ML: Example & Ethics

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Lectures :http://casimpkinsjr.radiantdolphinpress.com/pages/cogs108_ss1_23/index.html

Plan for today

- Announcements
- Review of last time
- Projects - checking in and reminders
- Datahub maintenance warning and finals week warning
- ML Examples and Ethics
- Dimensionality reduction

Upcoming deadlines

- Friday 7/28
  - D5, D6
  - A3
  - Checkpoint 2: EDA
  - Quiz 3

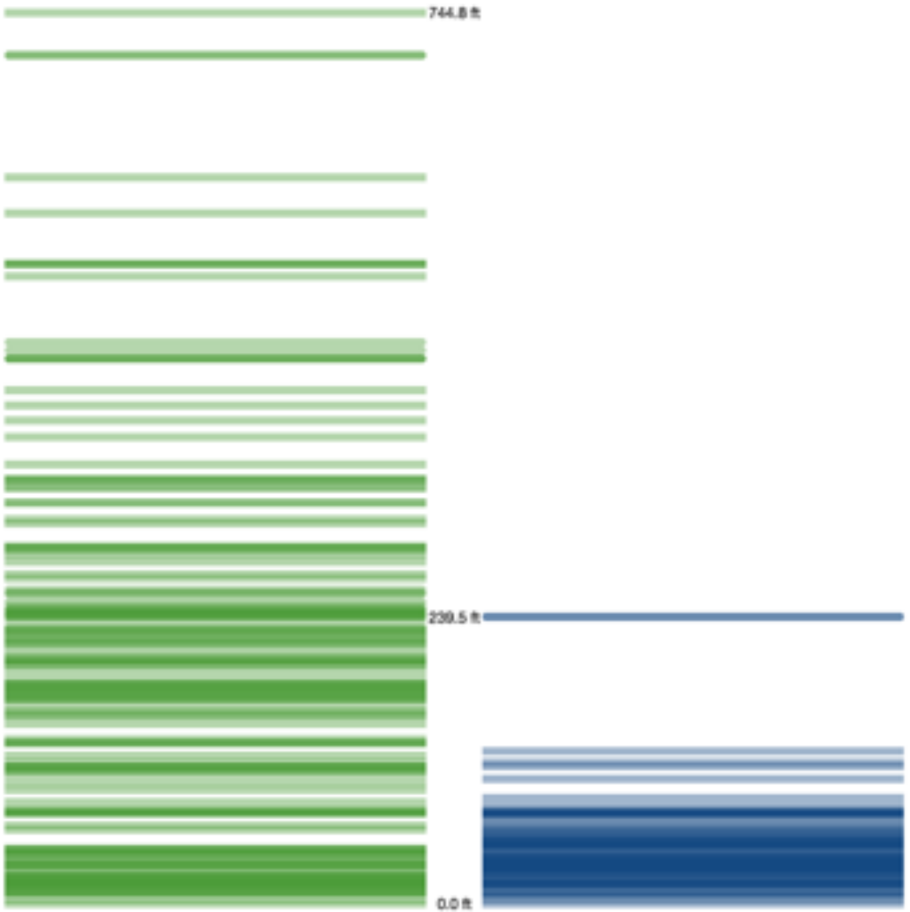
Projects

- EDA coming up
- What does this mean for how far you should have gone?
- How’s it going?
- Part of section today for project questions

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

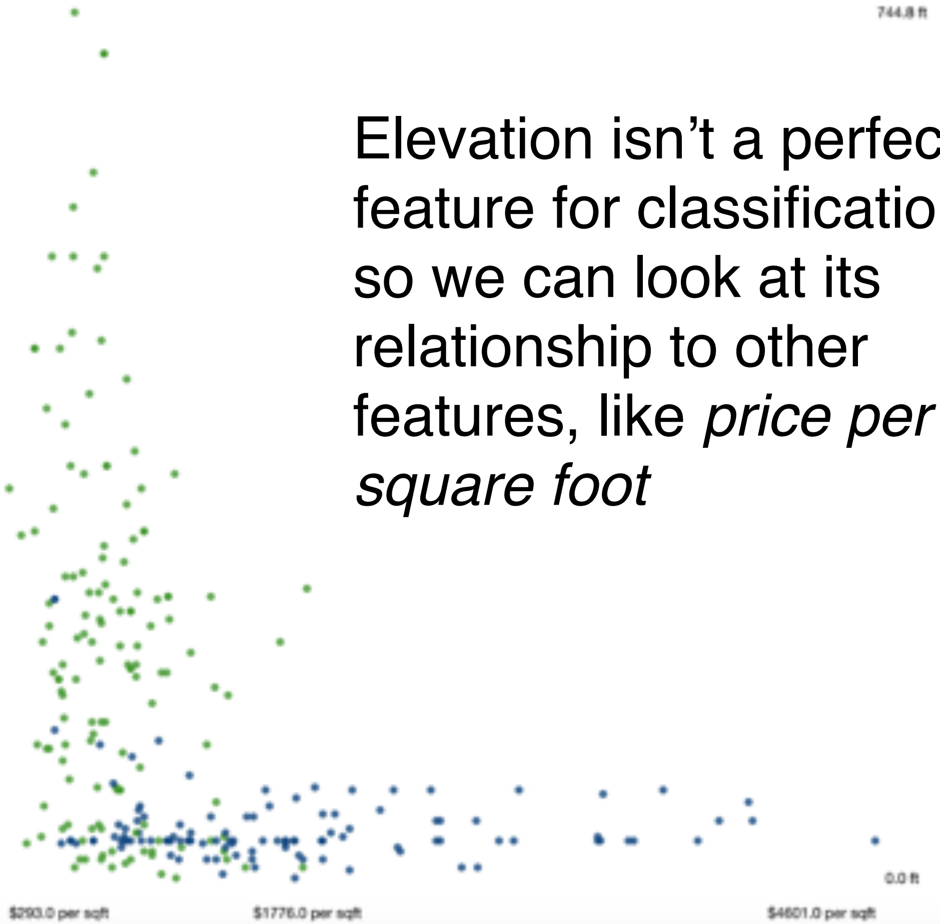
Adding nuance

Adding another **dimension** allows for more nuance. For example, New York apartments can be extremely expensive per square foot.

So visualizing elevation *and* price per square foot in a **scatterplot** helps us distinguish lower-elevation homes.

The data suggests that, among homes at or below 73 meters, those that cost more than $19,116.7 per square meter are in New York City.

Dimensions in a data set are called **features**, **predictors**, or **variables**. 1



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

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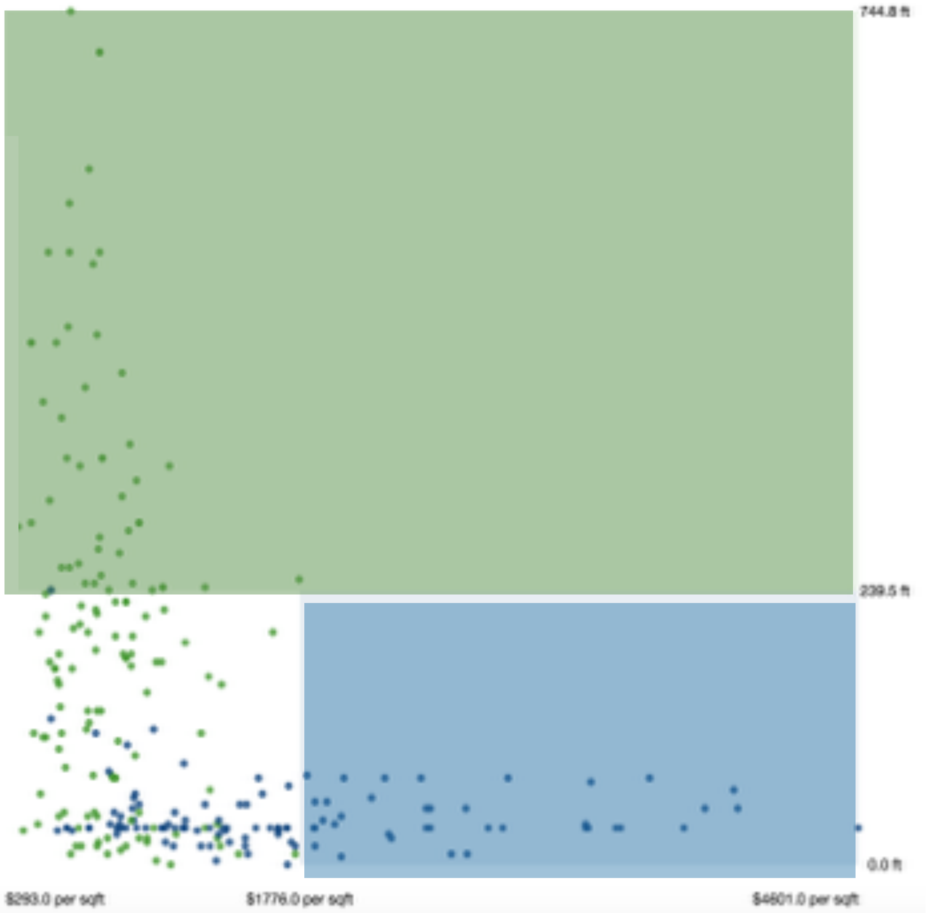
Drawing boundaries

- 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.



