Machine Learning

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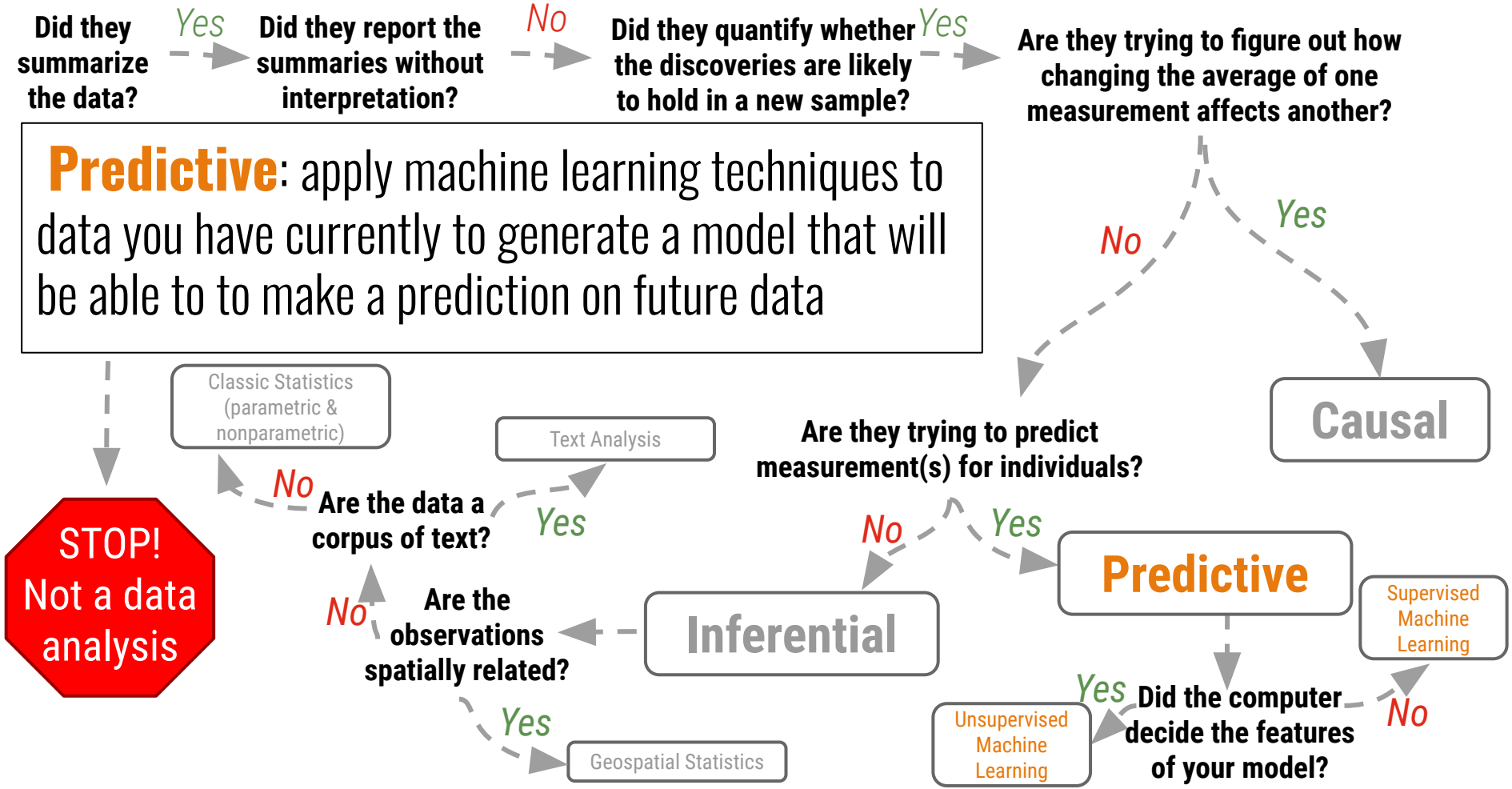
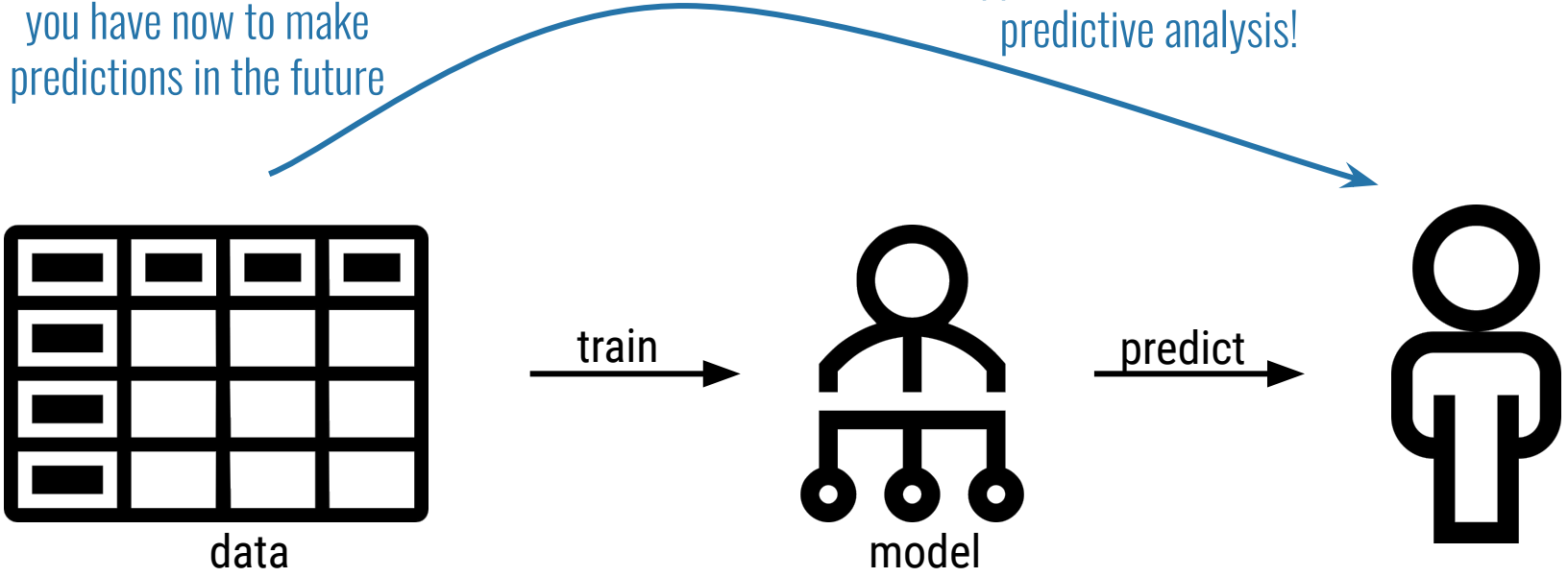

Did they summarize the data?
Yes
Did they report the summaries without interpretation?
No
Did they quantify whether the discoveries are likely to hold in a new sample?
Yes
Are they trying to figure out how changing the average of one measurement affects another?
Predictive: apply machine learning techniques to data you have currently to generate a model that will be able to to make a prediction on future data
No
Yes
Causal
Are they trying to predict measurement(s) for individuals?
No
Yes
Predictive
Supervised Machine Learning
Did the computer decide the features of your model?
Yes
Unsupervised Machine Learning
No
Inferential
Are the observations spatially related?
No
Yes
Geospatial Statistics
Are the data a corpus of text?
No
Yes
Text Analysis
Classic Statistics (parametric & nonparametric)
STOP! Not a data analysis

- **Problem:** Detecting whether credit card charges are fraudulent.
- **Data science question:** Can we use the time of the charge, the location of the charge, and the price of the charge to predict whether that charge is fraudulent or not?
- **Type of analysis:** Predictive analysis

predictive analysis uses data you have now to make predictions in the future

machine learning approaches are used for predictive analysis!



What is machine learning?

"Machine learning is the science of getting computers to act without being explicitly programmed"

- Andrew Ng, Stanford, ex-Google, chief scientist at Baidu, Coursera founder, Stanford Adjunct Faculty

Prediction Questions

Which of these questions is most appropriate for machine learning?

A How common is watching Sesame Street in the US?

B What is the effect of watching Sesame Street on children's brains?

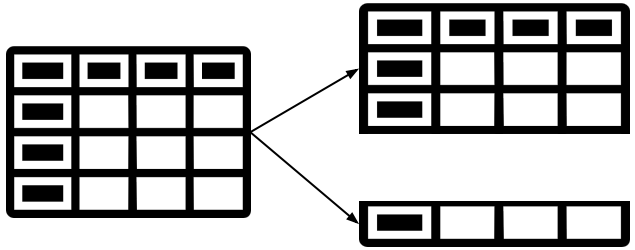
C What is the relationship between early childhood educational programming and success in elementary school?

D Can we use information about one's early childhood to predict their success in elementary school?

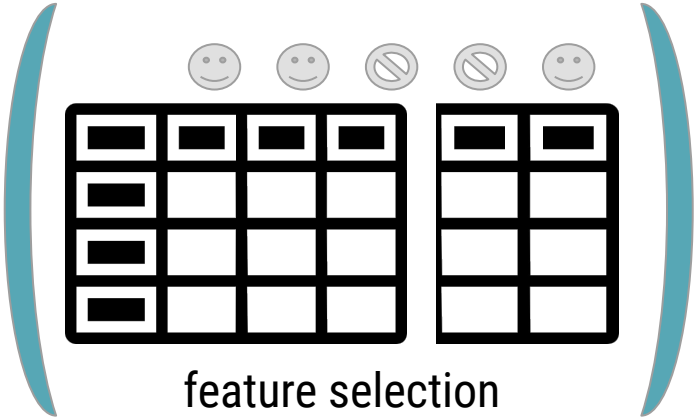
E How does Sesame Street cause an increase in educational attainment?

Machine Learning Generalizations

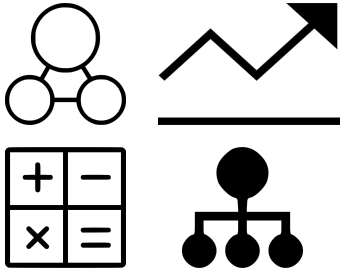
Basic Steps to Prediction



data
partitioning

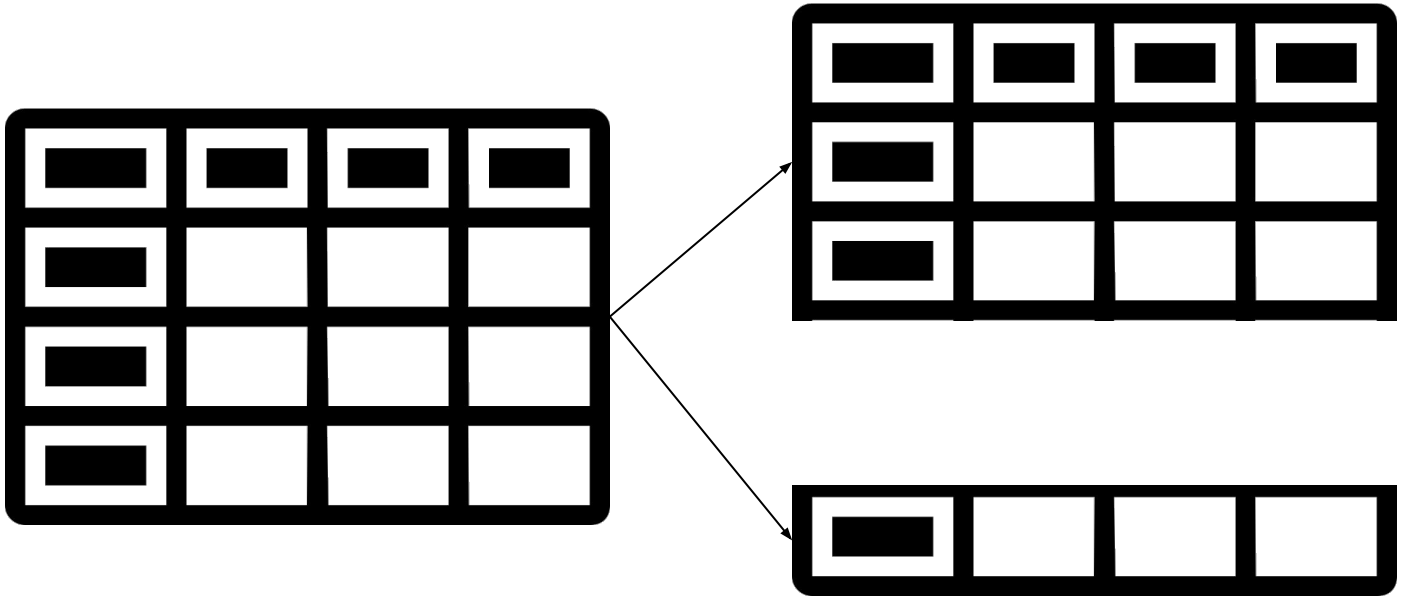


feature selection

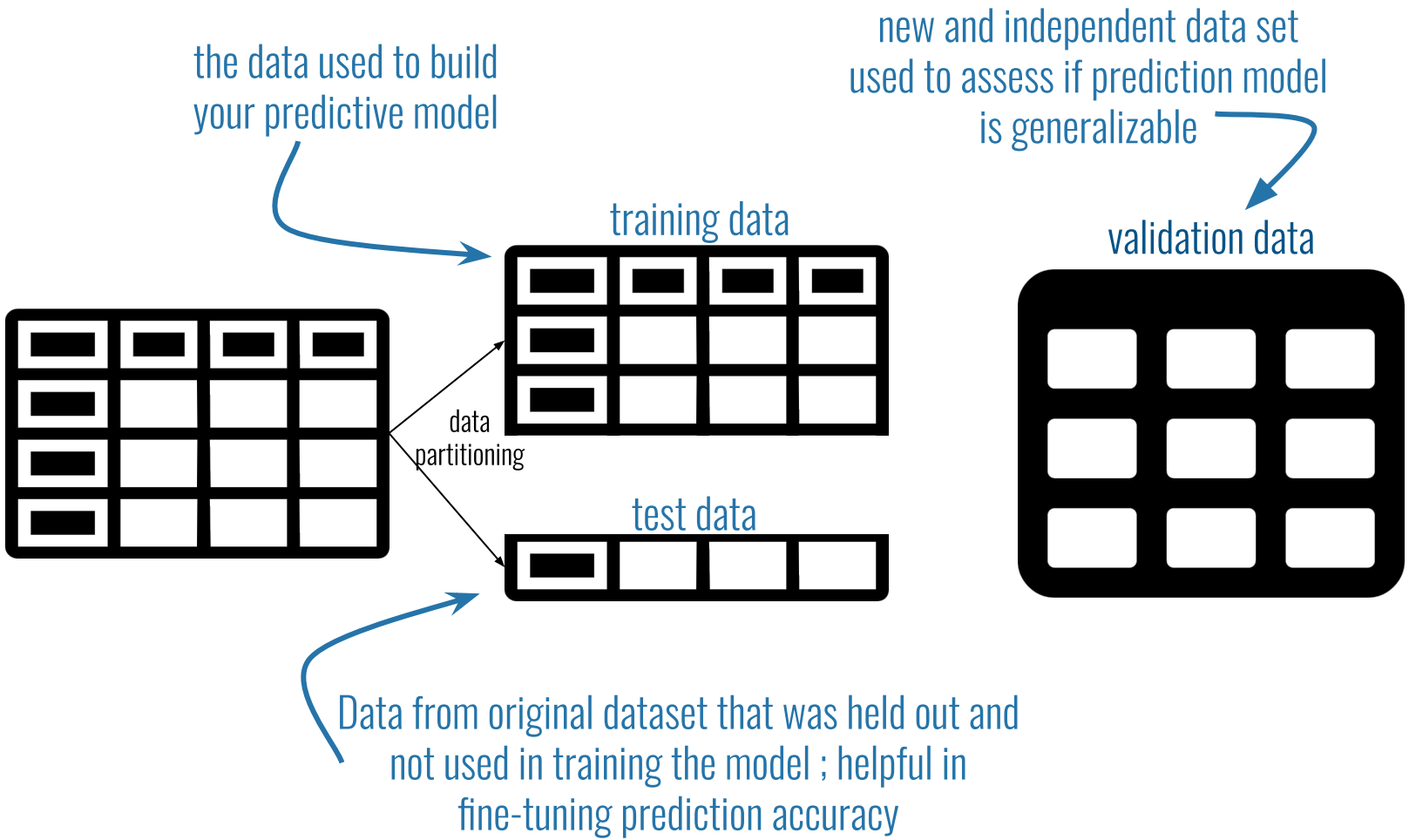


model selection

model assessment

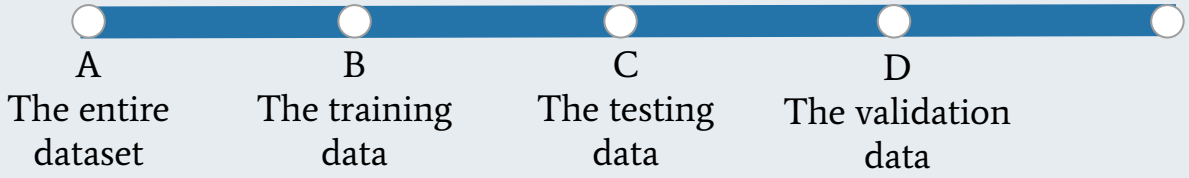


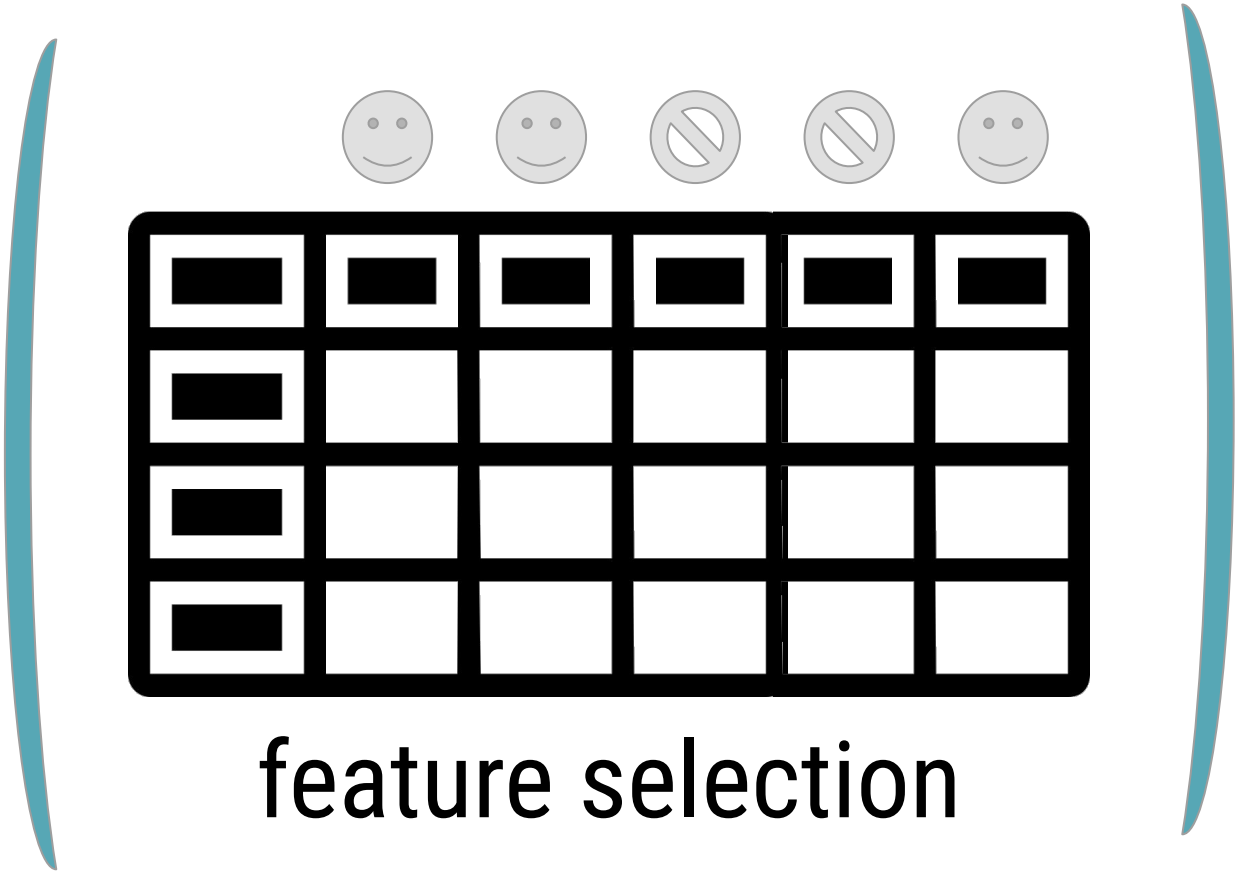
data partitioning


the data used to build your predictive model
new and independent data set used to assess if prediction model is generalizable
training data
validation data
data partitioning
test data
Data from original dataset that was held out and not used in training the model ; helpful in fine-tuning prediction accuracy

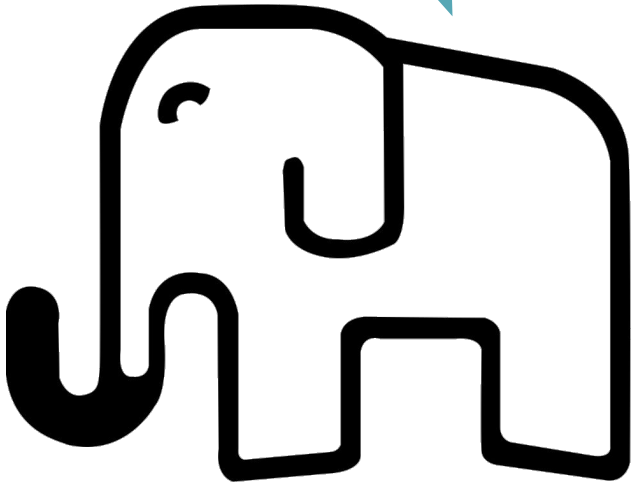
Data Partitioning

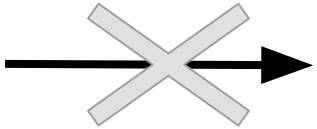
What portion of the data are typically used for generating the model?

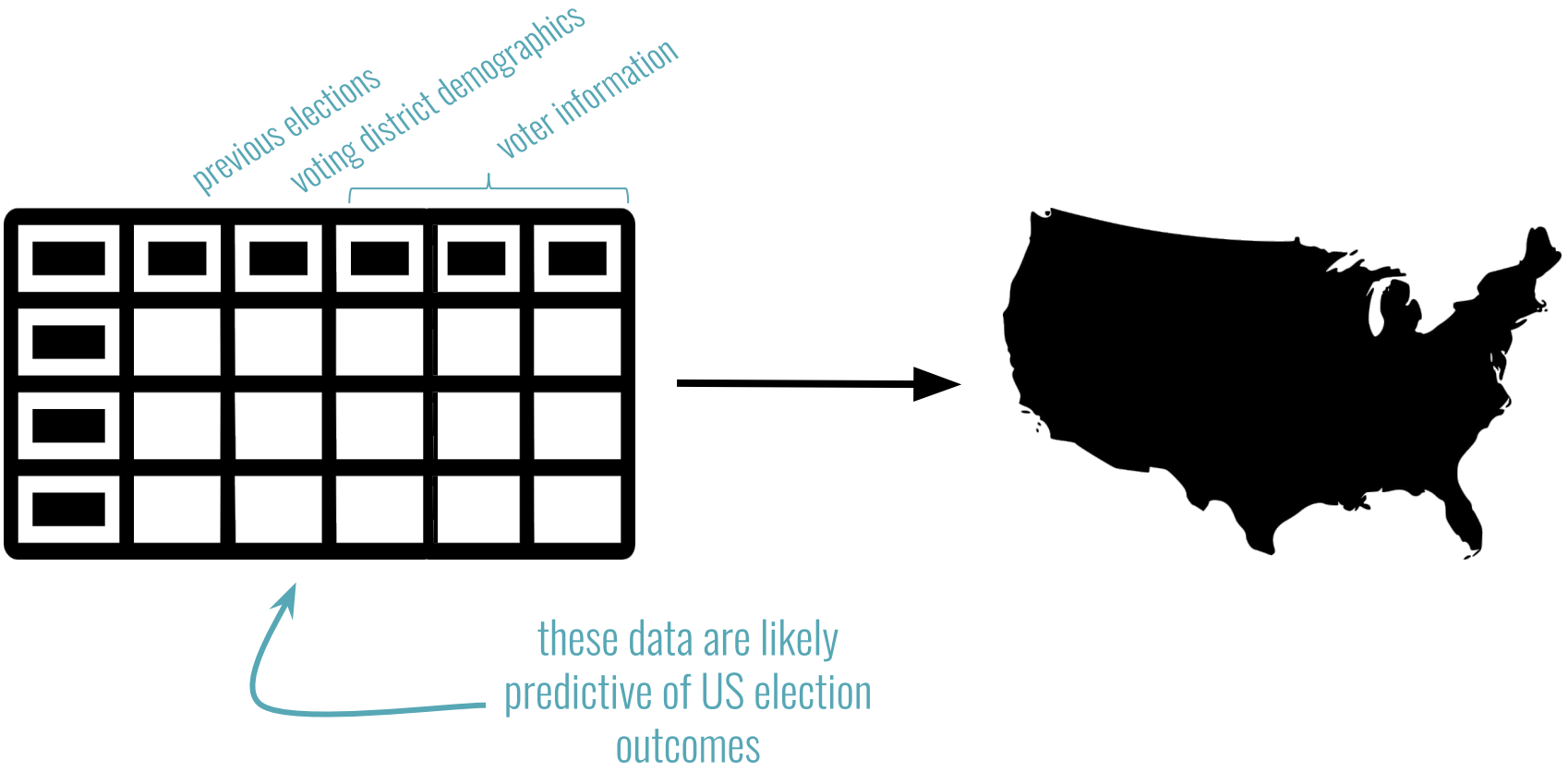


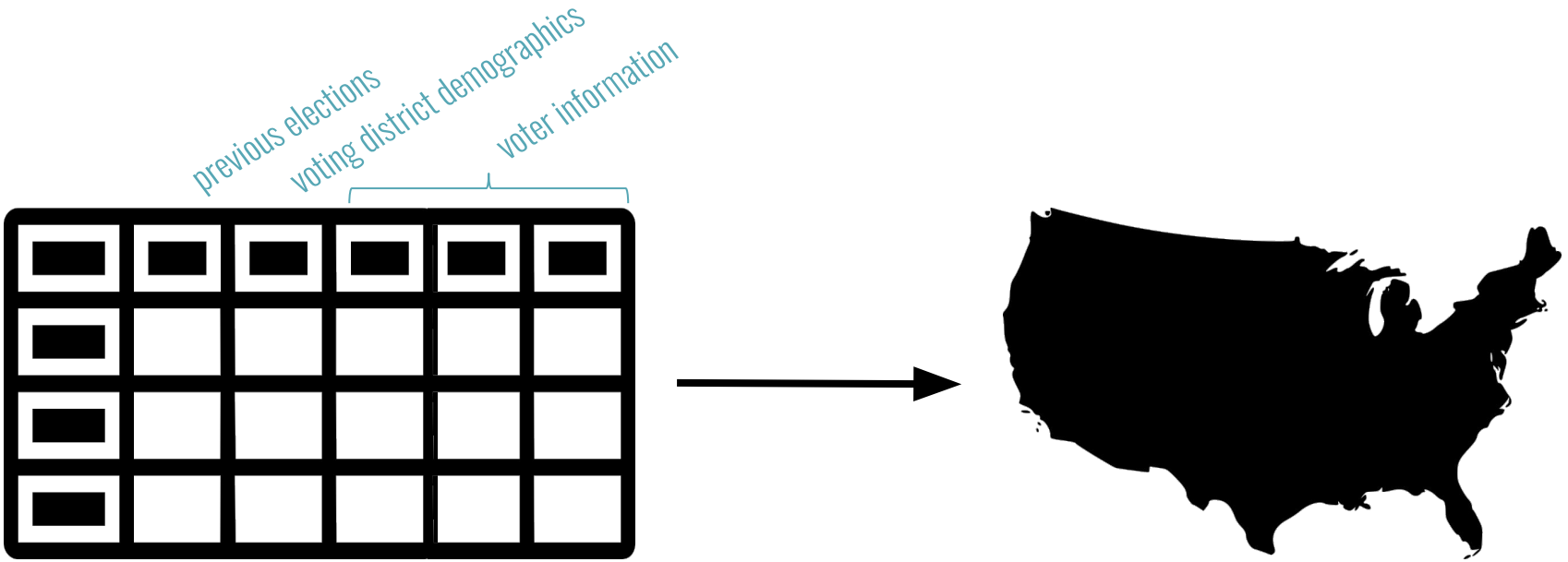

feature selection

elephant height data are likely
not predictive of US elections

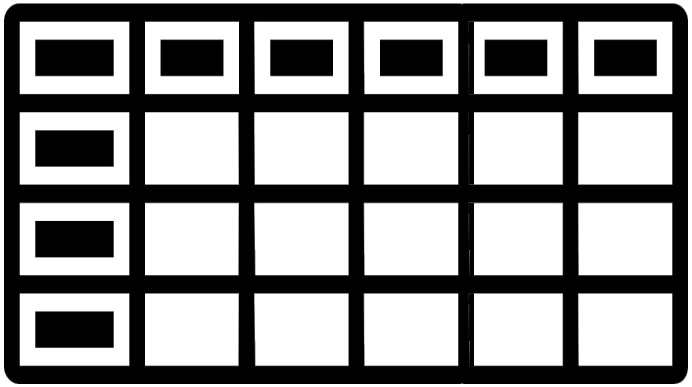





previous elections
voting district demographics
voter information
these data are likely predictive of US election outcomes



