure (yrs)	Bachelors'?	Predicted Pay	Error
$60k	35	2	Yes	$80k	$20k
$80k	45	27	No	$50k	-$30k
$40k	19	1	No	$30k	-$10k
$100k	53	20	No	$100k	$0
$180k	52	3	Yes	$200k	$20k

Mean absolute error

Average error = 0?

Pay	Age	Tenure (yrs)	Bachelors'?	Predicted Pay	Error
$60k	35	2	Yes	$80k	$20k
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Mean absolute error

Pay	Age	Tenure (yrs)	Bachelors'?	Predicted Pay	Error	Abs(Error)
$60k	35	2	Yes	$80k	$20k	$20k
$80k	45	27	No	$50k	-$30k	$30k
$40k	19	1	No	$30k	-$10k	$10k
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$180k	52	3	Yes	$200k	$20k	$20k

Mean absolute error

Average error = $16k

Pay	Age	Tenure (yrs)	Bachelors'?	Predicted Pay	Error	Abs(Error)
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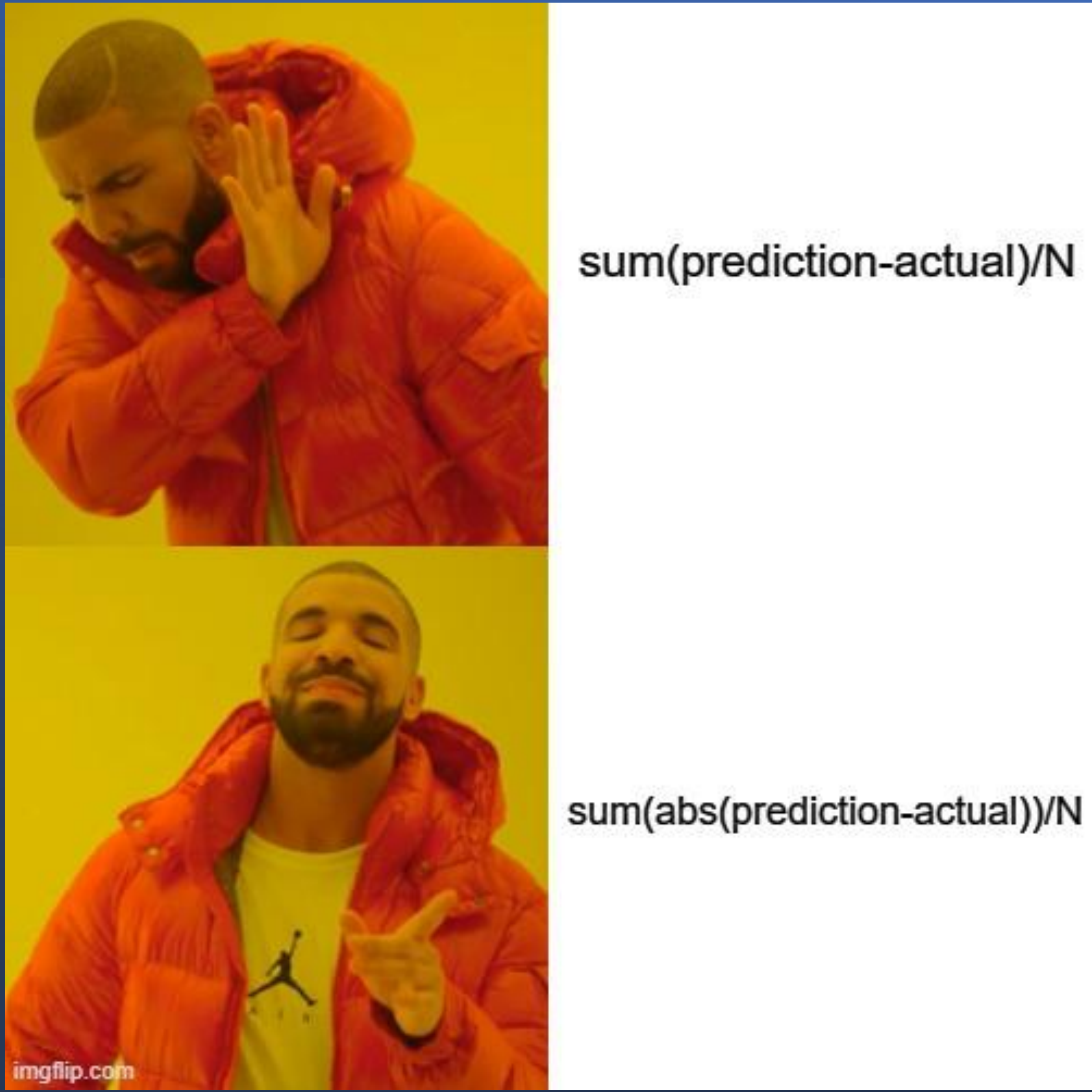
sum(prediction-actual)/N
sum(abs(prediction-actual))/N
imgflip.com

The practice: Quantifying prediction

Binary outcomes

- Accuracy
- AUC

Continuous outcomes

- Mean absolute error
- Pearson correlation

Evaluation	Lines of code	Days late	Pred. evaluation
-1	80	8	-0.8
1.3	105	3	1.5
0.1	95	4	0
-2	30	12	-2.1
…	…	…	
0.5	100	1	0.7

Evaluation	Lines of code	Days late	Pred. evaluation
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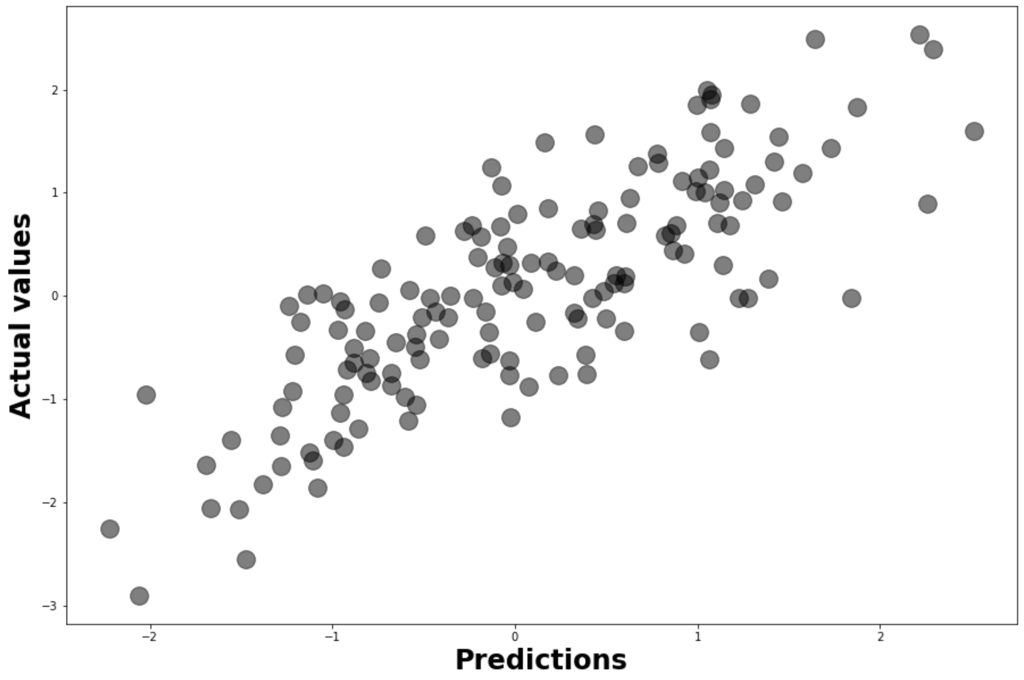

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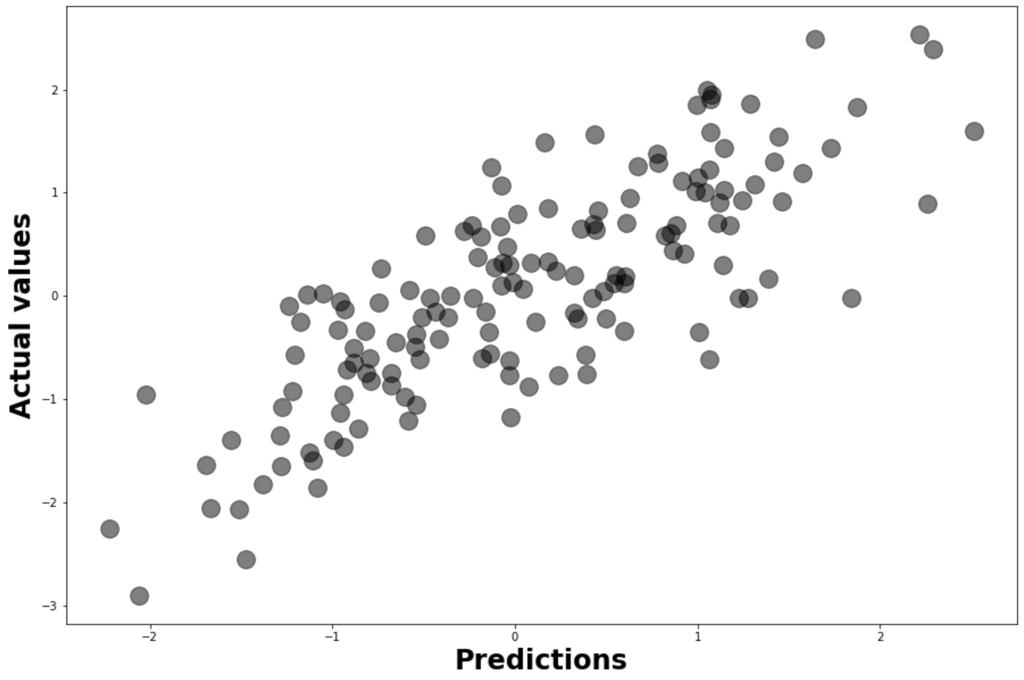

$$r = \frac{\sum_{i=1}^{N}([x_i - \bar{x}] * [y_i - \bar{y}])}{\sqrt{\sum_{i=1}^{N}(x_i - \bar{x})^2 * \sum_{i=1}^{N}(y_i - \bar{y})^2}}$$

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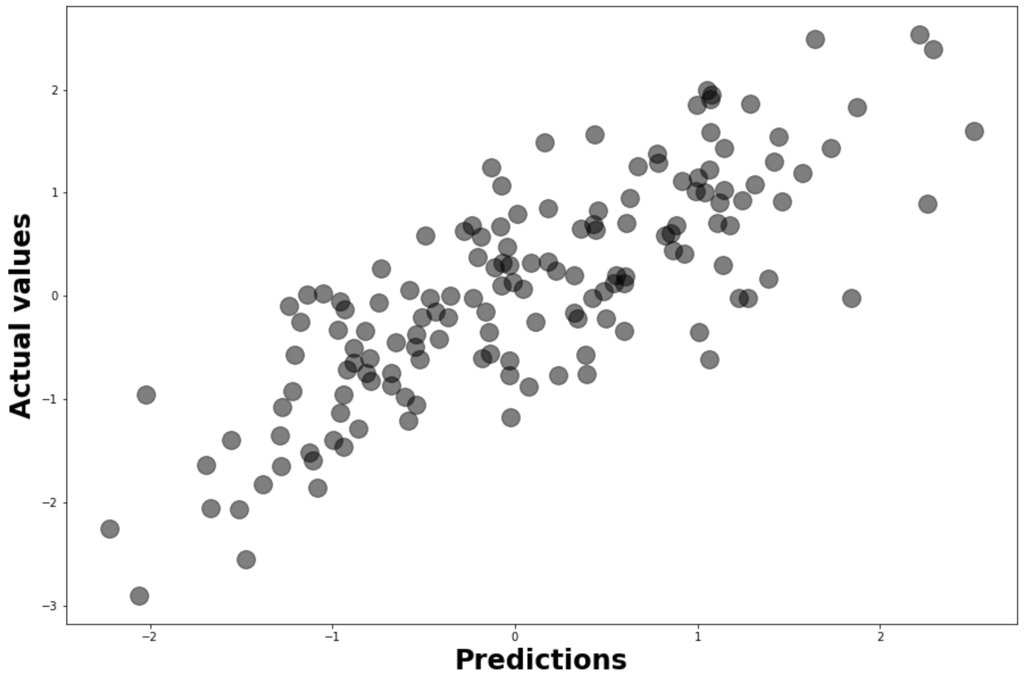

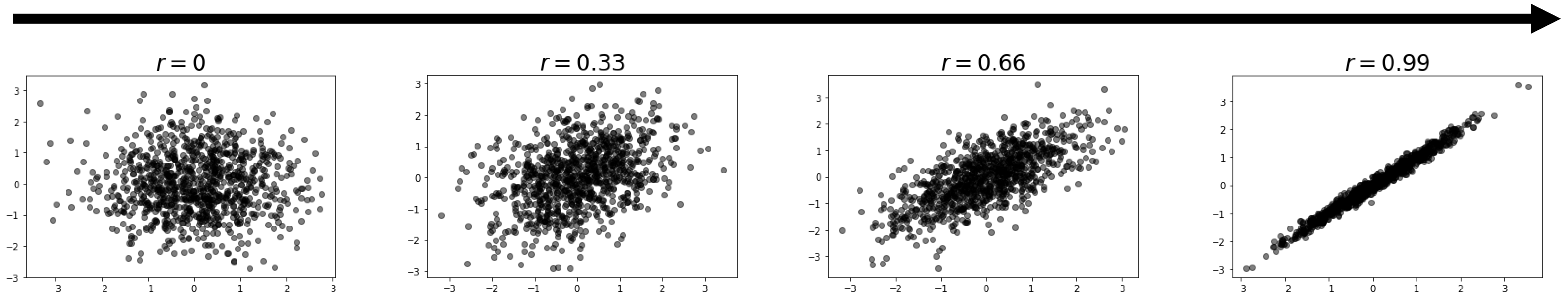

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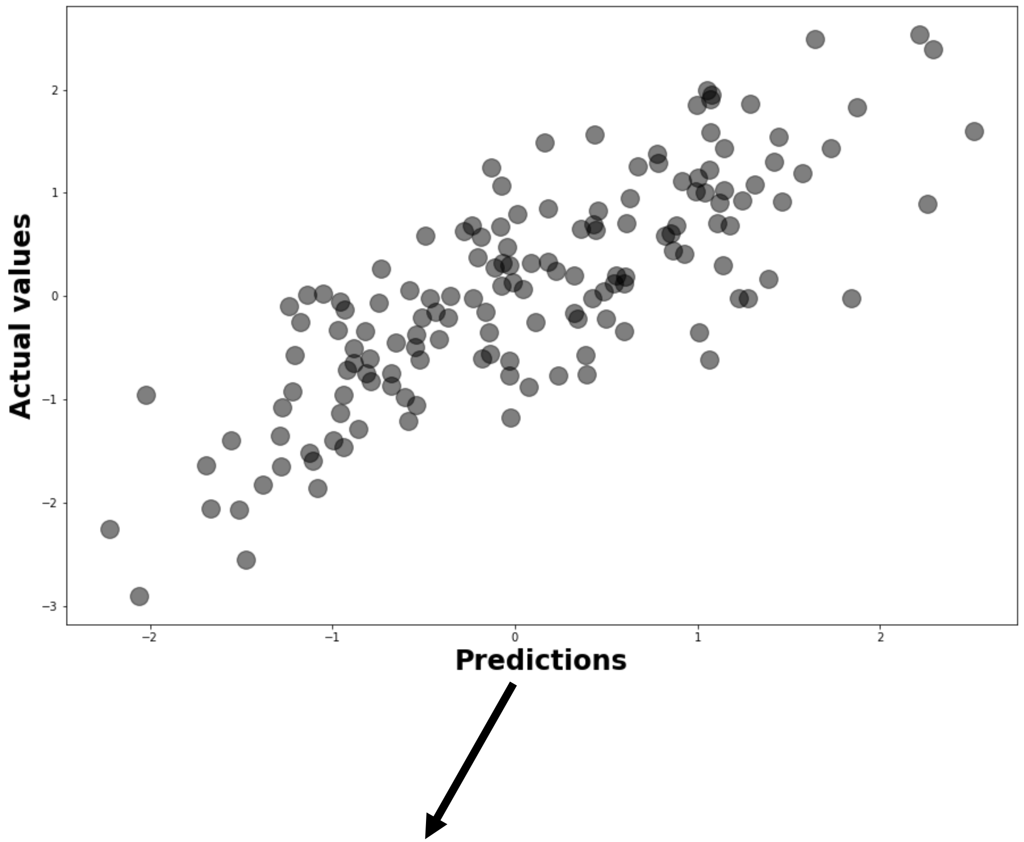
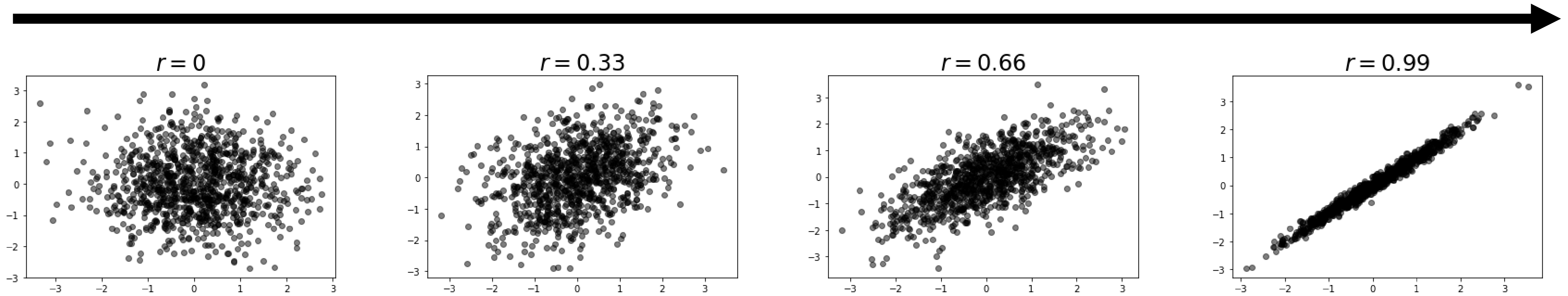