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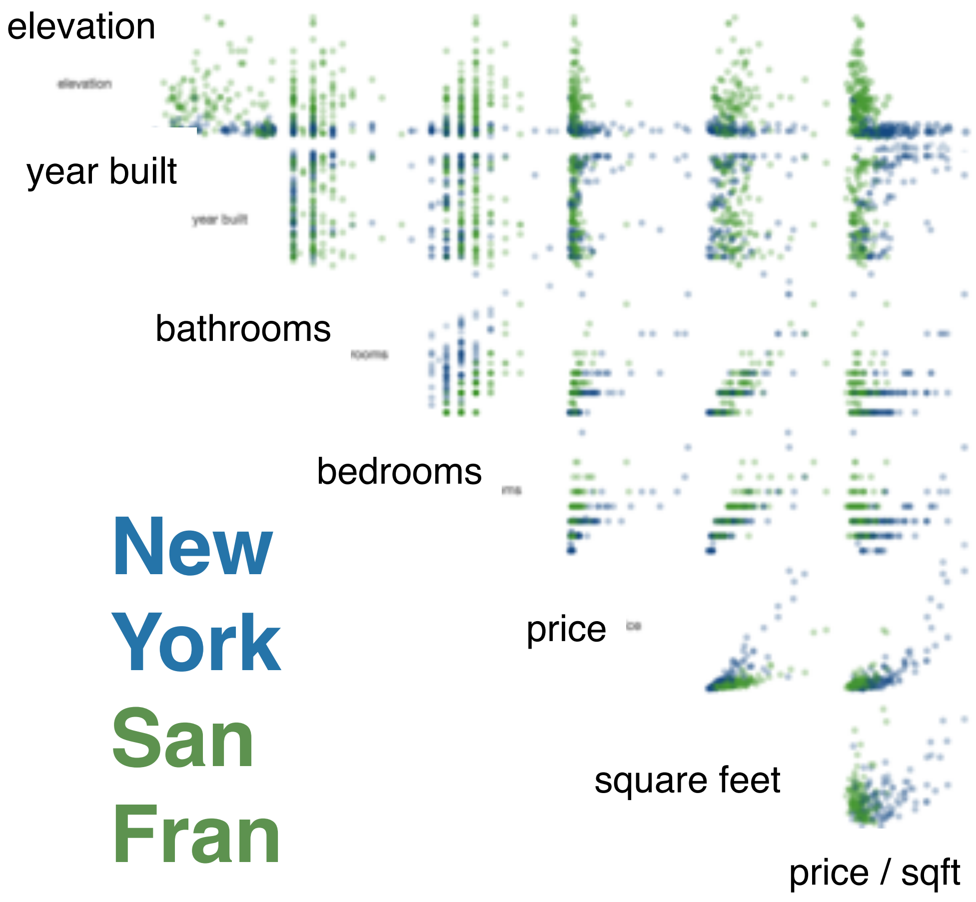
Our training set will use 7 different **features**. At the right we see the **scatterplot matrix** of the relationship between these features.

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



Our training set v
different **feature**
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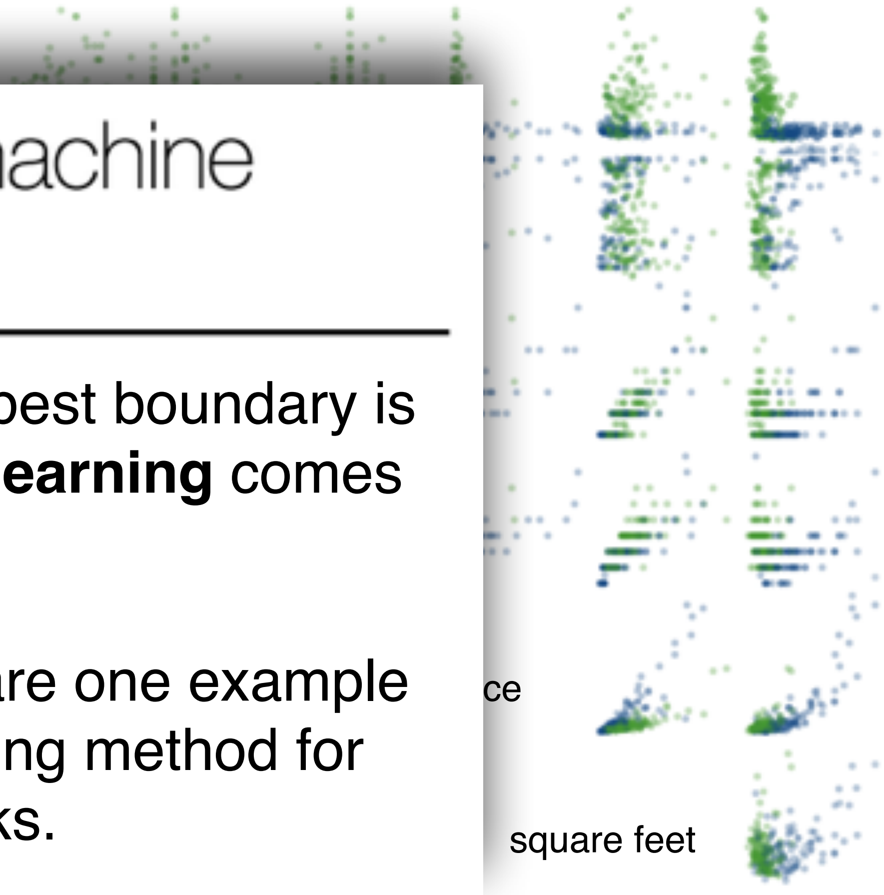
between these fe

Patterns are clea
boundaries for d
not obvious.

And now, machine learning

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

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



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Finding better boundaries

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

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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

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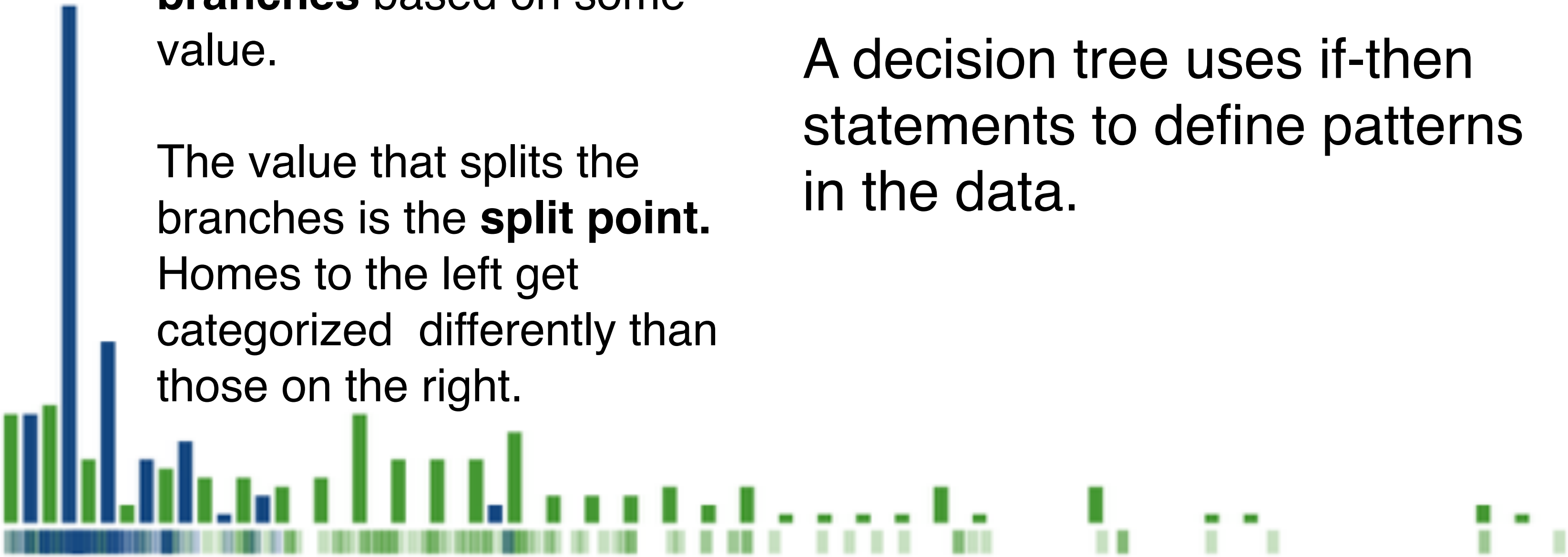
Your first fork