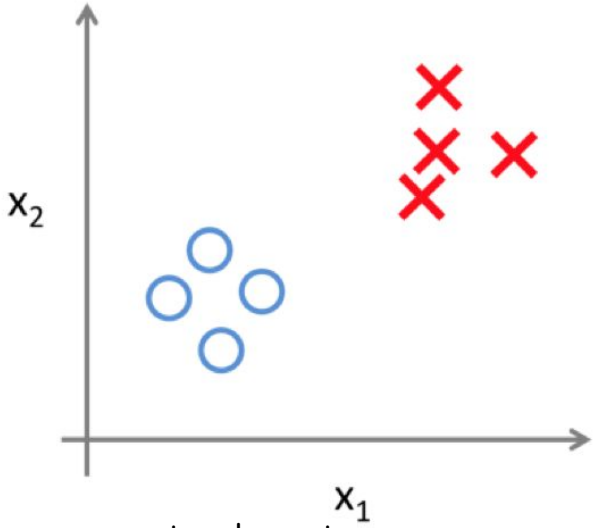
feature selection determines which variables are most predictive and includes them in the model



variables that can be used for accurate prediction exploit the relationship between the variables but do NOT mean that one causes the other

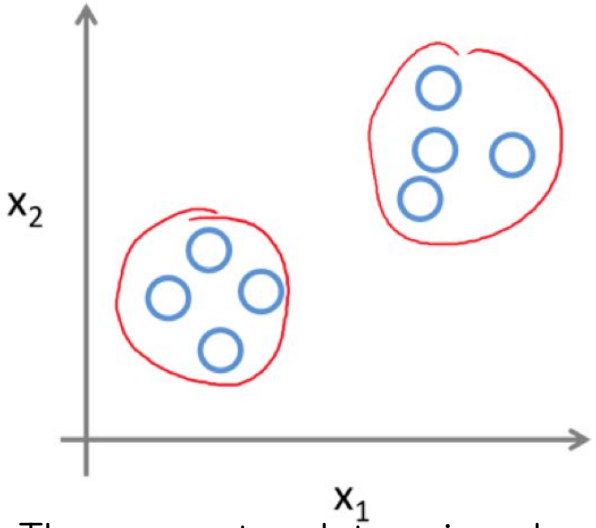
To modes of machine learning

Supervised Learning



You tell the computer how to classify the observations

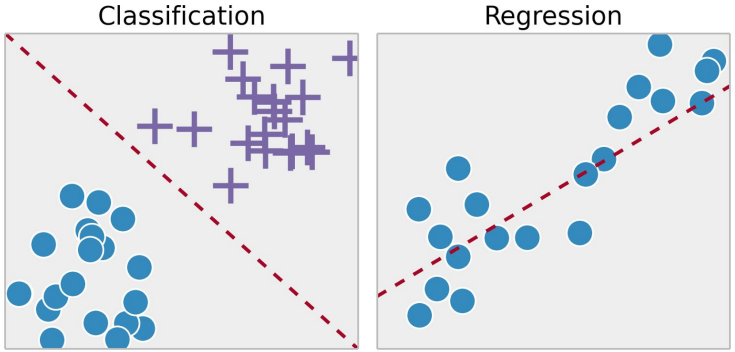
Unsupervised Learning



The computer determines how to classify based on properties within the data

Approaches to machine learning

Supervised Learning

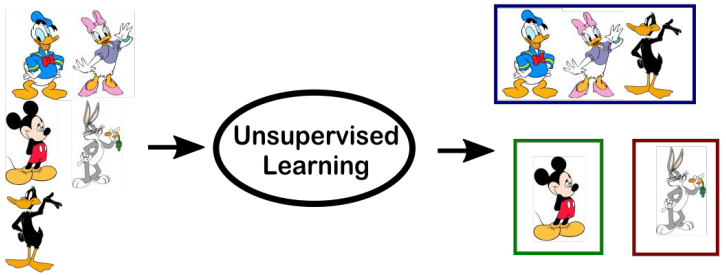


categorical variables

continuous variables

Prediction accuracy dependent on training data

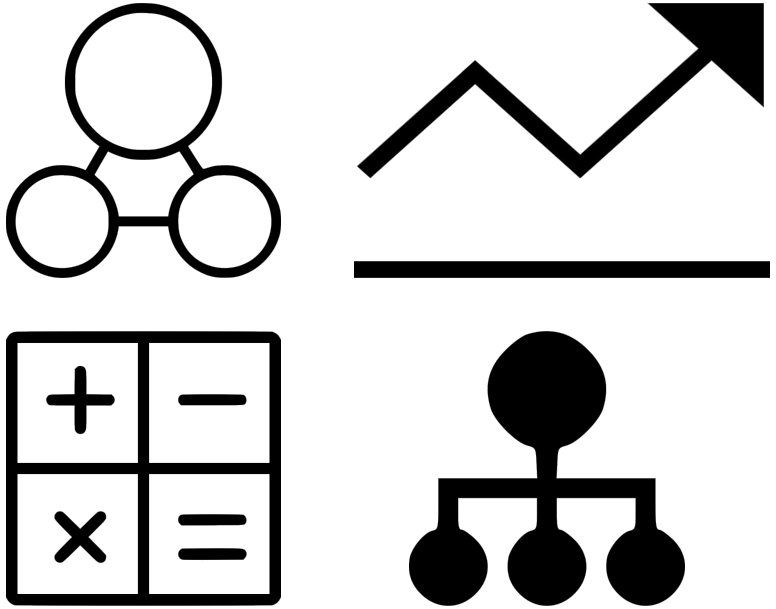
Unsupervised Learning



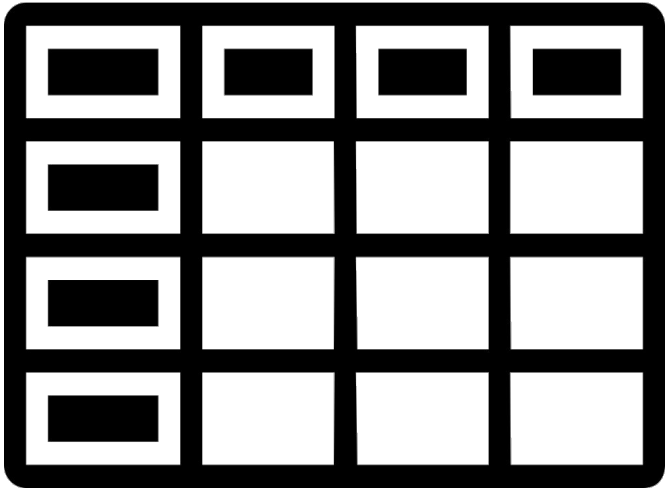
Clustering (categorical)
& dimensionality reduction (continuous)

can automatically identify structure in data

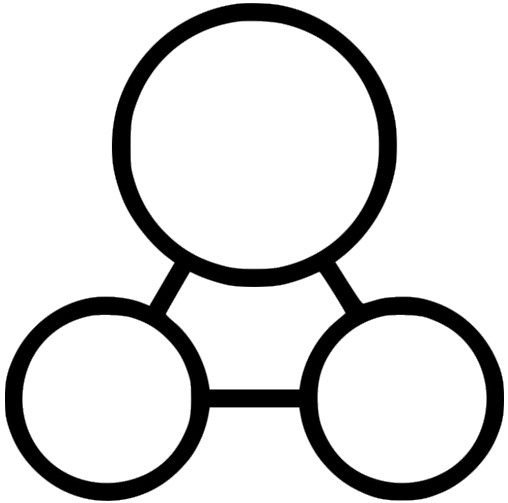
Image source: https://towardsdatascience.com/supervised-vs-unsupervised-learning-14f68e32ea8d



model selection

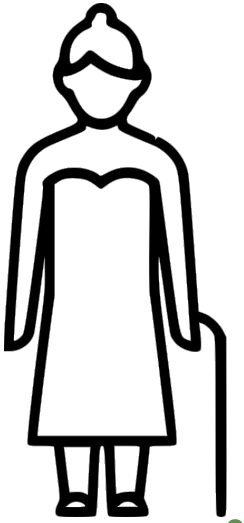


big
datasets



simple
models

Supervised Learning



Regression:

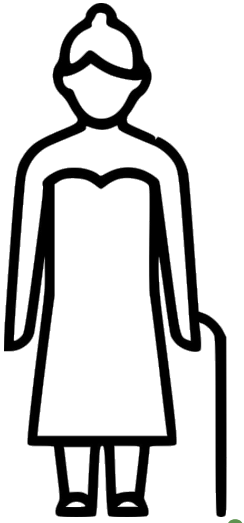
predicting continuous variables
(i.e. Age)

continuous variable prediction

Classification:

predicting categorical variables
(i.e. education level)

categorical variable prediction



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Supervised Learning

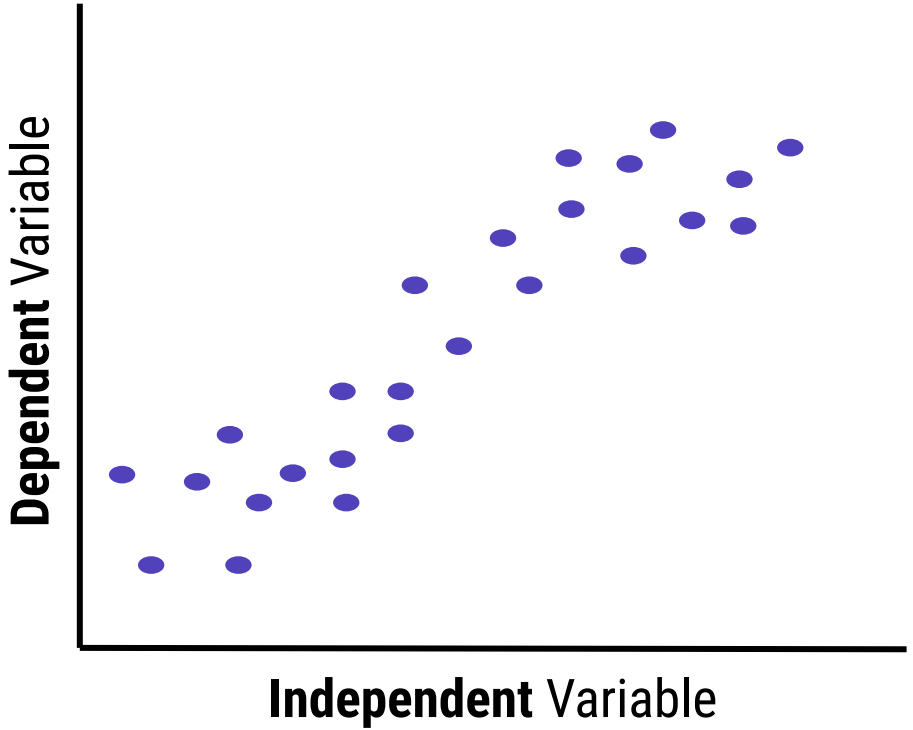
regression

continuous variable prediction

Supervised Learning

regression

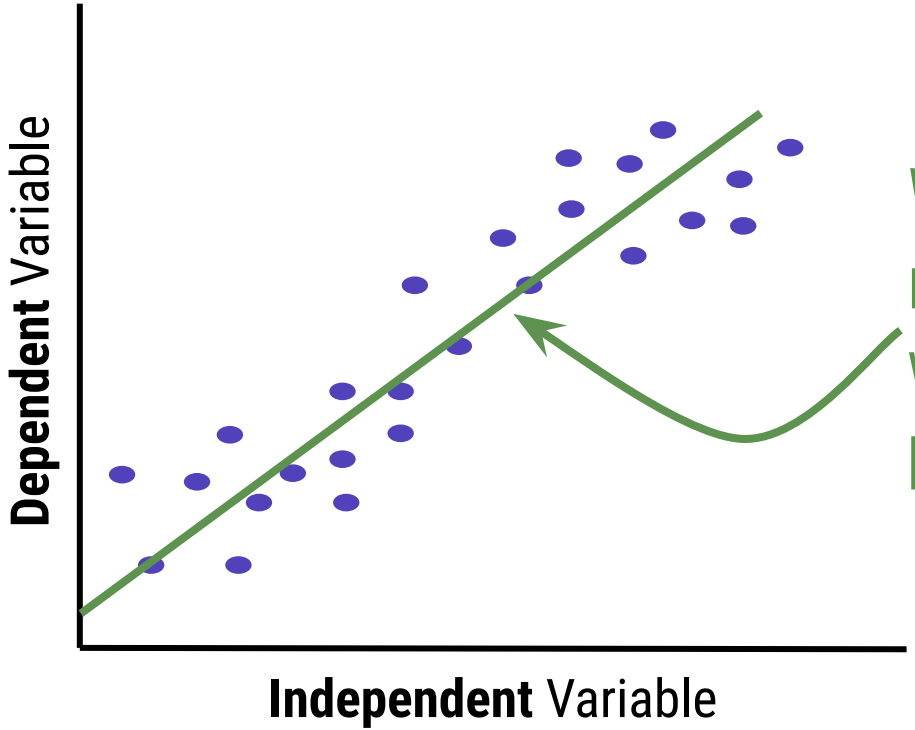
continuous variable prediction



Supervised Learning

regression

continuous variable prediction

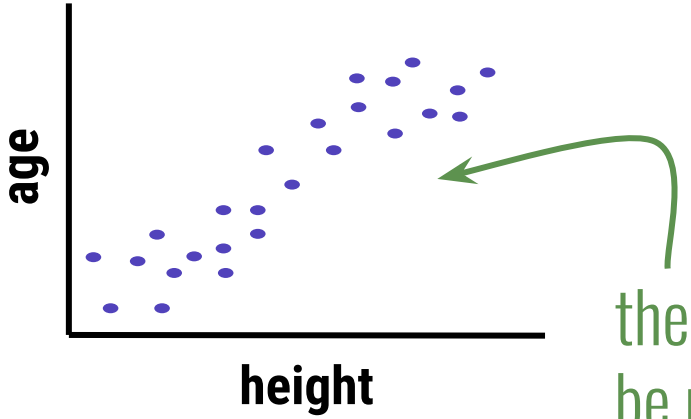


We'll use the linear relationship between variables to generate a **predictive model**

Supervised Learning

regression

continuous variable prediction

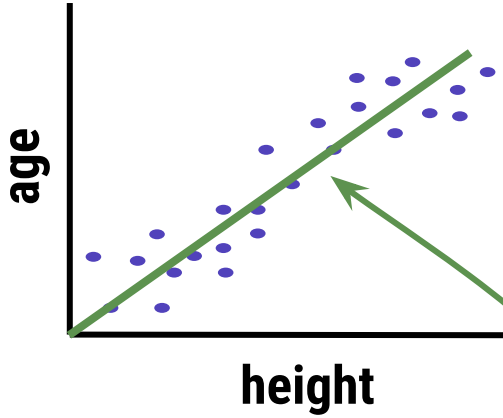


the training data will be used to build the predictive model

Supervised Learning

regression

continuous variable prediction

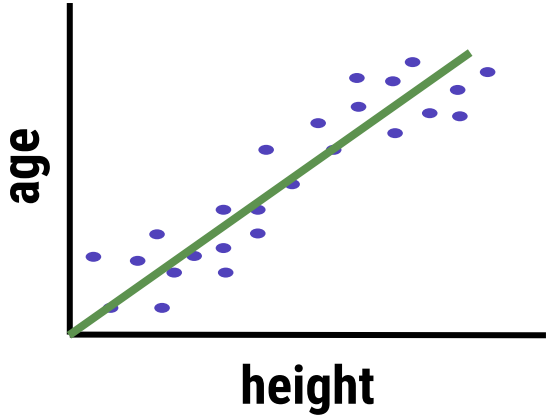


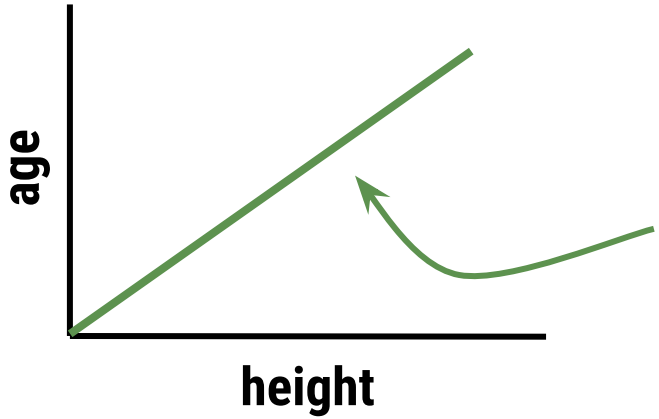
use linear regression to model the relationship

Supervised Learning

regression

continuous variable prediction



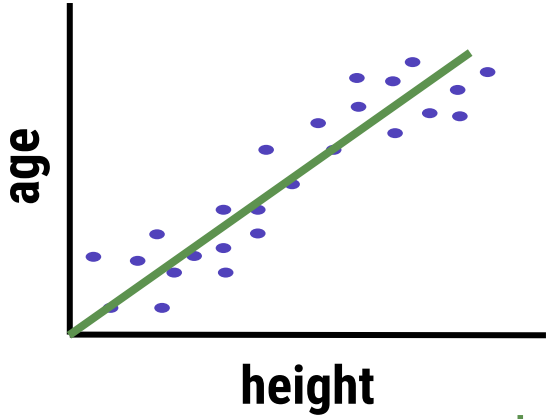


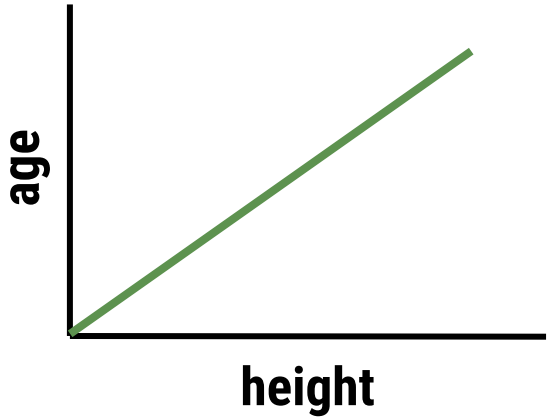
For prediction, the individual values in the training data are *not* important. We only need the model.

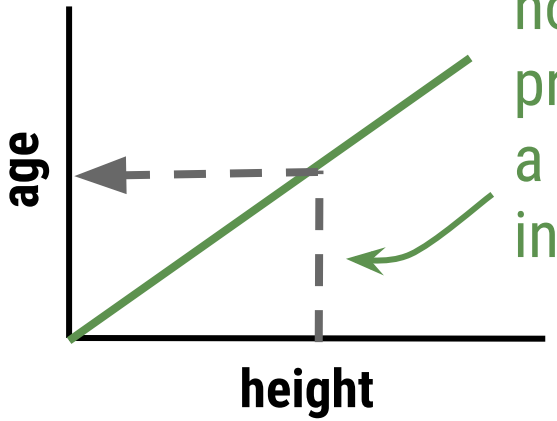
Supervised Learning

regression

continuous variable prediction





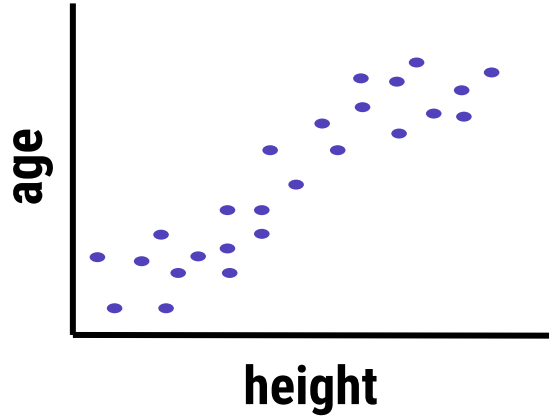


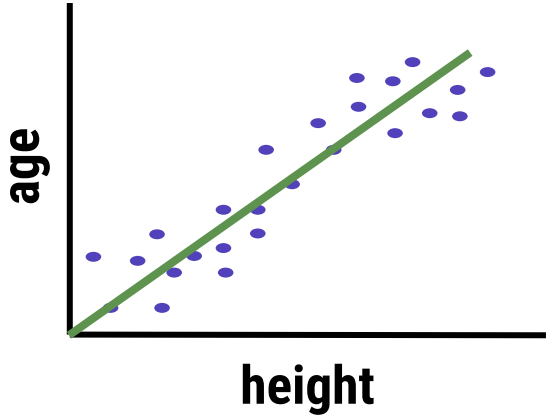
how we'll make predictions for a future individual

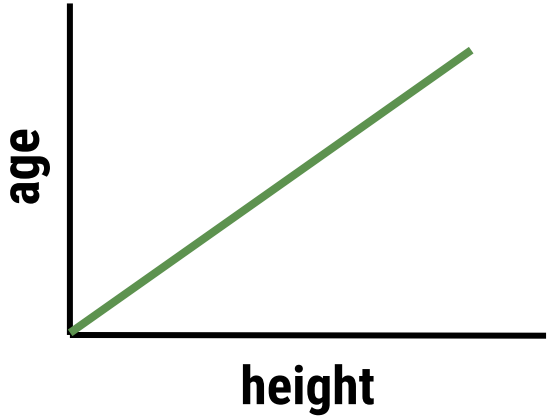
Supervised Learning

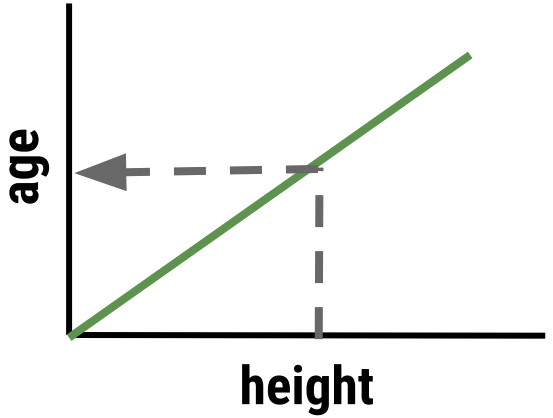
regression

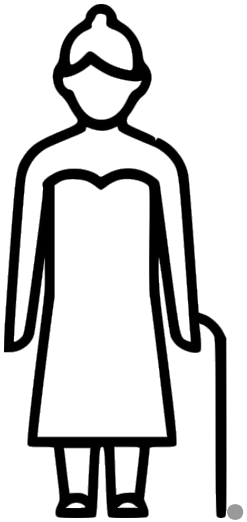
continuous variable prediction











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Supervised Learning

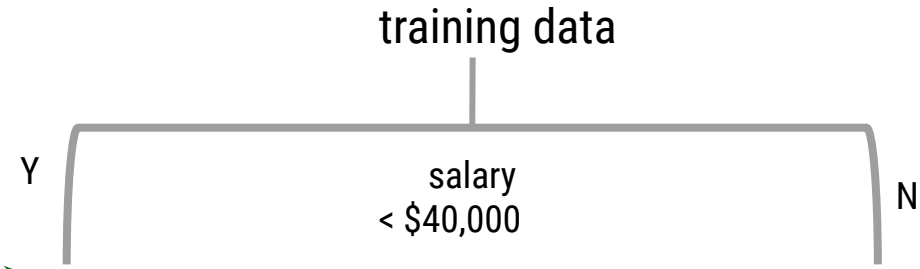
classification

categorical variable prediction

Supervised Learning

classification

categorical variable prediction



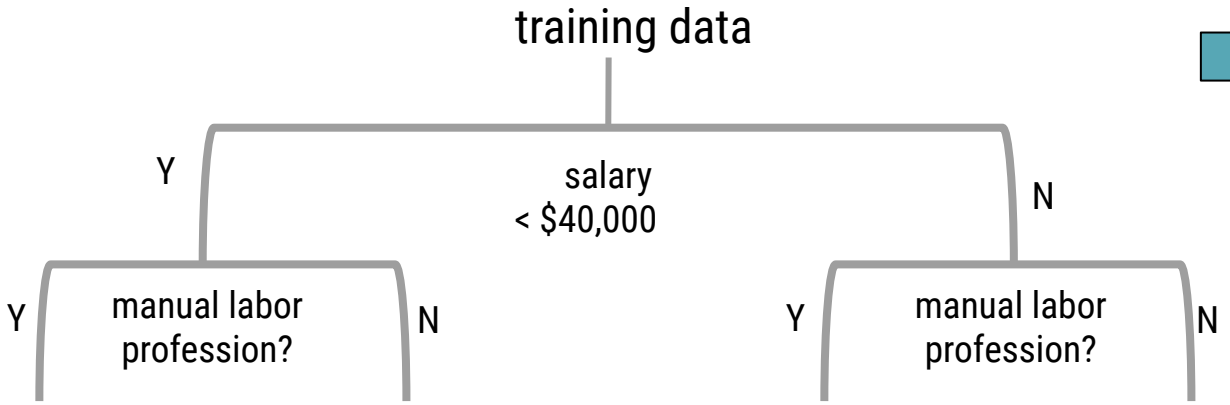
All the people who make *less* than 40K over here

All the people who make *more* than 40K over here

Supervised Learning

classification

categorical variable prediction

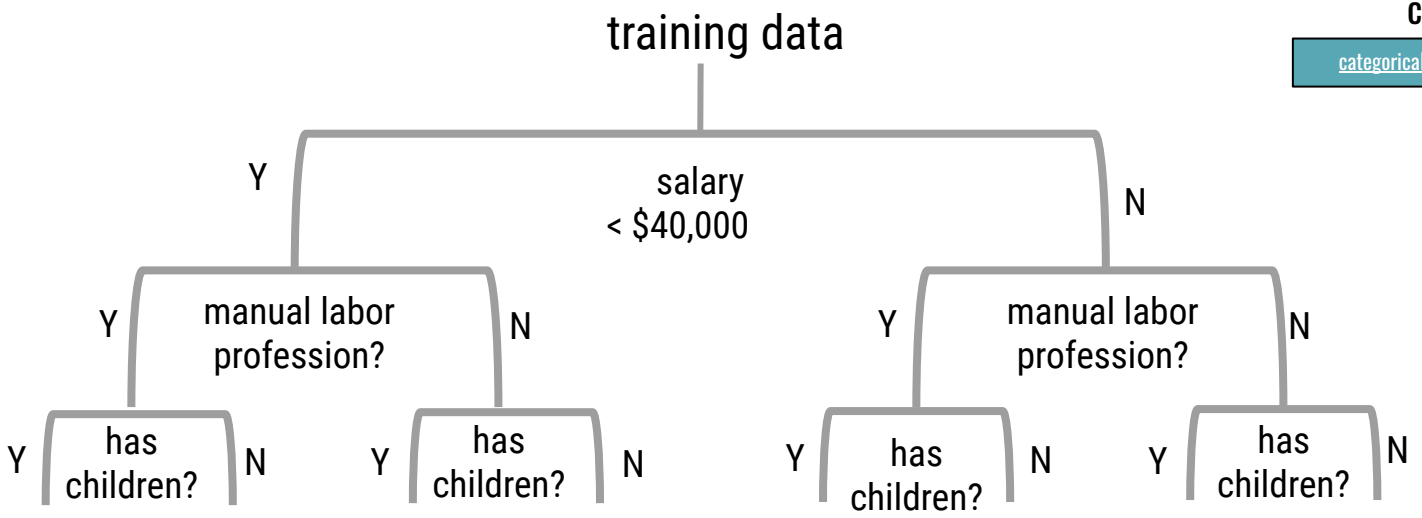


Continue adding *branches* to the **decision tree** where the variables and information in the training data decide which observations goes down which branch