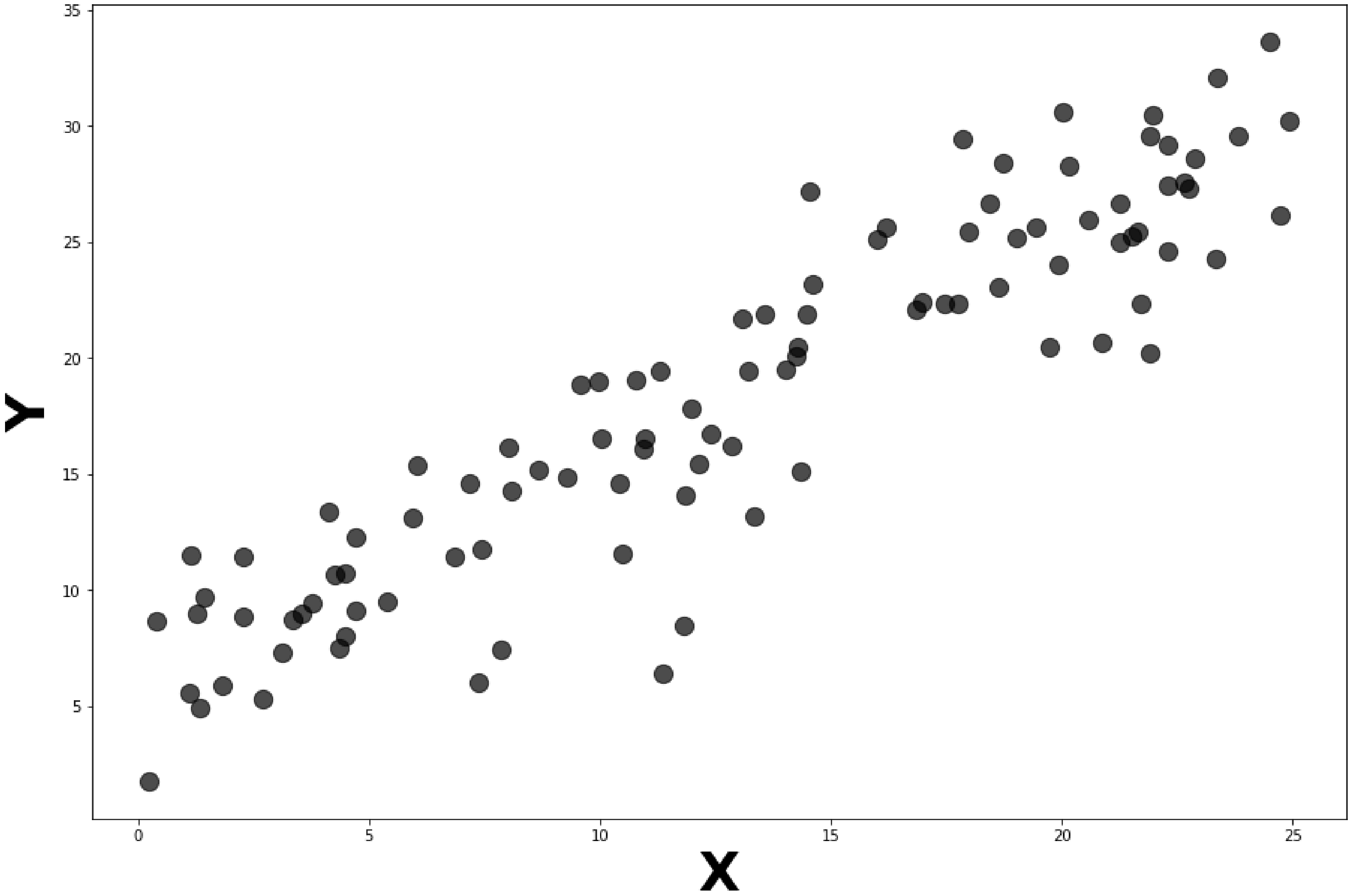
Meet the Algorithms

LINEAR REGRESSION

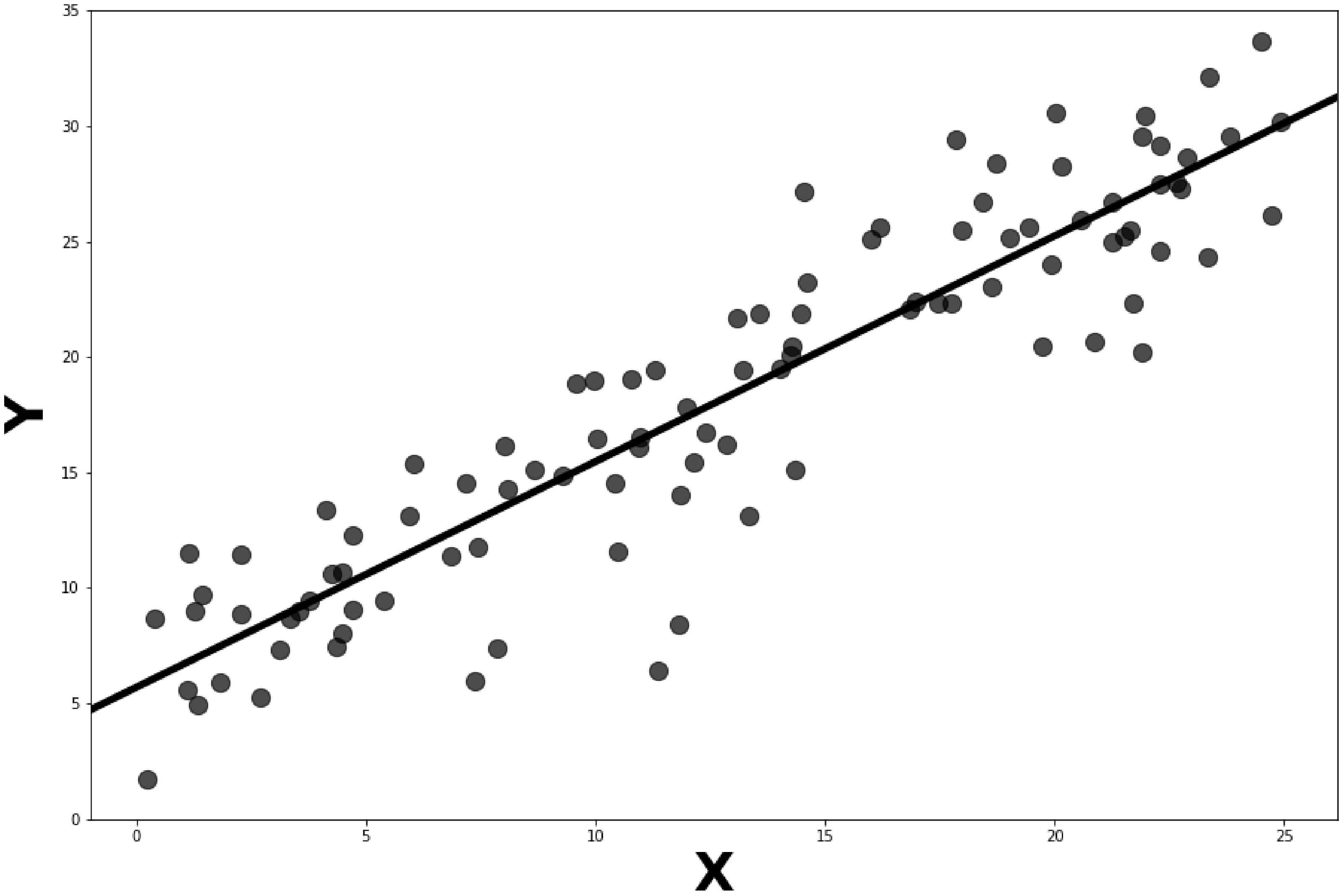
TREE-BASED METHODS

DEEP LEARNING

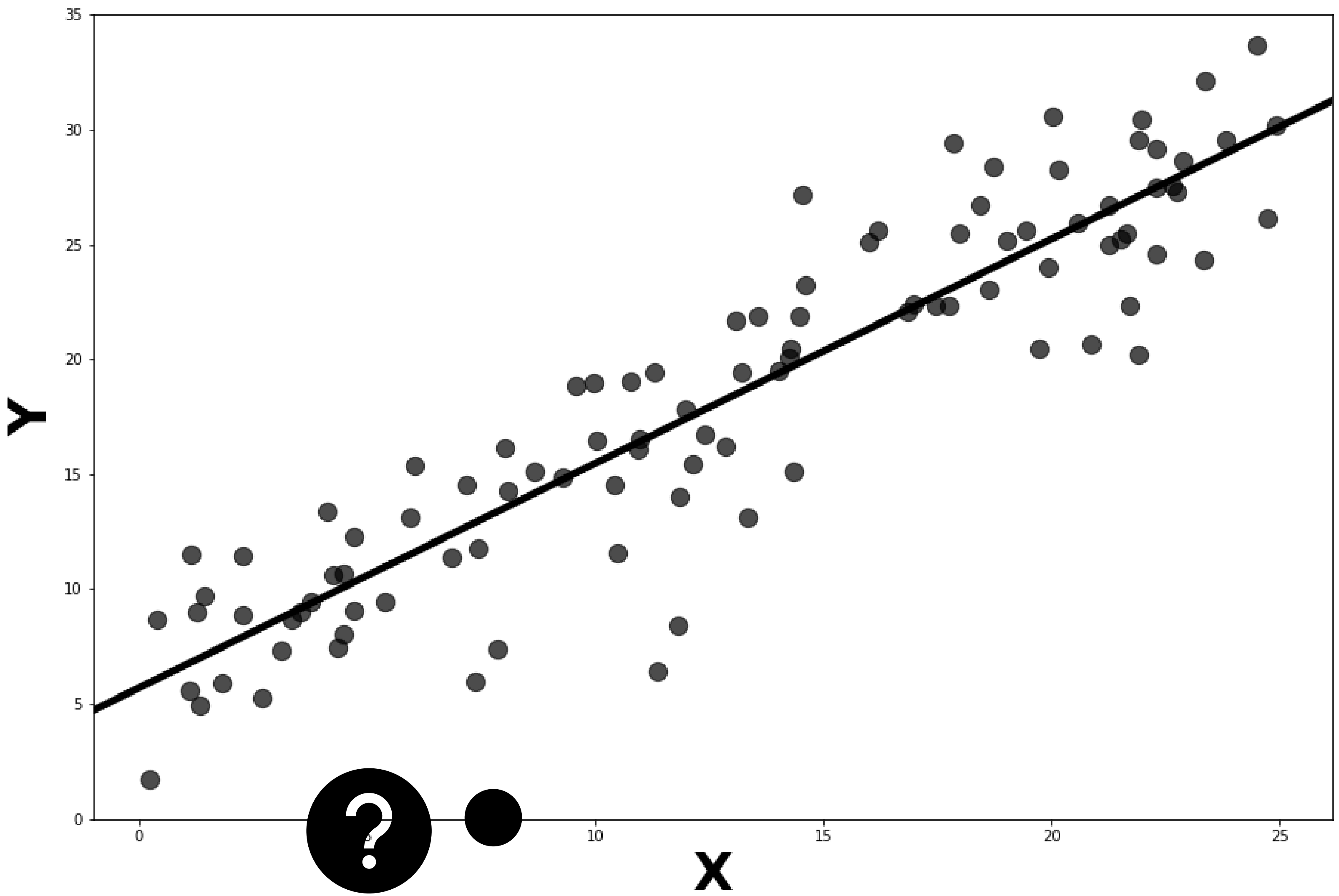
Meet the algorithms: Linear regression



Meet the algorithms: Linear regression



Meet the algorithms: Linear regression



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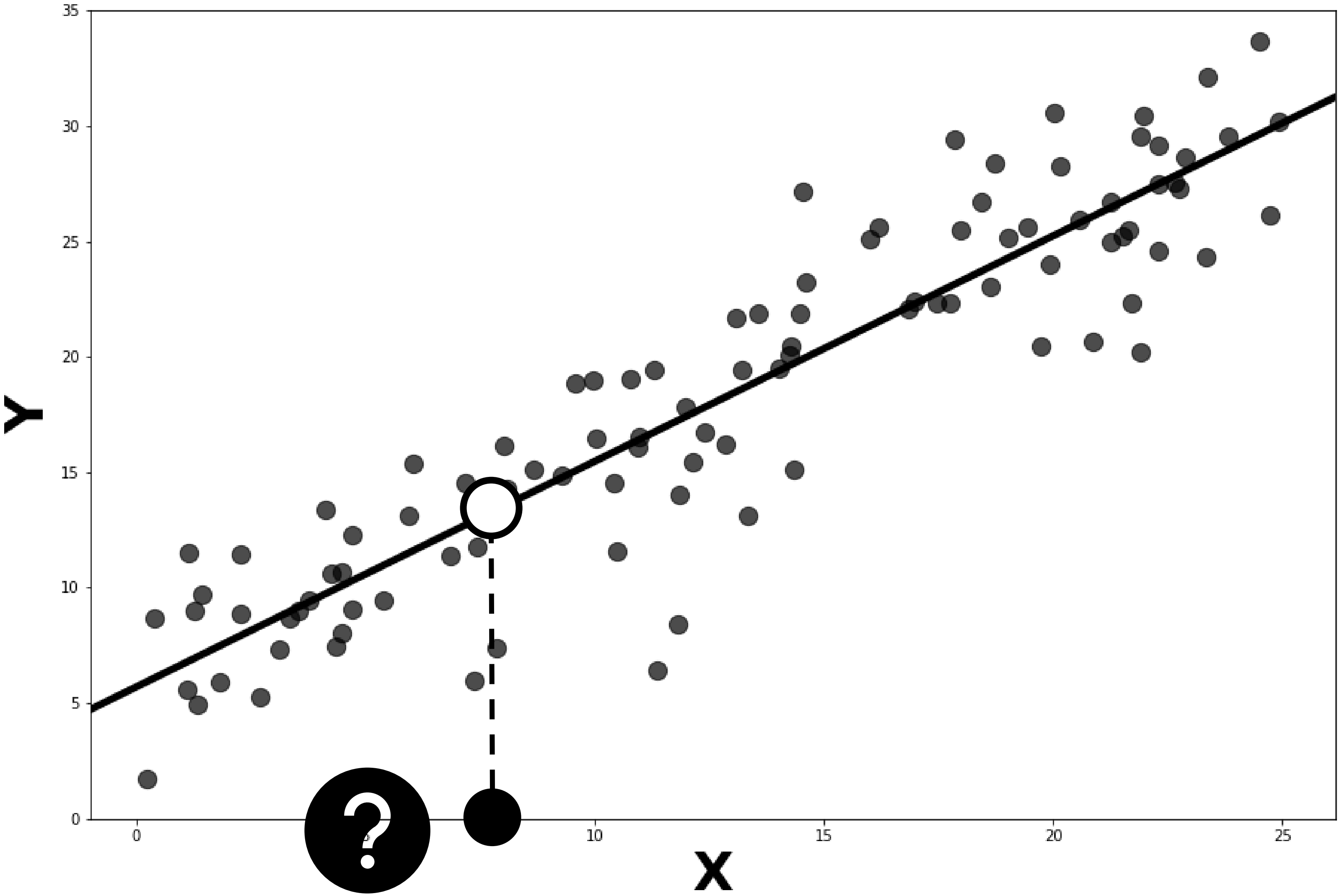

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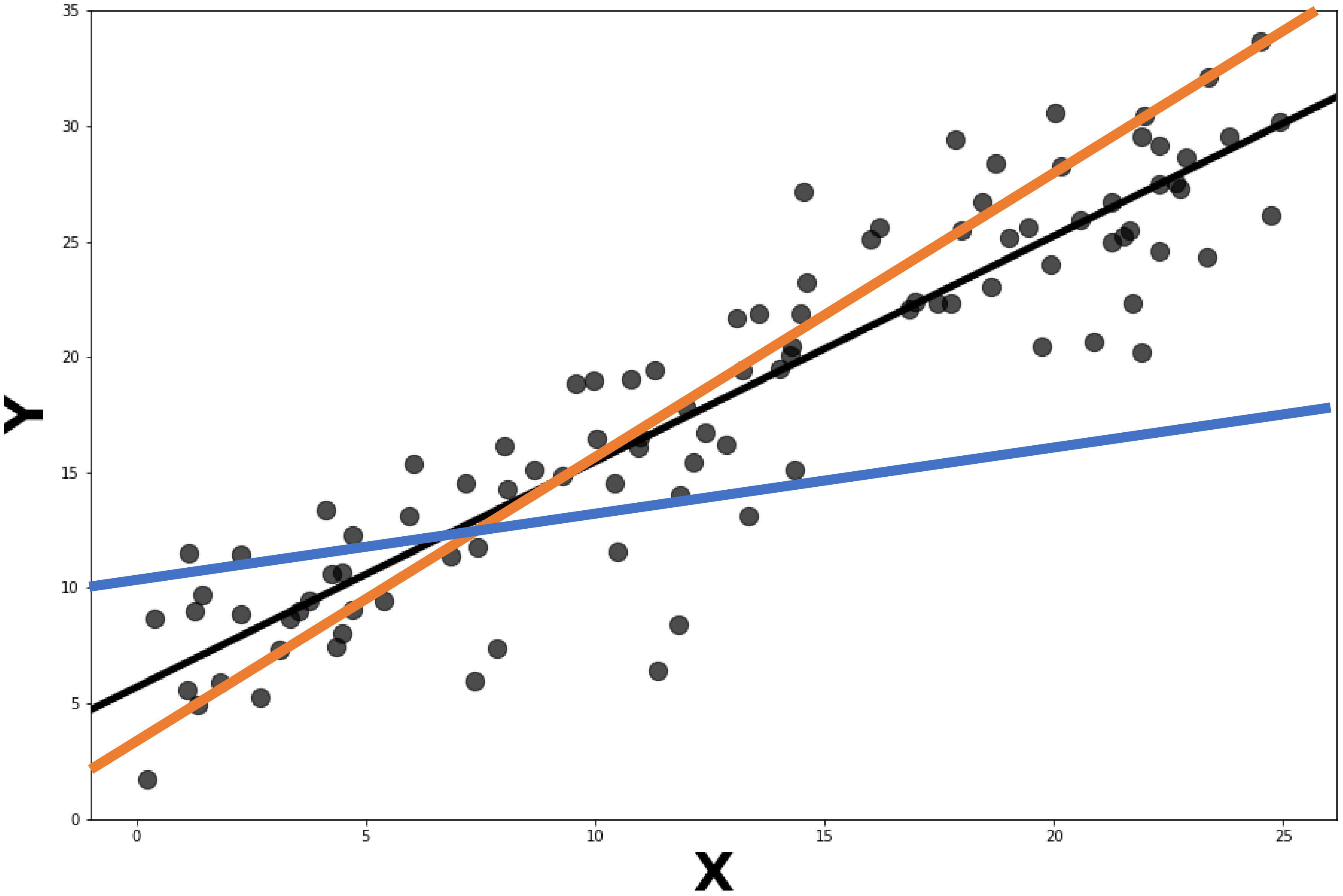
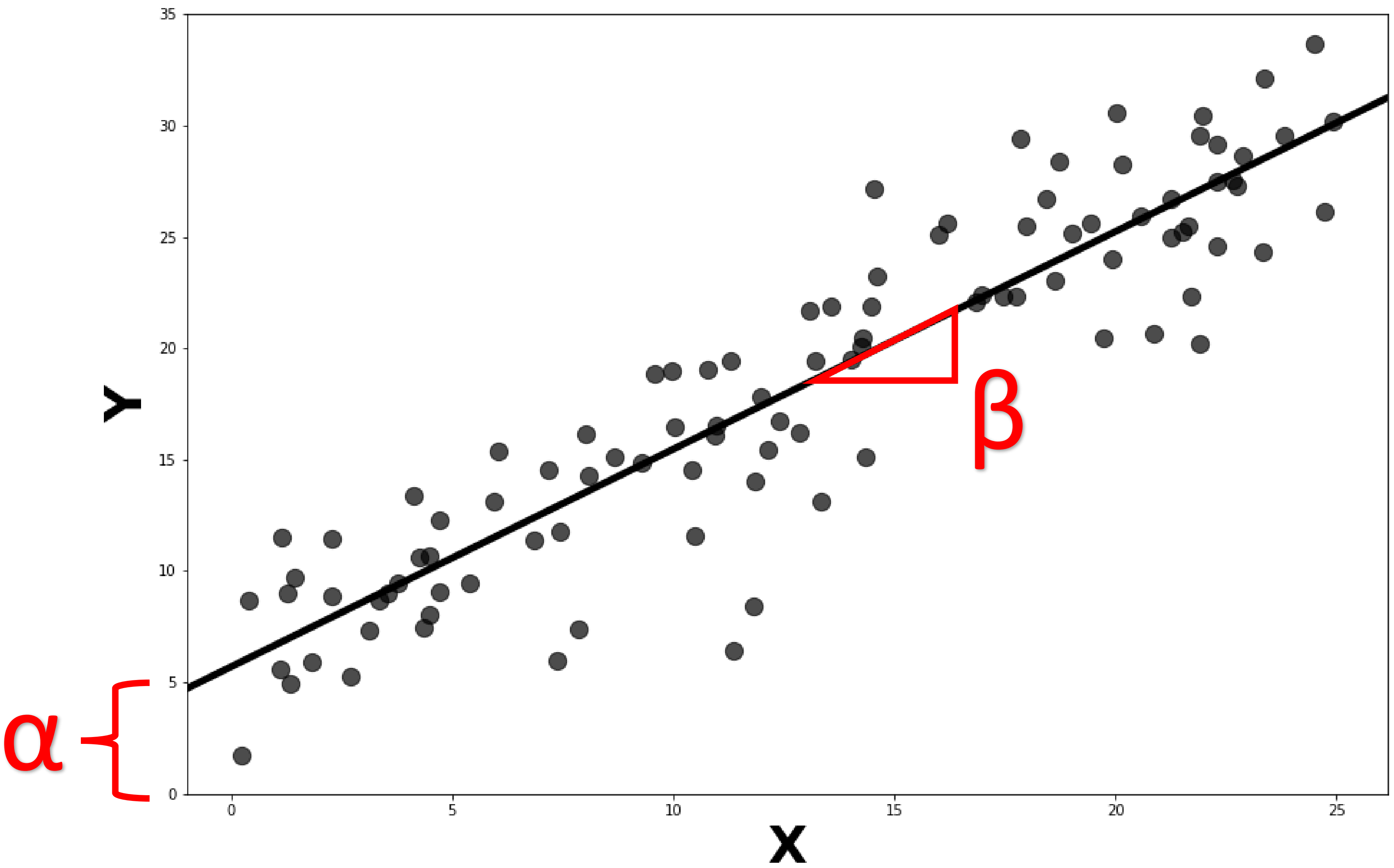