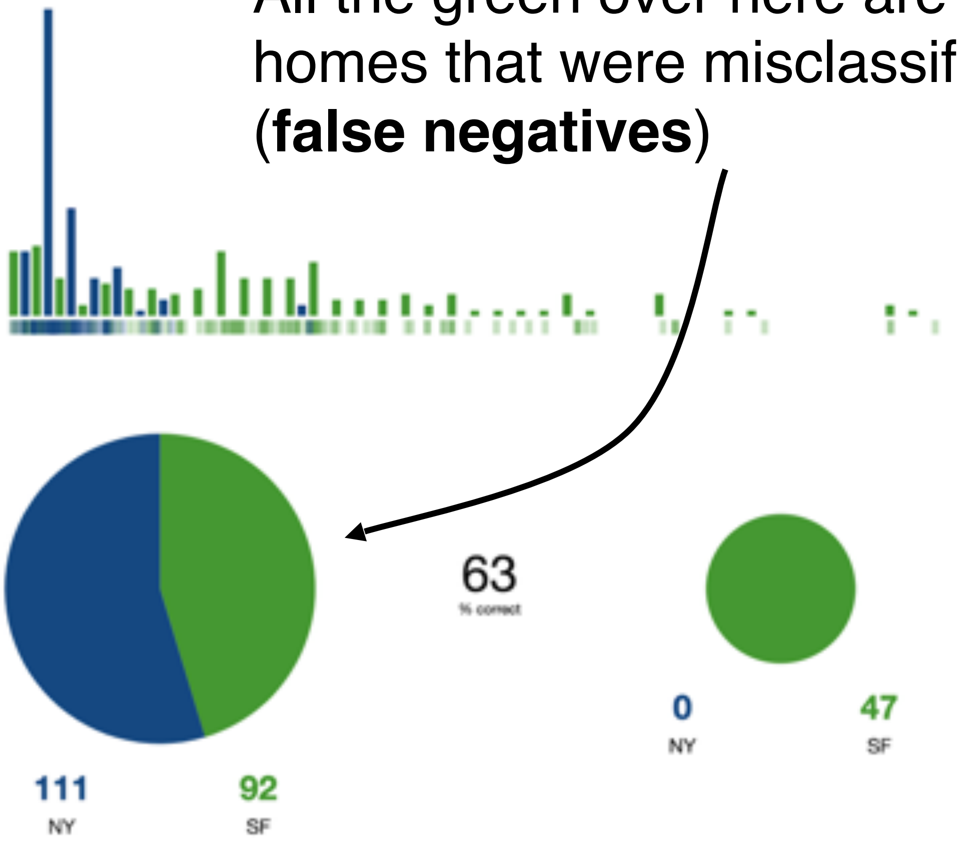
A decision tree uses if-then statements to define patterns in the data.

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.

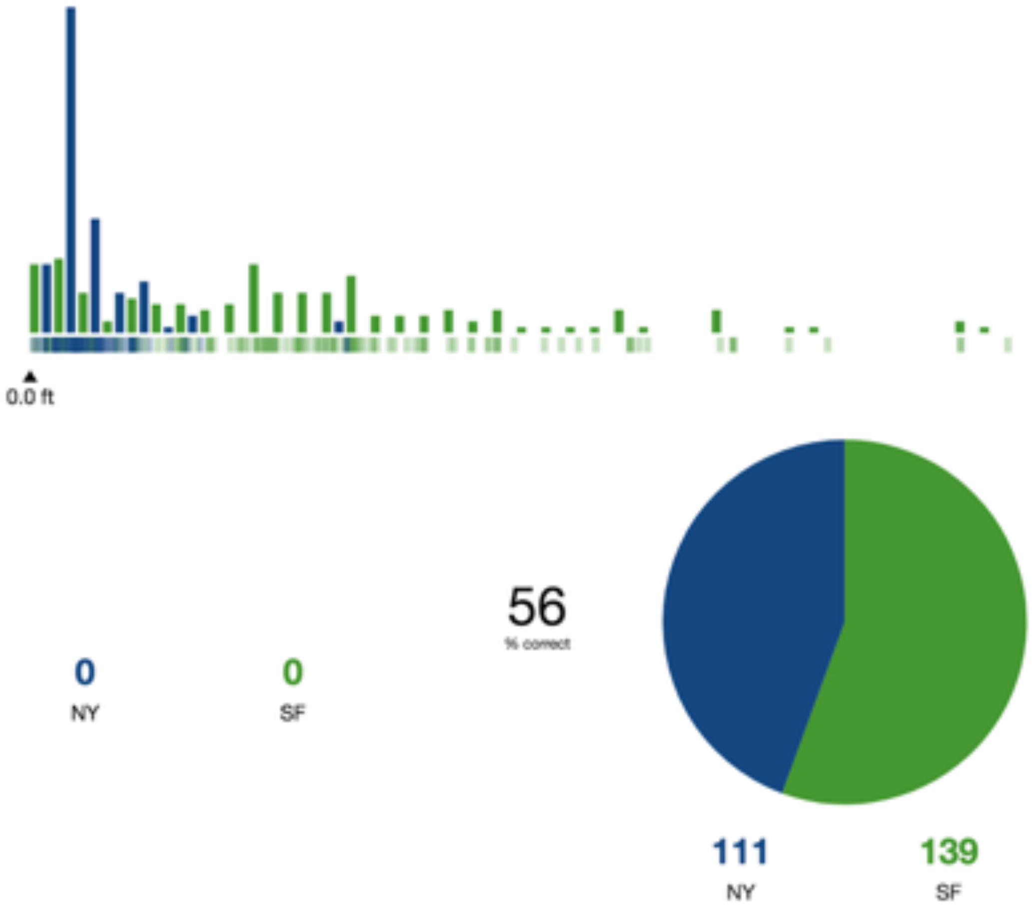


All the green over here are San Fran homes that were misclassified (**false negatives**)



Tradeoffs

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



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

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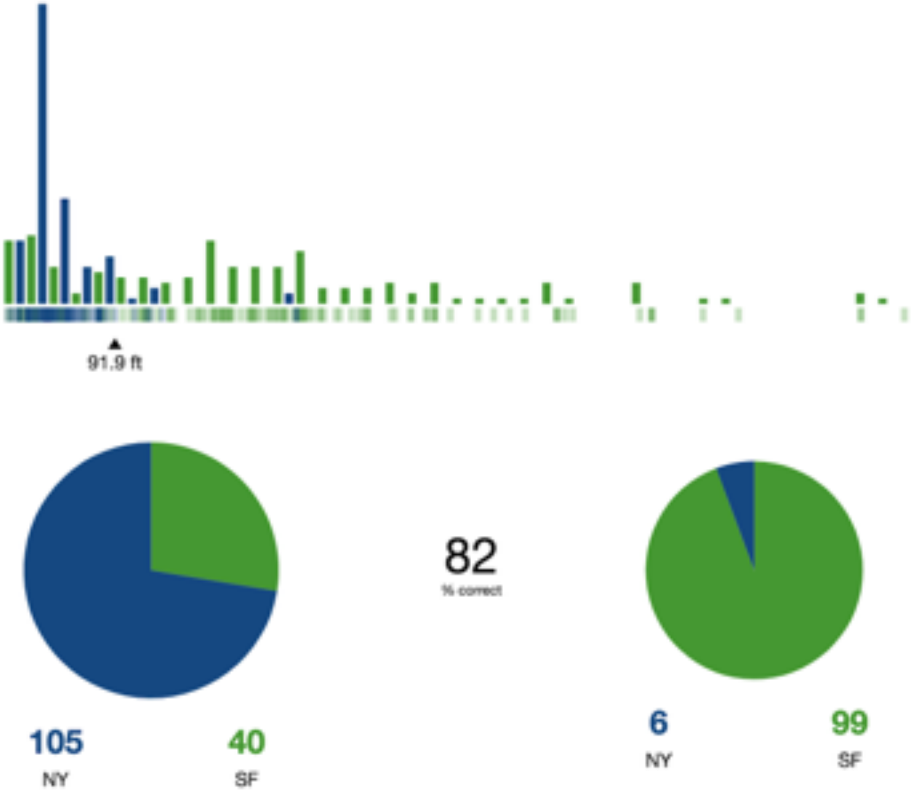