Supervised Learning

classification

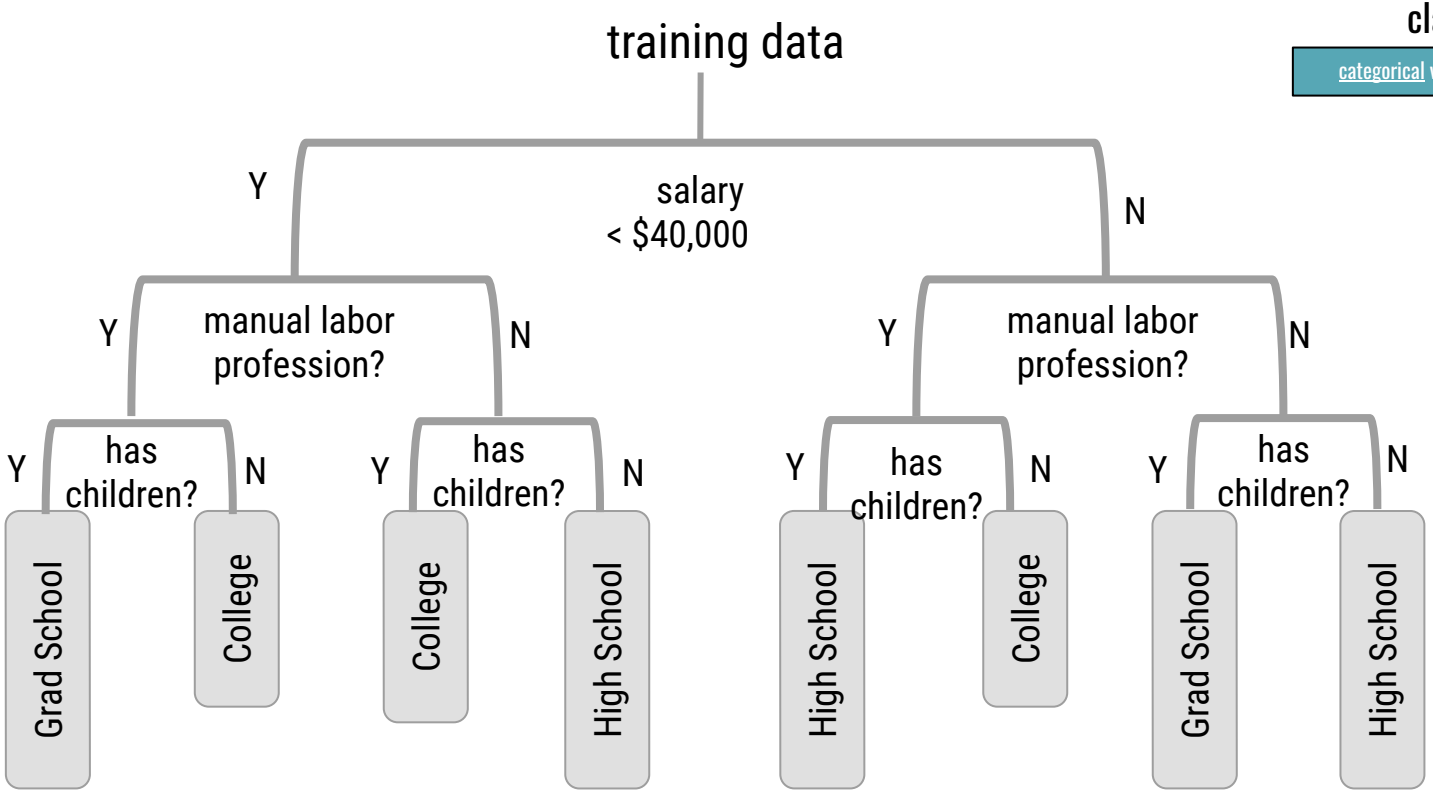
categorical variable prediction



Supervised Learning

classification

categorical variable prediction

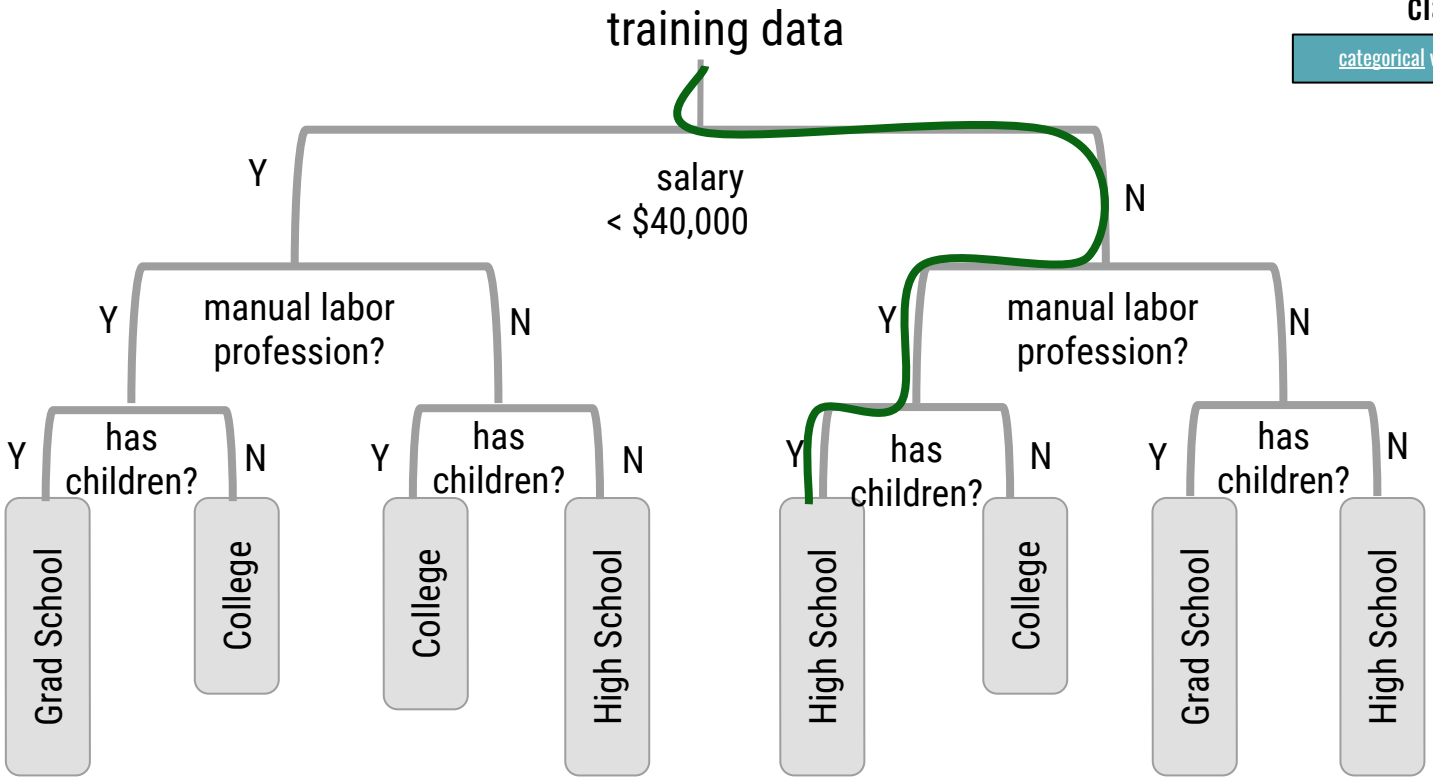


At the end of the tree, labels will be applied to each *leaf* of the tree

Supervised Learning

classification

categorical variable prediction

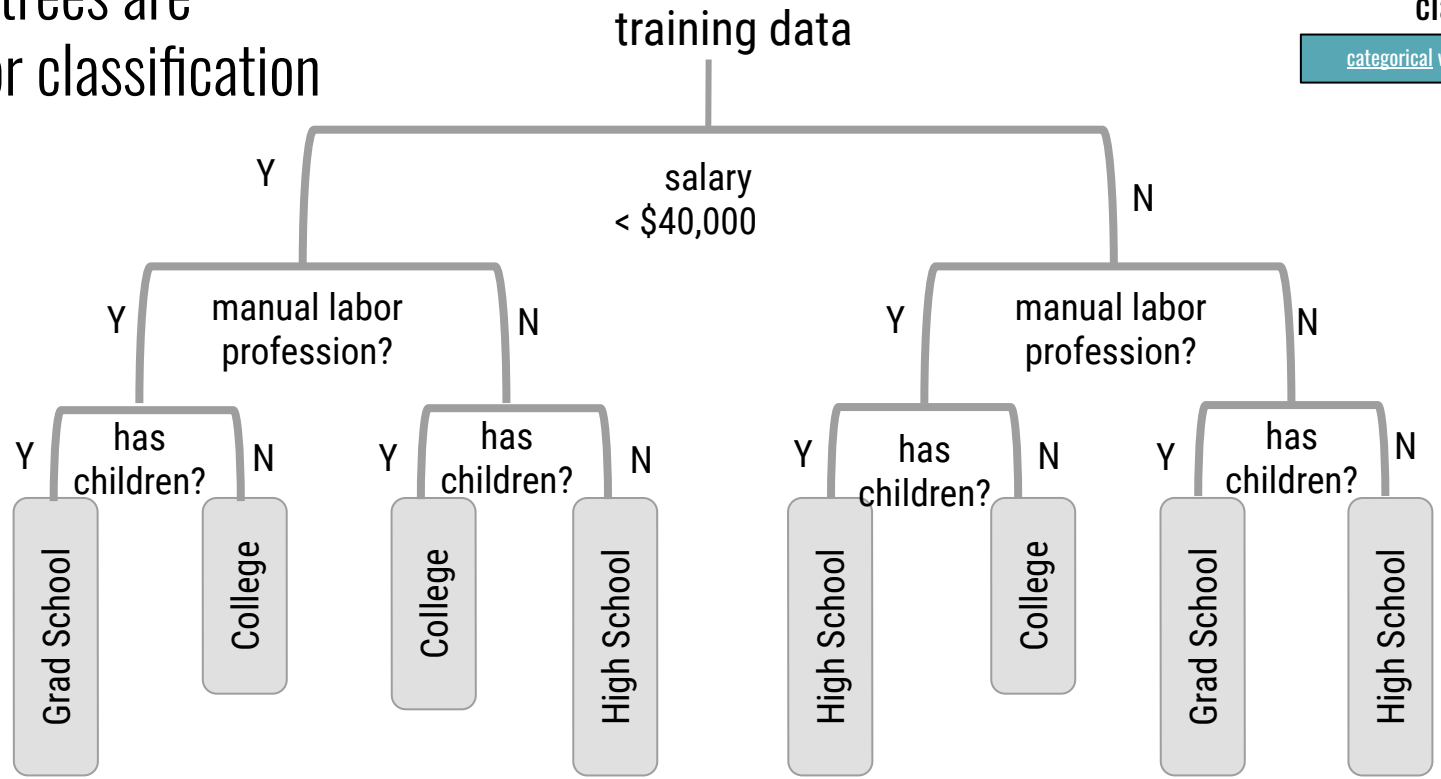


Decision trees are helpful for classification

Supervised Learning

classification

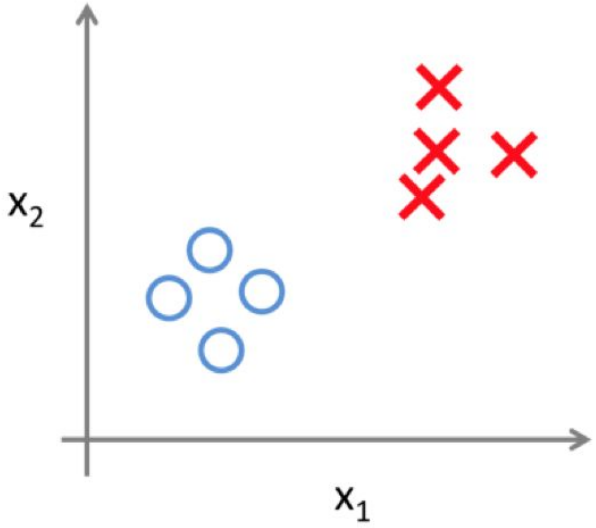
categorical variable prediction



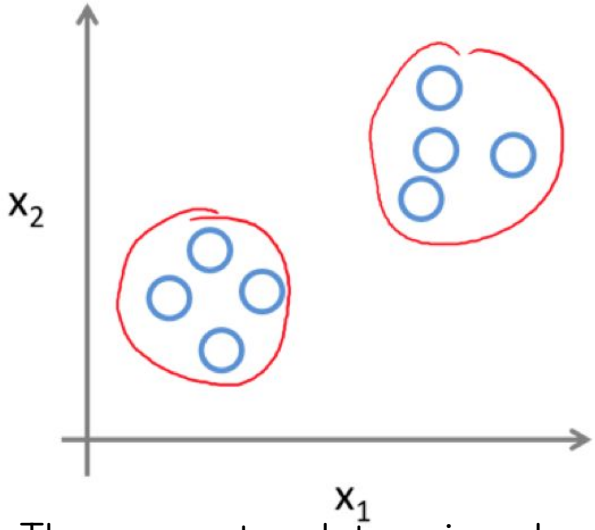
Unsupervised Learning

To modes of machine learning

Supervised Learning



Unsupervised Learning



The computer determines how to classify based on properties within the data

Features are given as inputs

model identifies patterns in the input data

predictions are output

No labels are provided during modeling

PCA, k-means clustering, t-SNE, neural nets, self-organizing maps, (i.e. facial recognition, image processing, EDA)

model identifies patterns
in the input data

Is it cake?

https://aczane.netlify.com/2018/02/08/the-first-and-namesake-post-is-it-cake/

model identifies patterns
in the input data

Is it cake?

1

2

https://aczane.netlify.com/2018/02/08/the-first-and-namesake-post-is-it-cake/

model identifies patterns in the input data

Is it cake?

1

2

new emoji

Is it cake?

No

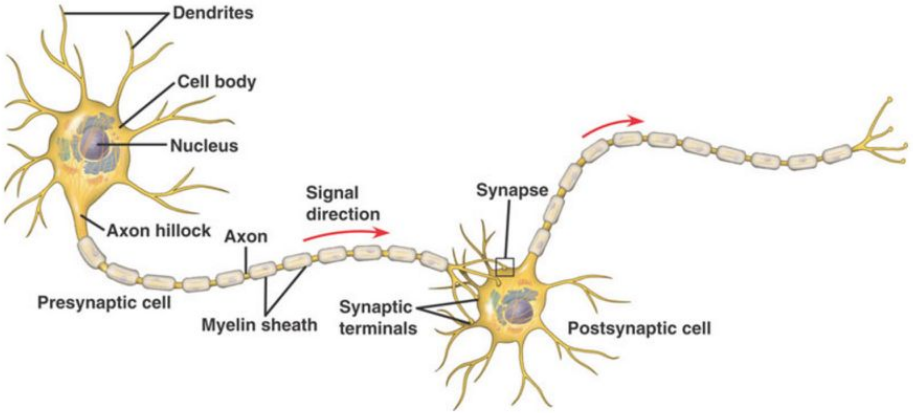
Class 1
NOT CAKE

Yes

Class 2
CAKE

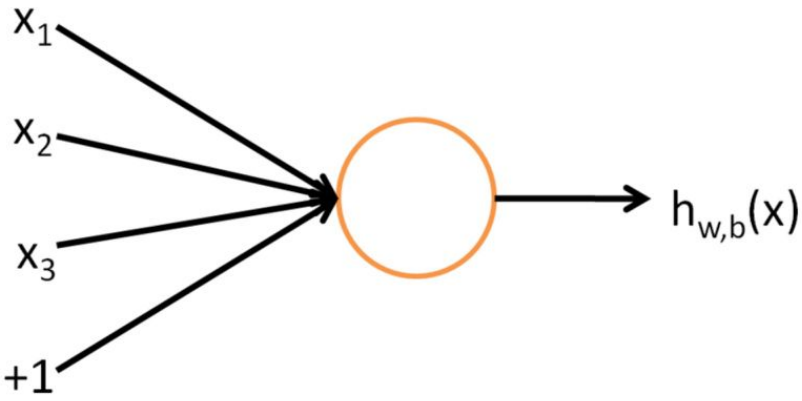
https://aczane.netlify.com/2018/02/08/the-first-and-namesake-post-is-it-cake/

WHAT IS A NEURON?



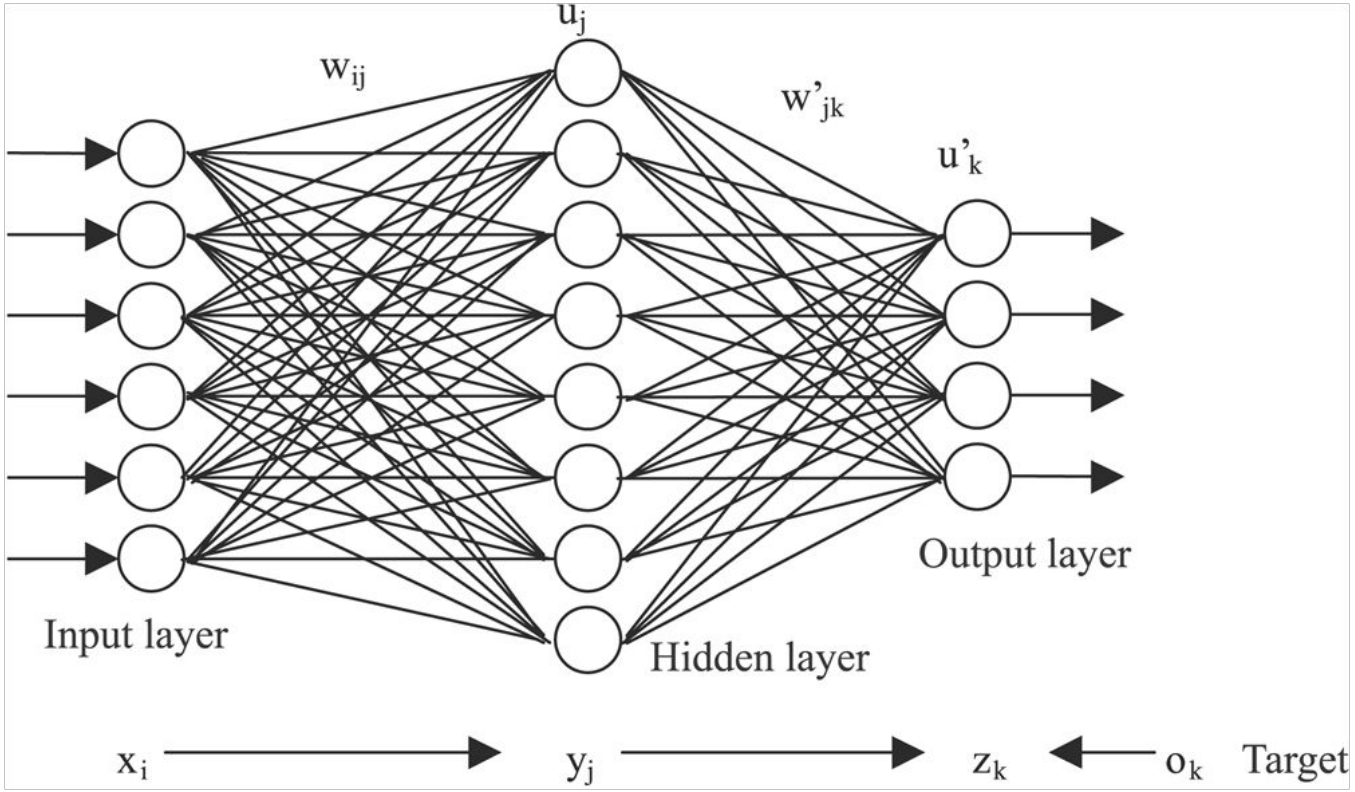
- Receives signal on synapse
- When trigger sends signal on axon

MATHEMATICAL NEURON



- Mathematical abstraction, inspired by biological neuron
- Either on or off based on sum of input

This will likely not be the last time you see this (mostly unhelpful) neural net image



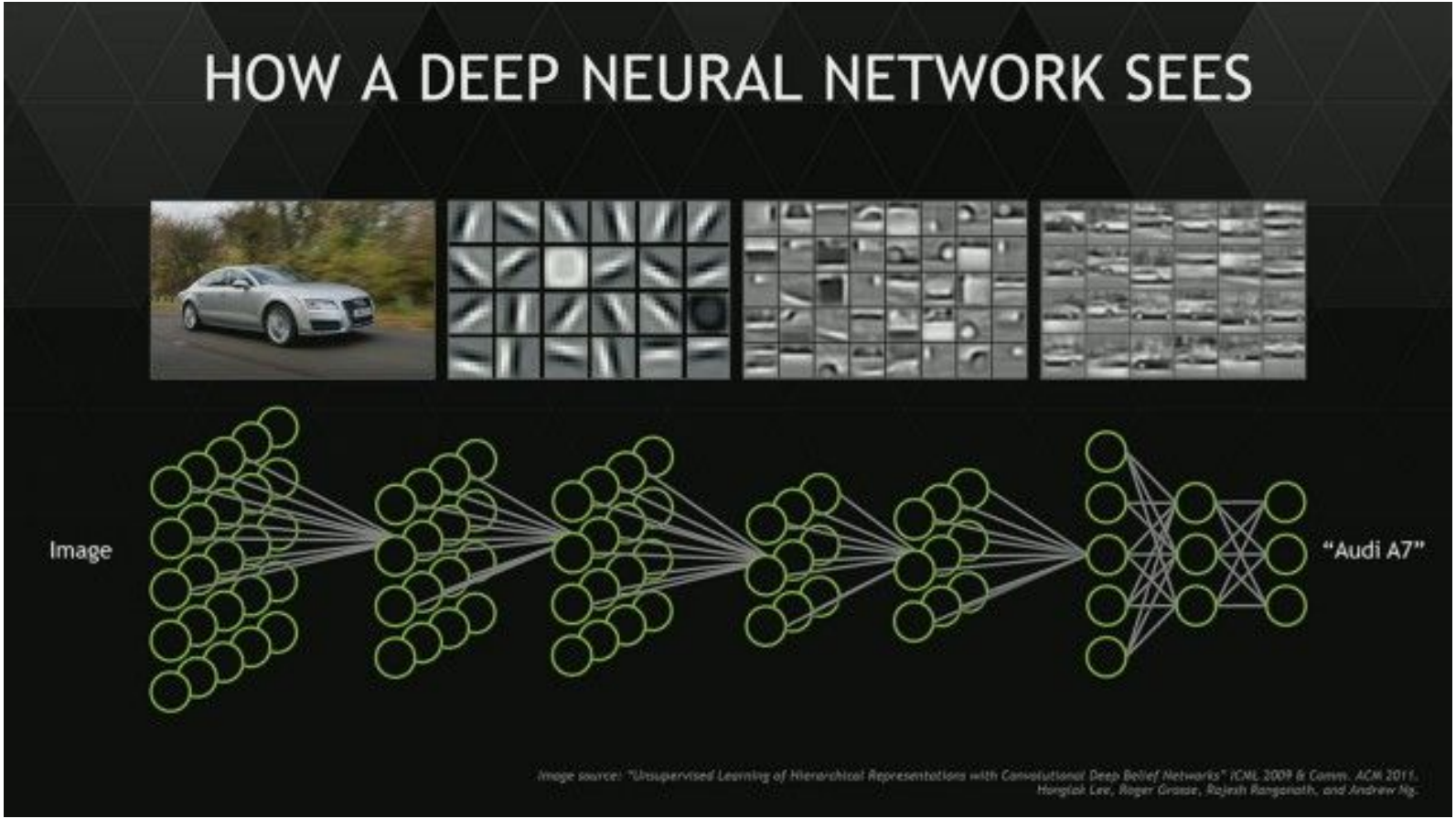
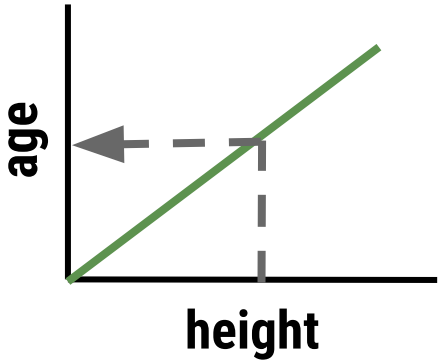
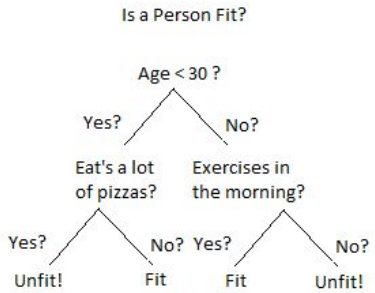


Image Source: https://towardsdatascience.com/understanding-residual-networks-9add4b664b03

Supervised Learning



continuous

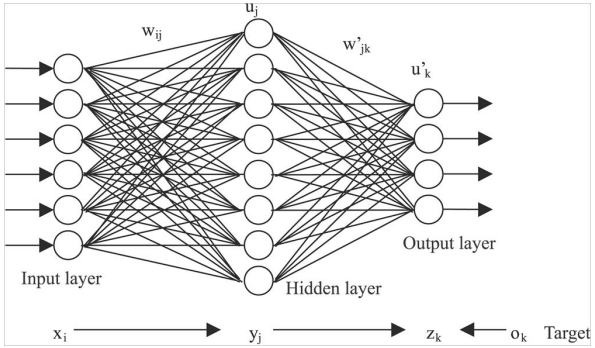


classification

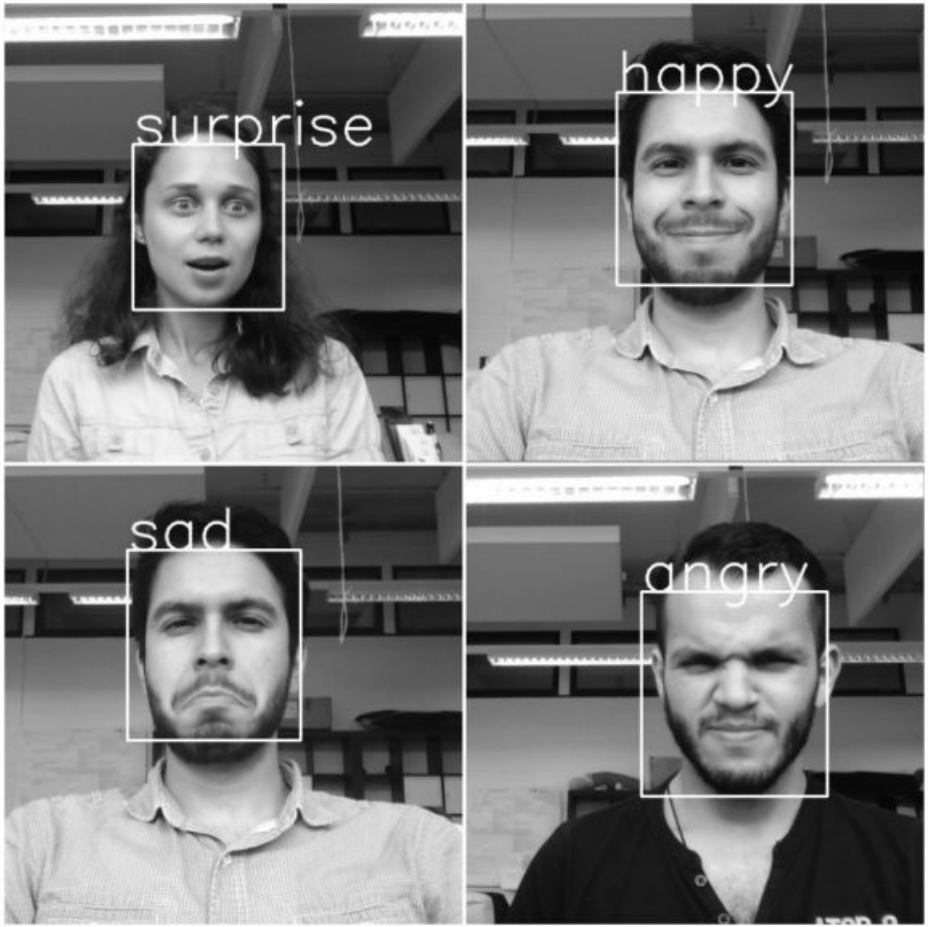
Unsupervised Learning

1

2



dimensionality reduction & clustering



https://github.com/oarriaga/face_classification

Prediction Approach

You want to predict someone's emotion based on an image.

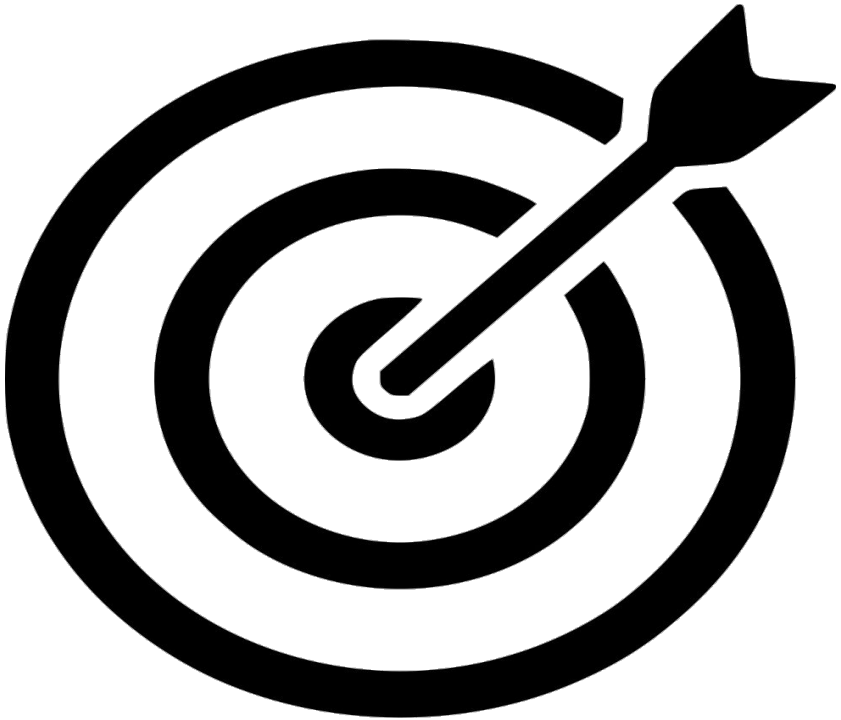
How would you approach this with machine learning?