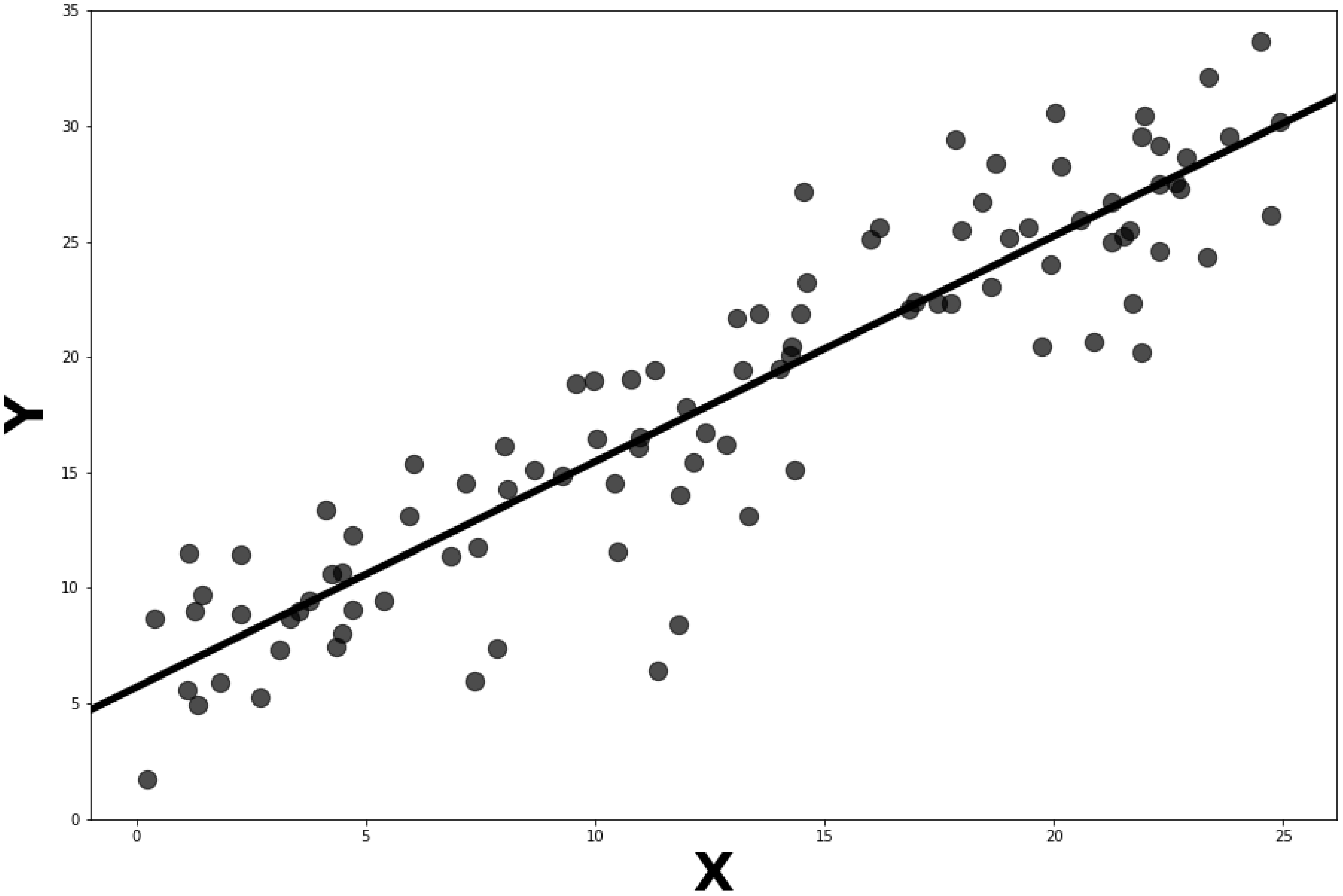
Meet the algorithms: Linear regression



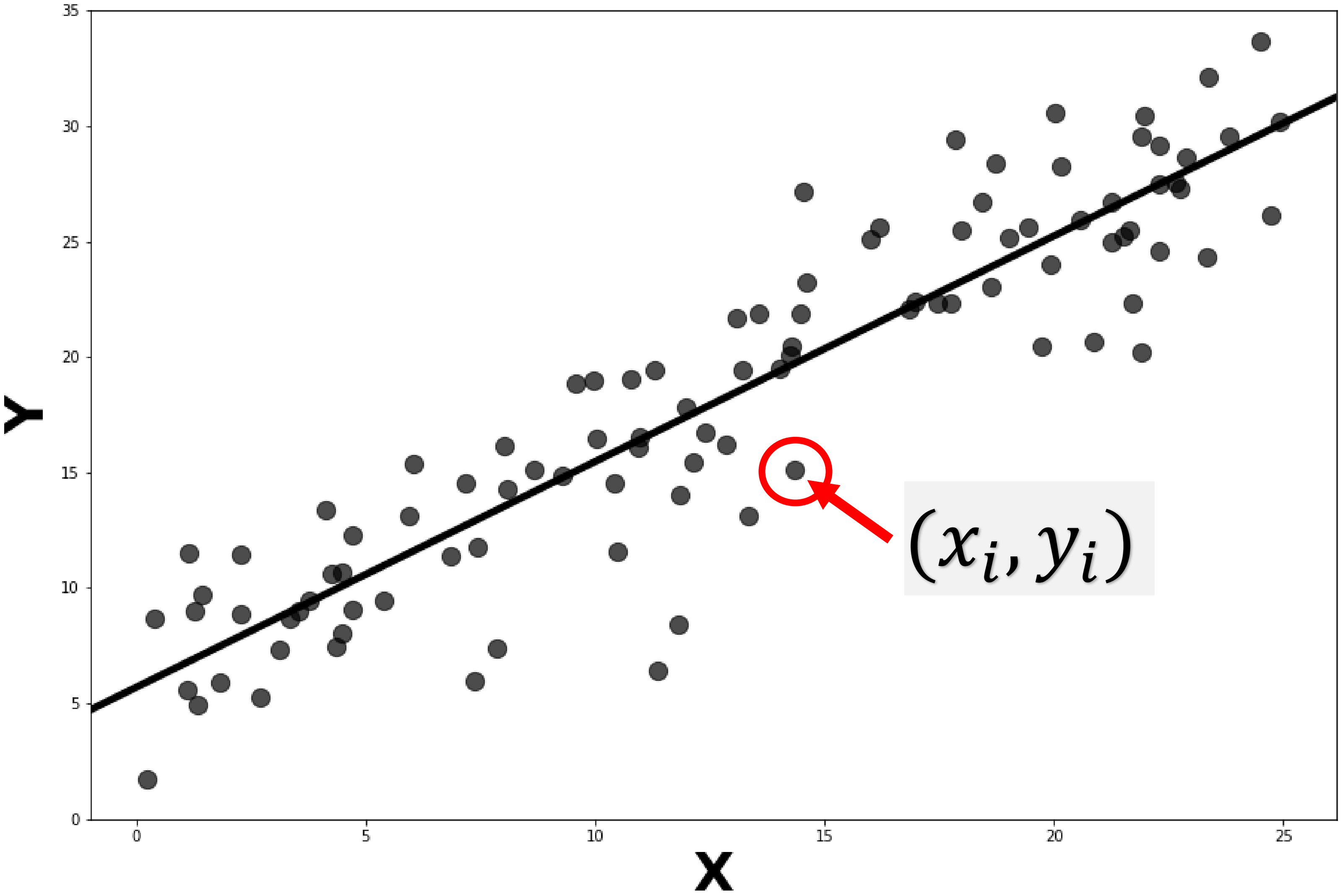
Meet the algorithms: Linear regression

$$SS_{\alpha,\beta} = \sum_{i=1}^{N} (y_i - [\alpha + \beta x_i])^2$$

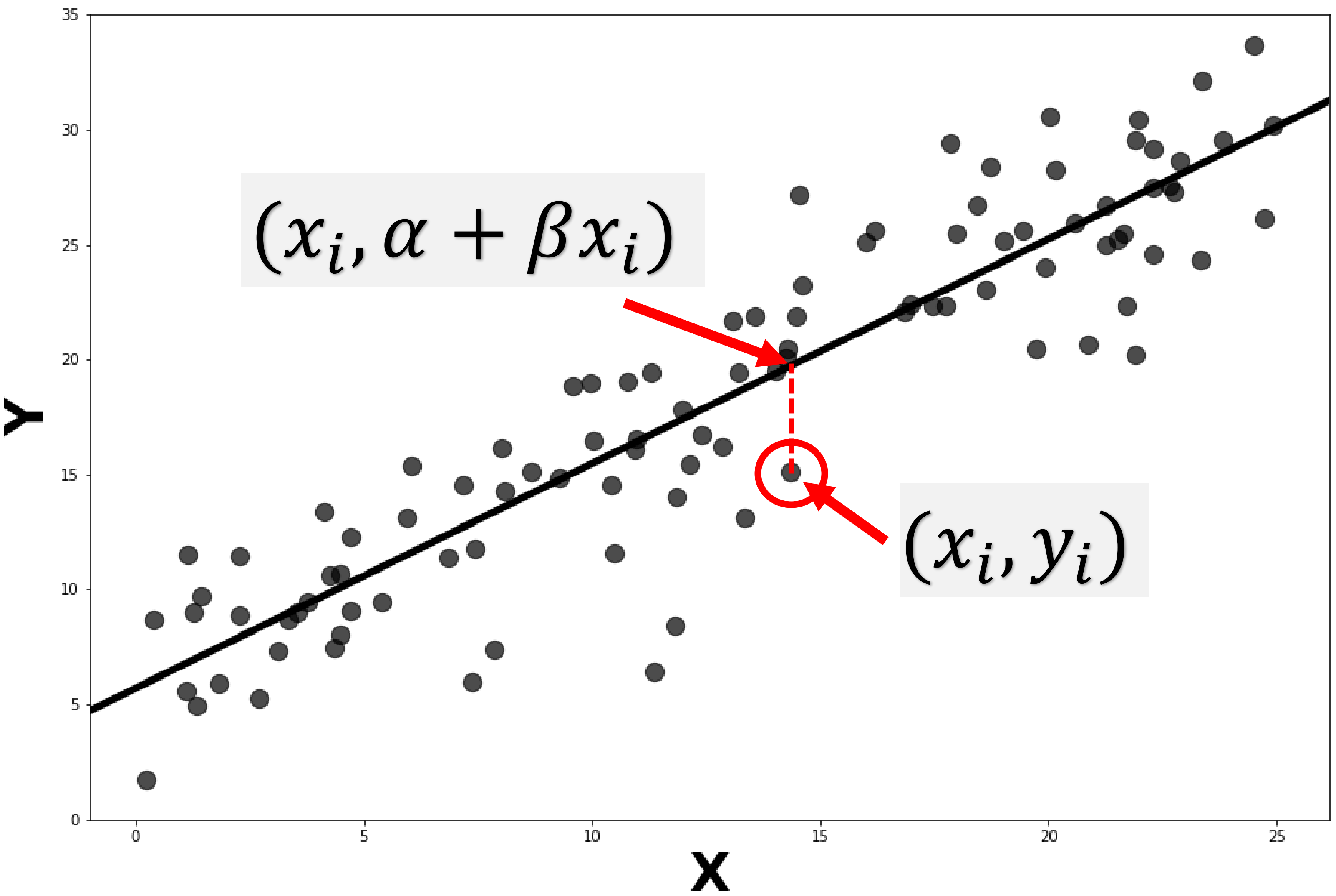
Meet the algorithms: Linear regression



Meet the algorithms: Linear regression



Meet the algorithms: Linear regression



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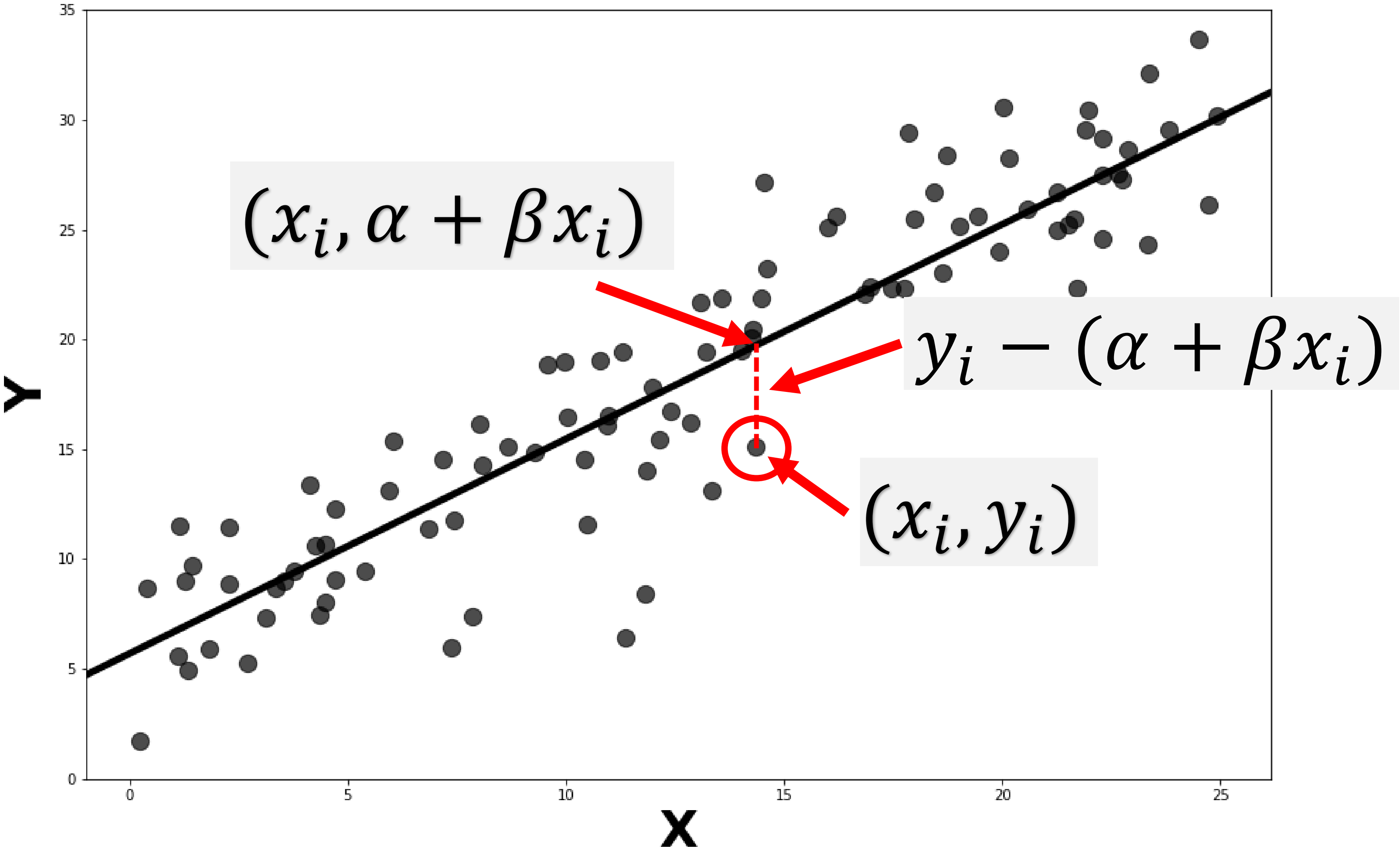
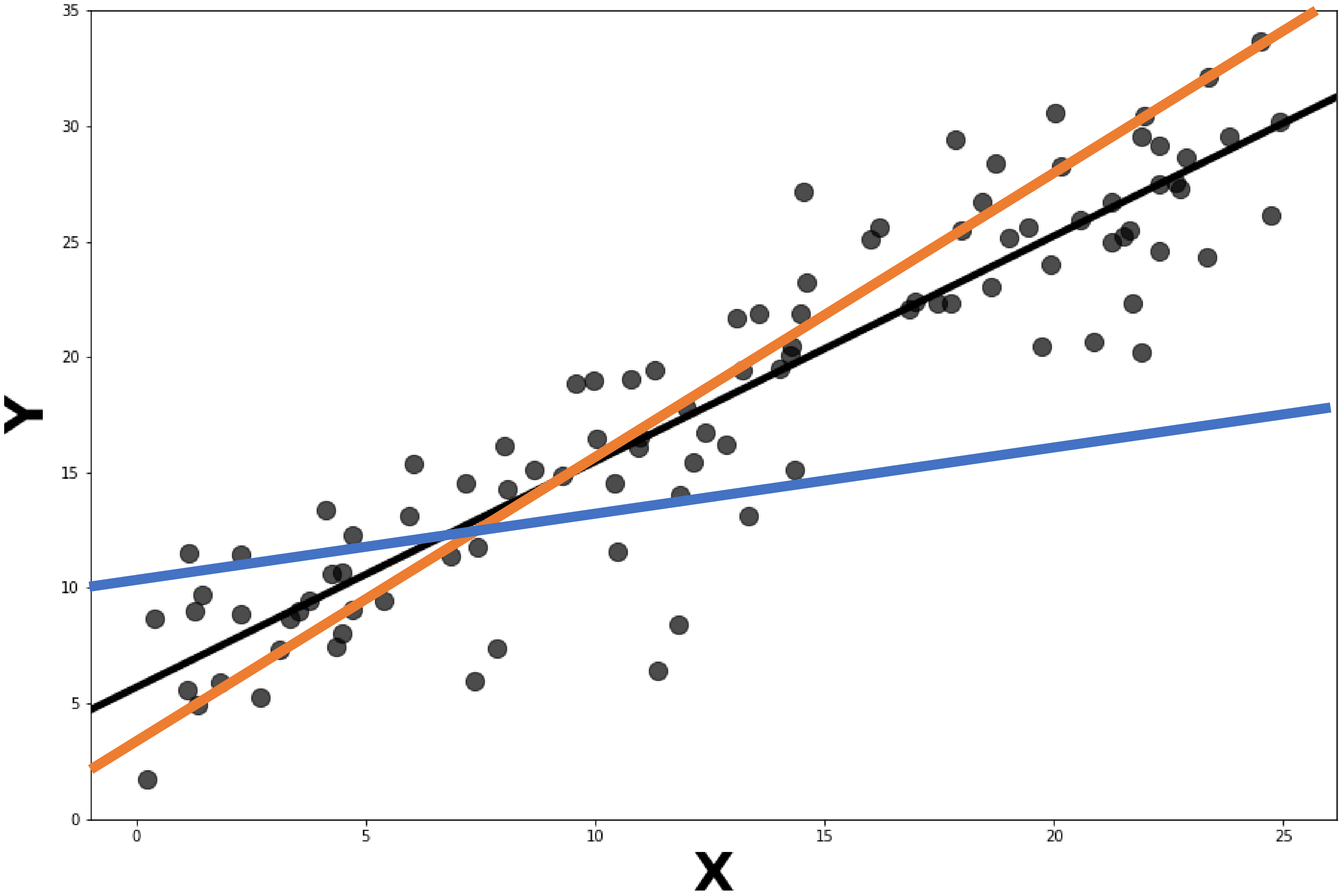