The best split

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

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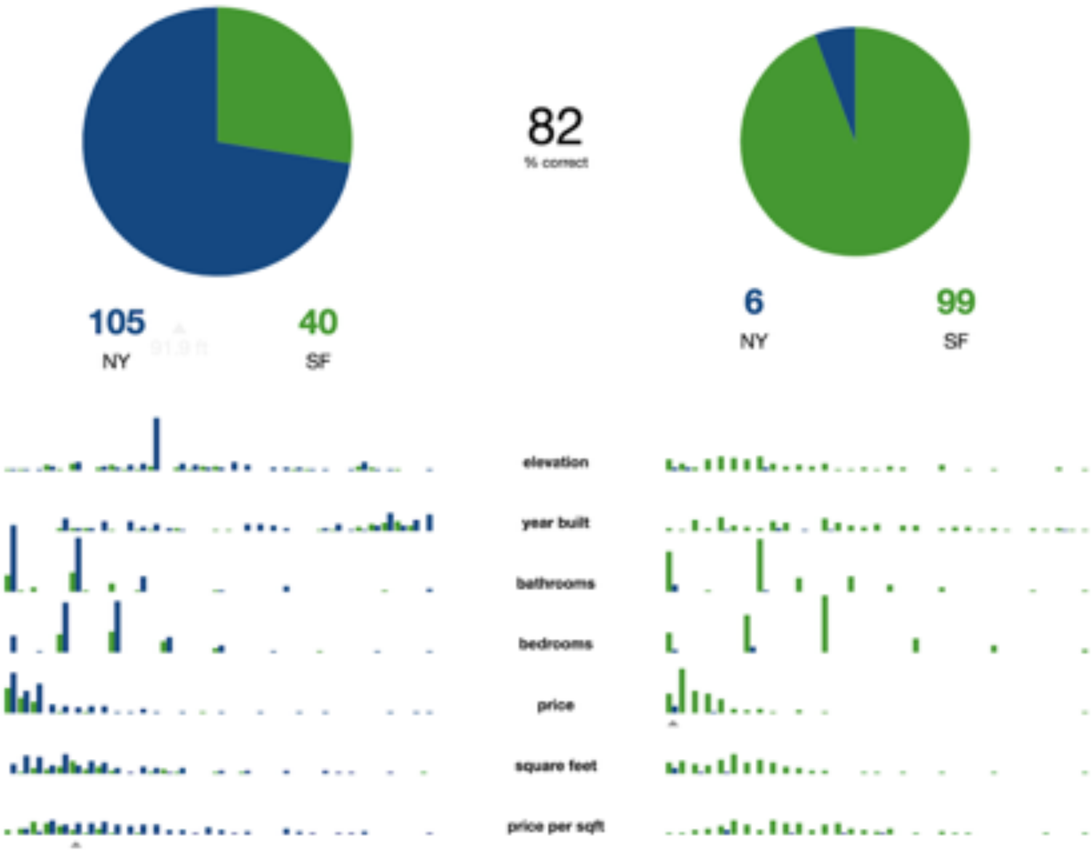

Recursion

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

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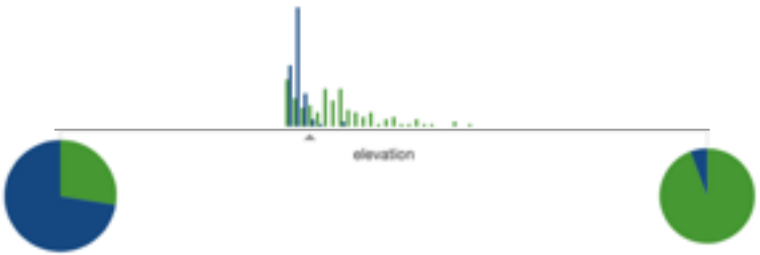

Growing a tree

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

Accuracy: 82%

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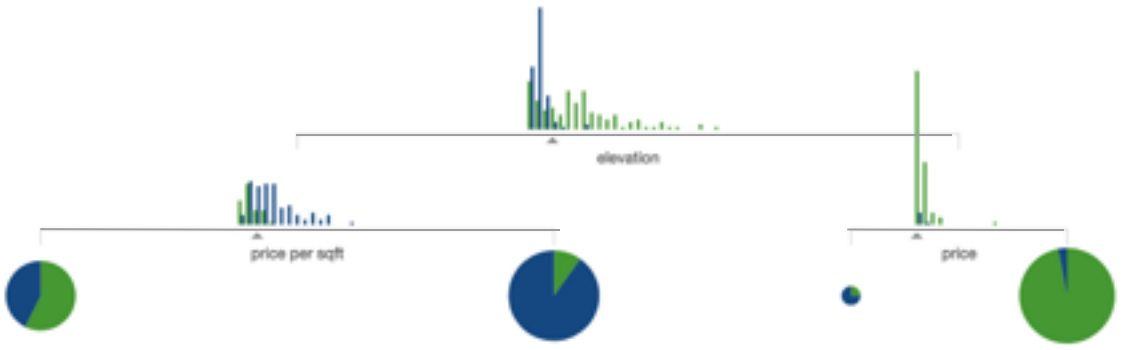
Growing a tree