A
Supervised, Regression

B
Supervised, Classification

C
Unsupervised, dimensionality reduction

D
Unsupervised, clustering



model assessment

continuous variable prediction

Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (Predicted_i - Actual_i)^2}{N}}$$

A few outliers can lead to a big increase in RMSE, even if all the other predictions are pretty good

categorical variable prediction

continuous variable prediction

$$\text{Accuracy} = \frac{\#\text{ of samples predicted correctly}}{\#\text{ of samples predicted}} * 100$$

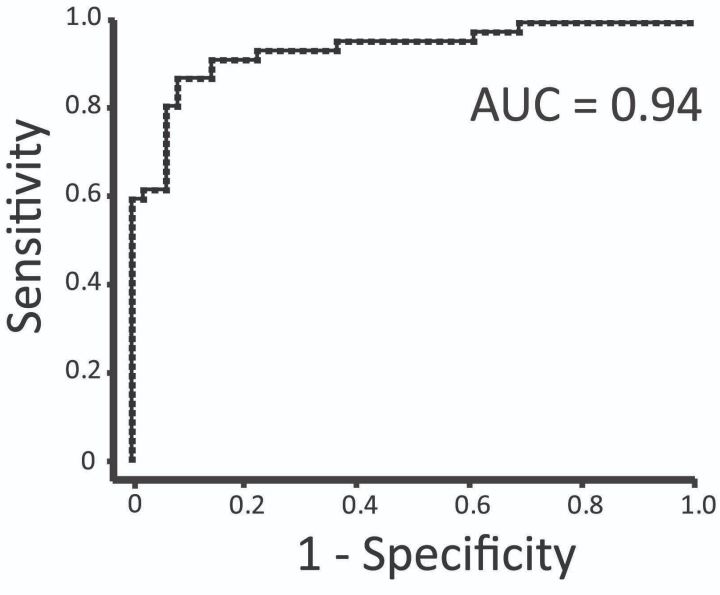
categorical variable prediction

		Actual	
		Positive	Negative
Predicted	Positive	True Positive (TP)	False Positive (FP)
	Negative	False Negative (FN)	True Negative (TN)

A 2x2 table is a type of confusion matrix

Sensitivity

$$\frac{TP}{TP + FN}$$



Specificity

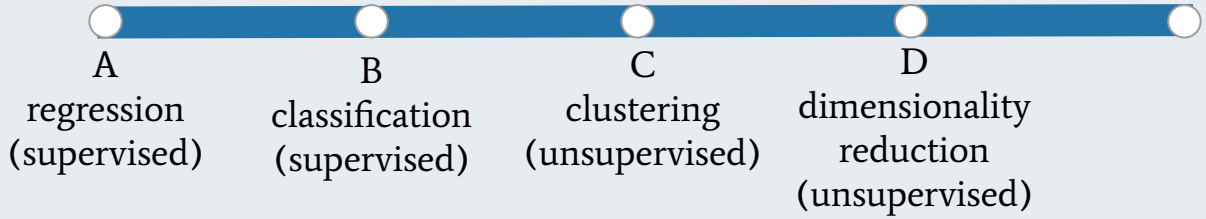
$$\frac{TN}{TN + FP}$$

Accuracy	What % were predicted correctly?
Sensitivity	Of those that *were* positives, what % were predicted to be positive?
Specificity	Of those that were *negatives*, what % were predicted to be negative?

Prediction Approach

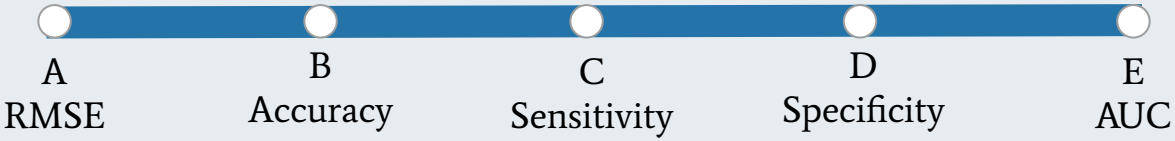
You've been given a dataset with a number of features and have been asked to predict each individual's age.

What prediction approach would you use?



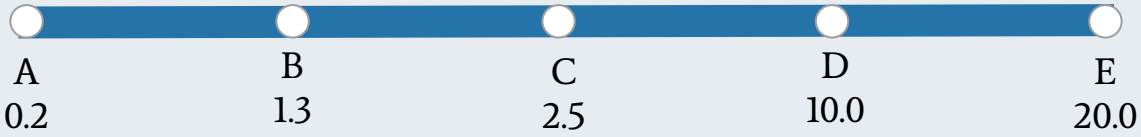
Prediction Approach

After predicting each person's age, how would you assess your model?

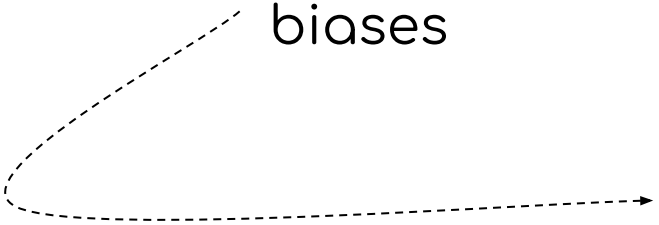


Prediction Approach

Which would be the error value you'd want from your model?



When models are trained on historical data, predictions will perpetuate historical biases



Predictive Analysis Ethics

Dare Obasanjo
@Carnage4Life

Product leader at Microsoft. My team is responsible for advertiser experience for Bing Ads; mobile apps, web UX, desktop apps & SDKs.

Dare Obasanjo
@Carnage4Life

Follow

Machine learning algorithms are driven more by the training data than math. Give an algorithm biased data then results will be biased. E.g.
• Amazon's resumé referral algo which auto rejected women
• Search ads algo which showed background check ads for "black sounding names"

Ryan Saavedra @RealSaavedra
Socialist Rep. Alexandria Ocasio-Cortez (D-NY) claims that algorithms, which are driven by math, are racist

8:59 PM - 22 Jan 2019

https://twitter.com/carnage4life/status/1087892442349678592?s=21

BUSINESS NEWS OCTOBER 9, 2018 / 8:12 PM / A MONTH AGO

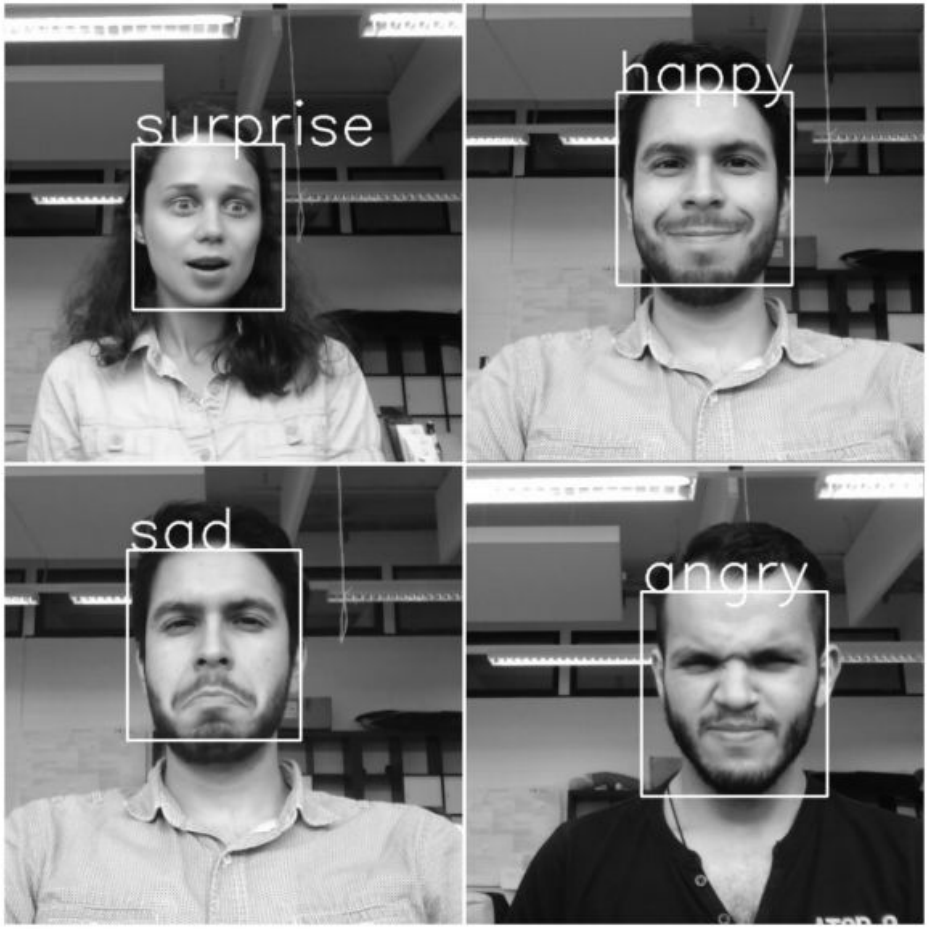
Amazon scraps secret AI recruiting tool that showed bias against women

Jeffrey Dastin

8 MIN READ

SAN FRANCISCO (Reuters) - Amazon.com Inc's (AMZN.O) machine-learning specialists uncovered a big problem: their new recruiting engine did not like women.

https://www.reuters.com/article/us-amazon-com-jobs-automation-insight/amazon-scraps-secret-ai-recruiting-tool-that-showed-bias-against-women-idUSKCN1MK08G



https://github.com/oarriaga/face_classification

https://twitter.com/nke_ise/status/897756900753891328

What to do about bias...

1. Anticipate and plan for potential biases before model generation. Check for bias after.
2. Have diverse teams.
3. Use machine learning to improve lives rather than for punitive purposes.
4. Revisit your models. Update your algorithms.
5. You are responsible for the models you put out into the world, unintended consequences and all.

Discussed so far…

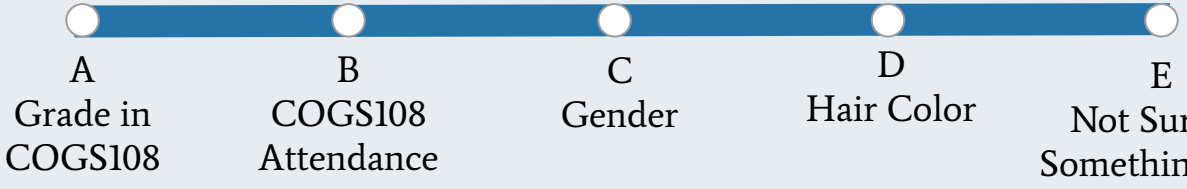
- data partitioning
- feature selection
- supervised & unsupervised machine learning
  - Continuous variables: regression (supervised) and dimensionality reduction (unsuperfied)
  - Categorical variables: classification (supervised; decision trees) or clustering (unsupervised)
- model assessment
  - Continuous: RMSE (& Accuracy)
  - Categorical: Accuracy, Sensitivity, Specificity, AUC
- biased data can & will lead to biased predictions

Data Science Question

Based on data I have about you all, can I predict who in this course will be successful?

Prediction Approach

Which would be the most predictive of your future success?



N = 254

train the model:
N = 178
(70% of the data)

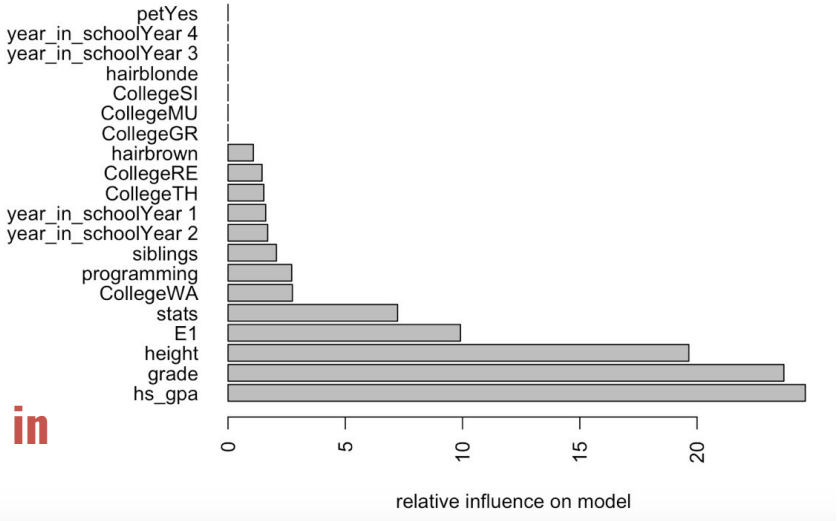
test the model:
N = 76
(30% of the data)

train the model

predicted success in test set

	Accuracy	Sensitivity	Specificity
training set	71.2%	76%	67%
test set	49.1%	40%	60%

Assess Prediction Model



N = 254

train the model:
N = 178
(70% of the data)

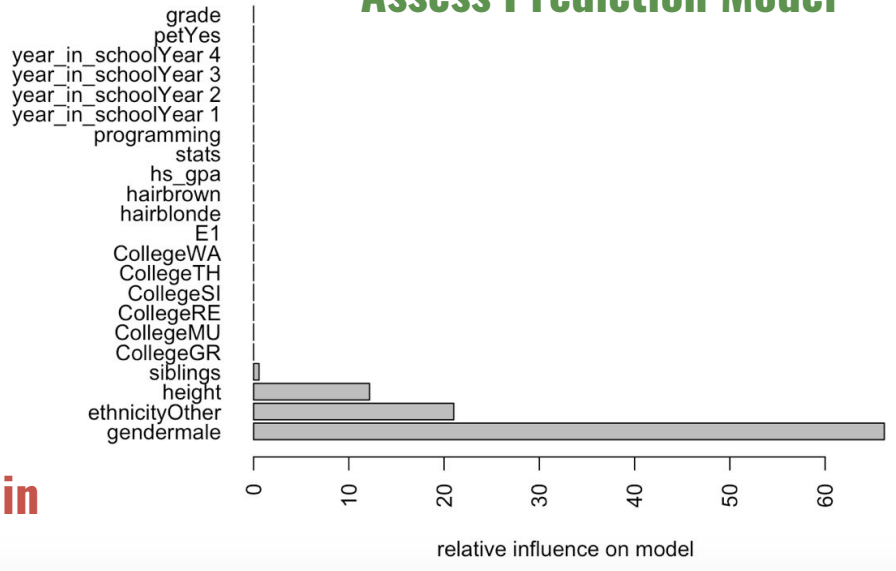
test the model:
N = 76
(30% of the data)

train the model

predicted success in test set

	Accuracy	Sensitivity	Specificity
training set	100%	100%	100%
test set	100%	100%	100%

Assess Prediction Model



What if I were using these data to determine who I should write recommendation letters for?

Or to determine which students I focus my attention on?

Or whose projects I read?

Or who I allow to come to office hours?

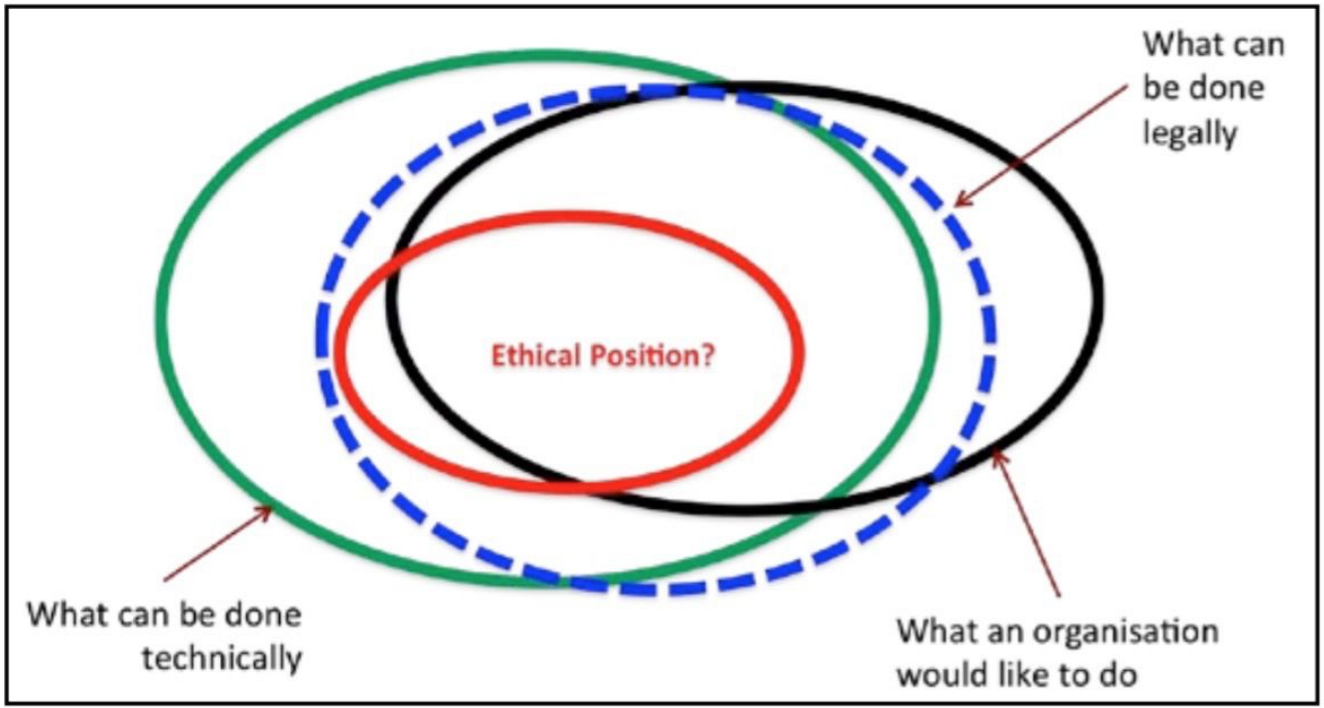
Or who UCSD allows to be data science majors?

What to do about bias...

1. Anticipate and plan for potential biases before model generation. Check for bias after.
2. Have diverse teams.
3. Use machine learning to improve lives rather than for punitive purposes.
4. Revisit your models. Update your algorithms.
5. You are responsible for the models you put out into the world, unintended consequences and all.

Think about whether the models you're building should even be built.

Big Data Ethics



Source: IBM

adapted from Brad Voytek

Predictive algorithms should (*at a minimum*) be FAT

Fair: lacking biases which create unfair and discriminatory outcomes

- For whom does this algorithm fail?
- Steps to take:
  1. Verify data about individual is correct
  2. Carry out “sensitivity test”

Accountable/Accurate: answerable to the people subject to them

- Correct data used? Is there a mechanism for appeal?

Transparent: open about how and why particular decisions were made

- Think *carefully* about what transparency is (Handing over source code likely isn’t the answer)

Sources: https://www.datacamp.com/community/podcast/weapons-math-destruction & https://ironholds.org/resources/papers/mulching.pdf

A Mulching Proposal

Analysing and Improving an Algorithmic System for Turning the Elderly into High-Nutrient Slurry

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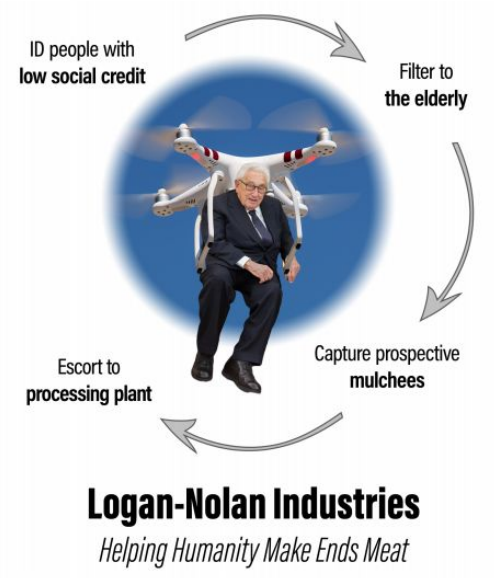
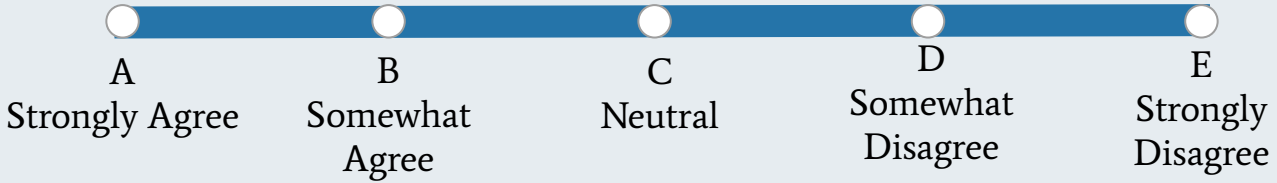


Figure 1: A publicity image for the project, produced by Logan-Nolan Industries

https://dl.acm.org/citation.cfm?id=3310433 (*CHI* 2019)

Prediction Thoughts

We should start using this algorithm to mulch up the elderly



A Mulching Proposal

FAIR - equally considers all elderly individuals

ACCURATE - pre- has mechanism for appeal; post - compensation

TRANSPARENT - website with all features ; testable

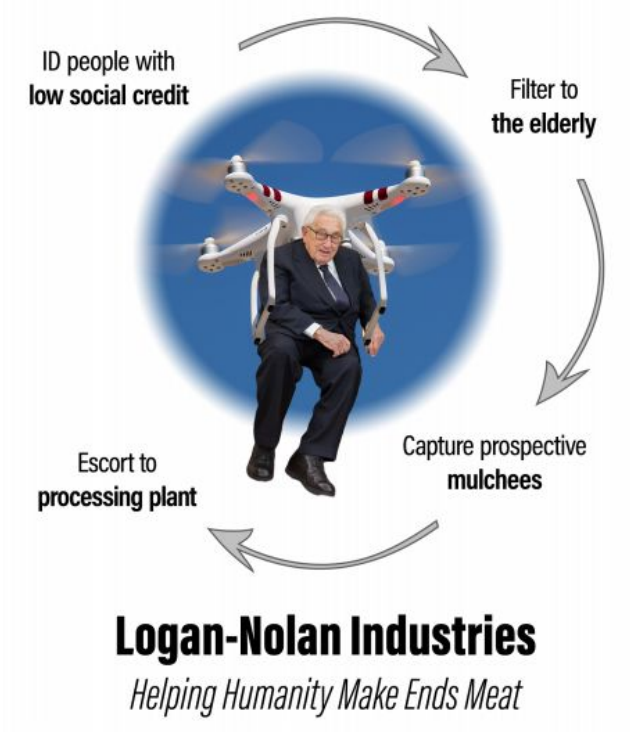


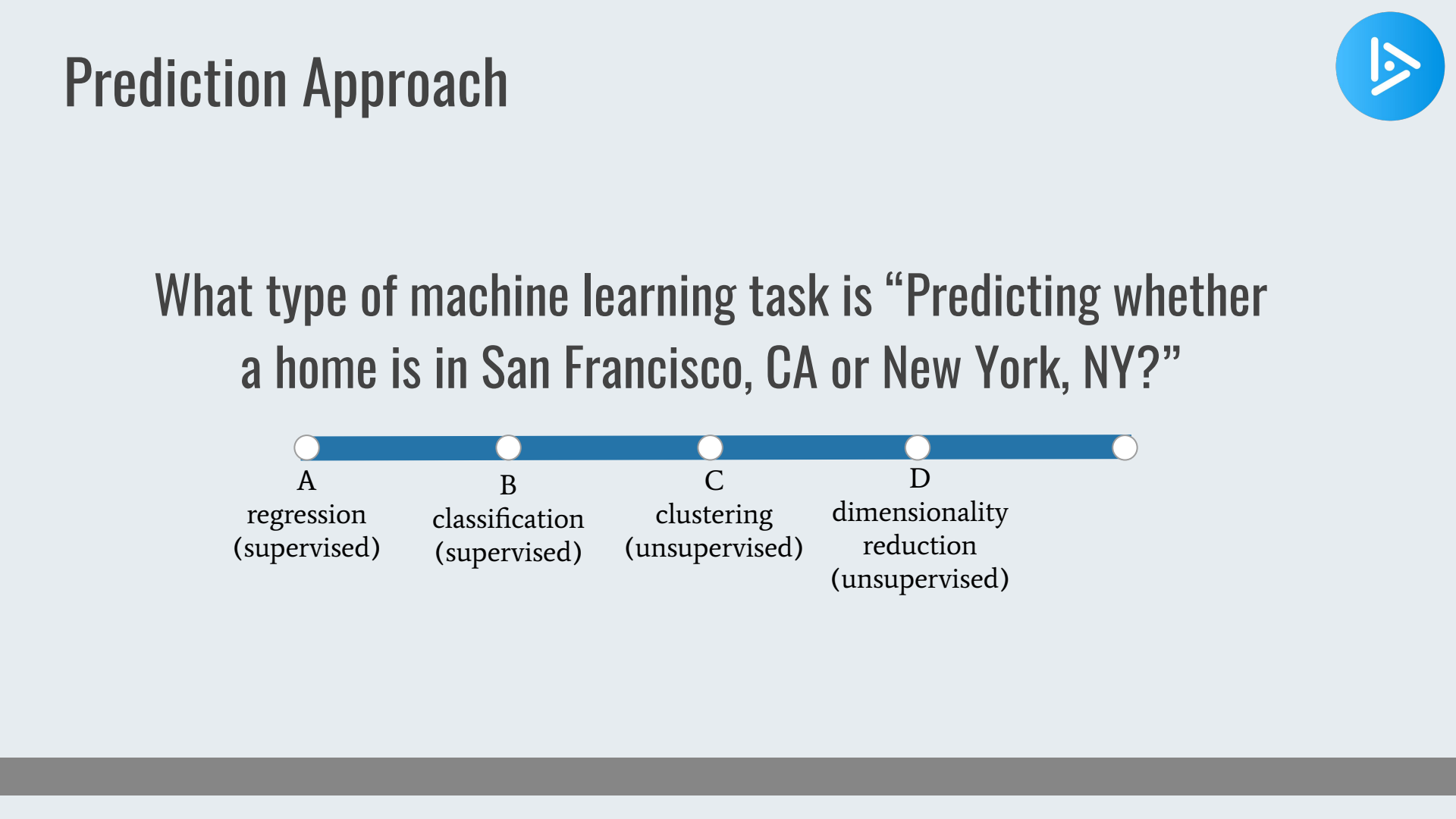
Figure 1: A publicity image for the project, produced by Logan-Nolan Industries

Checklists are helpful, but they’re not and excuse for thoughtlessness.

Worked Example I:

Predicting whether a home is in San Francisco, CA or New York, NY

Prediction Approach



What type of machine learning task is “Predicting whether a home is in San Francisco, CA or New York, NY?”

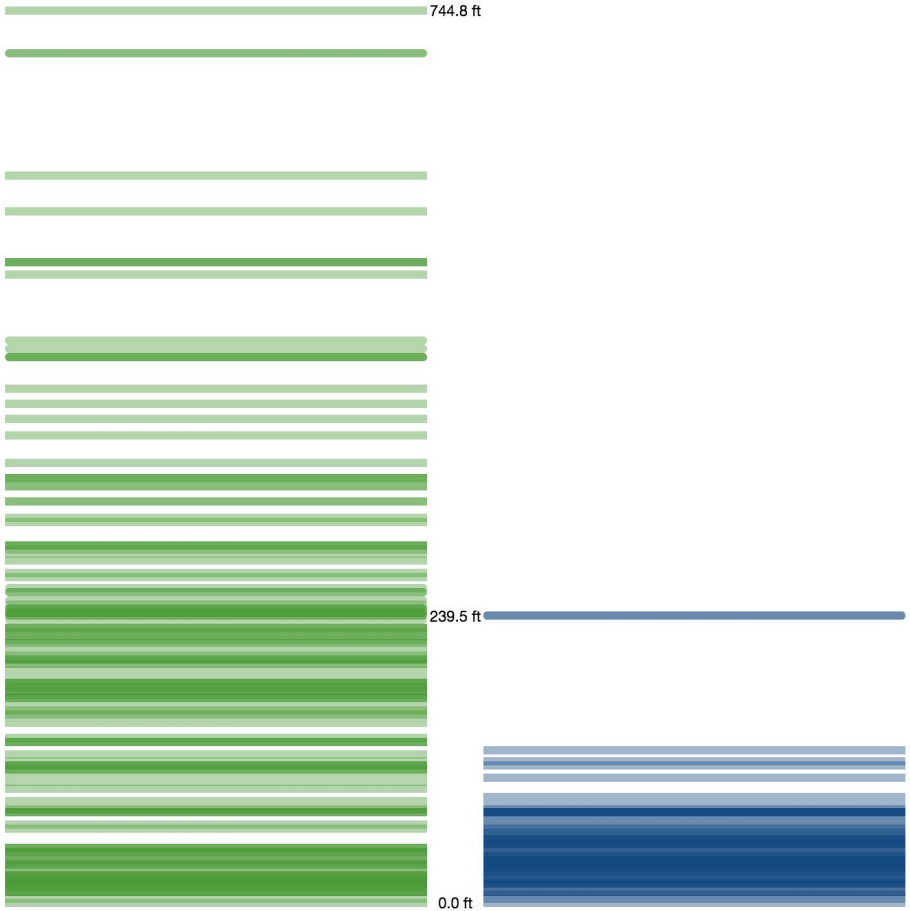
What features distinguish a house in New York from a house in San Francisco?