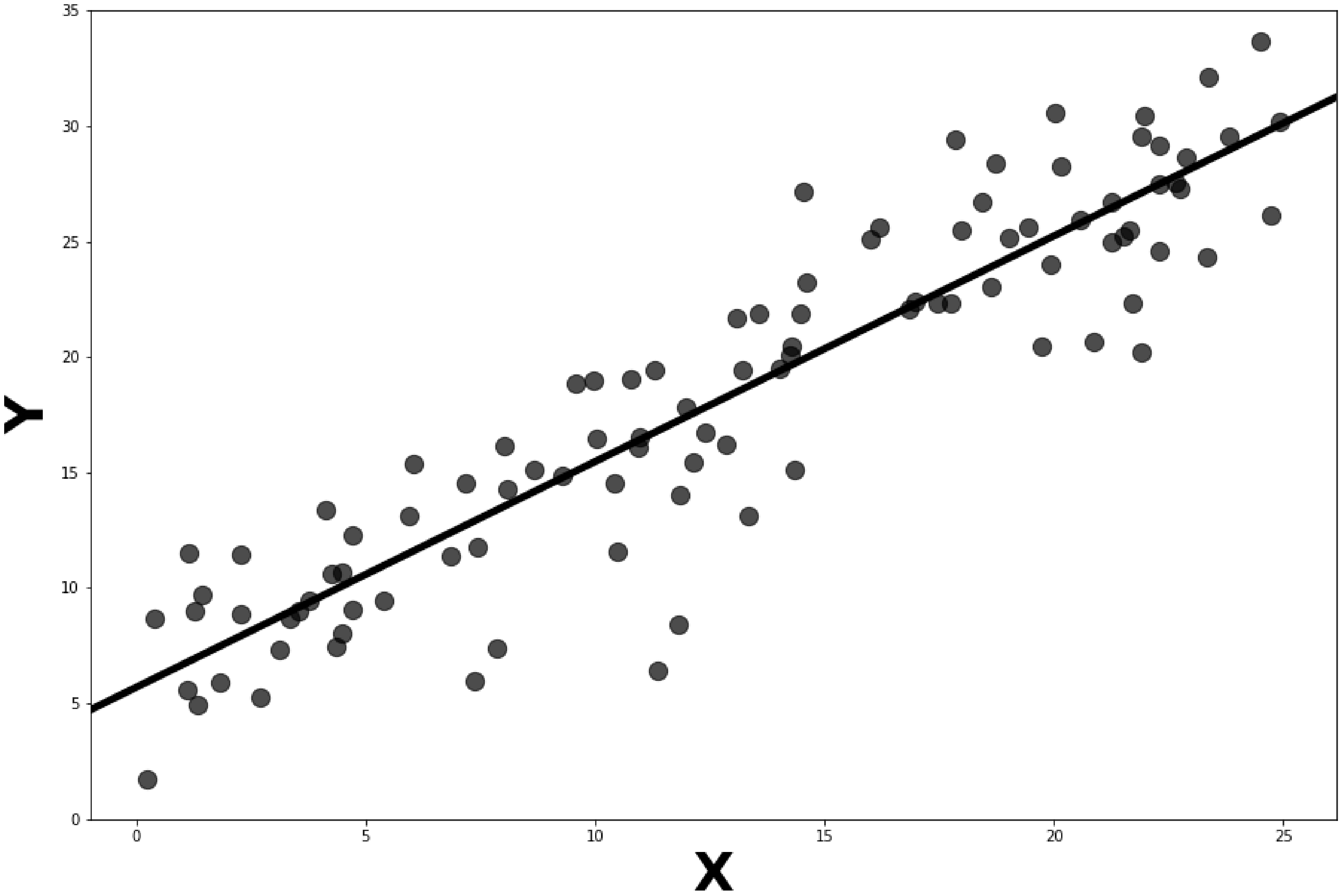
Meet the algorithms: Linear regression

$$SS_{\alpha,\beta} = \underbrace{\sum_{i=1}^{N}}_{\text{The sum of...}} \underbrace{(\overbrace{y_i}^{\text{Actual } y} - \overbrace{[\alpha + \beta x_i]}^{\text{Our guess of } y \text{ based on } x})^2}_{\text{How off the line is}}$$

Meet the algorithms: Linear regression



Meet the algorithms: Linear regression



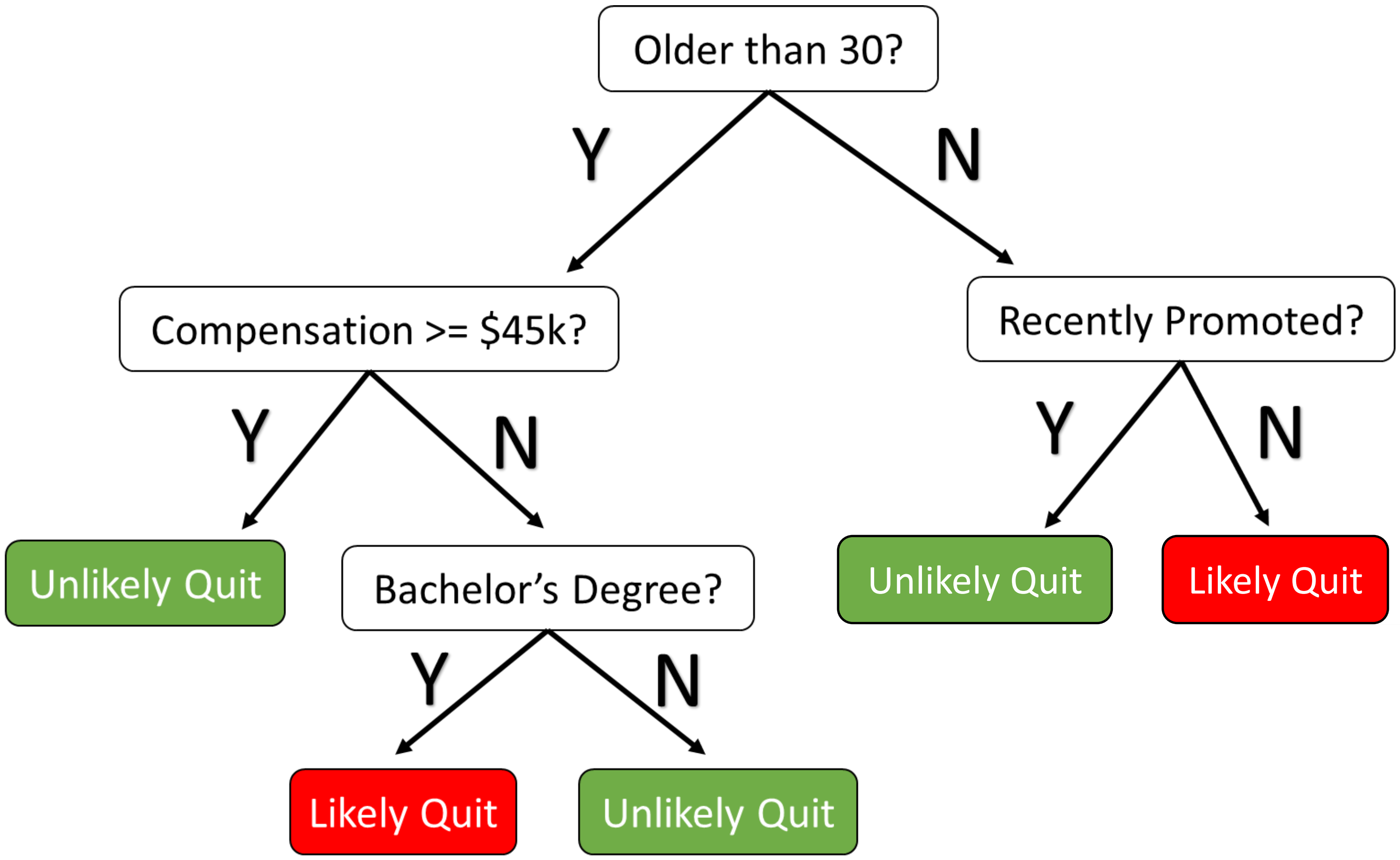
Going further: Multiple regression

$$SS_{\alpha,\beta} = \sum_{i=1}^{N} \left(y_i - [\alpha + \sum_{k=1}^{K} \beta_k x_{ik}] \right)^2$$

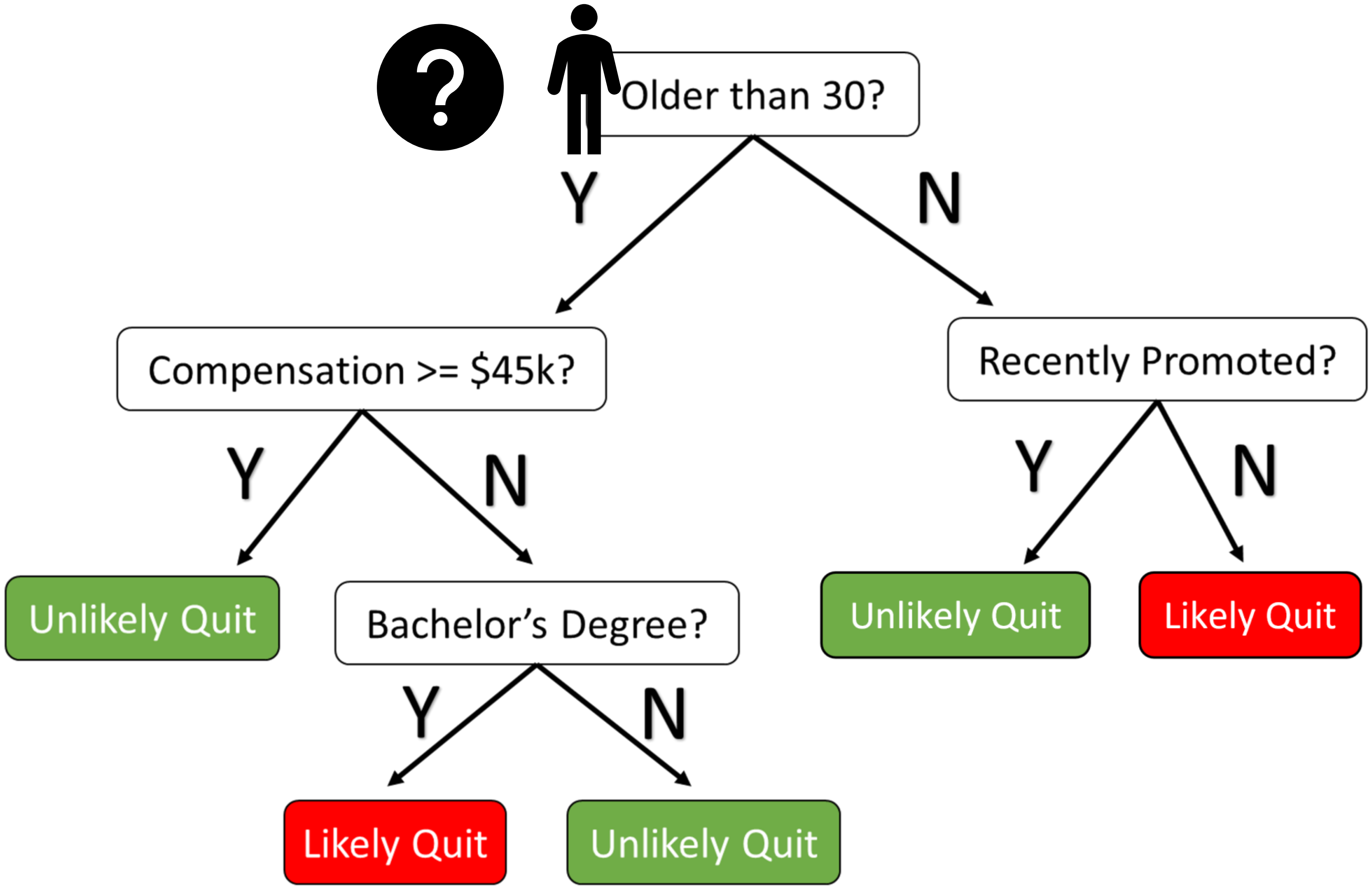
Going further: Penalized regression (LASSO)

$$SS_{\alpha,\beta} = \sum_{i=1}^{N} \left(y_i - [\alpha + \sum_{k=1}^{K} \beta_k x_{ik}] \right)^2 + \lambda \sum_{k=1}^{K} |\beta_k|$$

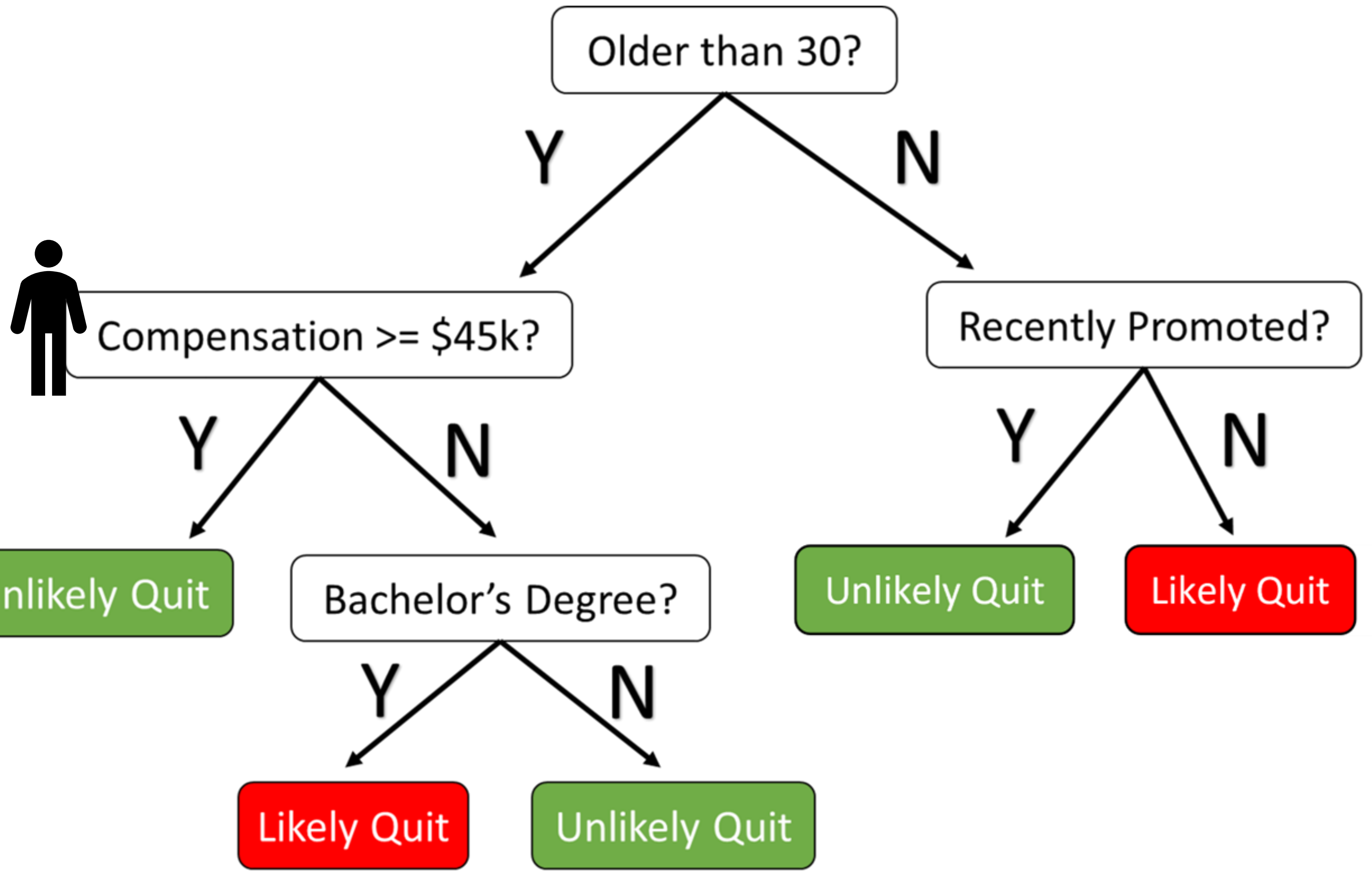
Meet the algorithms: Tree-based learning



Meet the algorithms: Tree-based learning



Meet the algorithms: Tree-based learning



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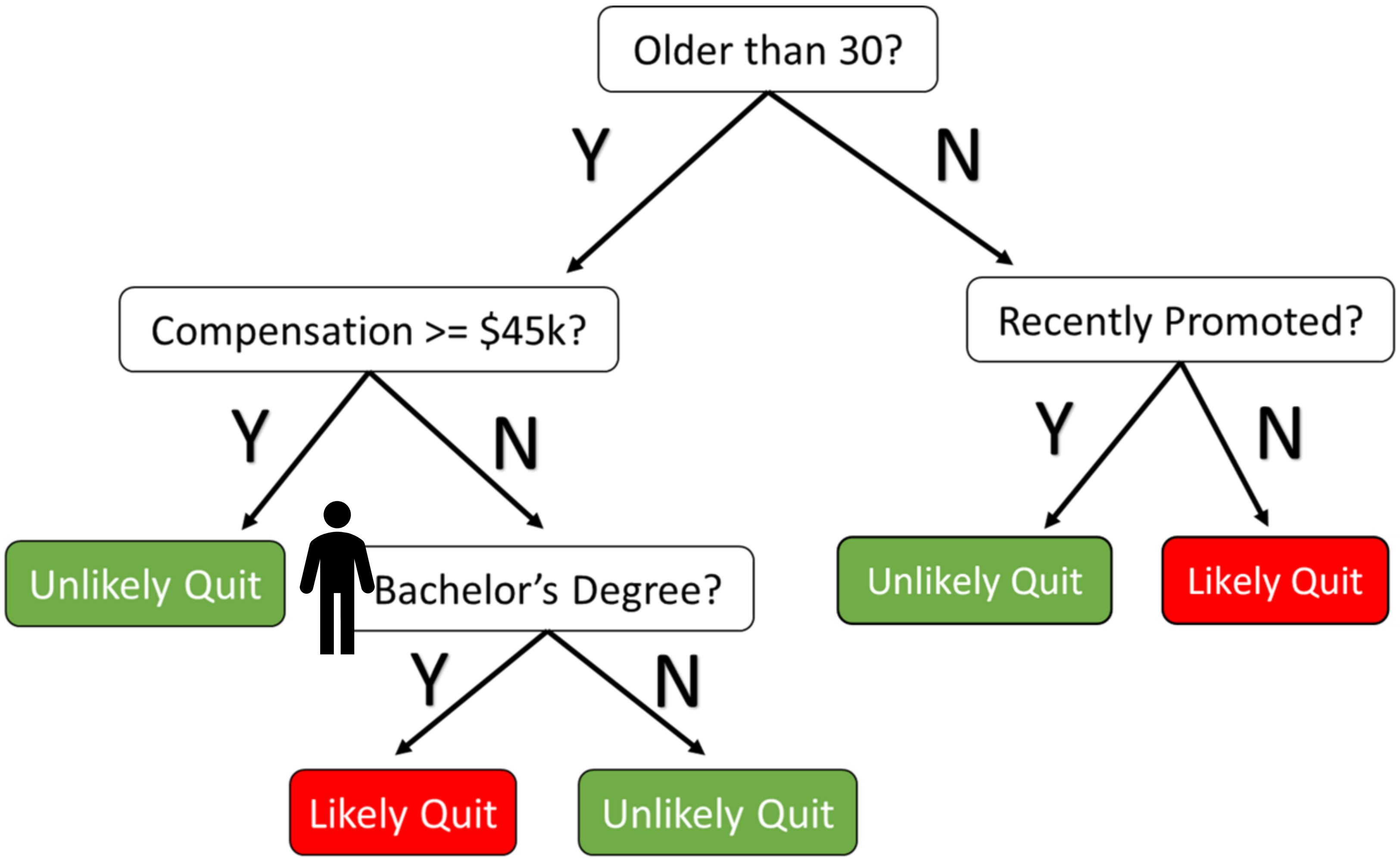