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

Accuracy: 86%

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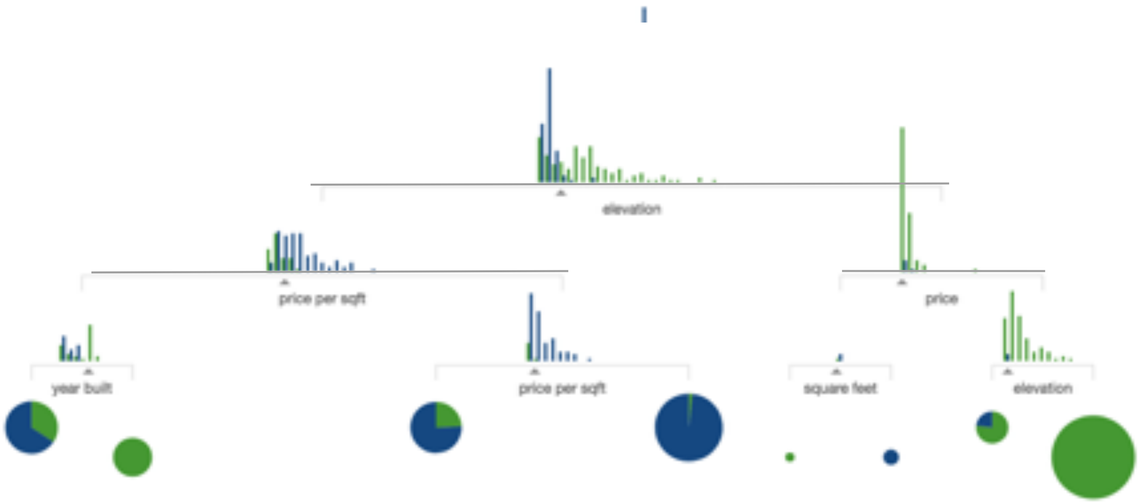
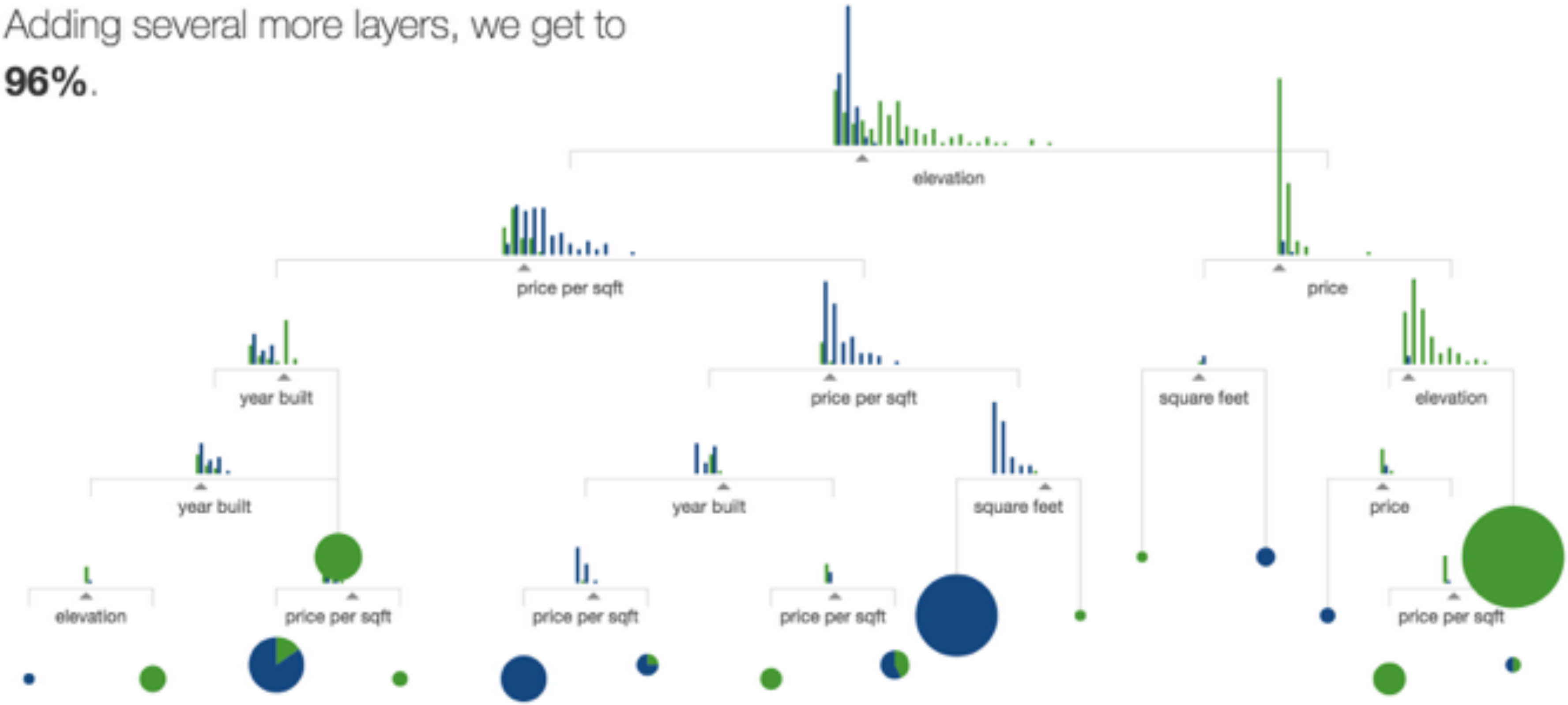
Growing a tree



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

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



Accuracy: 96%

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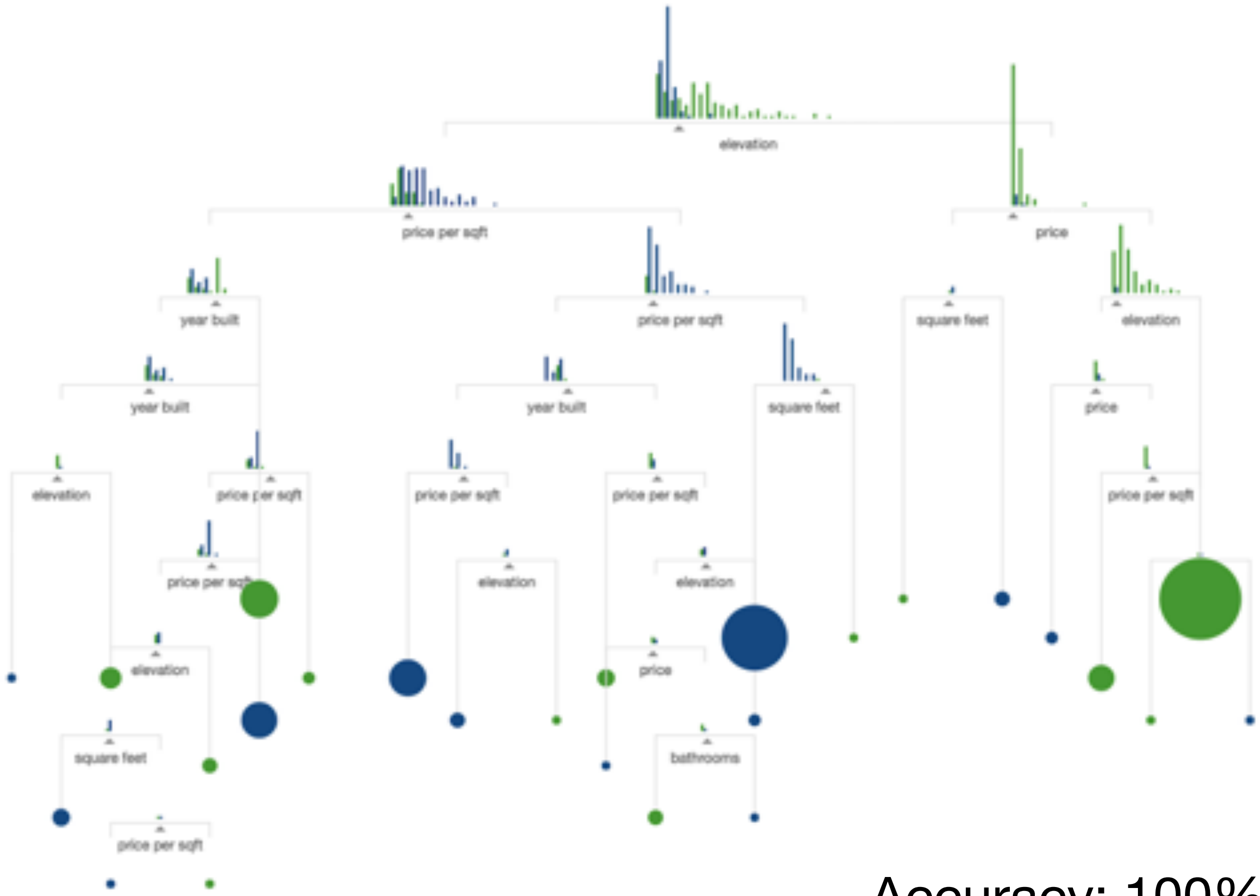
It's possible to add branches until your model is **100% accurate**.