First, some intuition

Let's say you had to determine whether a home is in **San Francisco** or in **New York**. In machine learning terms, categorizing data points is a **classification** task.

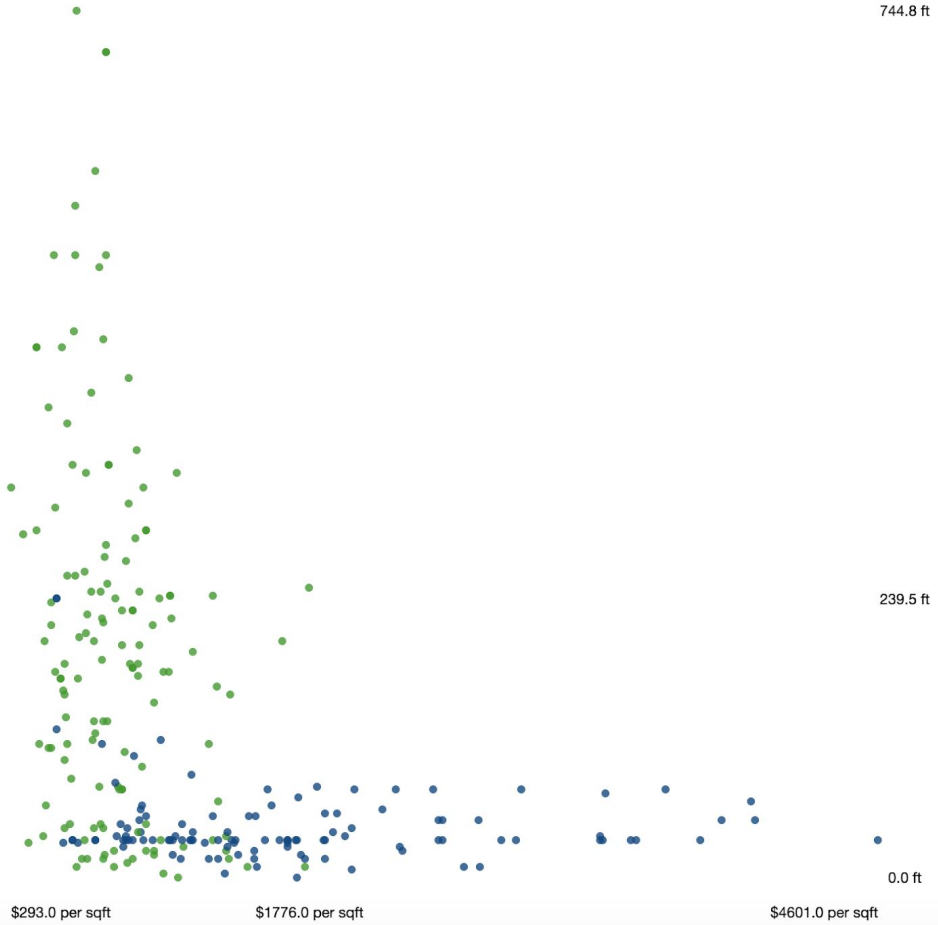
San Fran is hilly ...so elevation may be a helpful feature.

With the data here, homes > ~73m should be classified as San Fran homes



Adding nuance

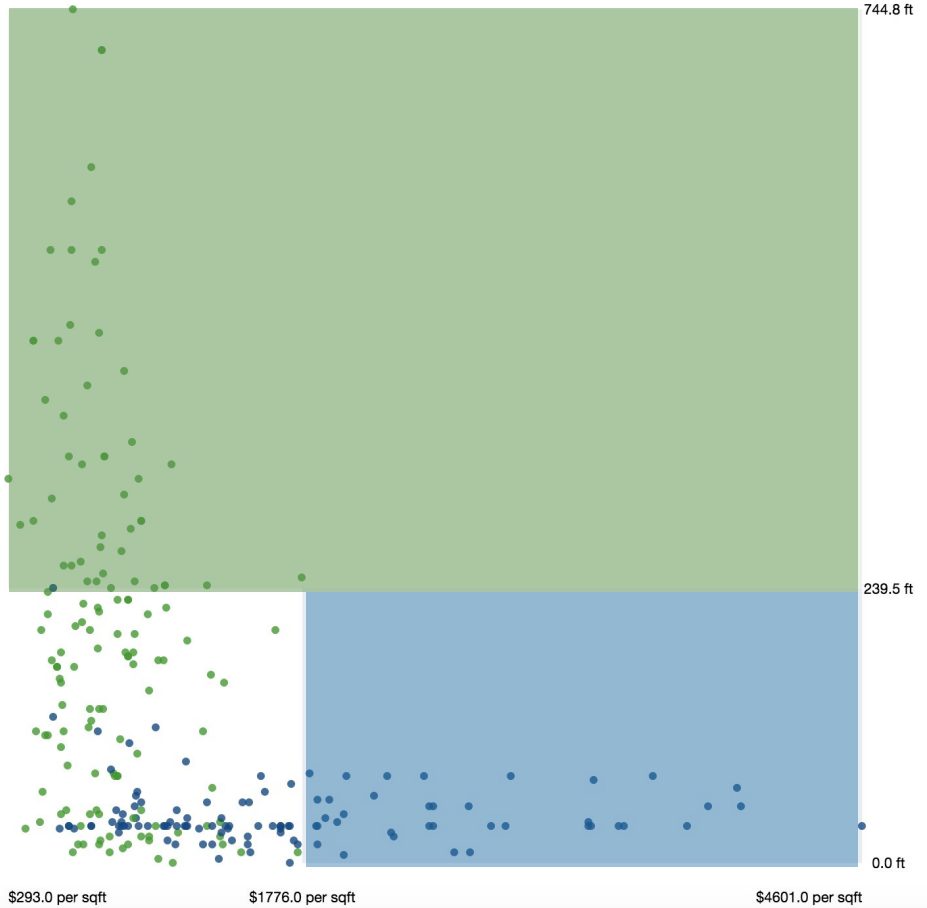
Elevation isn't a perfect feature for classification, so we can look at its relationship to other features, like *price per square foot*



http://www.r2d3.us/visual-intro-to-machine-learning-part-1/?from=@

Drawing boundaries

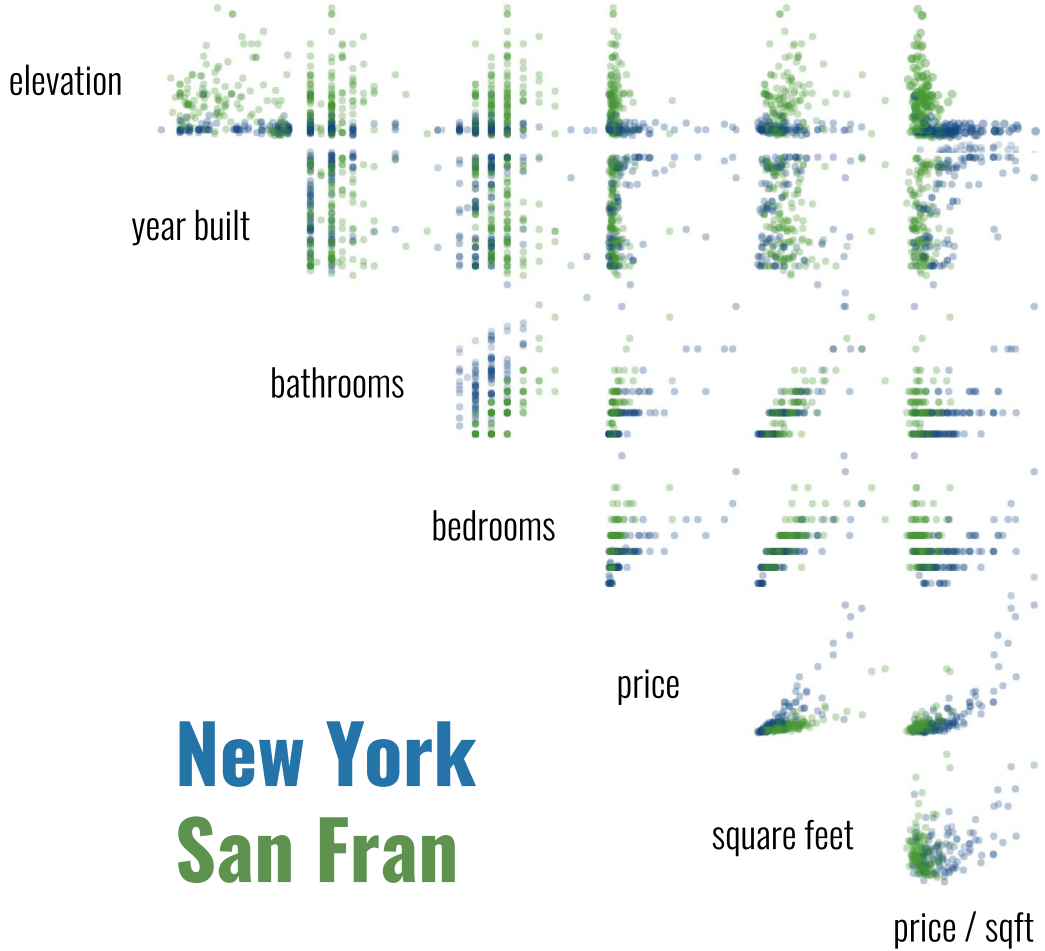
Boundaries can be drawn so that if a house falls in the green box, it's classified as a San Fran home. Blue box, New York. Statistical learning figures out how to best draw these boxes.



http://www.r2d3.us/visual-intro-to-machine-learning-part-1/?from=@

Our training set will use 7 different **features**. At the right we see the **scatterplot matrix** of the relationship between these features.

Patterns are clear, but boundaries for delineation are not obvious.



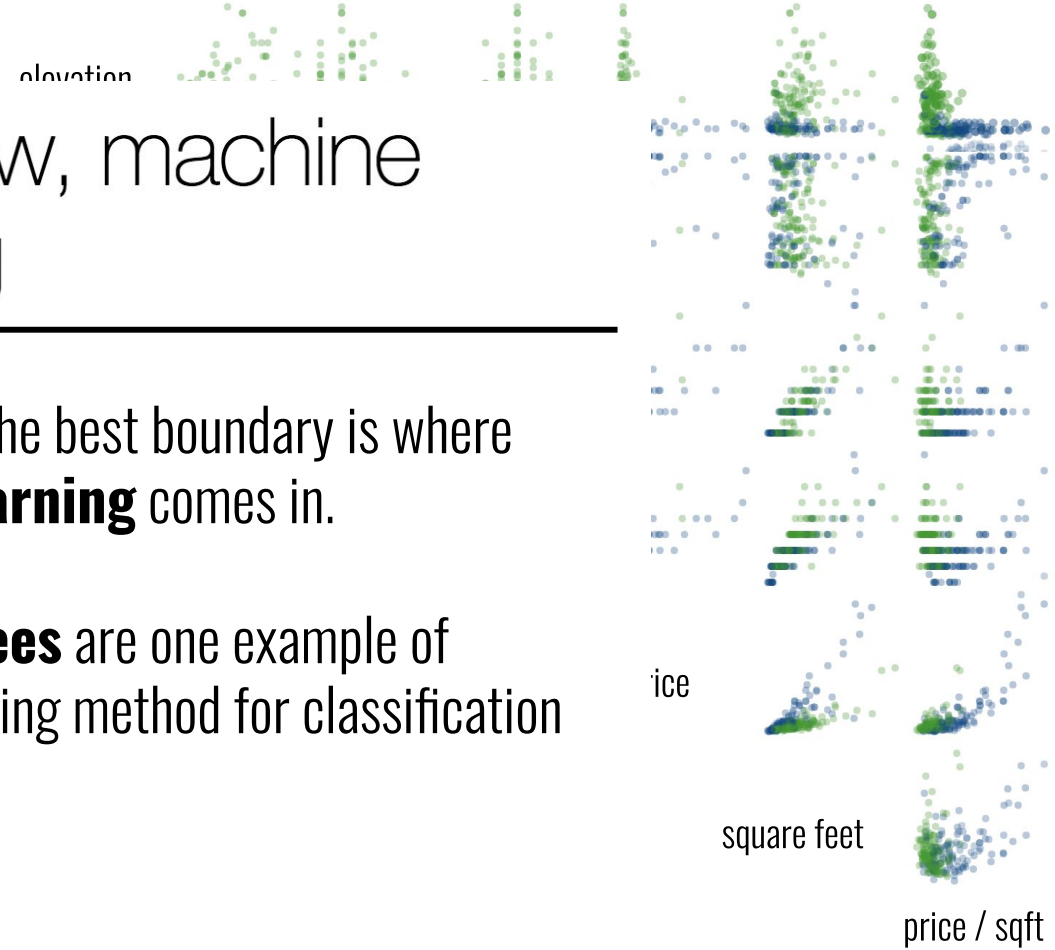
And now, machine learning

Our training set will u
features. At the righ
scatterplot matrix
relationship between

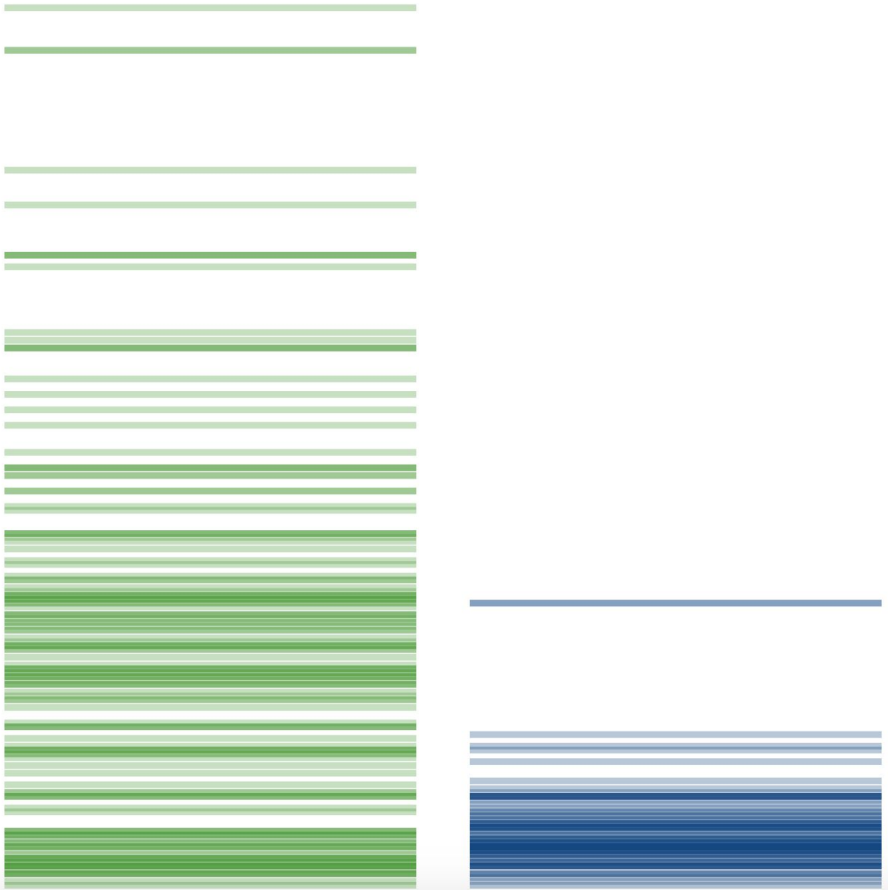
Patterns are clear, bu
delineation are not ob

Determining the best boundary is where **machine learning** comes in.

Decision trees are one example of machine learning method for classification tasks.



http://www.r2d3.us/visual-intro-to-machine-learning-part-1/?from=@



Finding better boundaries

We guessed ~73m before. Let's improve on that guess...

http://www.r2d3.us/visual-intro-to-machine-learning-part-1/?from=@

A **histogram** helps display frequency of homes by elevation more easily.

73m is the highest home in New York, but most of them have lower elevations

http://www.r2d3.us/visual-intro-to-machine-learning-part-1/?from=@

Your first fork

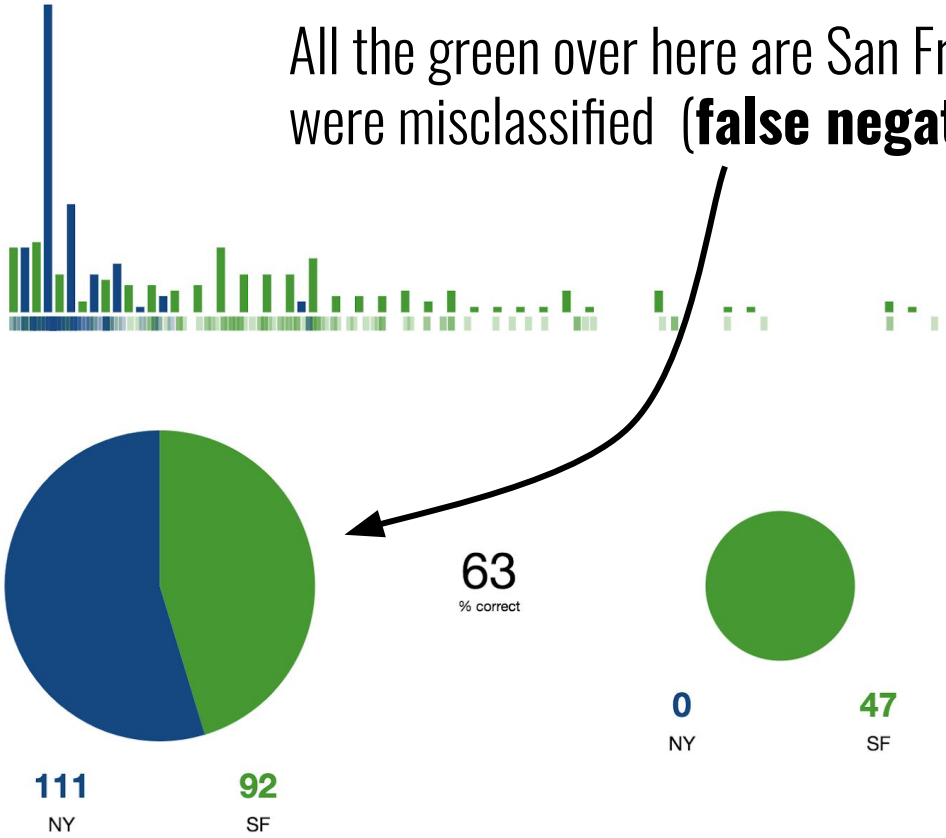
A decision tree uses if-then statements to define patterns in the data.

In machine learning, the splits are called **forks** and they split the data into **branches** based on some value.

The value that splits the branches is the **split point.** Homes to the left get categorized differently than those on the right.

http://www.r2d3.us/visual-intro-to-machine-learning-part-1/?from=@

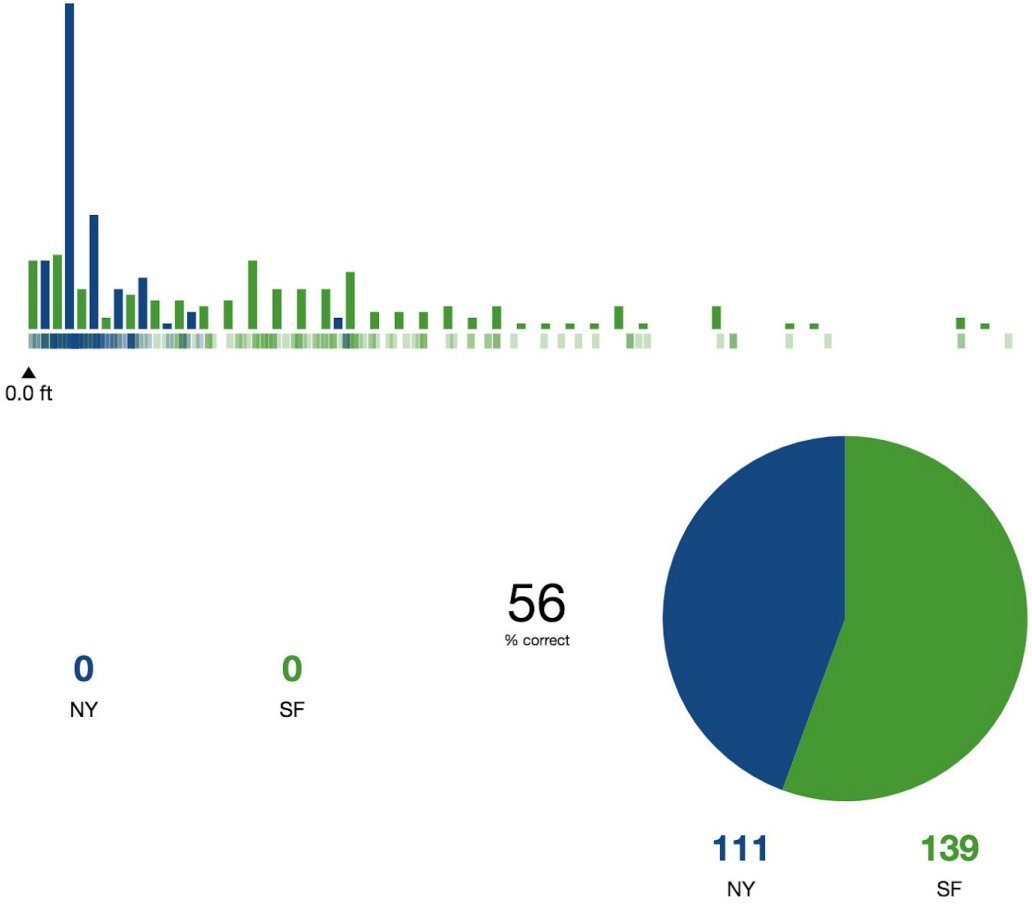
All the green over here are San Fran homes that were misclassified (**false negatives**)



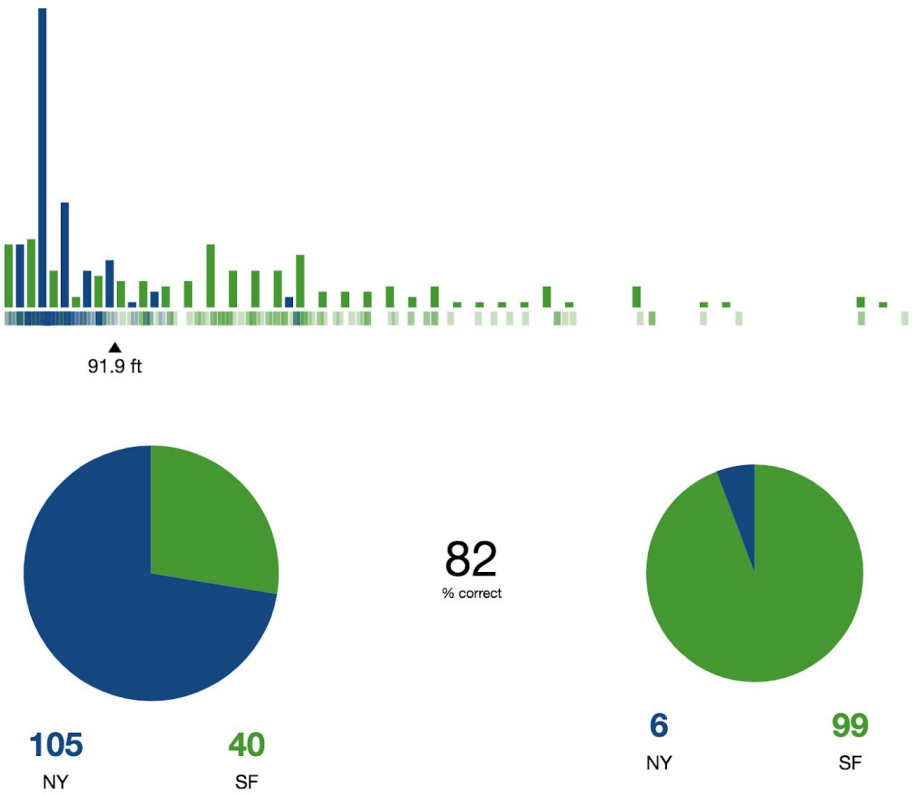
Tradeoffs

Splitting at ~73m incorrectly classifies some San Francisco homes as New York homes.

http://www.r2d3.us/visual-intro-to-machine-learning-part-1/?from=@

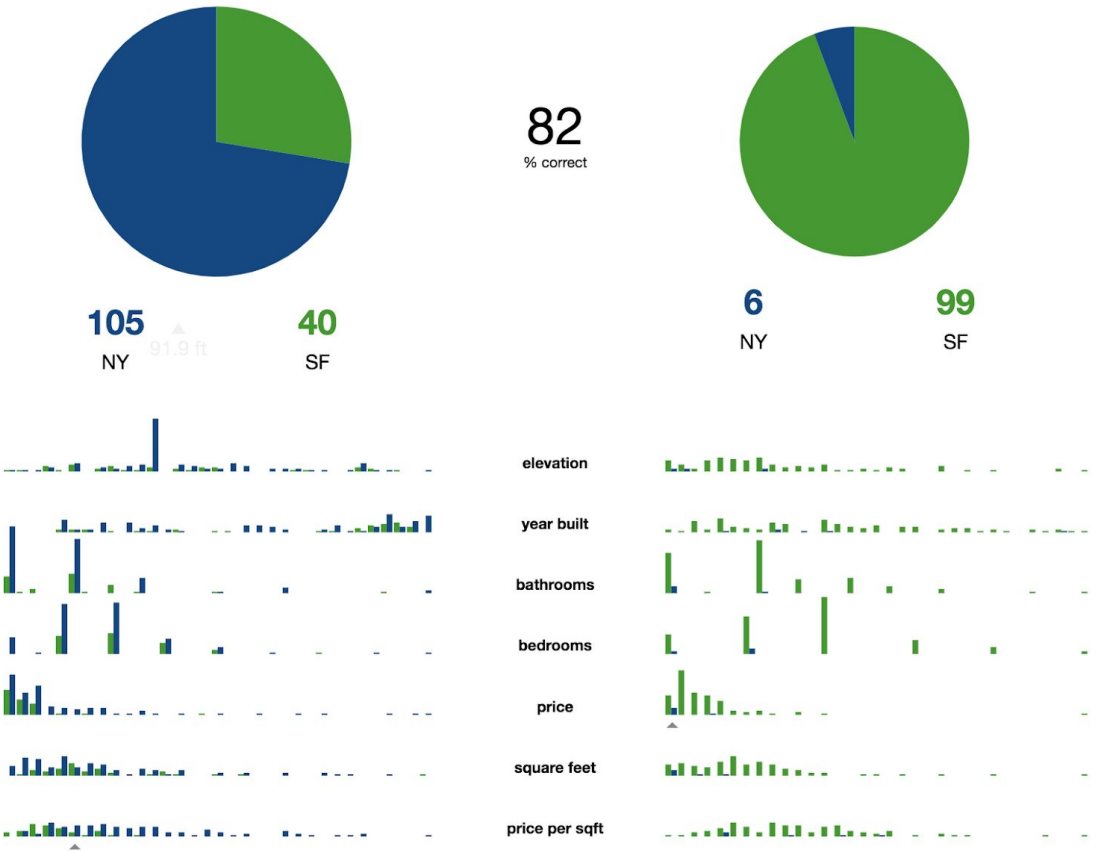


If you split to capture *every* home in San Fran, you'll also get a bunch of New York homes (**false positives**)



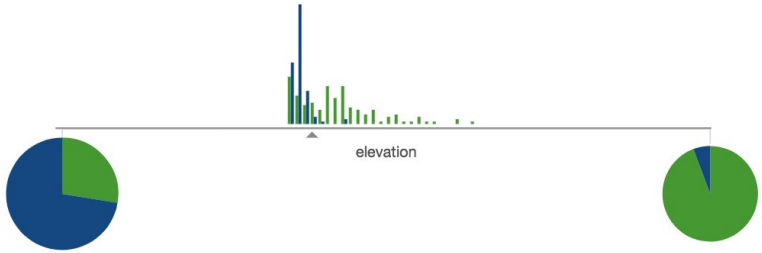
The best split

The best split point aims for branches that are as homogenous (pure) as possible



Recursion

Additional split points are determined through repetition (**recursion**)



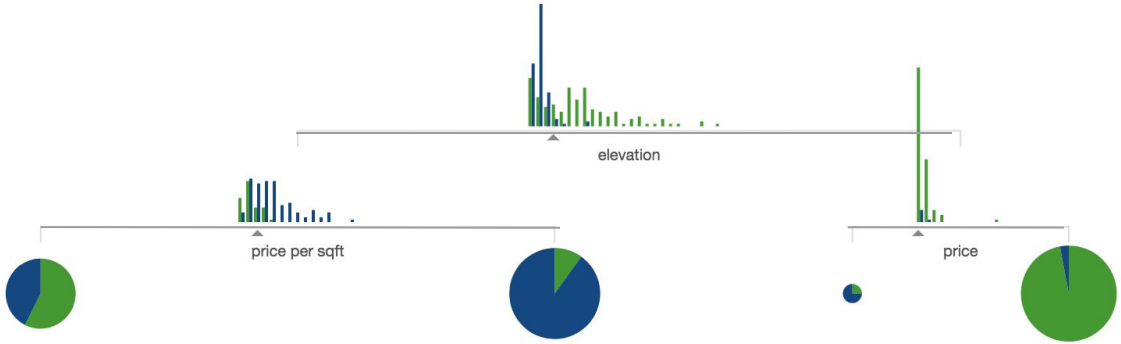
Growing a tree

Additional forks add new information to improve **prediction accuracy**.