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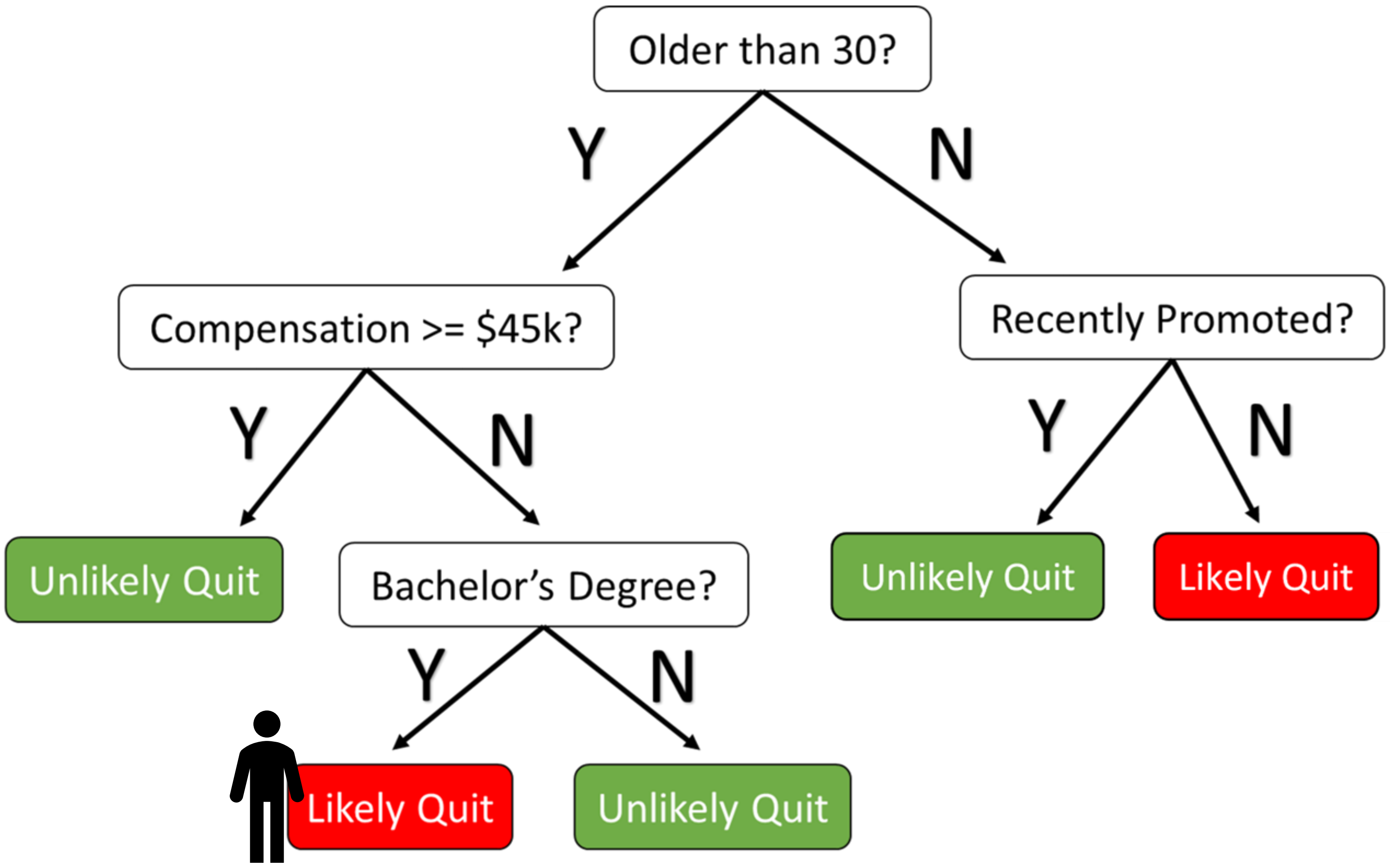

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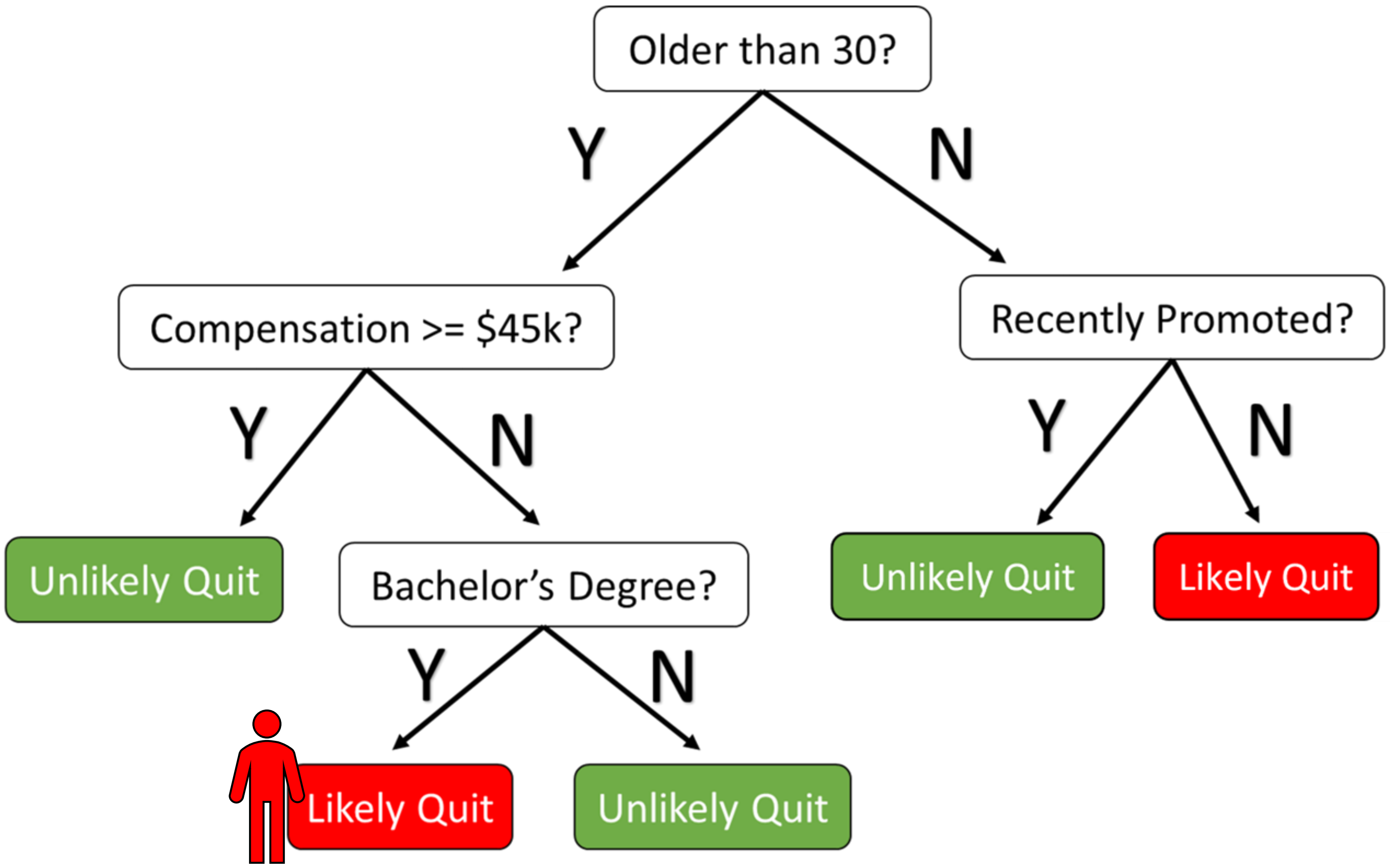
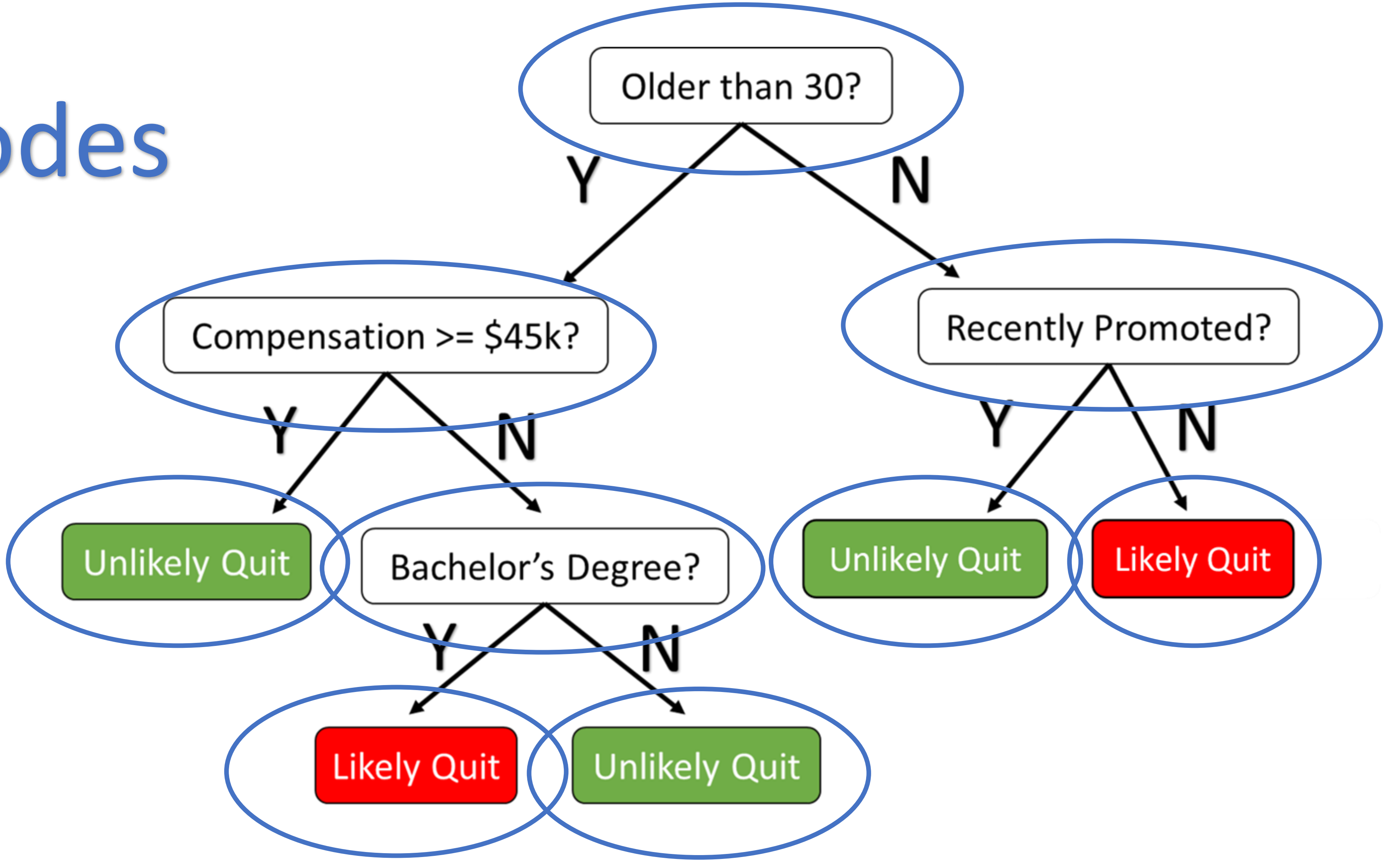


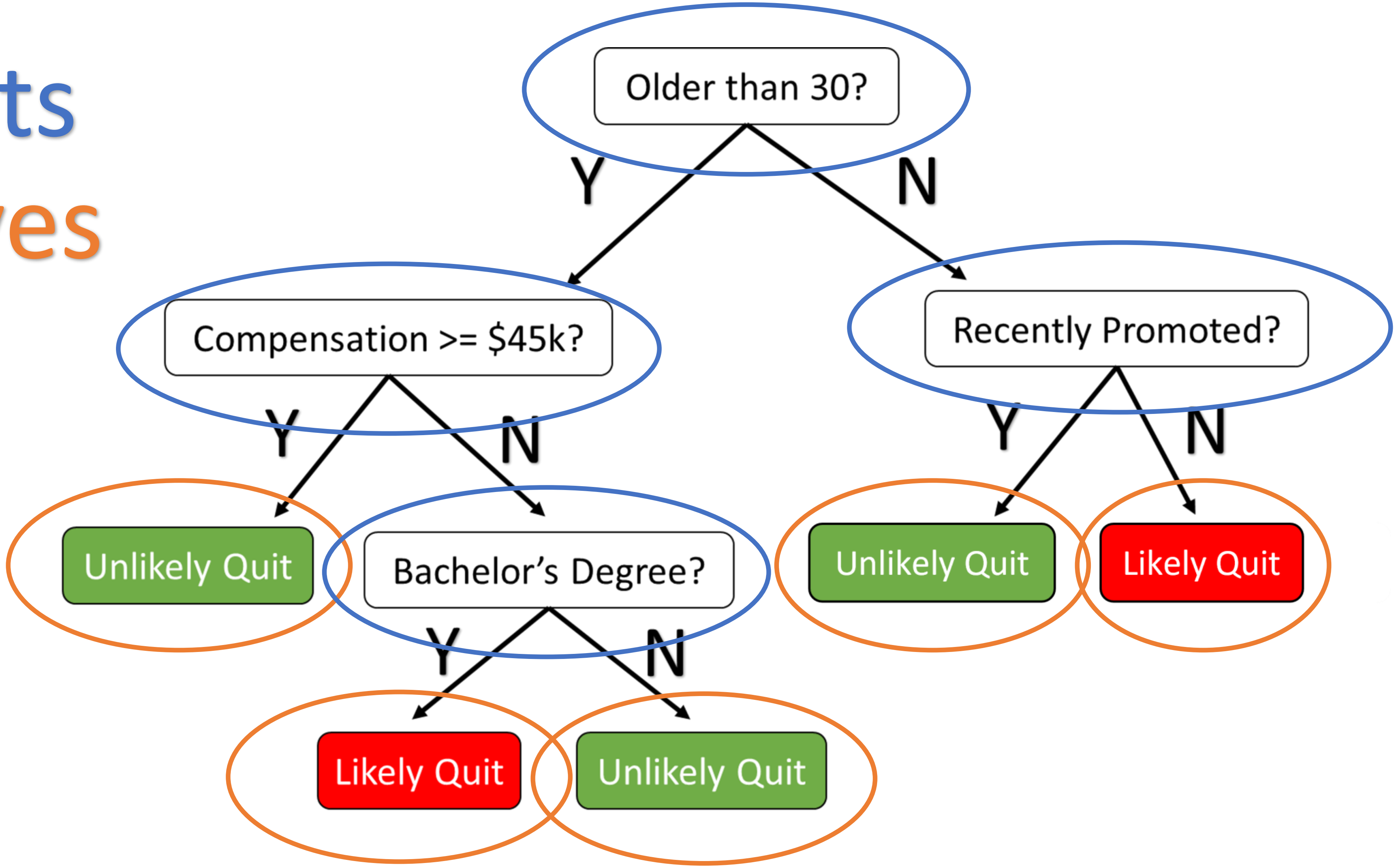
Meet the algorithms: Tree-based learning

Nodes



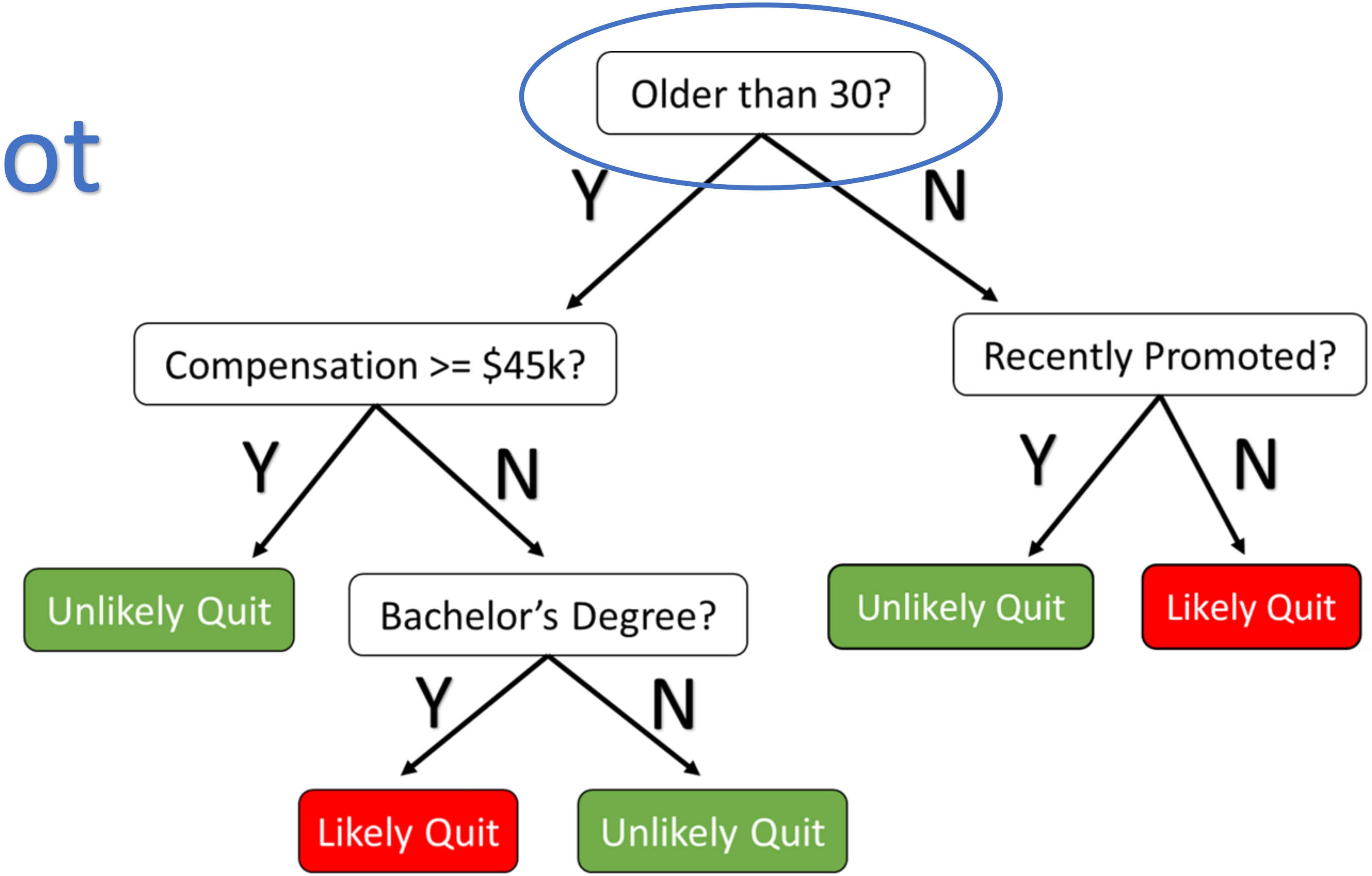
Meet the algorithms: Tree-based learning