Accuracy: 100%

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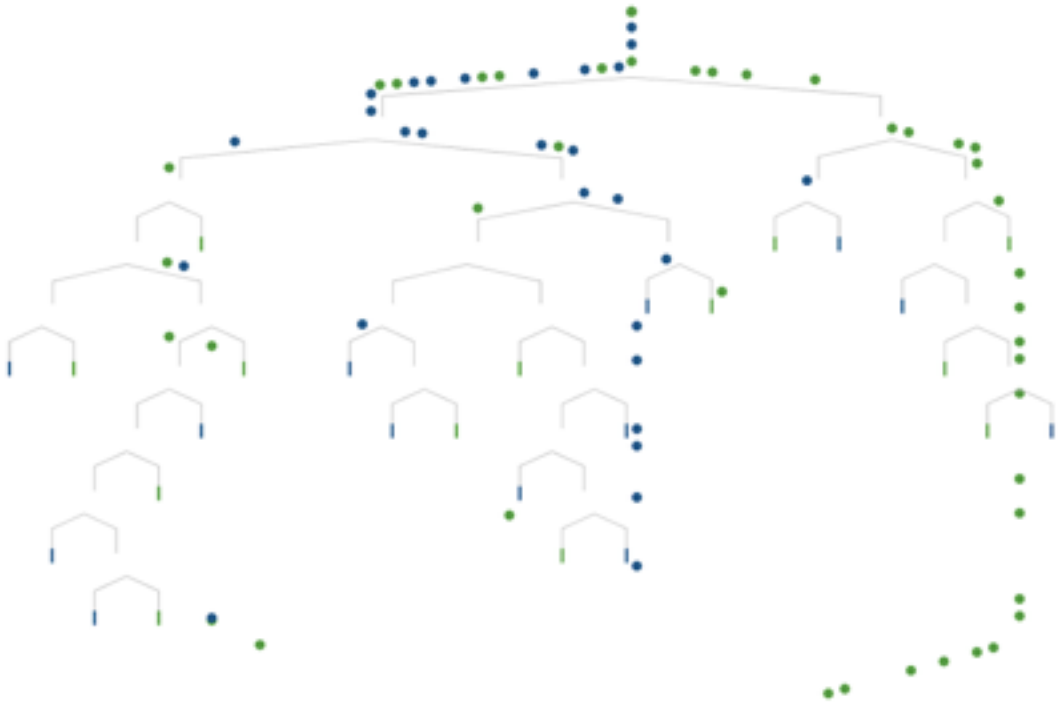
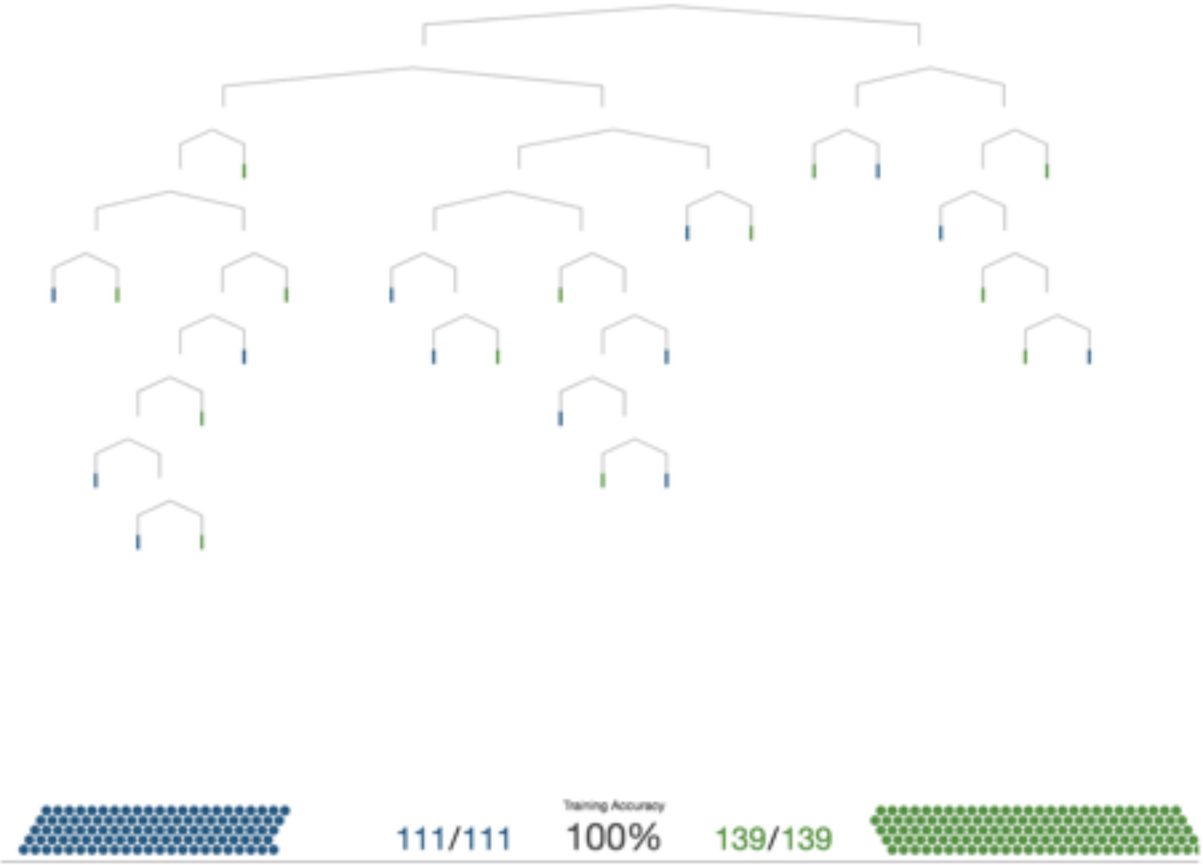
Making predictions

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

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



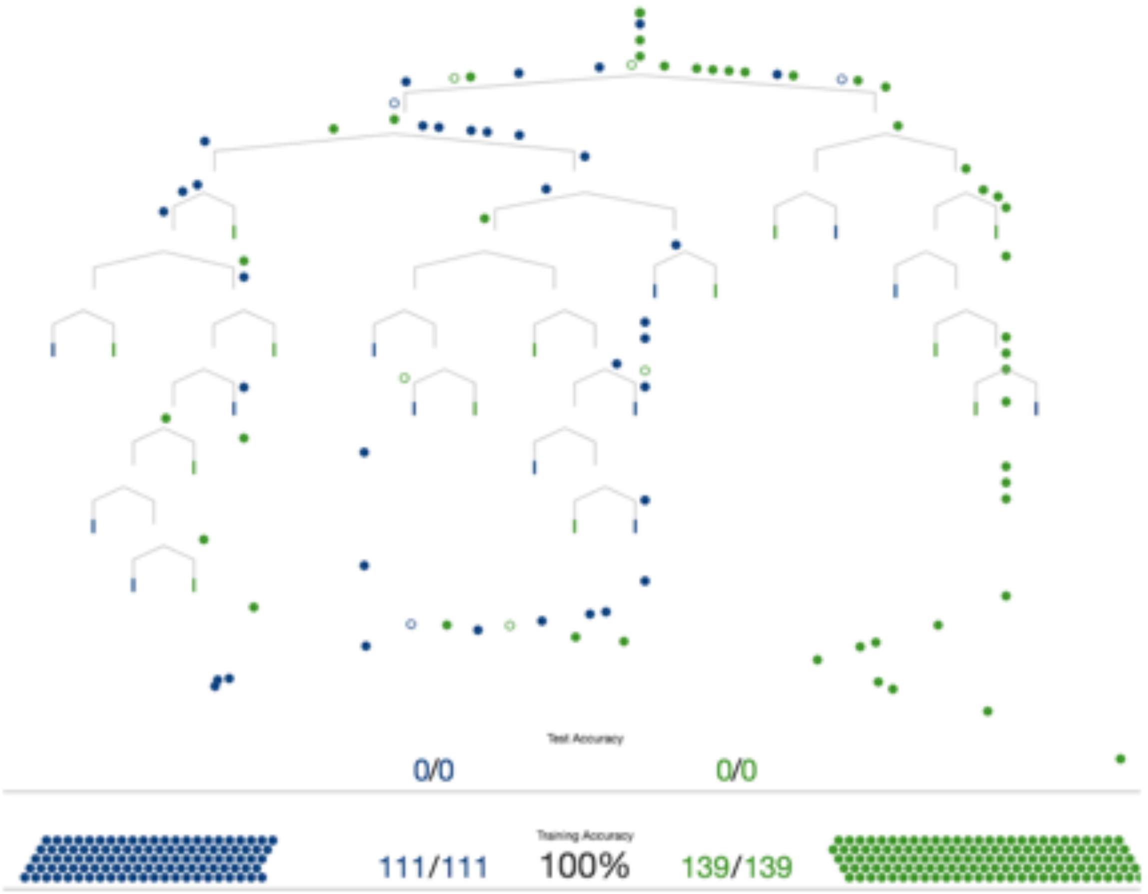
Because our tree was trained on this data and we grew the tree to 100% accuracy, each house is perfectly sorted