Accuracy: 82%

Growing a tree

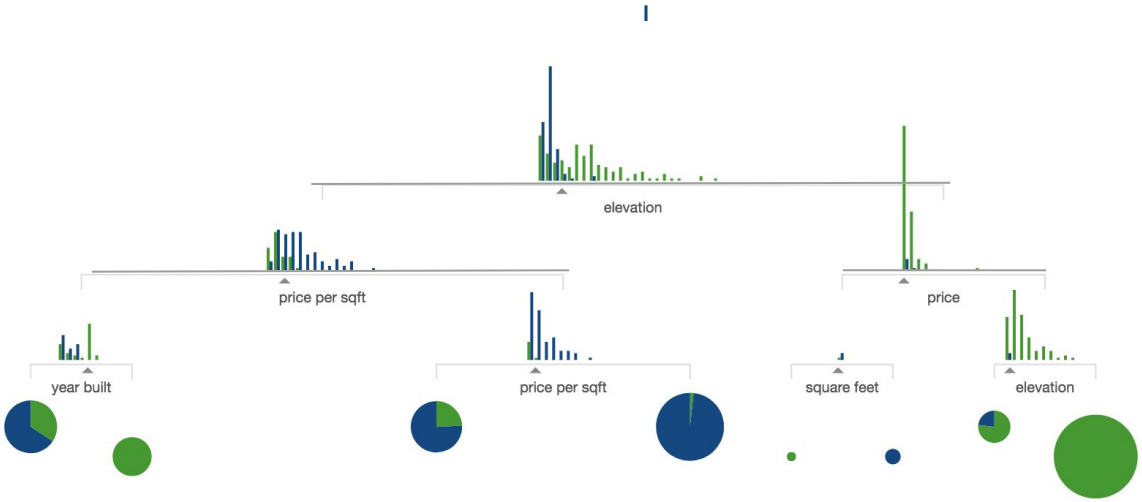
Additional forks add new information to improve **prediction accuracy**.



Accuracy: 86%

Growing a tree

Additional forks add new information to improve **prediction accuracy**.



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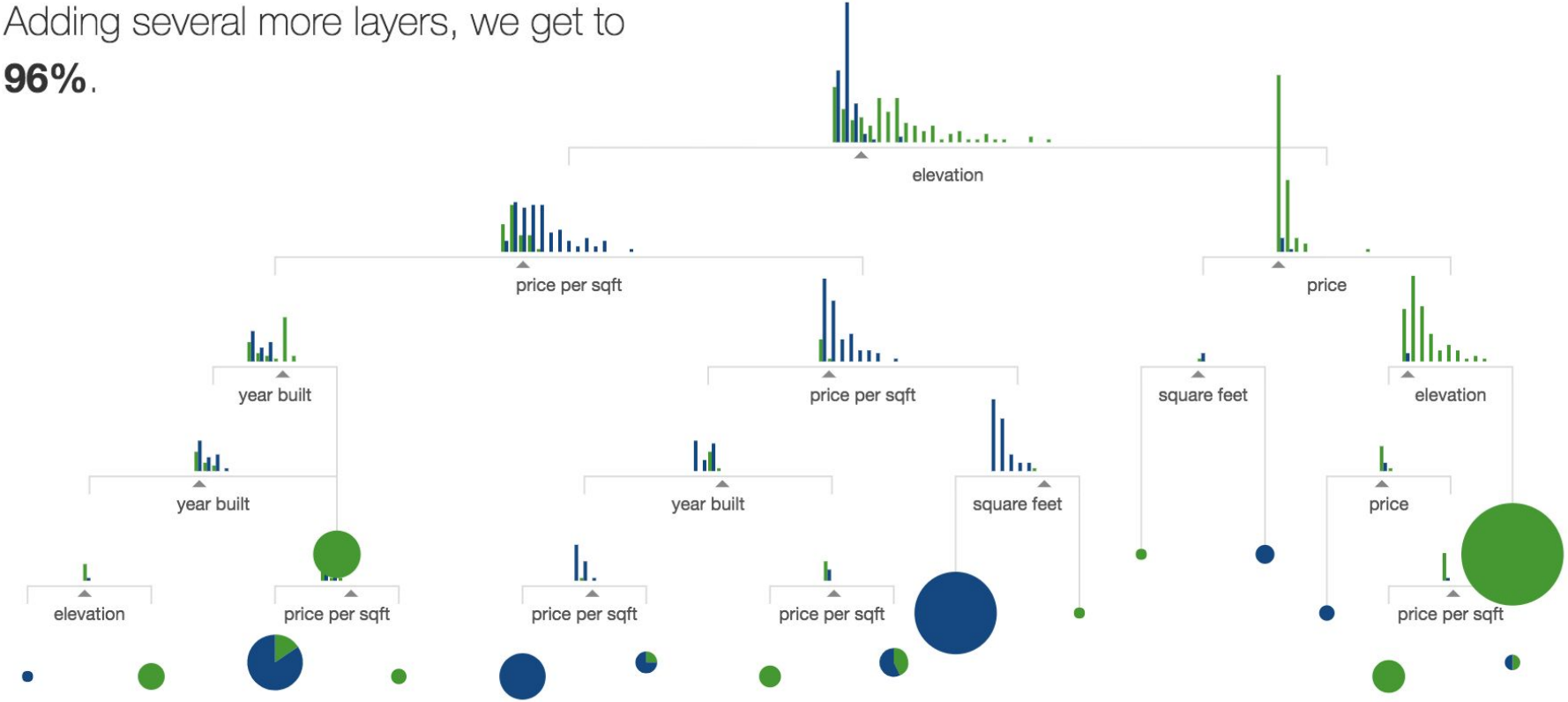
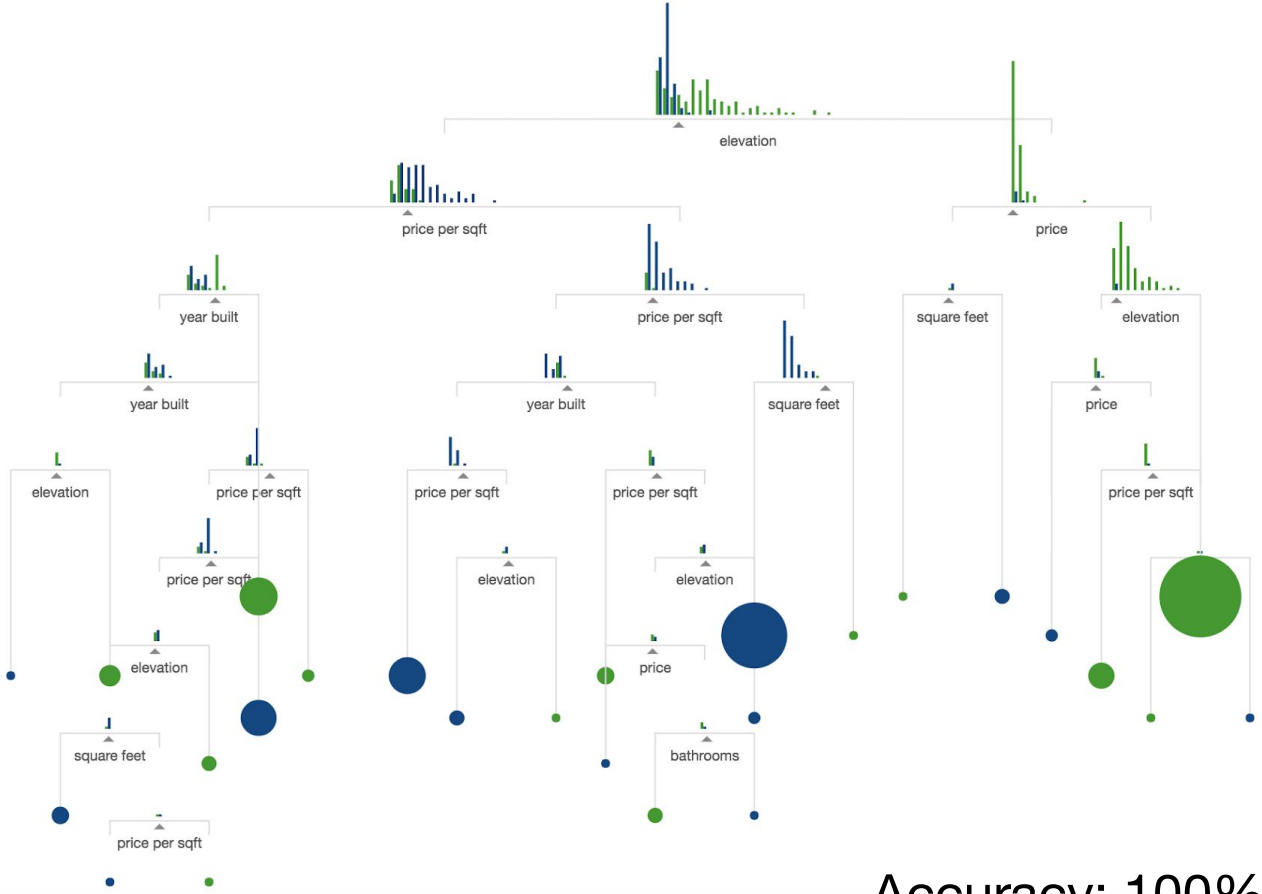
Adding several more layers, we get to **96%**.



Accuracy: 96%

It’s possible to add branches until your model is **100% accurate**.

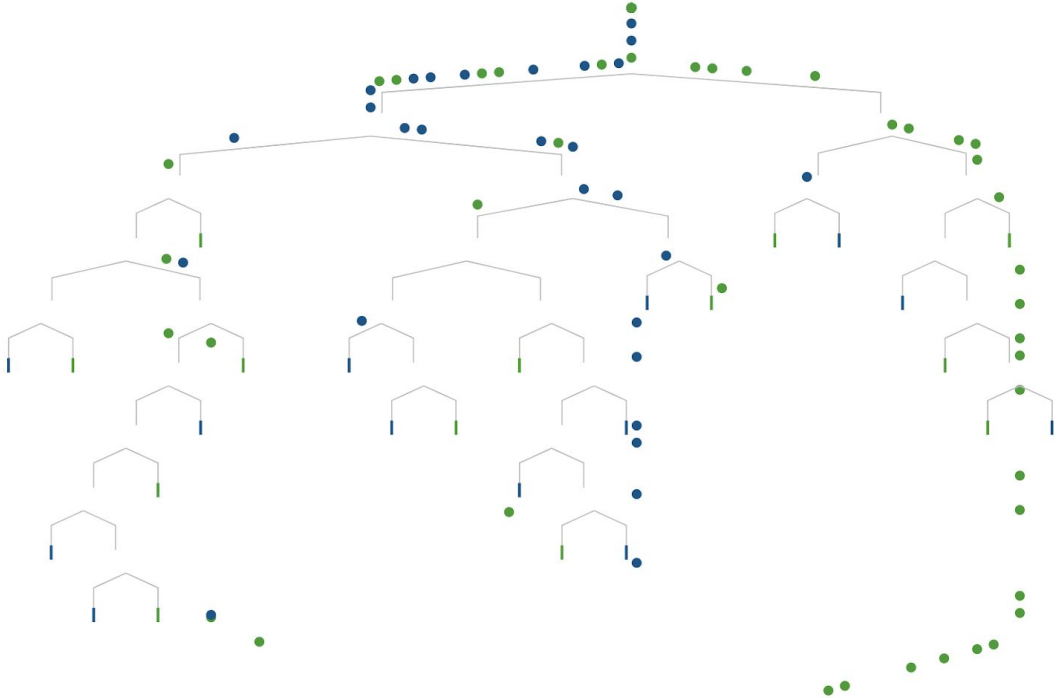


Accuracy: 100%

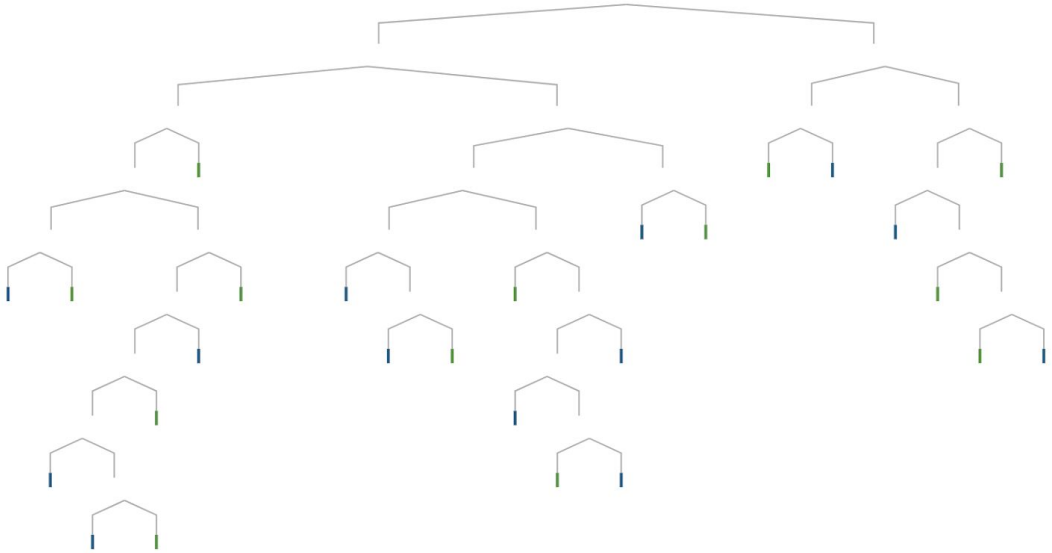
Making predictions

The decision tree **model** can then predict which homes are in which city.

Here, we're using the **training data**.



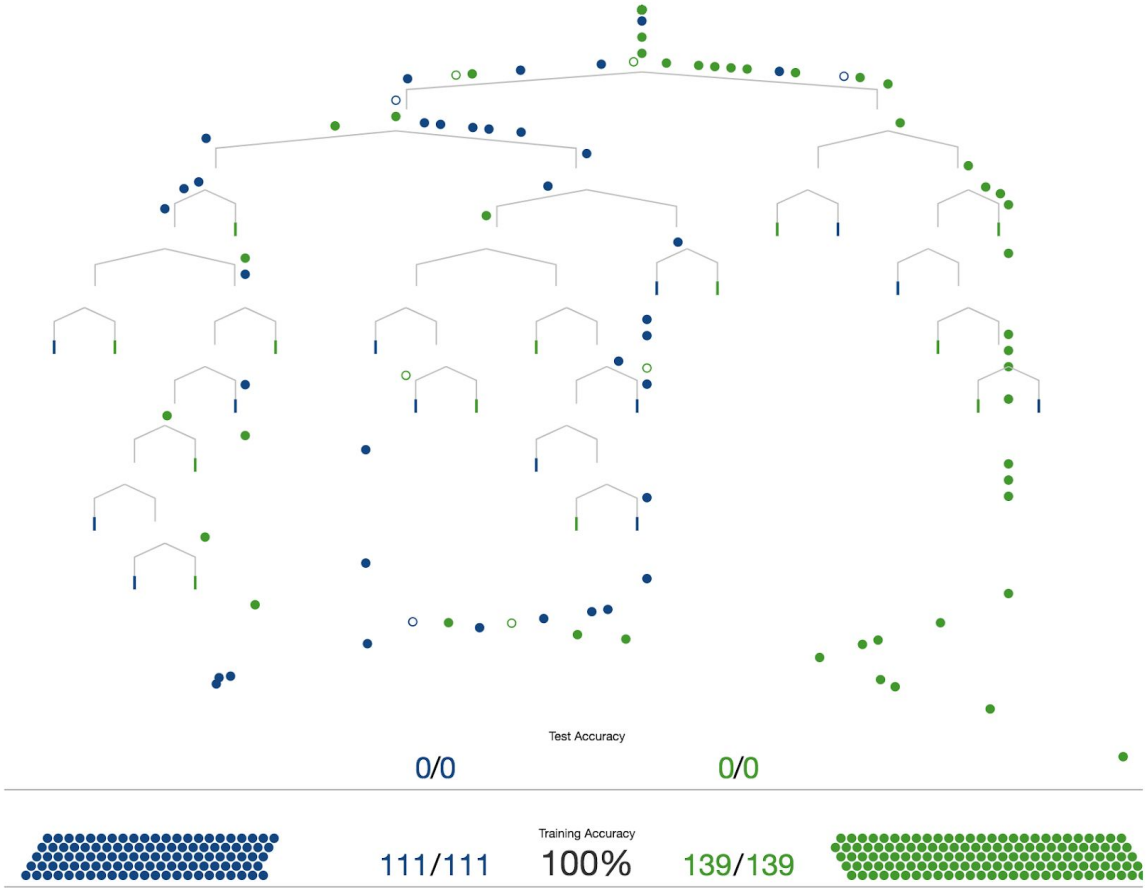
Because our tree was trained on this data and we grew the tree to 100% accuracy, each house is perfectly sorted



Reality check

But…how does this tree on data that the model hasn't seen before?

The **test set** then makes it way through the decision tree.



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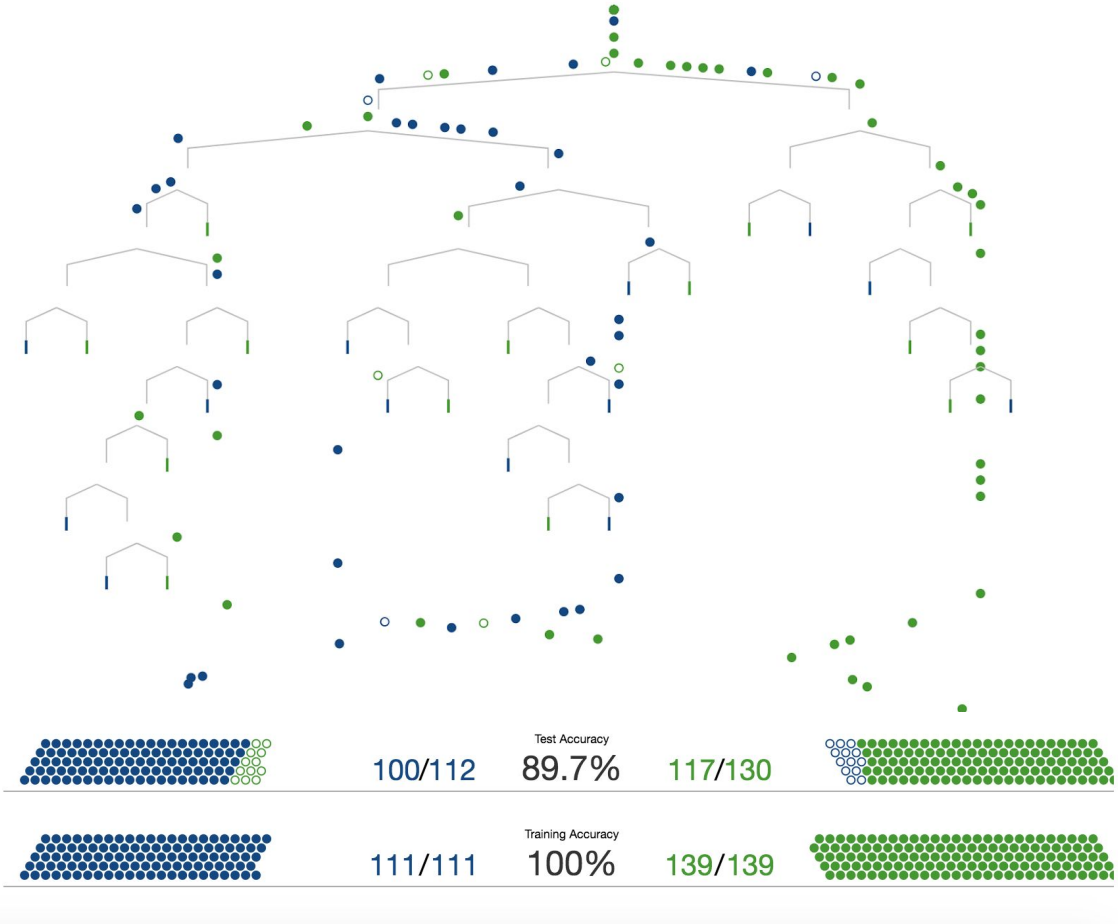
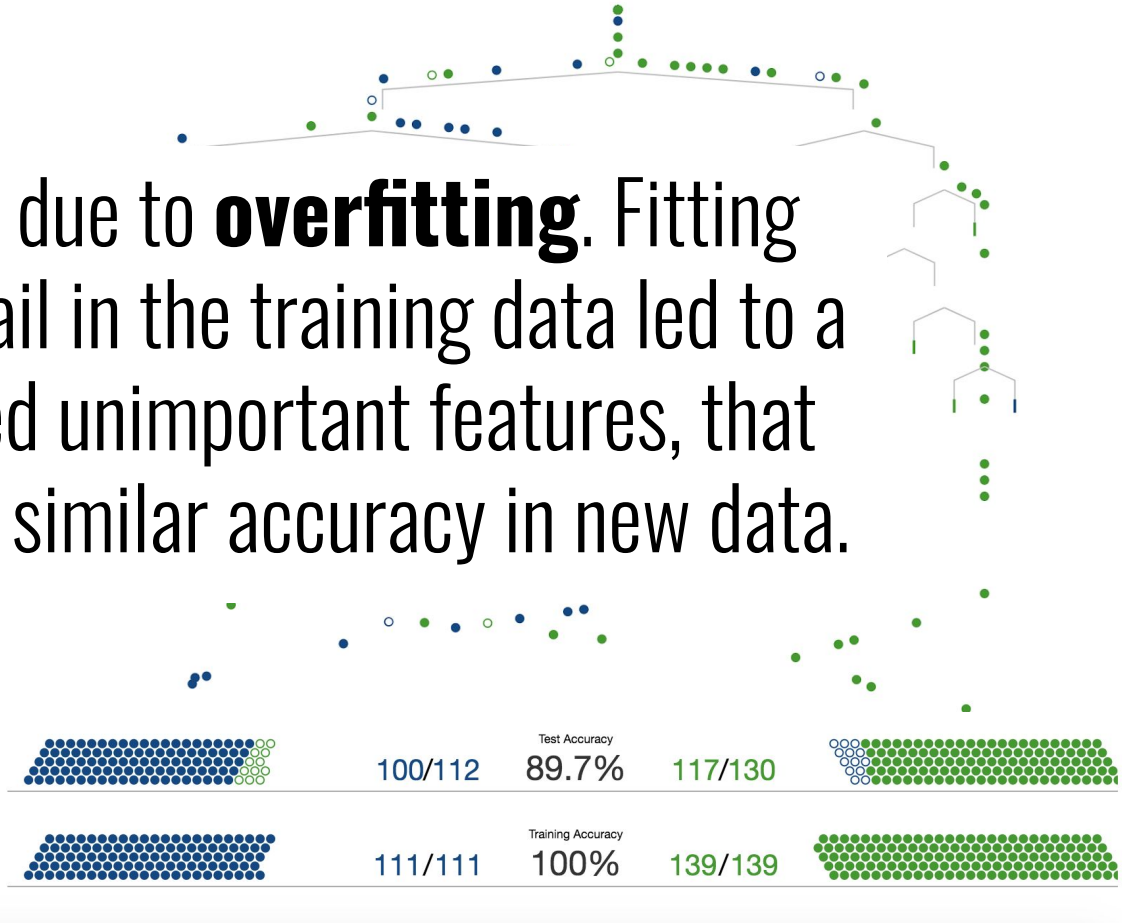
Ideally the tree should perform similarly on both known and unknown data



http://www.r2d3.us/visual-intro-to-machine-learning-part-1/?from=@

These errors are due to **overfitting**. Fitting every single detail in the training data led to a tree that modeled unimportant features, that did not allow for similar accuracy in new data.



http://www.r2d3.us/visual-intro-to-machine-learning-part-1/?from=@

Recap

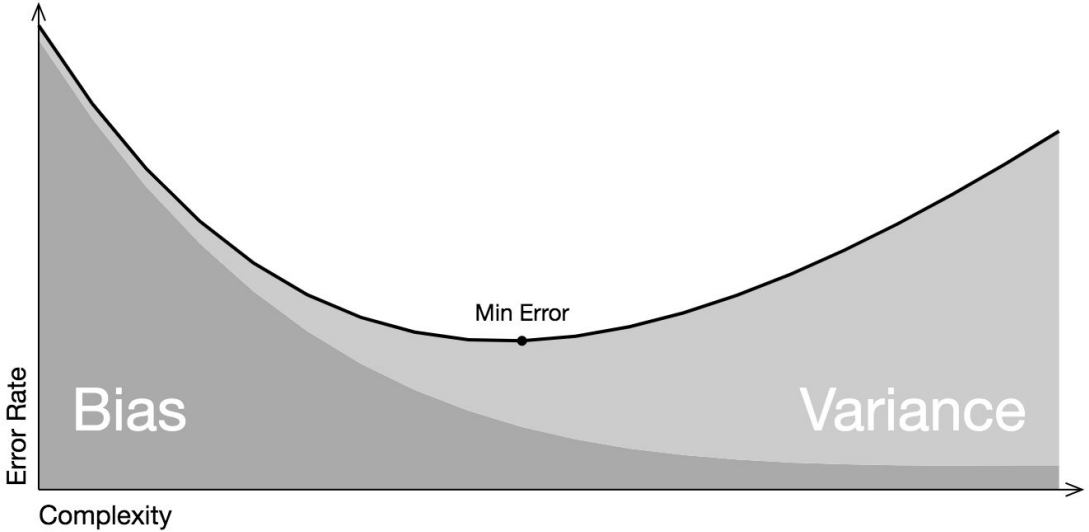
1. Machine learning identifies patterns using **statistical learning** and computers by unearthing **boundaries** in data sets. You can use it to make predictions.

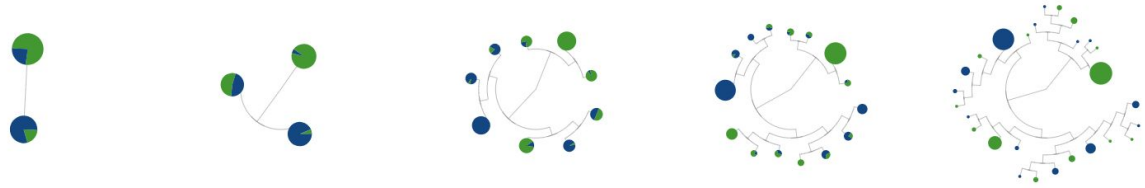
2. One method for making predictions is called a decision trees, which uses a series of if-then statements to identify boundaries and define patterns in the data.

3. **Overfitting** happens when some boundaries are based on on *distinctions that don't make a difference*. You can see if a model overfits by having test data flow through the model.

So...what can we do about overfitting?