Splits
Leaves



Meet the algorithms: Tree-based learning

Root



Meet the algorithms: Tree-based learning

Pay	Age	Promoted?	College?	Quit?
30	60	No	No	No
34	64	No	No	No
42	21	Yes	Yes	No
32	35	Yes	Yes	Yes
40	50	No	Yes	Yes
44	23	No	No	Yes
44	27	No	No	Yes
46	33	No	Yes	No
80	40	No	Yes	No
160	18	Yes	No	No
60	19	No	Yes	Yes
120	25	No	Yes	Yes

Meet the algorithms: Tree-based learning

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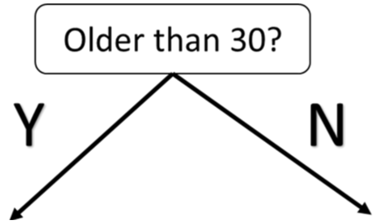

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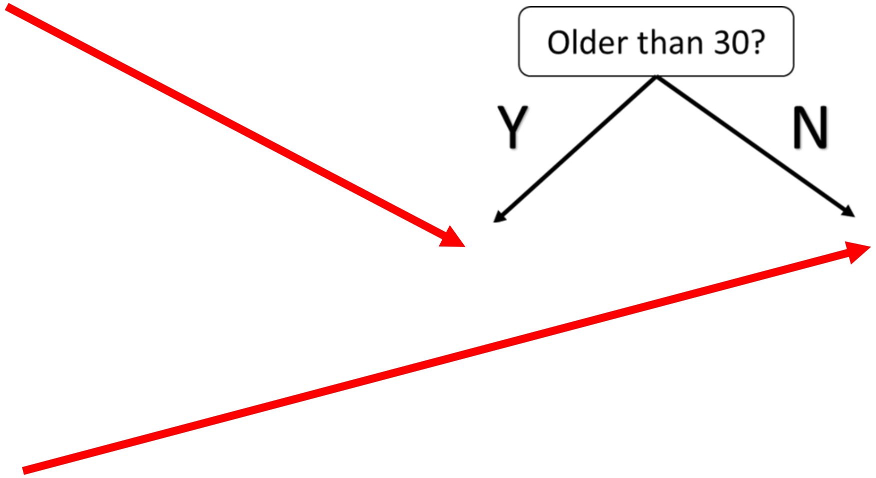

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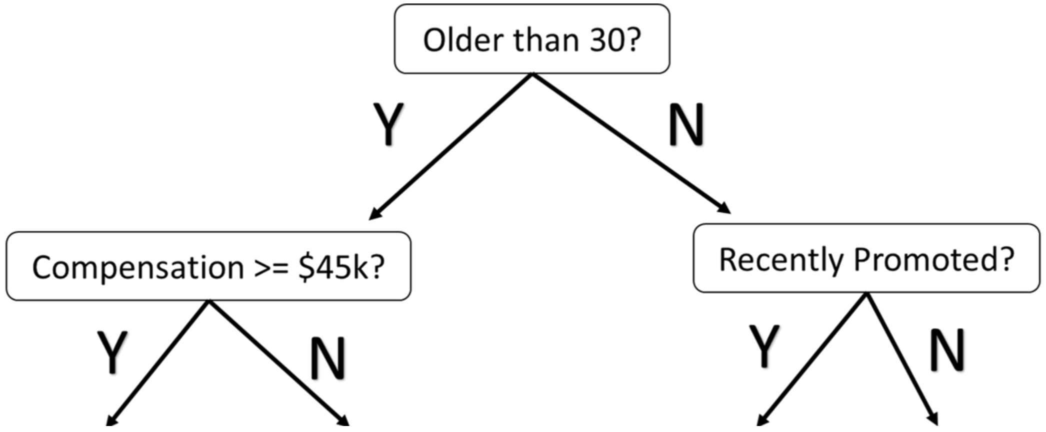

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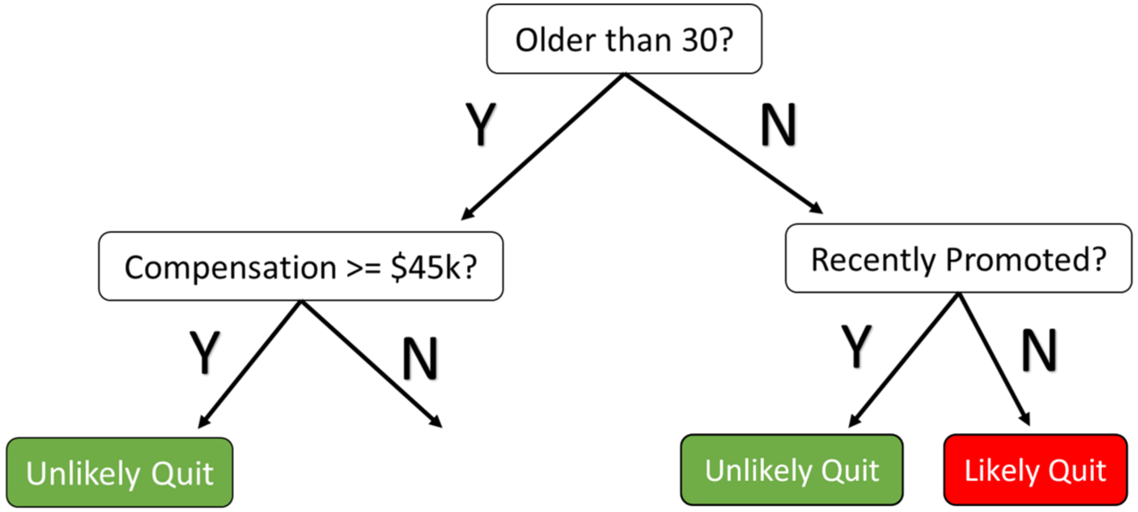

Meet the algorithms: Tree-based learning

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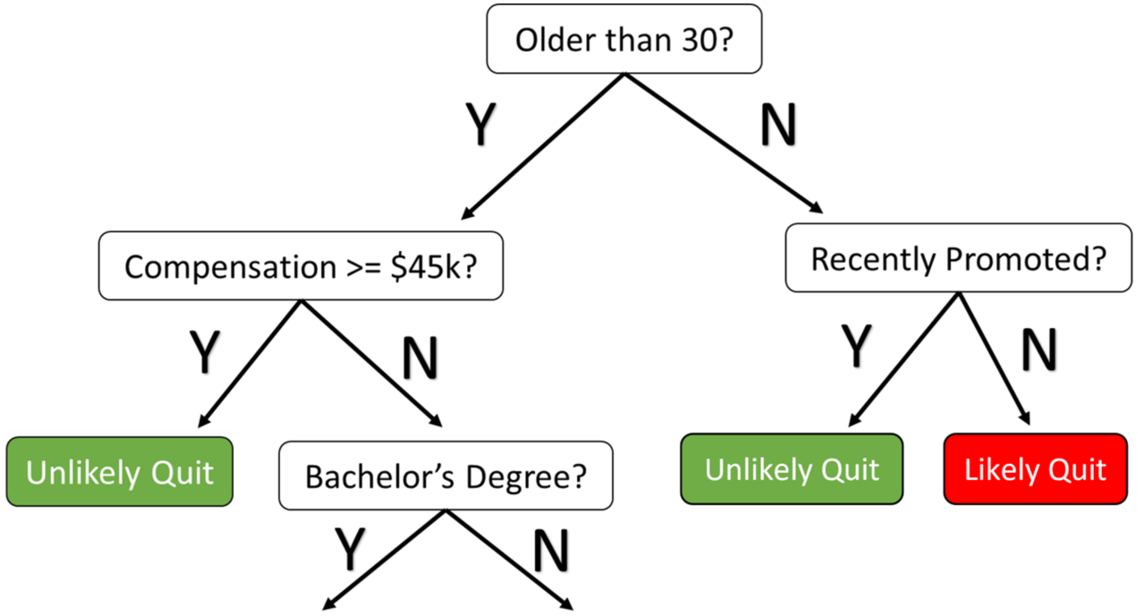

Meet the algorithms: Tree-based learning

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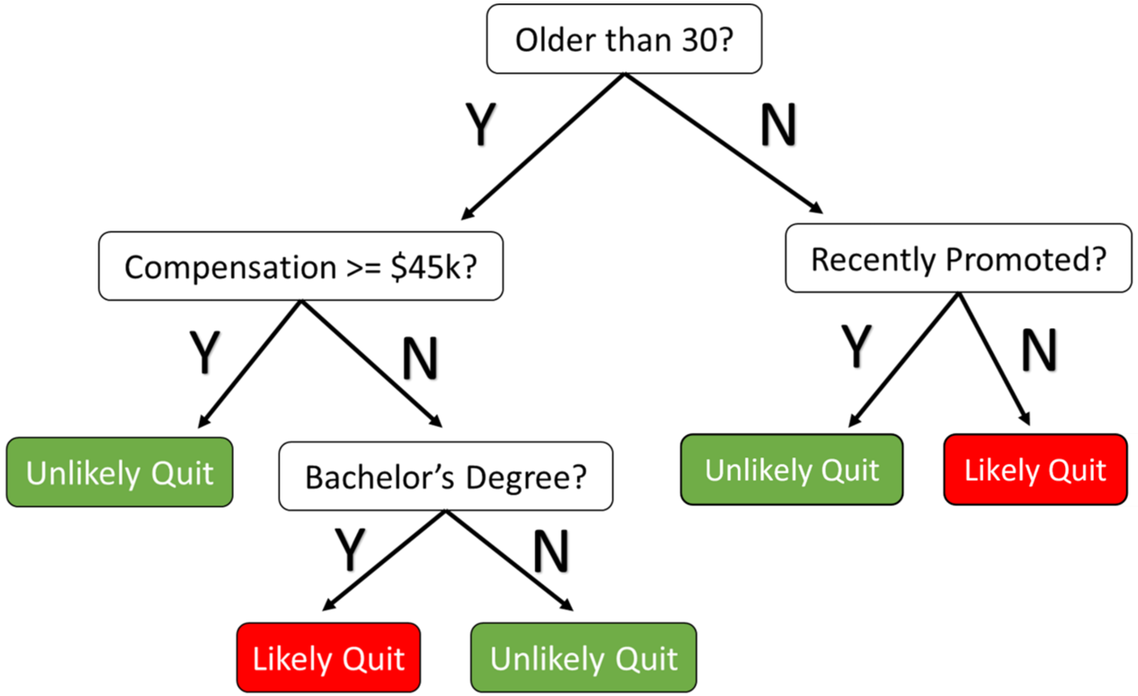
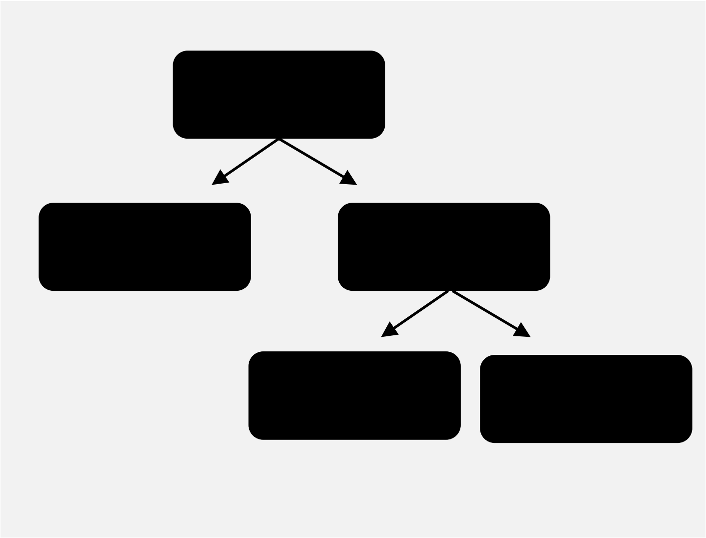
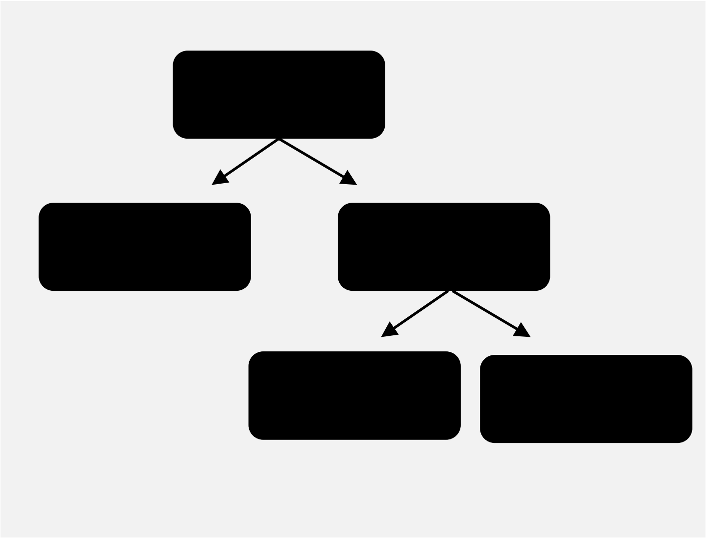
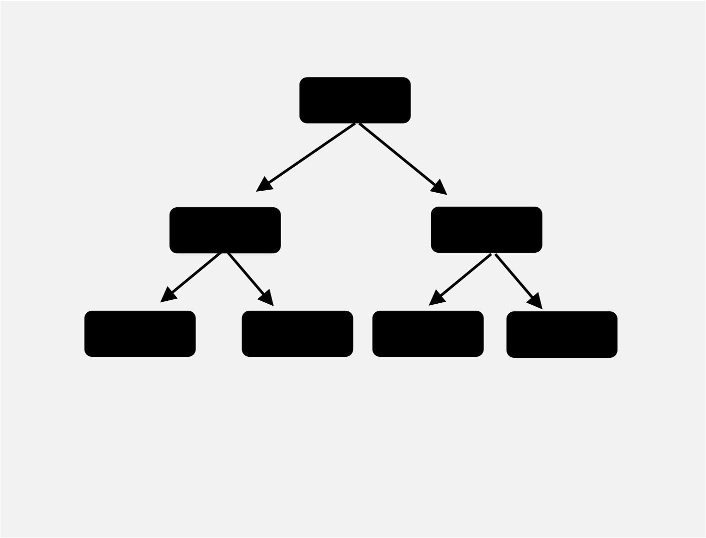
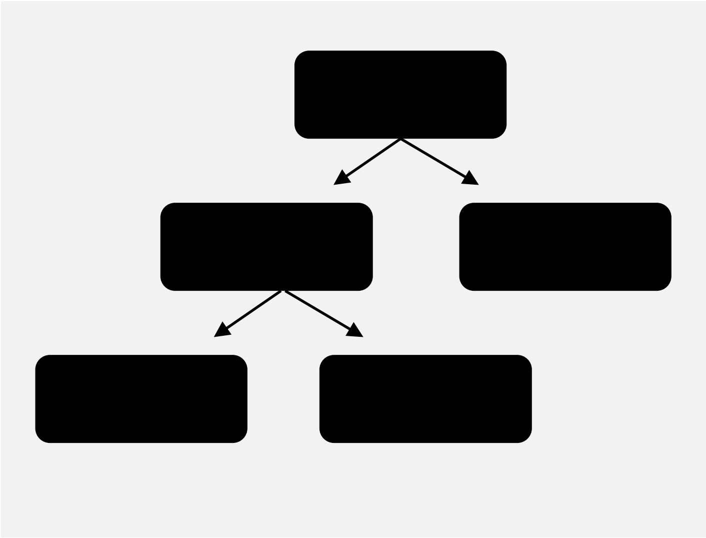
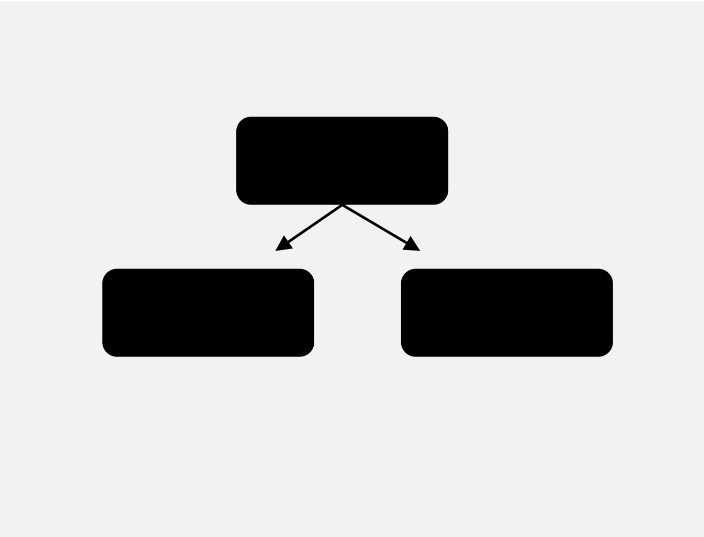
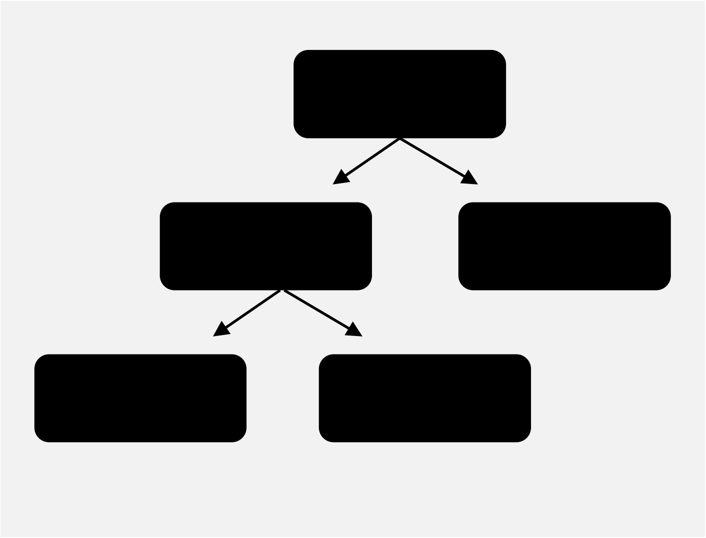
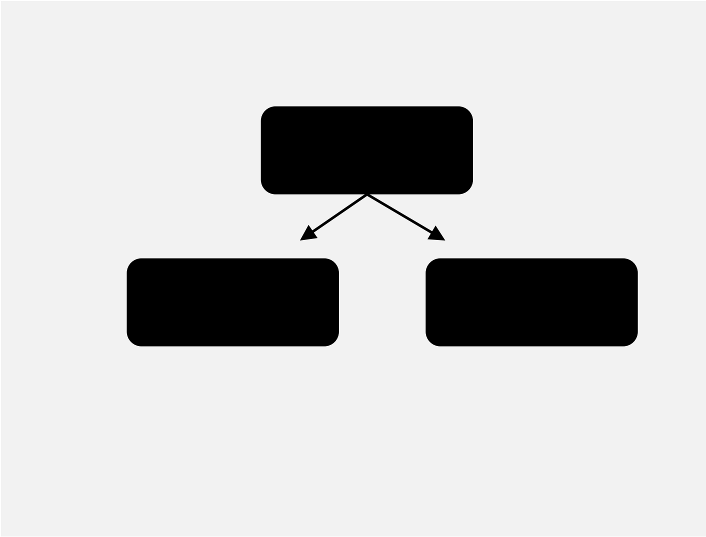
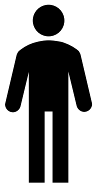
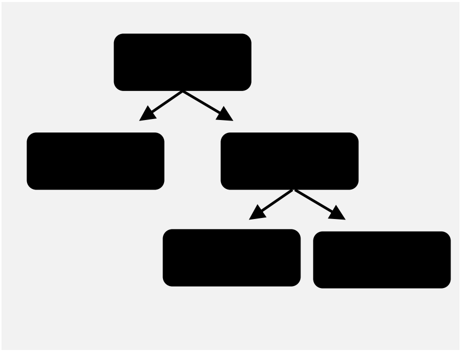
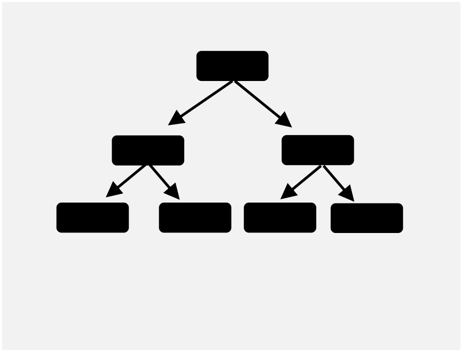
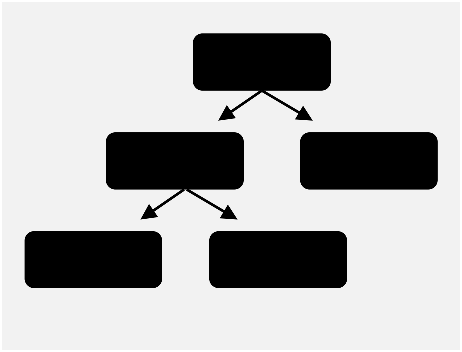
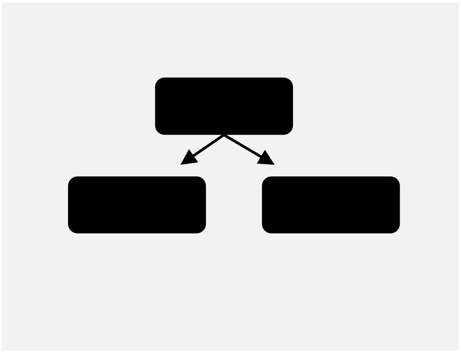
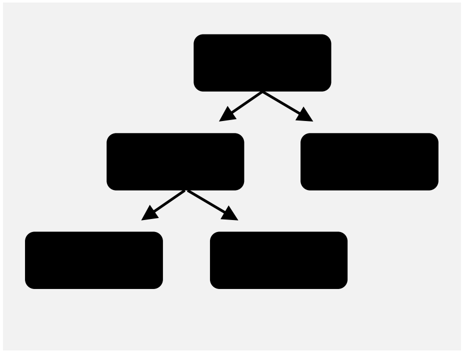
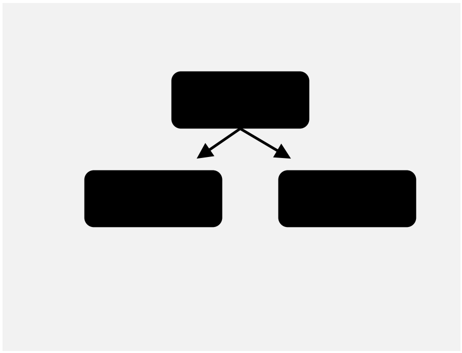
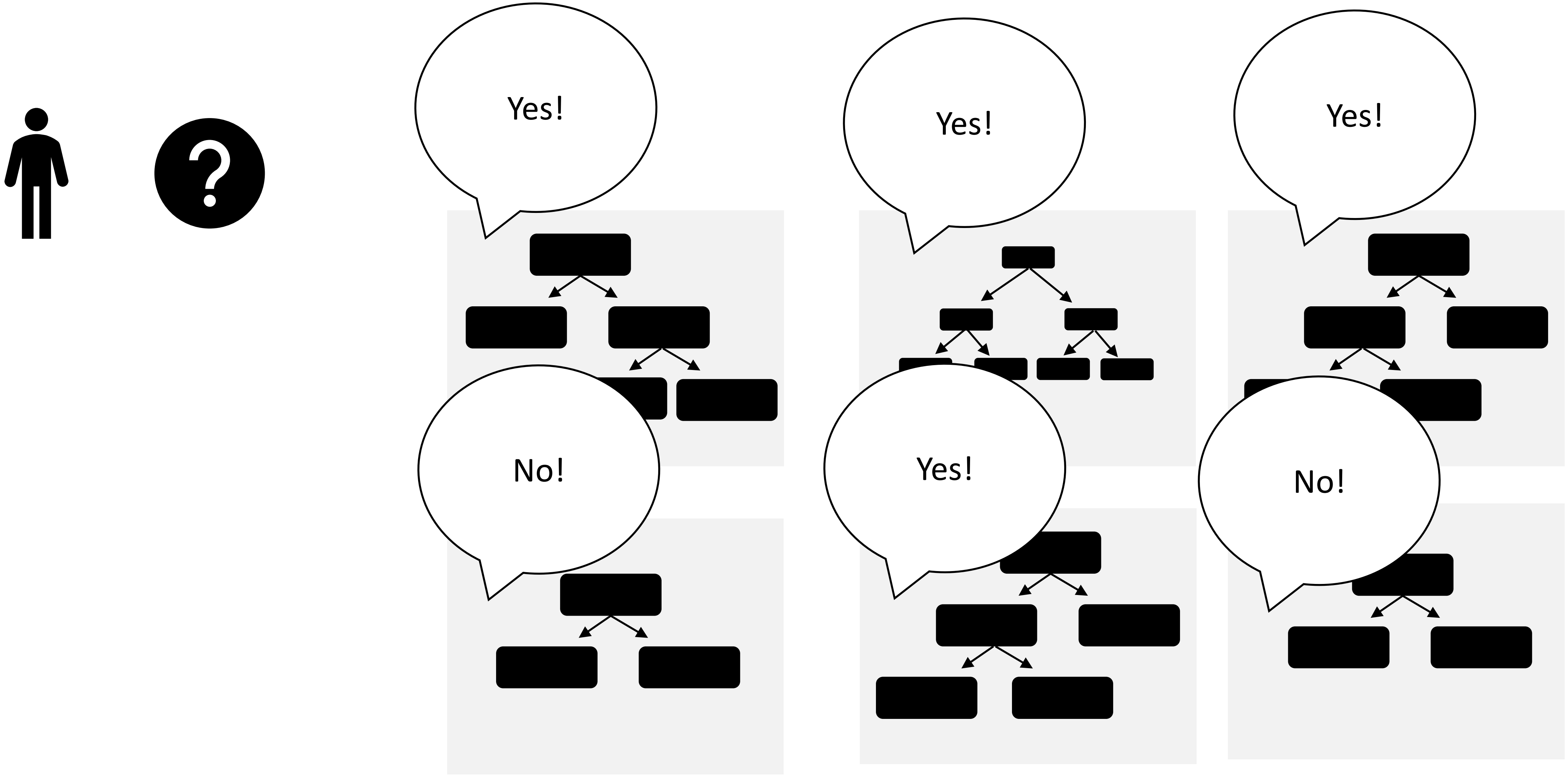