Reality check

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

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



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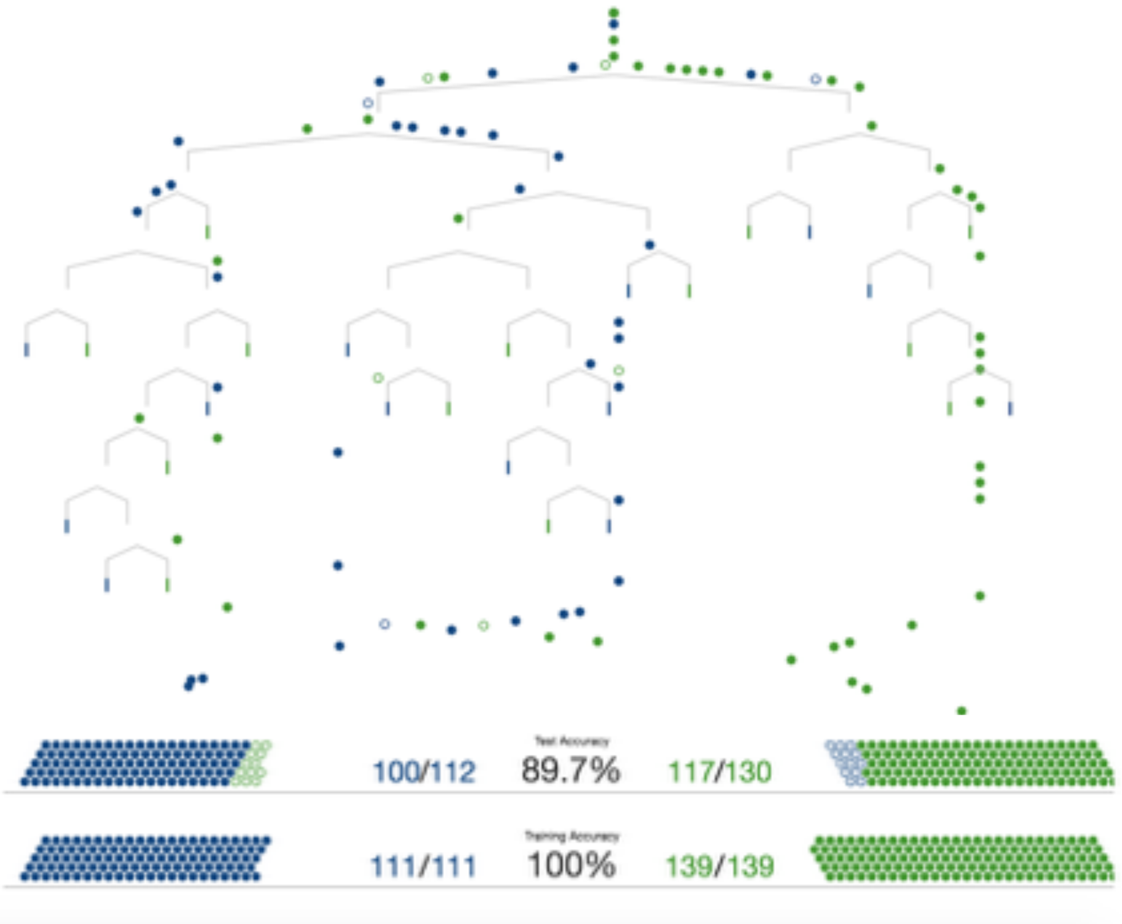

Ideally the tree should perform similarly on both known and unknown data

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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.

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 tree , 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.

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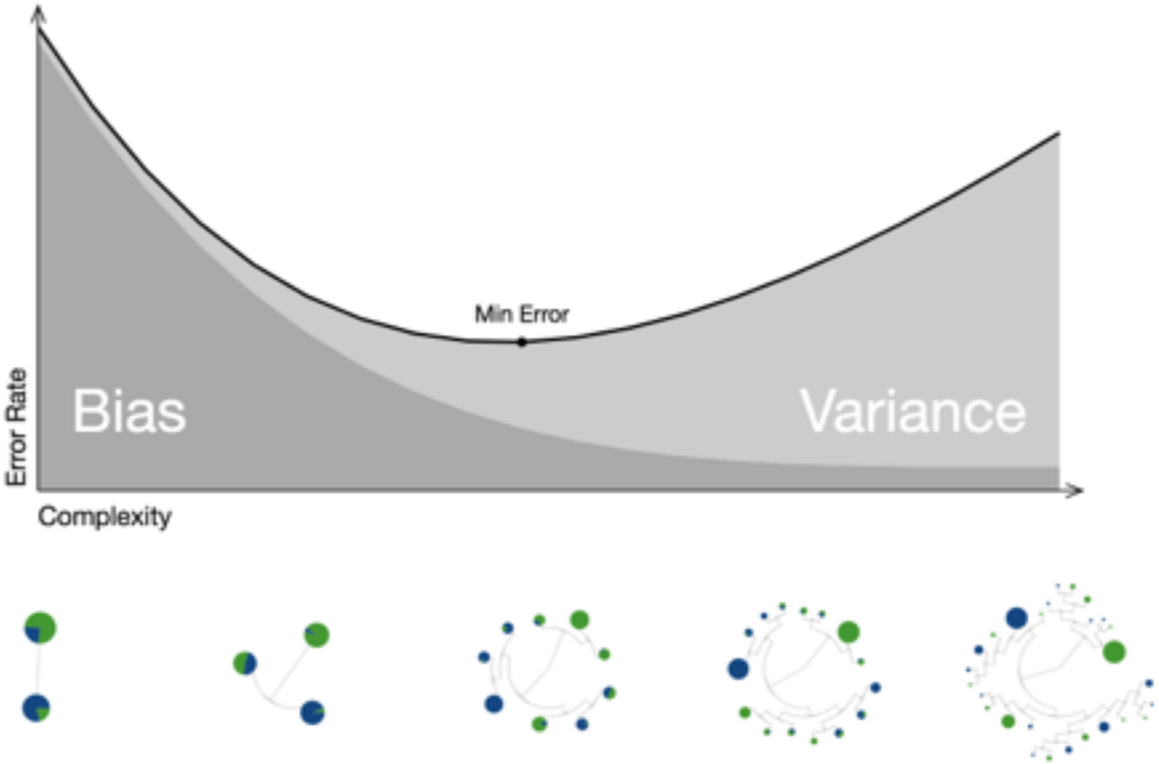
So...what can we do about overfitting?

Bias-variance tradeoff



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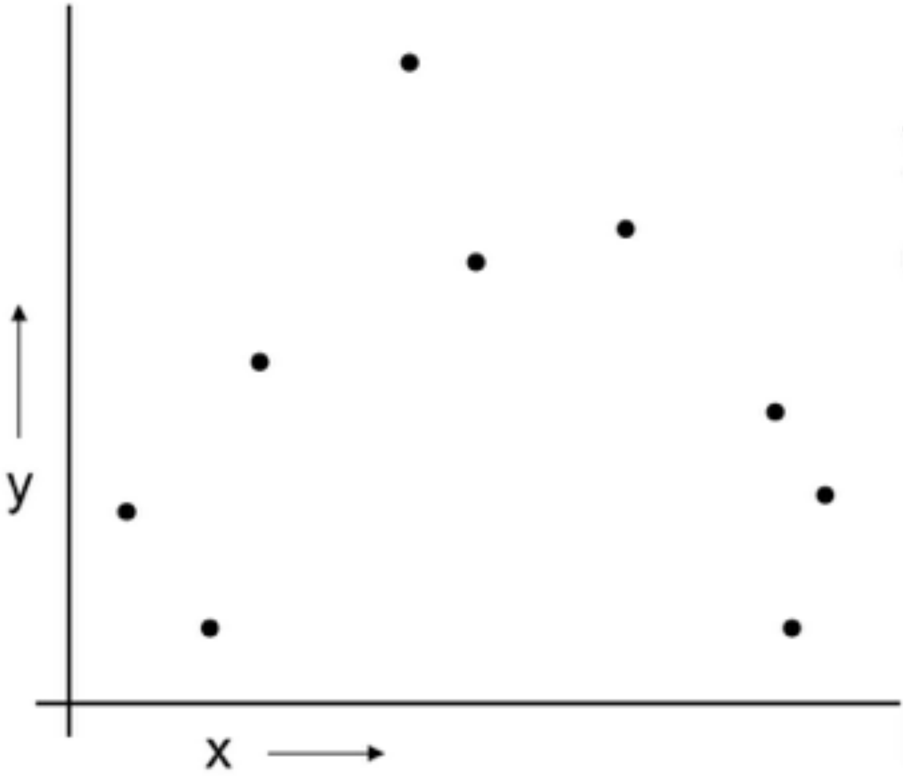
Bias-variance tradeoff