Bias-variance tradeoff

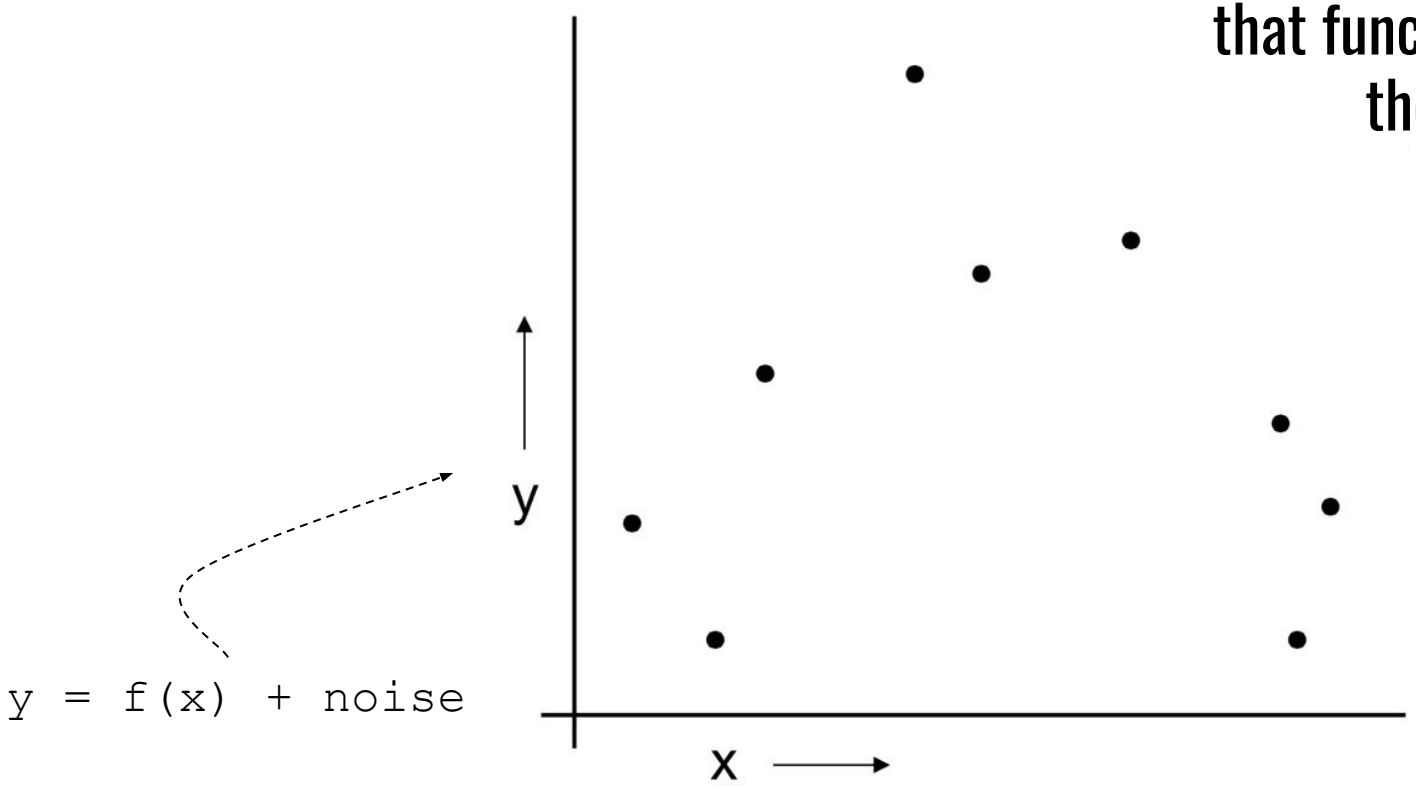




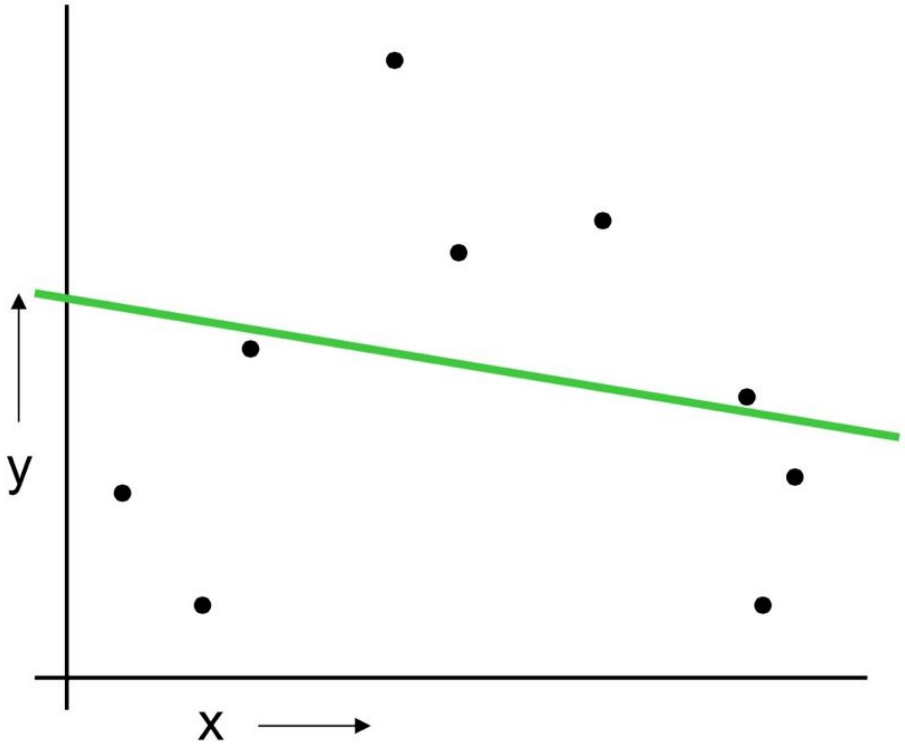
Bias-variance tradeoff

- **High variance** models make mistakes in *inconsistent* ways.
- **Biased models** tend to be overly simple and not reflect reality
- What to do:
  - Consider tuning parameters in the model
    - can avoid overfitting by setting minimum node size threshold (fewer splits; variance decreased)
  - Changing model approach
    - Bagging, boosting, & ensemble methods
  - Re-consider data splitting approach
    - Training + test?
    - LOOCV
    - K-fold CV

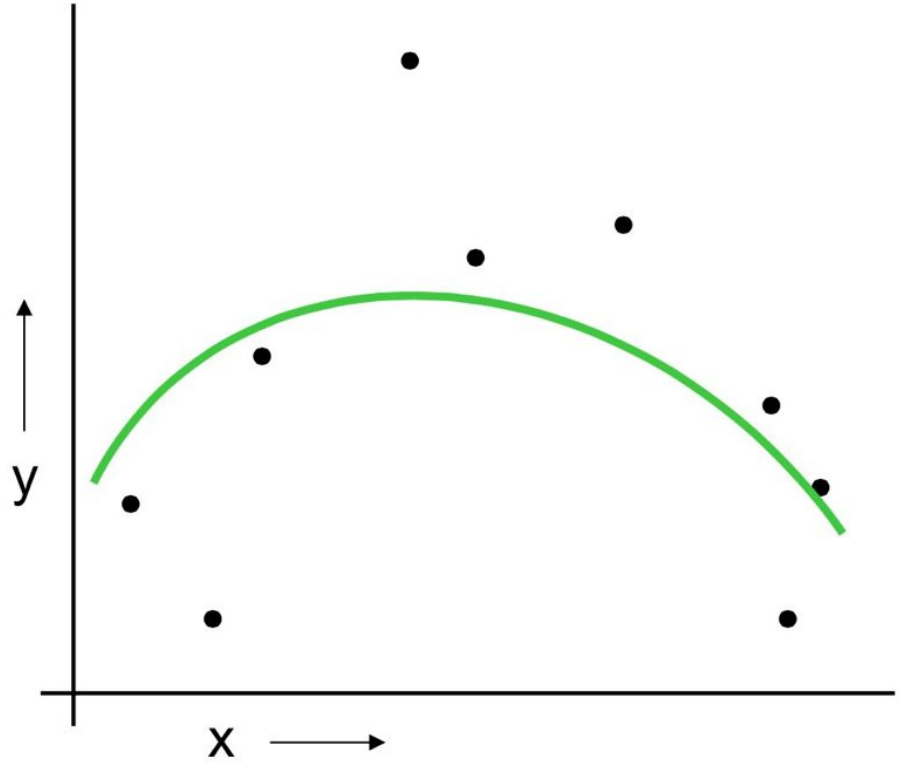
Can we determine what that function (`f`) *is* using these data?



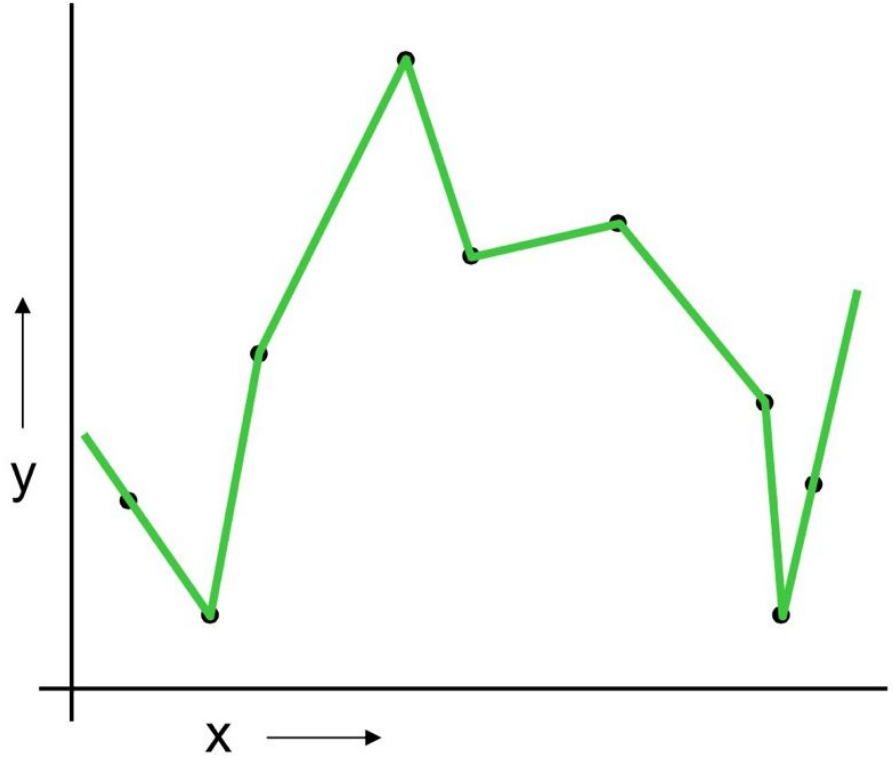
Linear regression



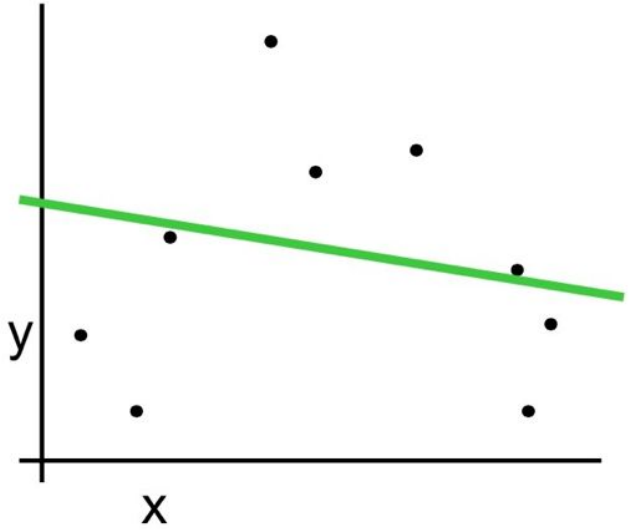
Quadratic regression

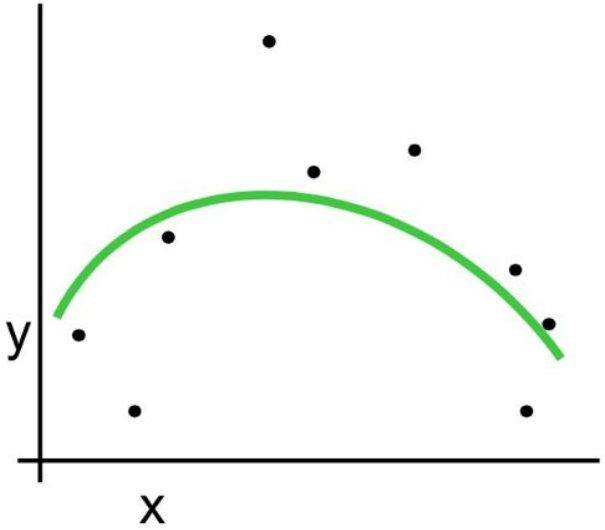


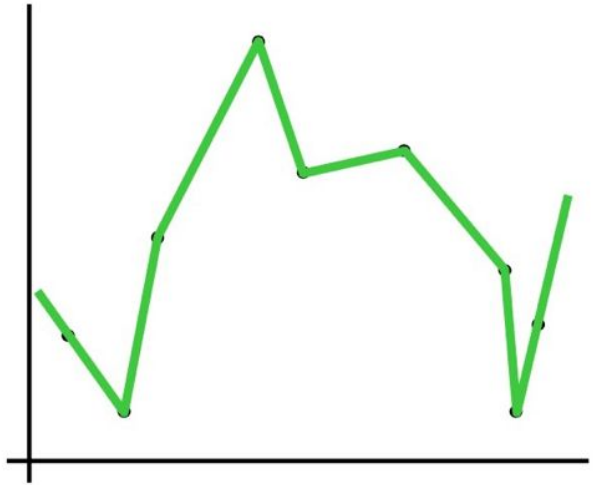
Piecewise linear nonparametric regression



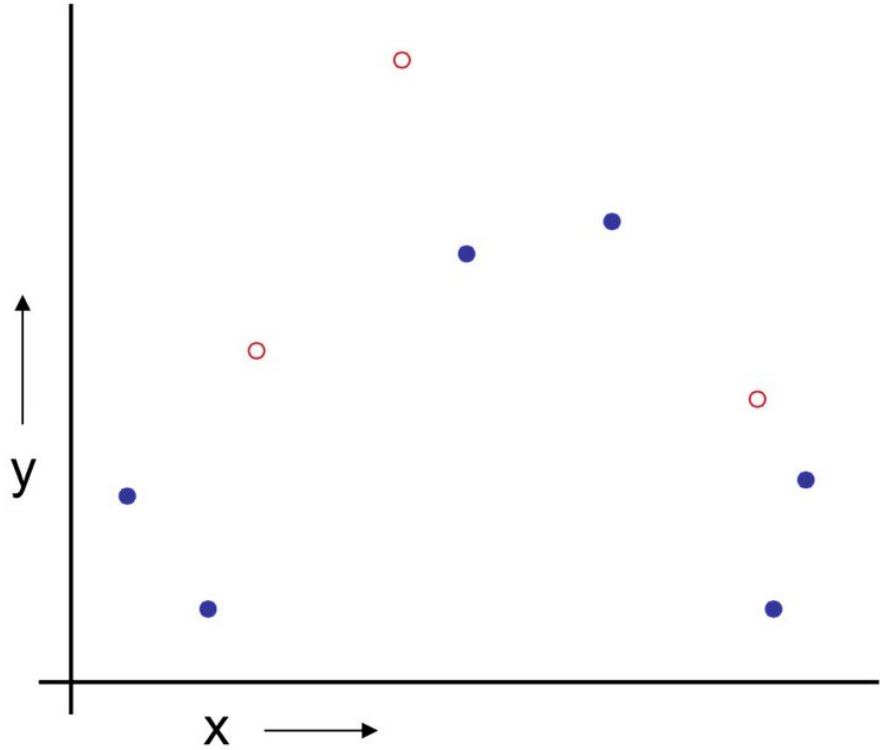
Which to choose?







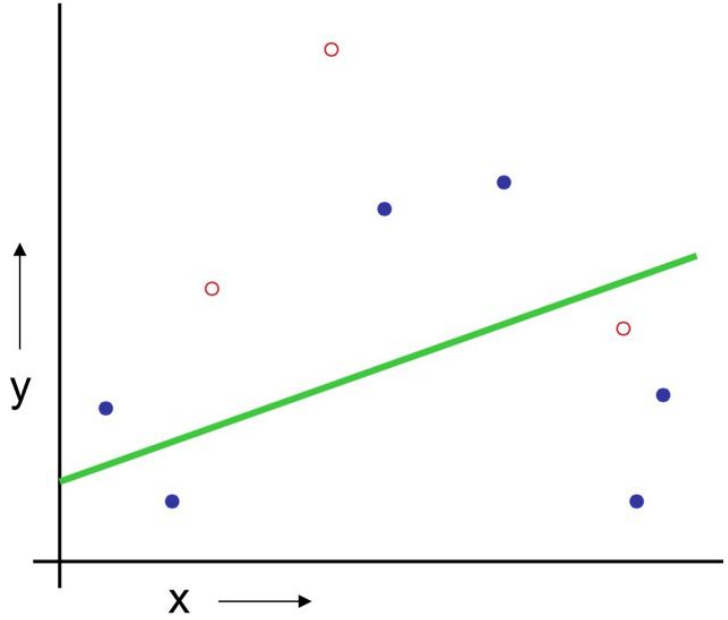
The data partition method



1. Randomly choose 30% of the data to be in a test set

2. The remainder is a training set

Train the model on your training set



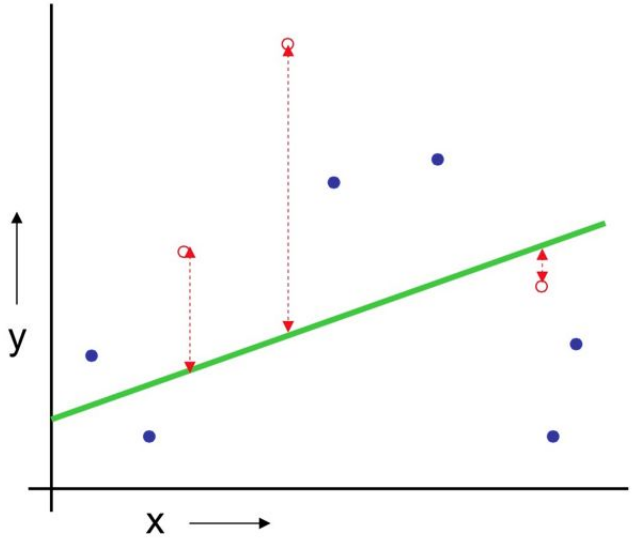
(Linear regression example)

1. Randomly choose 30% of the data to be in a test set

2. The remainder is a training set

3. Perform your regression on the training set

Assess future performance using the test set



(Linear regression example)

Mean Squared Error = 2.4

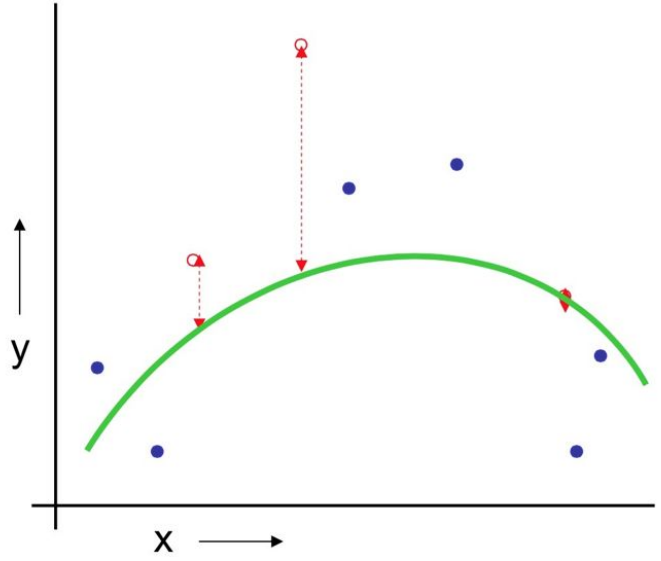
1. Randomly choose 30% of the data to be in a test set

2. The remainder is a training set

3. Perform your regression on the training set

4. Estimate your future performance with the test set

Go through this process for each possible model



(Quadratic regression example)

Mean Squared Error = 0.9

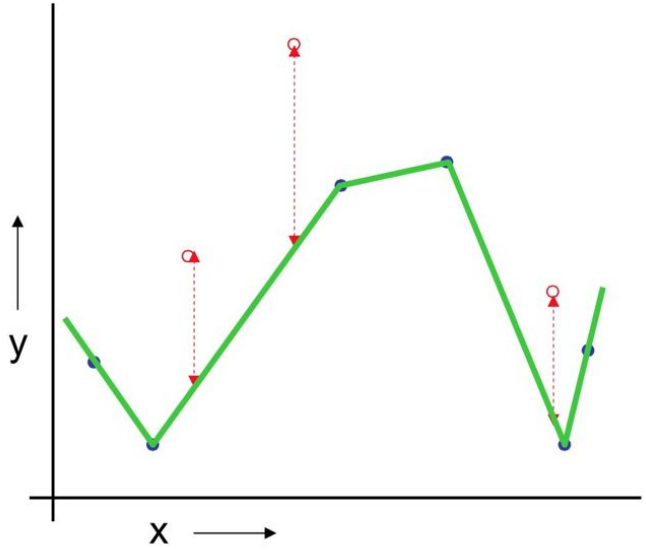
1. Randomly choose 30% of the data to be in a test set

2. The remainder is a training set

3. Perform your regression on the training set

4. Estimate your future performance with the test set

Go through this process for each possible model



(Join the dots example)

Mean Squared Error = 2.2

1. Randomly choose 30% of the data to be in a test set

2. The remainder is a training set

3. Perform your regression on the training set

4. Estimate your future performance with the test set

Pros and cons of data partitioning

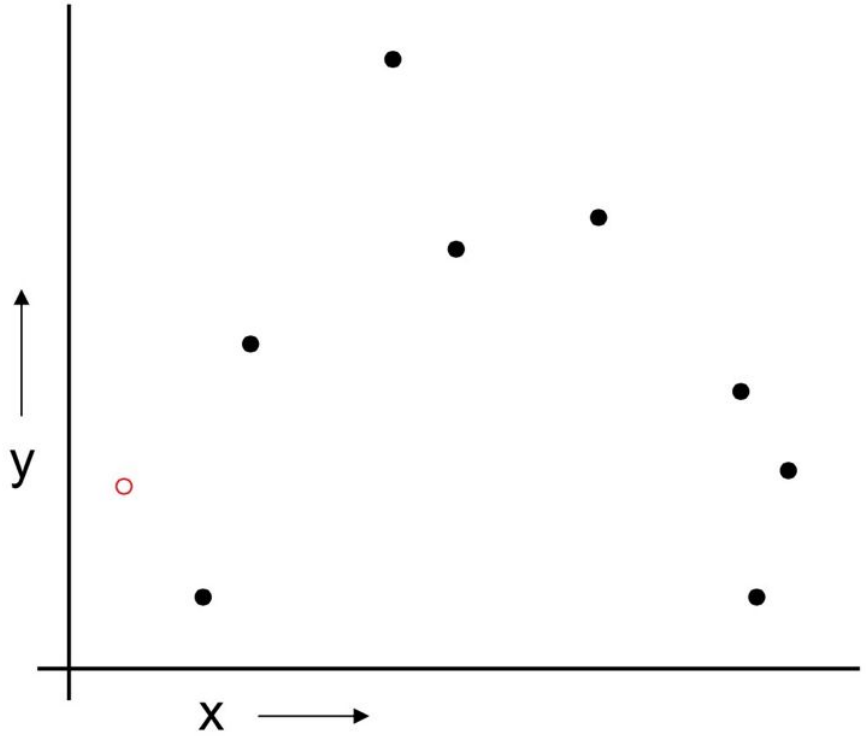
Pros:

- Simple approach
- Can choose model with best test-set score

Cons:

- Model fit on 30% less data than you have
- Without a large data set, removing 30% of the data could bias prediction

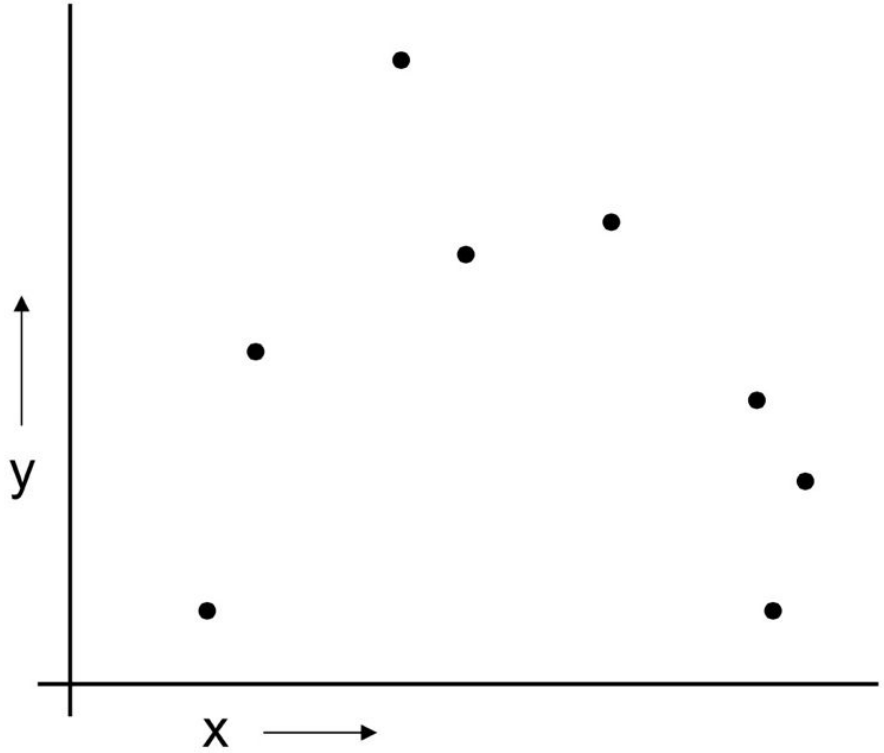
Leave one out cross validation (LOOCV)



For k=1 to R

1. Let (x_k, y_k) be the k^{th} record

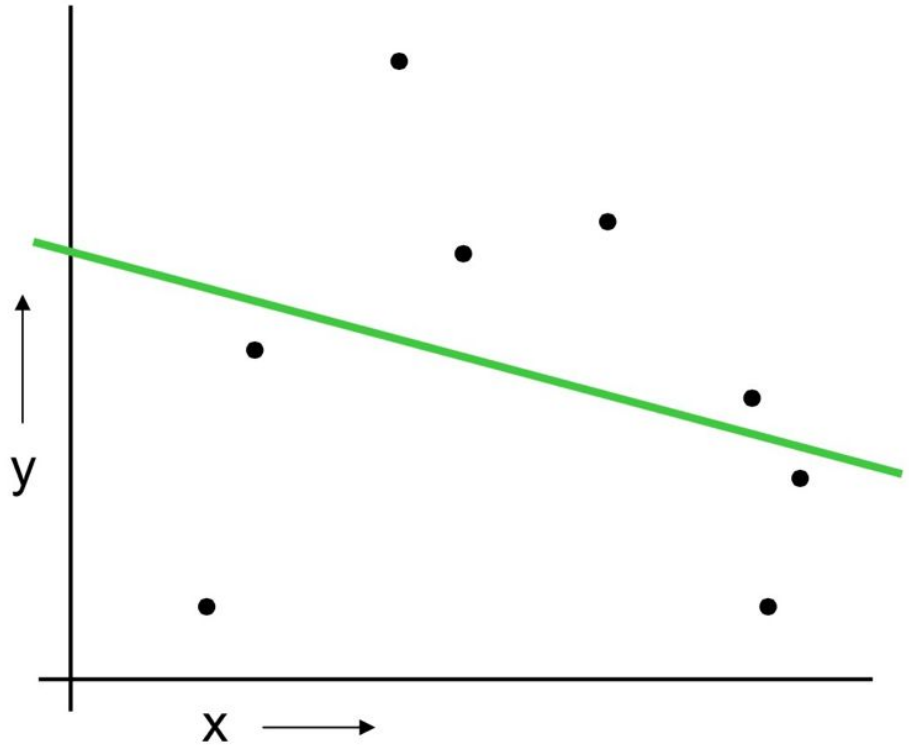
Leave one out cross validation (LOOCV)



For k=1 to R

1. Let (x_k, y_k) be the k^{th} record
2. Temporarily remove (x_k, y_k) from the dataset

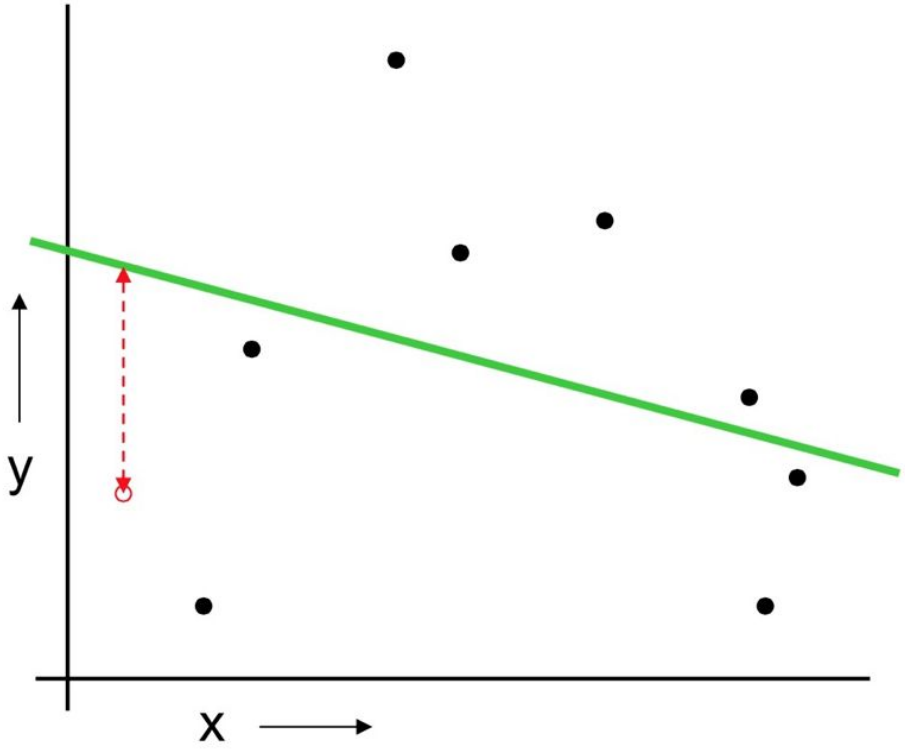
Leave one out cross validation (LOOCV)



For k=1 to R

1. Let (x_k, y_k) be the k^{th} record
2. Temporarily remove (x_k, y_k) from the dataset
3. Train on the remaining R-1 datapoints