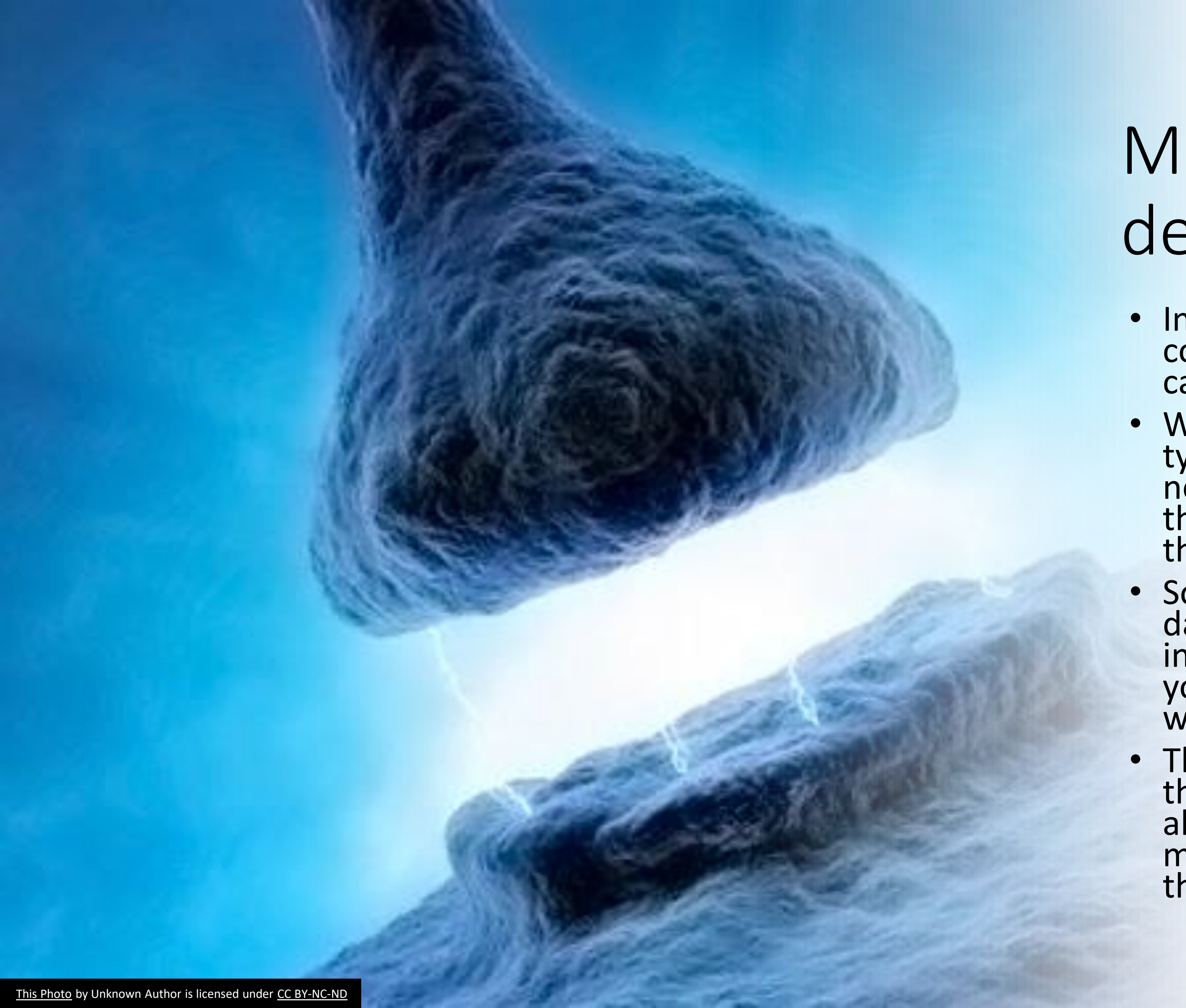




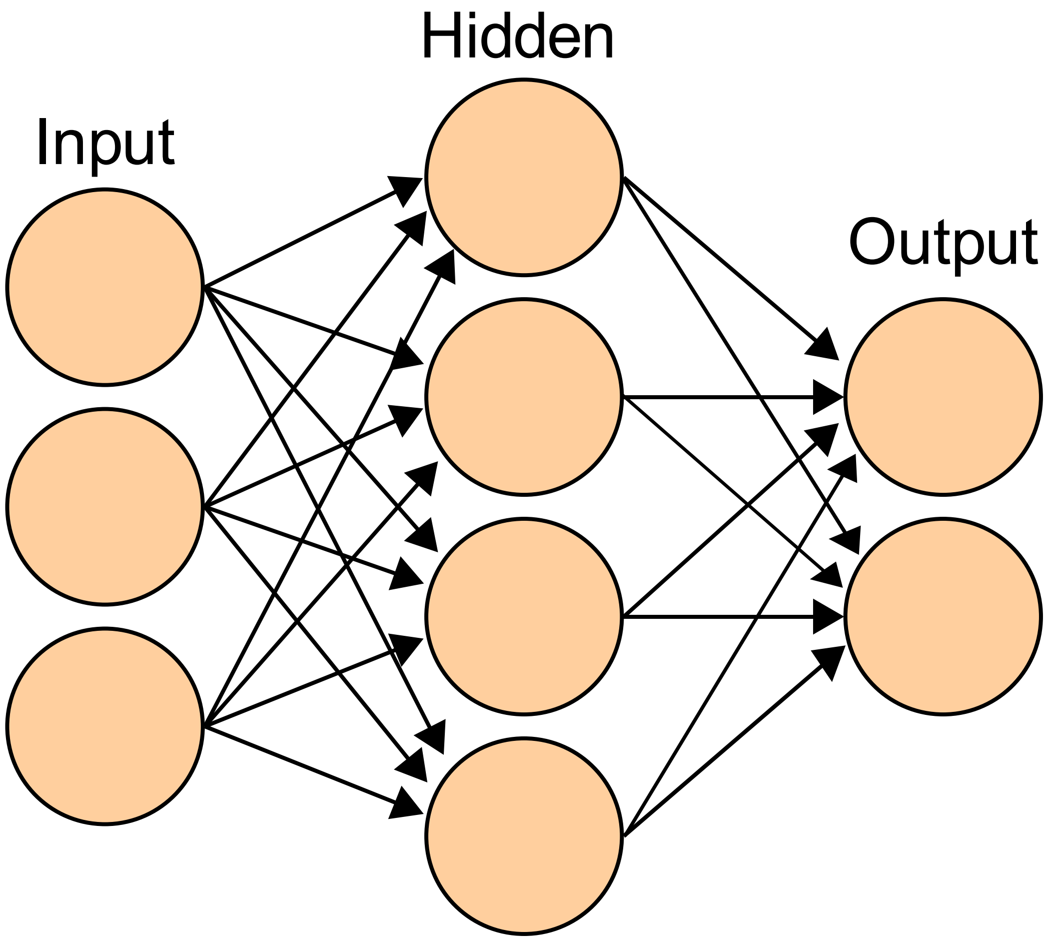

Yes!
Yes!
Yes!
No!
Yes!
No!



Motivating deep learning

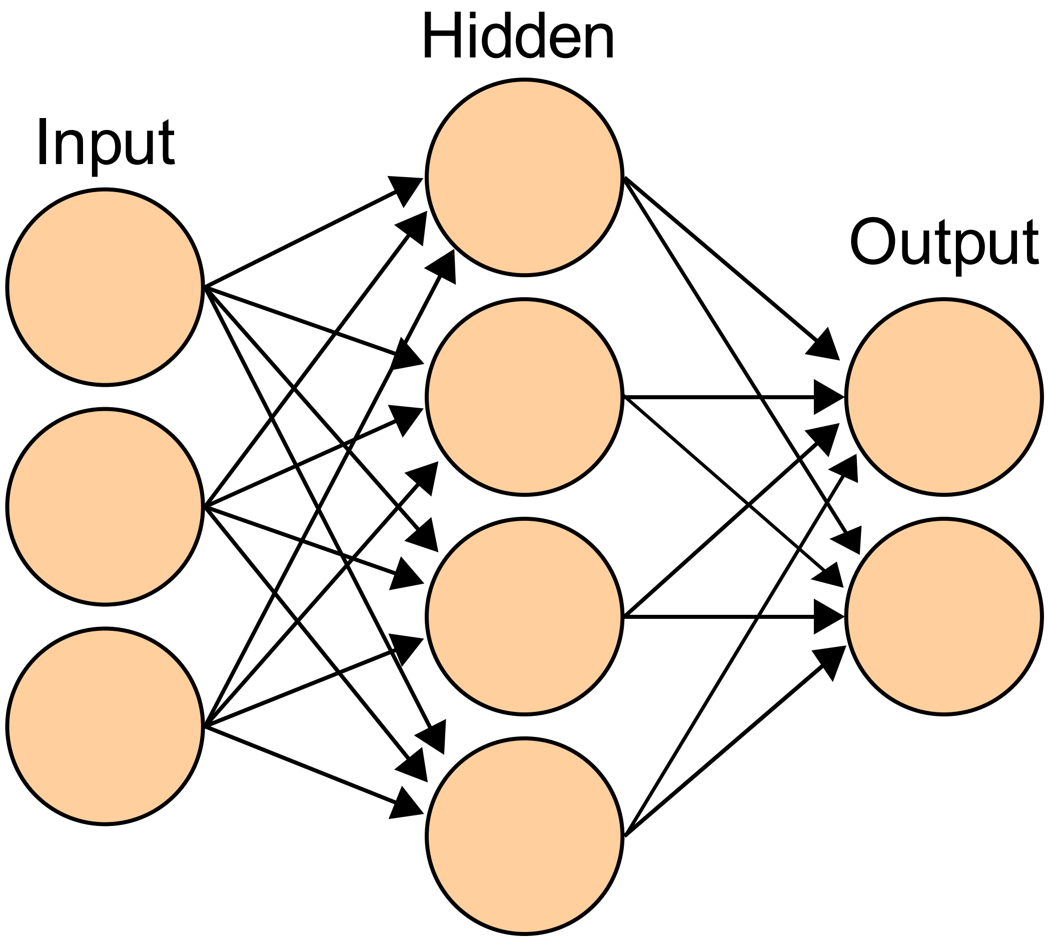
- In animal brains, **neurons** are connected to each other (at sites called **synapses**)
- When a neuron becomes **activated**, it typically sends signals to other neurons which in turn can activate them (in some cases it also inhibits them)
- So, when your brain receives sense data, a giant **network** of interconnected neurons fire so that you can make sense of and respond to what you're seeing
- The human brain is, in some ways, the thing we want to mimic with these algorithms. So why don't we try making an ML algorithm that copies these ideas?