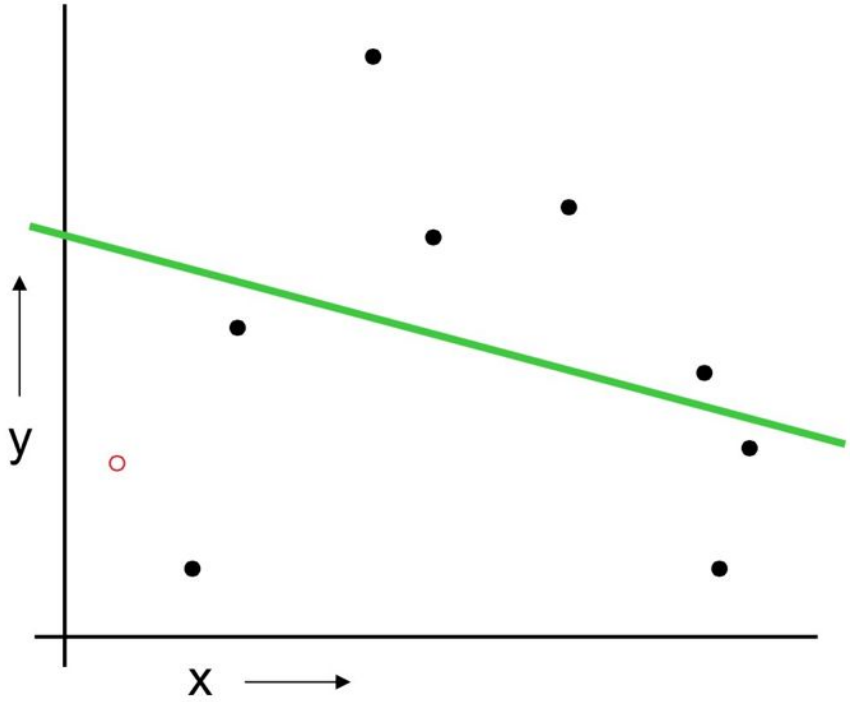
Leave one out cross validation (LOOCV)



For k=1 to R

1. Let (x_k, y_k) be the k^{th} record
2. Temporarily remove (x_k, y_k) from the dataset
3. Train on the remaining R-1 datapoints
4. Note your error (x_k, y_k)

Leave one out cross validation (LOOCV)

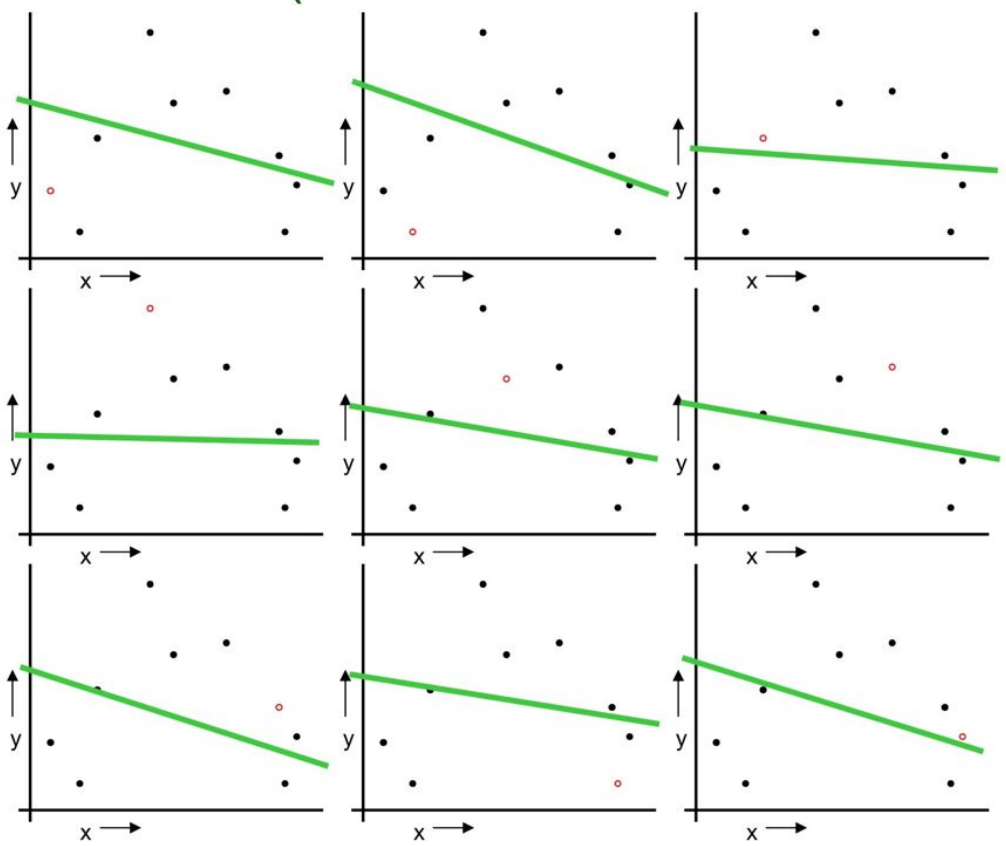


For k=1 to R

1. Let (x_k, y_k) be the k^{th} record
2. Temporarily remove (x_k, y_k) from the dataset
3. Train on the remaining R-1 datapoints
4. Note your error (x_k, y_k)

When you've done all points, report the mean error.

Leave one out cross validation (LOOCV)



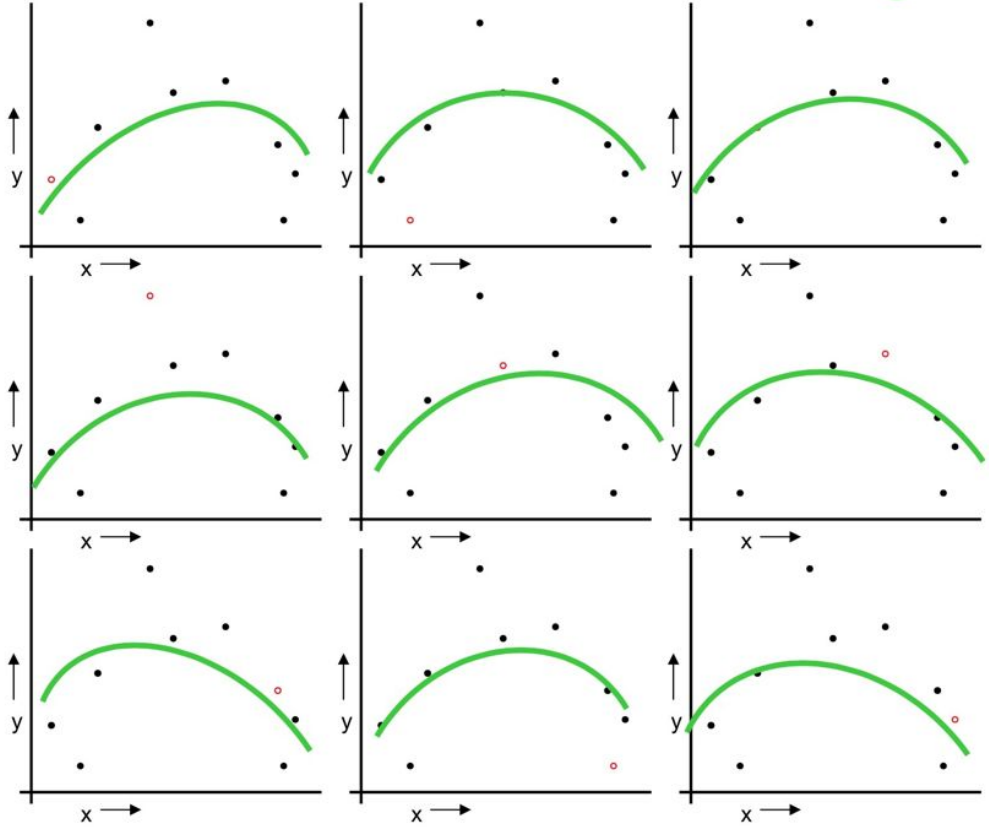
For k=1 to R

1. Let (x_k, y_k) be the k^{th} record
2. Temporarily remove (x_k, y_k) from the dataset
3. Train on the remaining R-1 datapoints
4. Note your error (x_k, y_k)

When you've done all points, report the mean error.

$MSE_{LOOCV} = 2.12$

Leave one out cross validation (LOOCV)



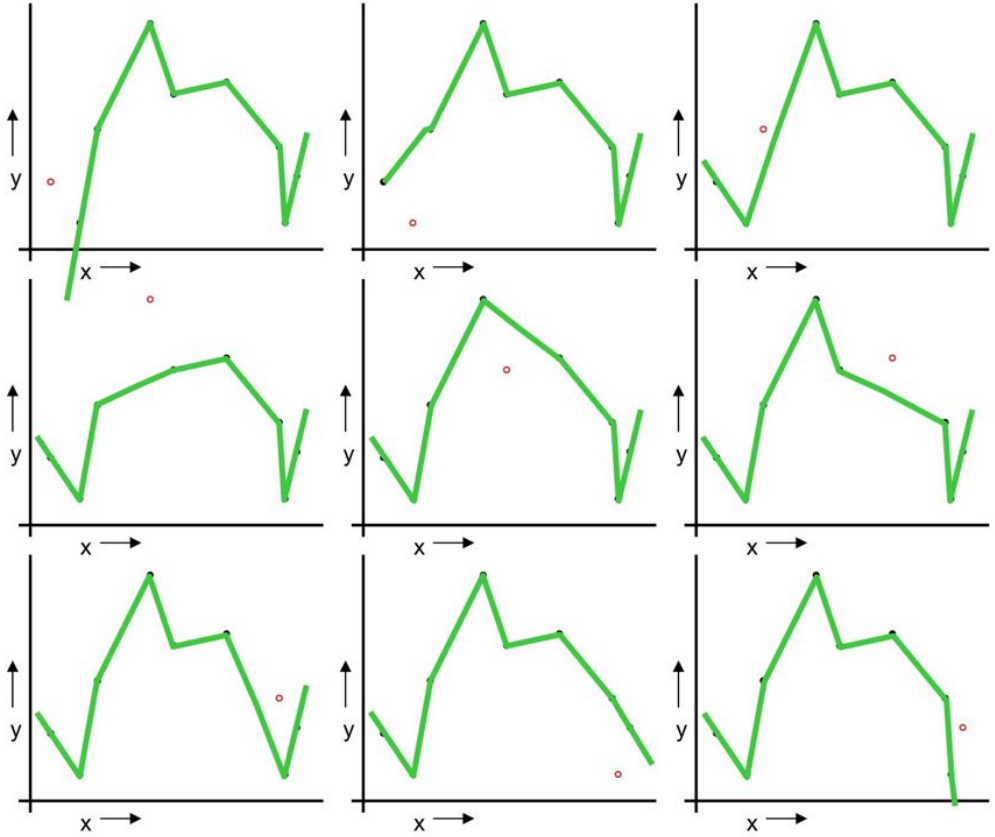
For k=1 to R

1. Let (x_k, y_k) be the k^{th} record
2. Temporarily remove (x_k, y_k) from the dataset
3. Train on the remaining R-1 datapoints
4. Note your error (x_k, y_k)

When you've done all points, report the mean error.

$MSE_{LOOCV} = 0.962$

Leave one out cross validation (LOOCV)



For k=1 to R

1. Let (x_k, y_k) be the k^{th} record
2. Temporarily remove (x_k, y_k) from the dataset
3. Train on the remaining R-1 datapoints
4. Note your error (x_k, y_k)

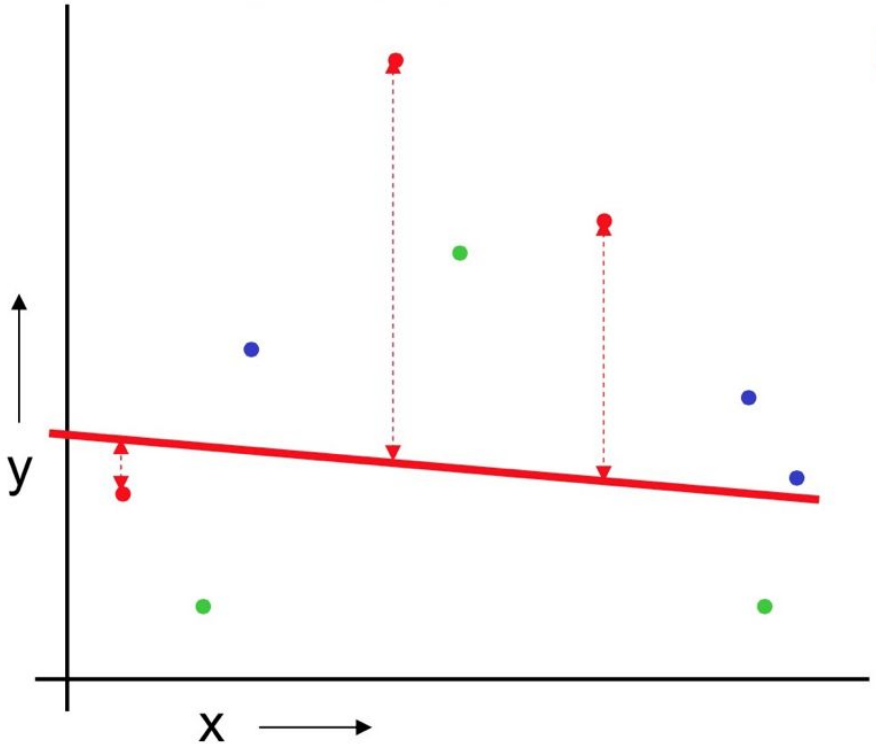
When you've done all points, report the mean error.

$MSE_{LOOCV} = 3.33$

Method Comparison

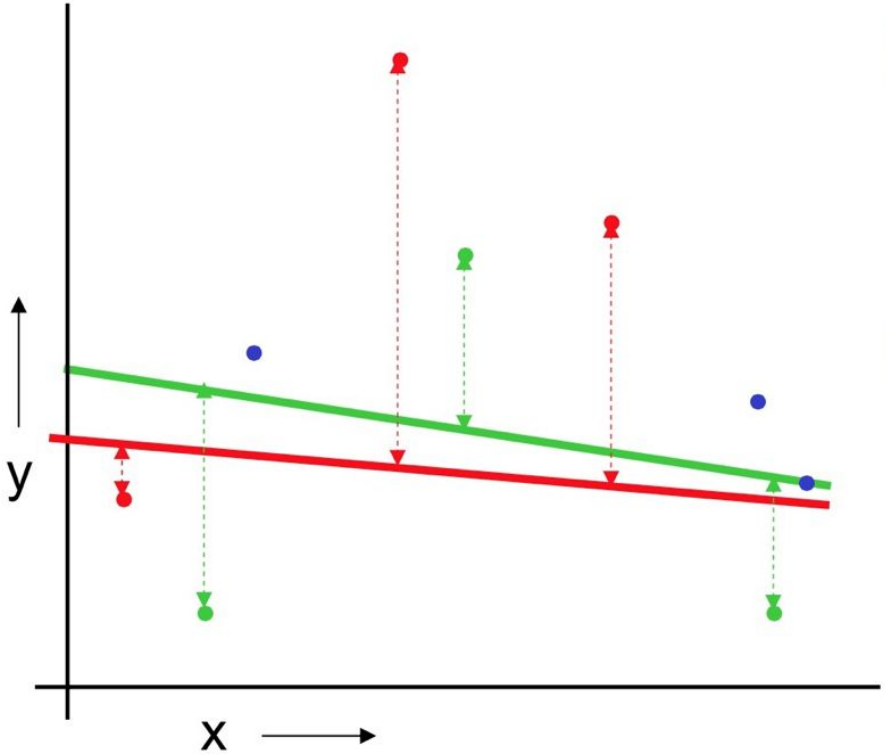
	Cons	Pros
Data partitioning	Variance: unreliable estimate of future performance	Cheap
LOOCV	Computationally expensive; has weird behavior	Uses all your data

k-fold cross validation



For the red partition: Train on all the points not in the red partition. Find the test-set sum of errors on the red points.

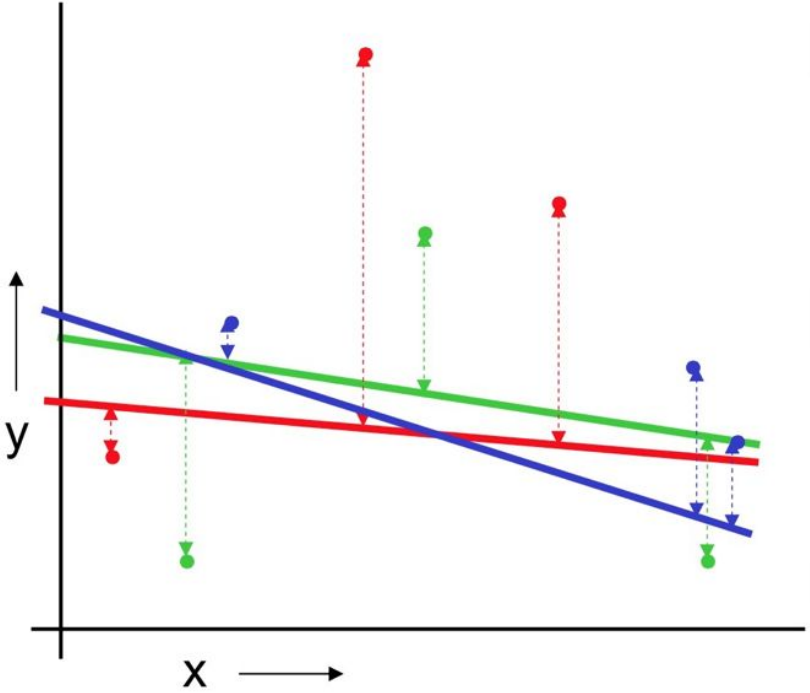
k-fold cross validation



For the red partition: Train on all the points not in the red partition. Find the test-set sum of errors on the red points.

For the green partition: Train on all the points not in the green partition. Find the test-set sum of errors on the green points.

k-fold cross validation

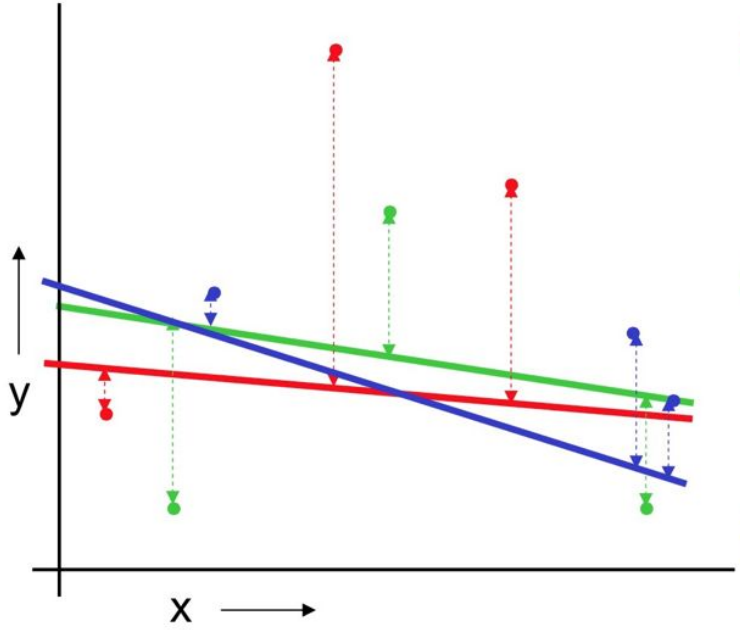


For the red partition: Train on all the points not in the red partition. Find the test-set sum of errors on the red points.

For the green partition: Train on all the points not in the green partition. Find the test-set sum of errors on the green points.

For the blue partition: Train on all the points not in the blue partition. Find the test-set sum of errors on the blue points.

k-fold cross validation



Linear Regression

$MSE_{3FOLD}=2.05$

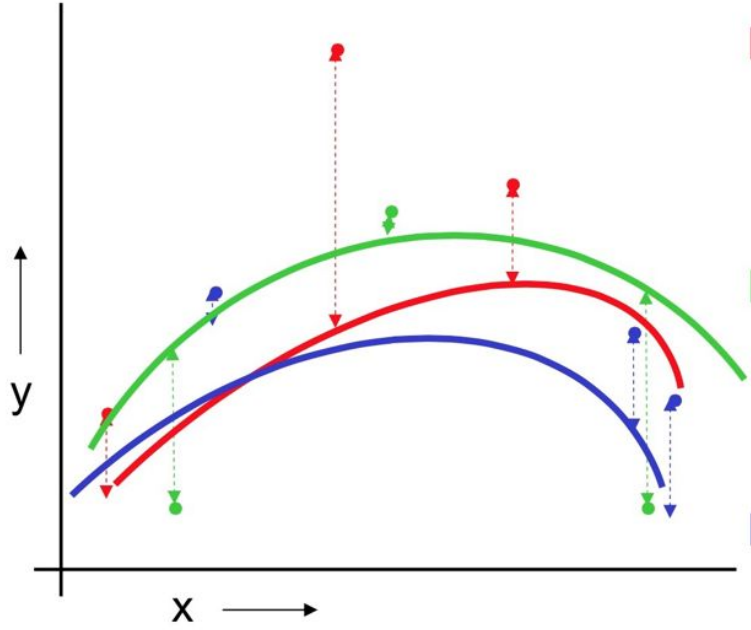
For the red partition: Train on all the points not in the red partition. Find the test-set sum of errors on the red points.

For the green partition: Train on all the points not in the green partition. Find the test-set sum of errors on the green points.

For the blue partition: Train on all the points not in the blue partition. Find the test-set sum of errors on the blue points.

Then report the mean error

k-fold cross validation



Quadratic Regression

$MSE_{3FOLD}=1.11$

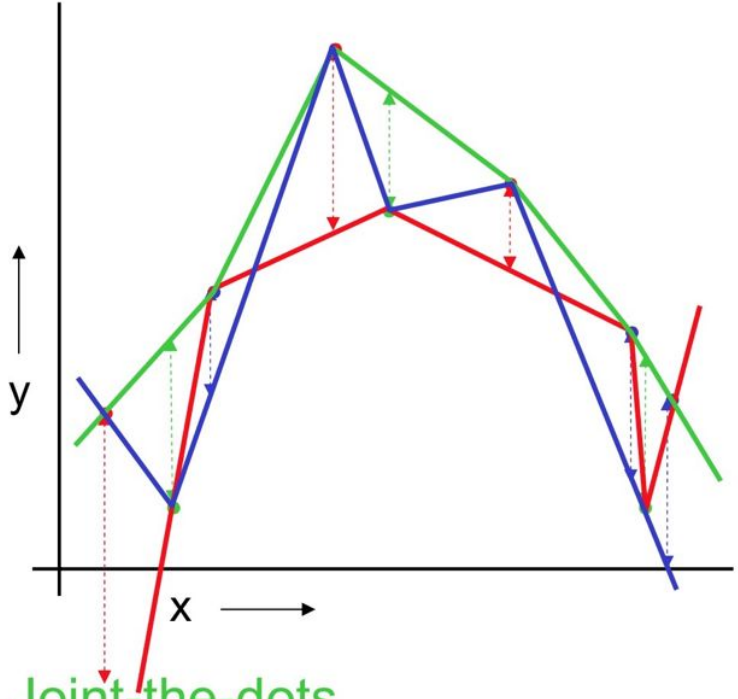
For the red partition: Train on all the points not in the red partition. Find the test-set sum of errors on the red points.

For the green partition: Train on all the points not in the green partition. Find the test-set sum of errors on the green points.

For the blue partition: Train on all the points not in the blue partition. Find the test-set sum of errors on the blue points.

Then report the mean error

k-fold cross validation



Joint-the-dots

$MSE_{3FOLD}=2.93$

For the red partition: Train on all the points not in the red partition. Find the test-set sum of errors on the red points.

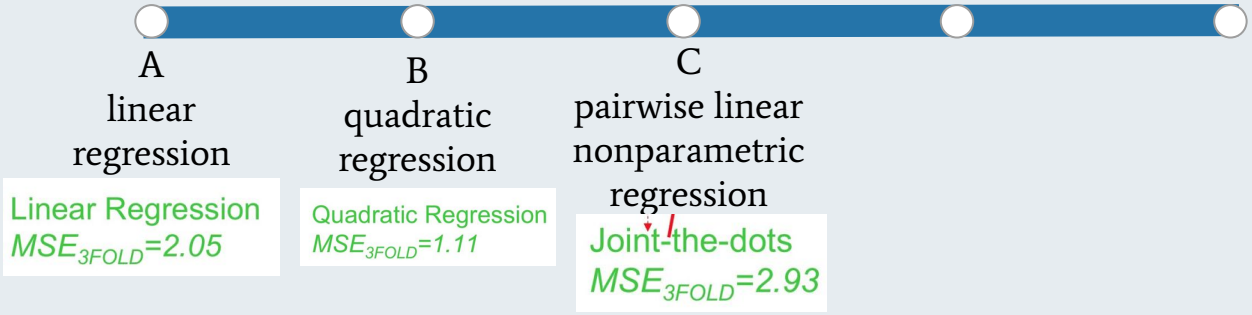
For the green partition: Train on all the points not in the green partition. Find the test-set sum of errors on the green points.

For the blue partition: Train on all the points not in the blue partition. Find the test-set sum of errors on the blue points.

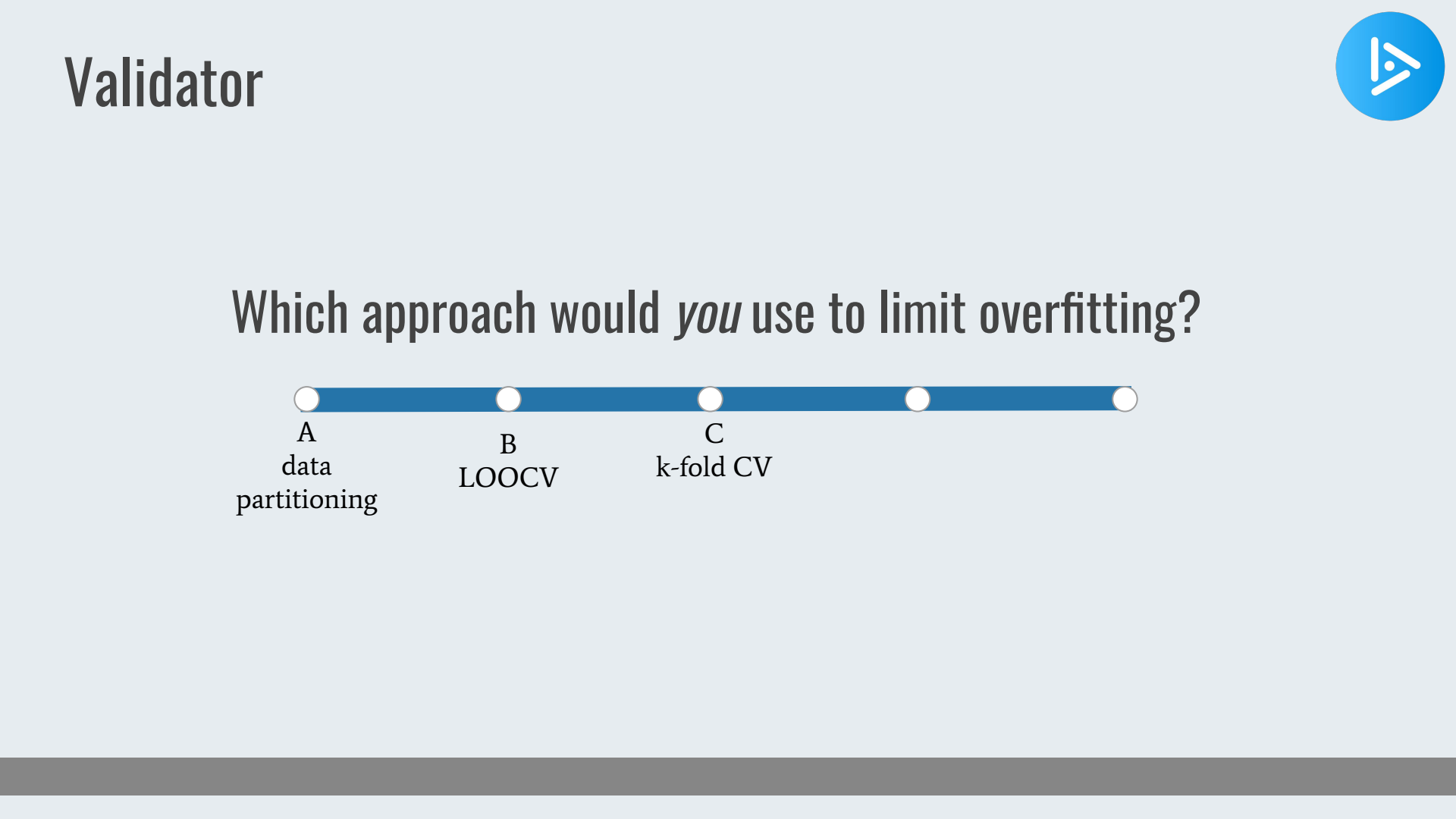
Then report the mean error

Validator

Given the example we just worked, how would *you* model these data?



Validator


Which approach would *you* use to limit overfitting?
A
data
partitioning
B
LOOCV
C
k-fold CV