Meet the algorithms: Deep learning



Meet the algorithms: Deep learning

Happy?	Rich?	Enjoys work?	Has dog?
Yes	No	Yes	Yes
No	No	No	No
Yes	Yes	No	Yes
No	Yes	Yes	No



Meet the algorithms: Deep learning

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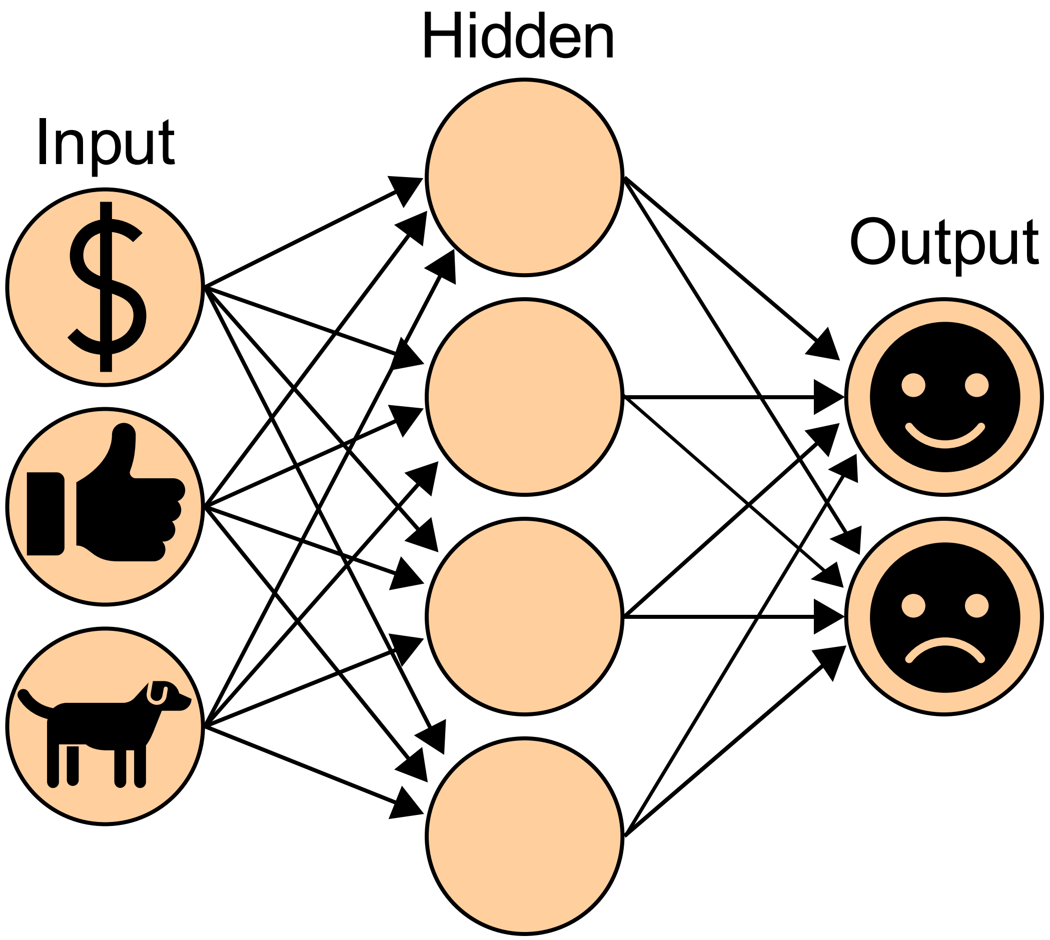

Meet the algorithms: Deep learning

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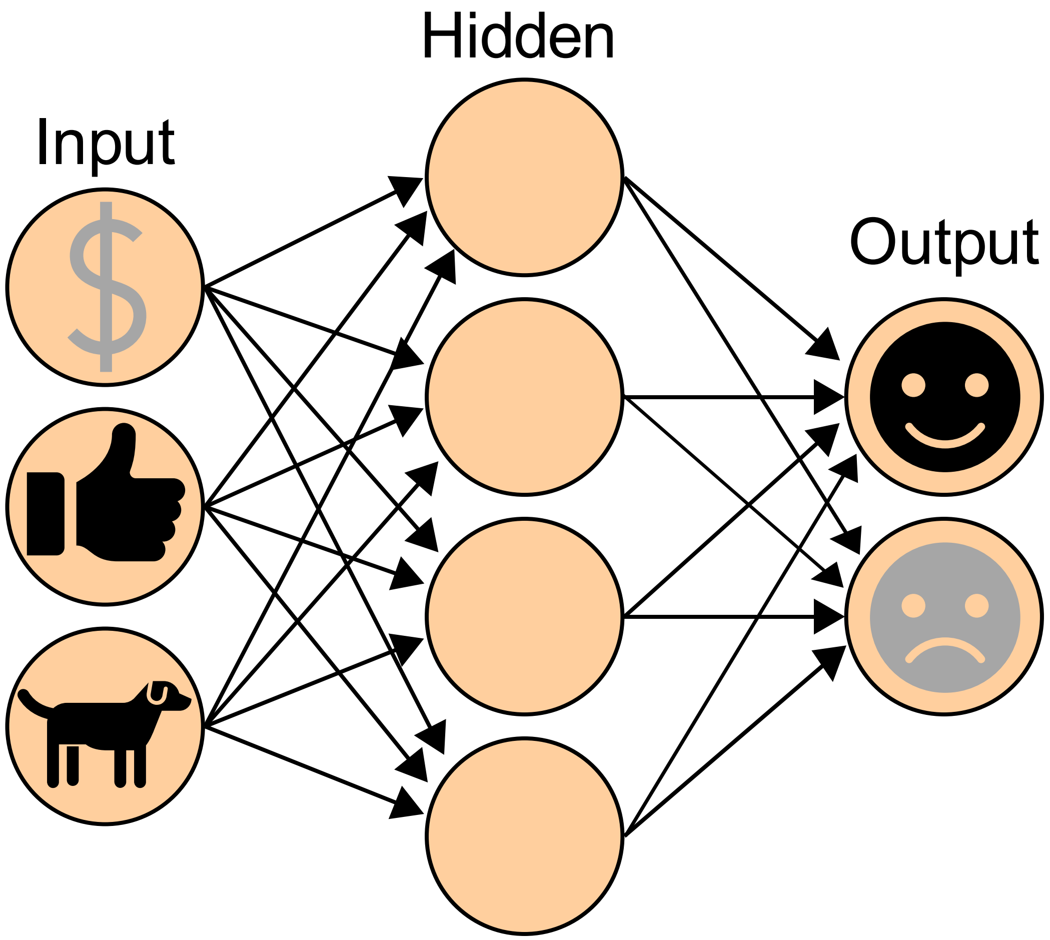
Yes	Yes	No	Yes
No	Yes	Yes	No



Meet the algorithms: Deep learning

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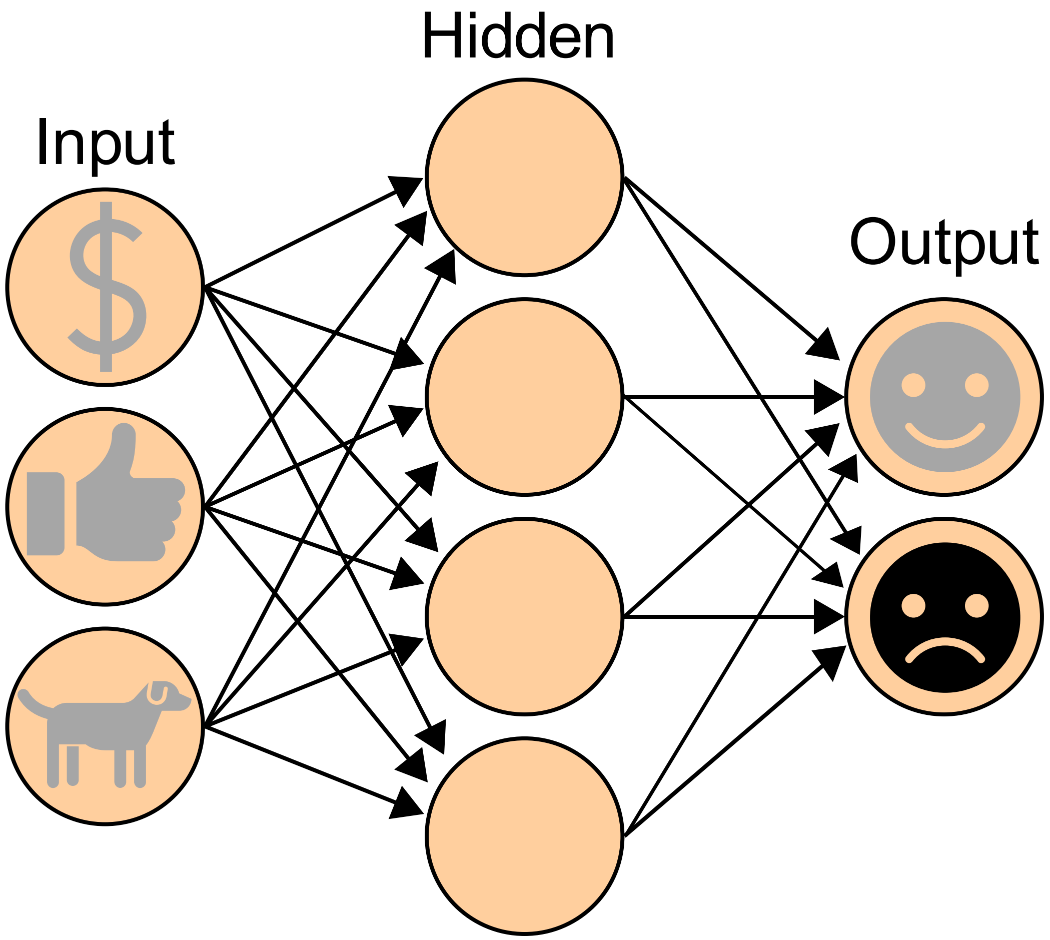
Yes	Yes	No	Yes
No	Yes	Yes	No



Meet the algorithms: Deep learning

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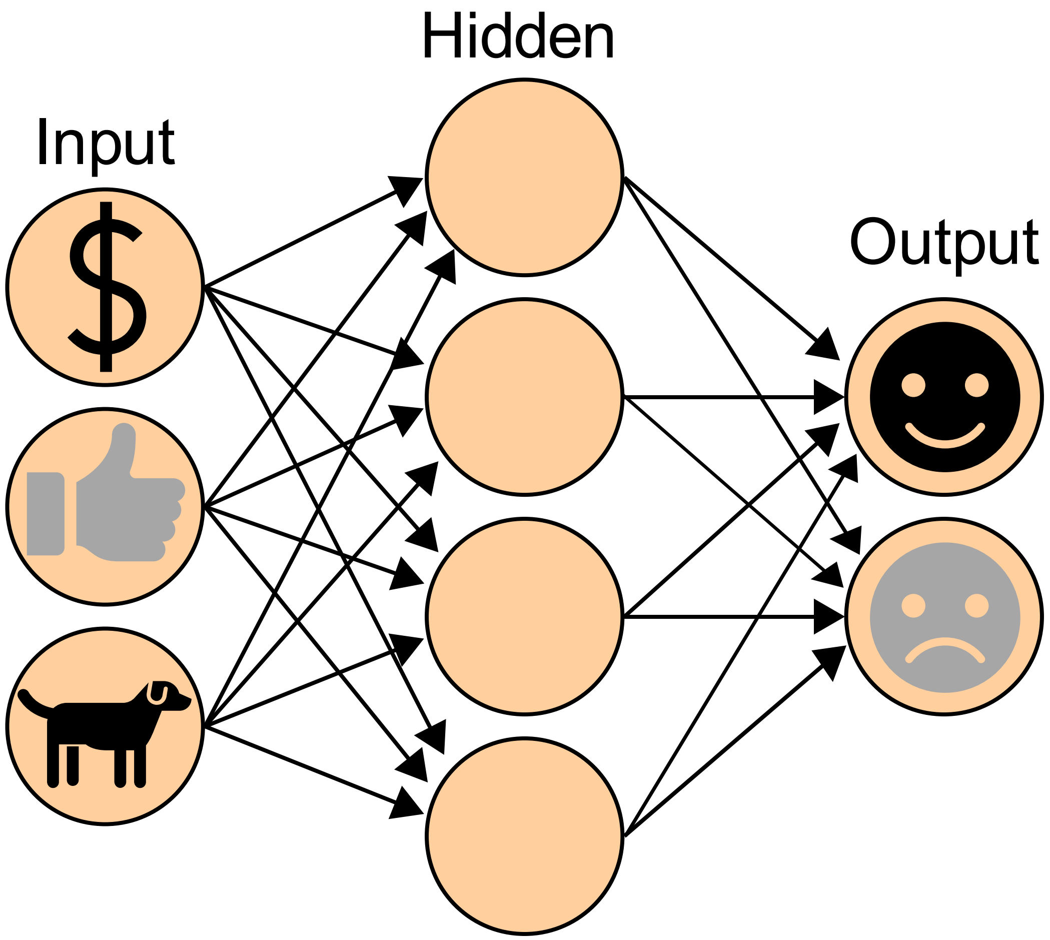
No	No	No	No
Yes	**Yes**	**No**	**Yes**
No	Yes	Yes	No



Meet the algorithms: Deep learning

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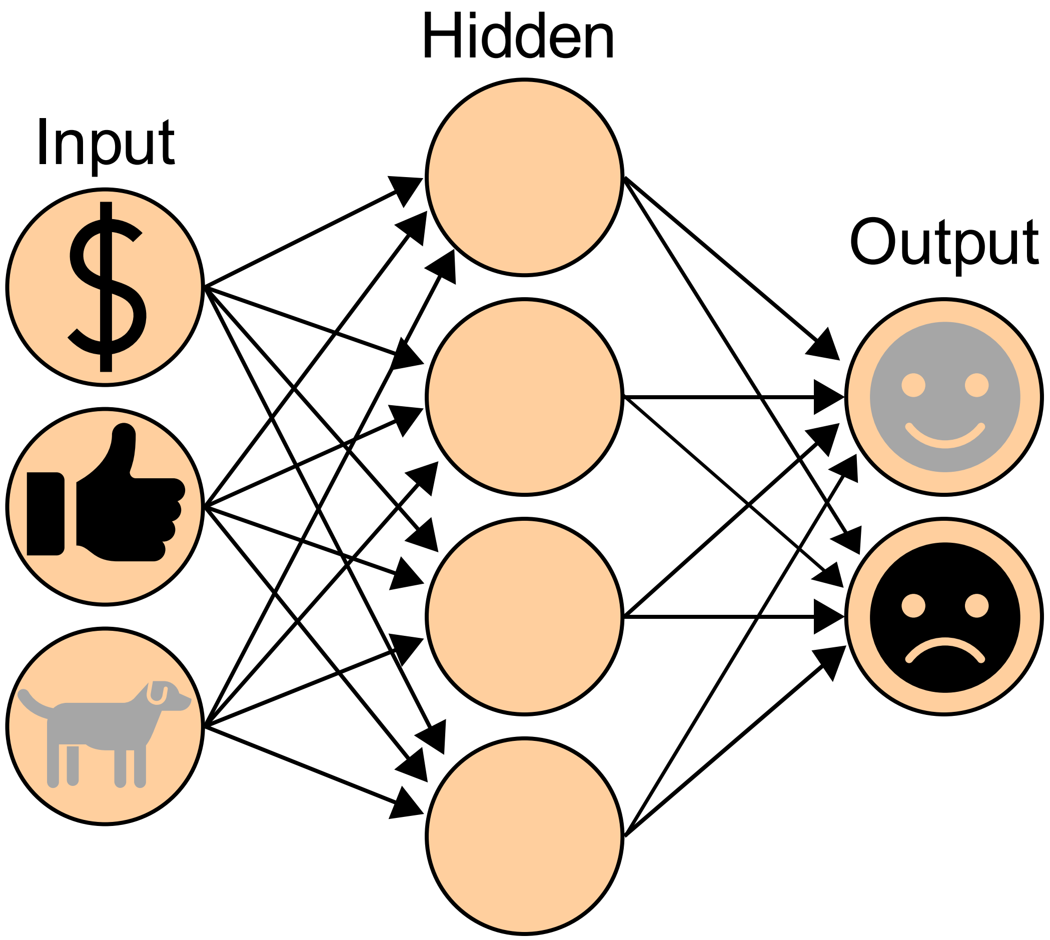

Meet the algorithms: Deep learning

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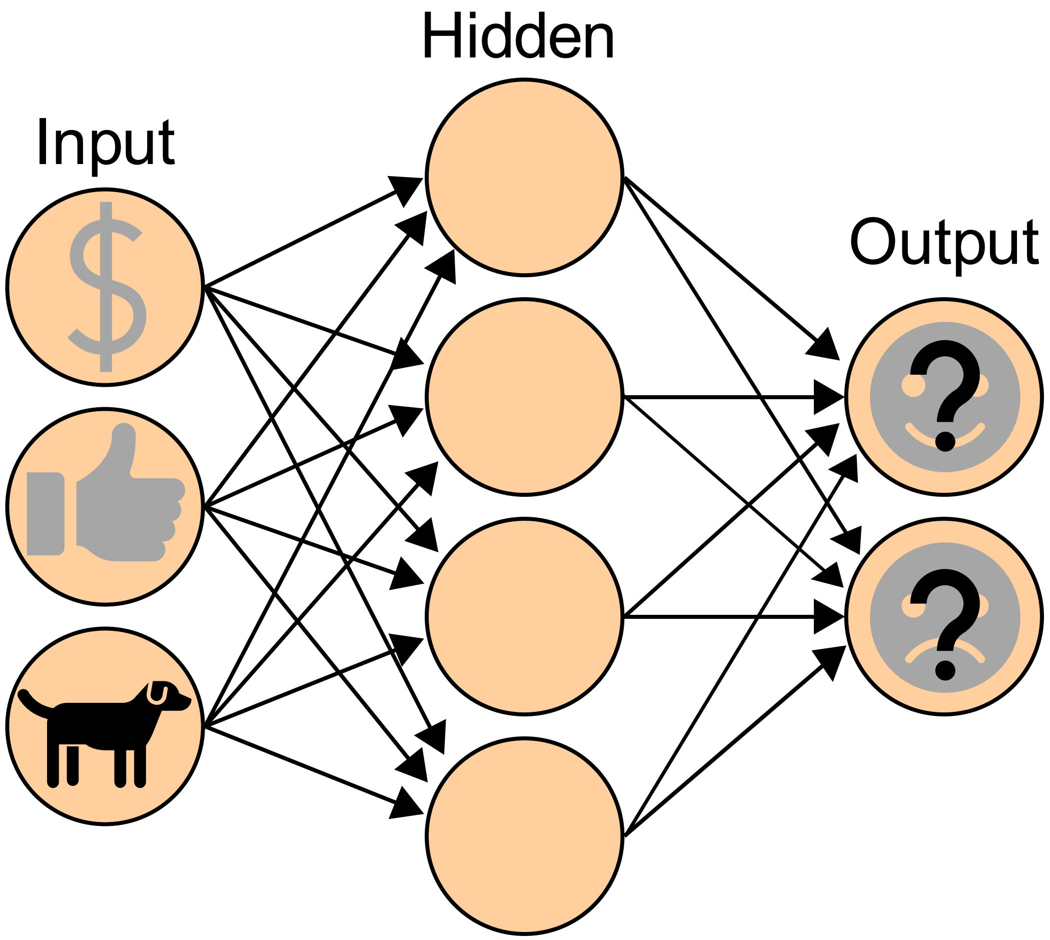

Other important topics

- Cross-validation
- Support vector machines
- Unsupervised ML (K-means, autoencoders)
- Reinforcement learning
- Adversarial learning

Reminders

- I’ve extended the deadline for discussion papers for the organizational theory readings… They are now due this Thursday (6/30) before class.
- Method Module 1 is available on Canvas now. If you want to complete it for credit on your final paper, finish it and turn it in on Canvas before class a week from today (7/5)
- Office hours are tomorrow in my office from 11 AM to noon.

See everyone Thursday!

If you’d like to take a quick look at the Methods Module, I’m happy to do so now