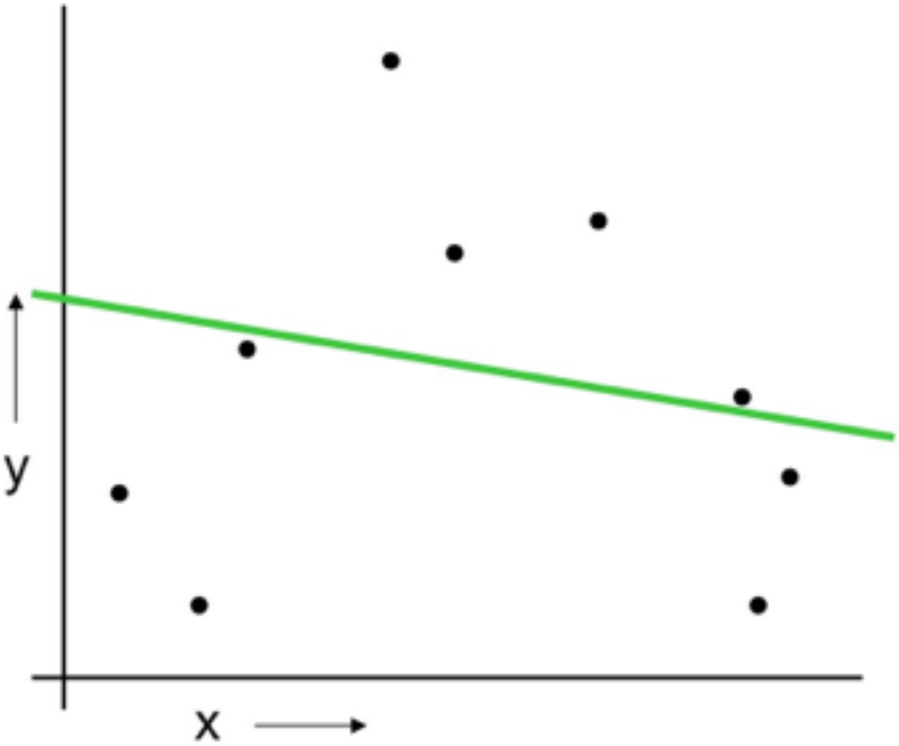
- **High variance** models make mistakes in *inconsistent* ways.
- **Biased models** tend to be overly simple and not reflect reality
- What to do:
    - Consider tuning parameters in the model
        - Can avoid overfitting by setting minimum node size threshold (fewer splits; variance decreased)
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

Can we determine what f(x) is using this data?

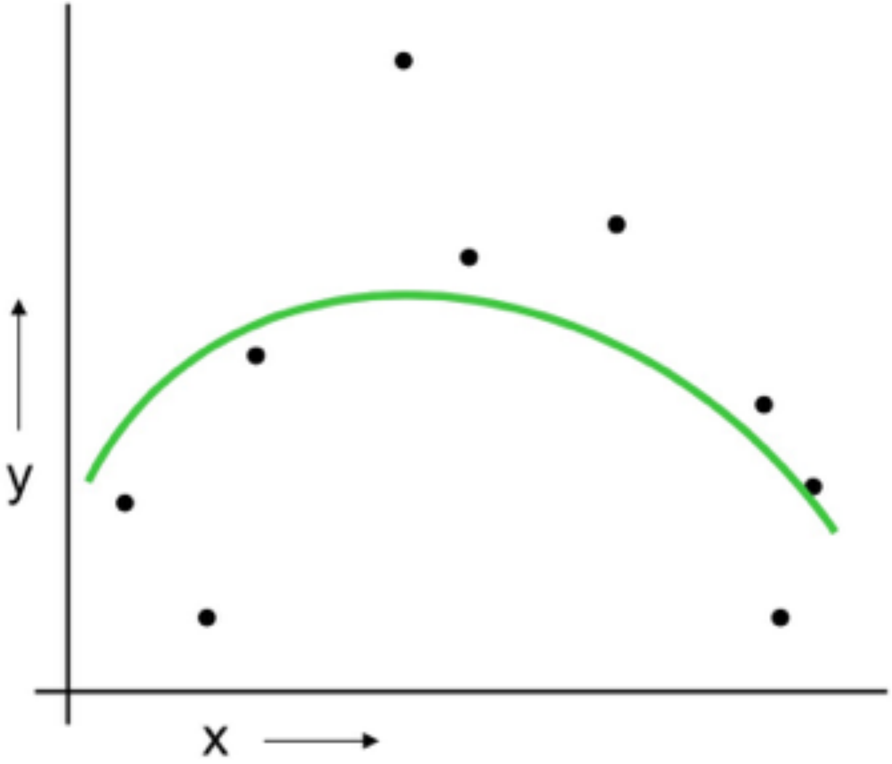


`y = f(x) + noise`

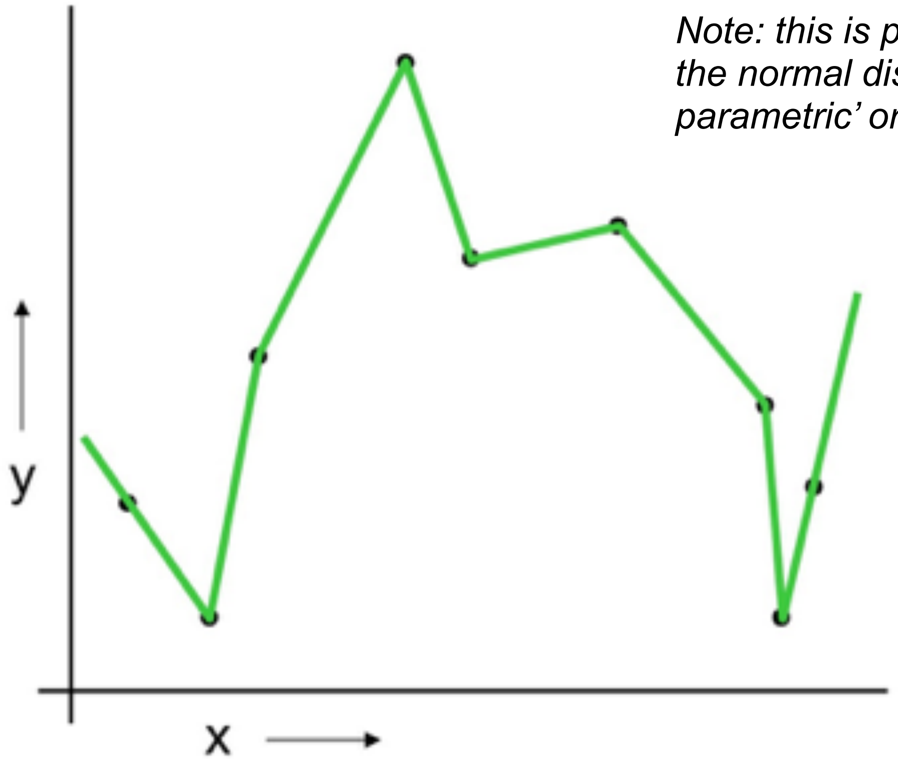
Linear regression



Quadratic regression

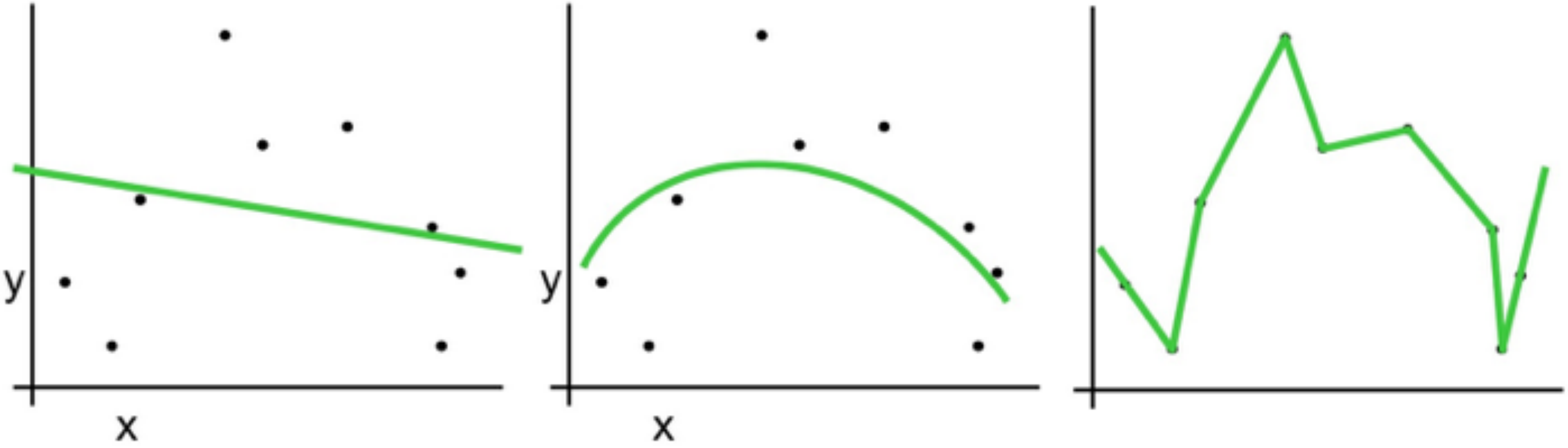


Piecewise linear nonparametric regression (LERP)



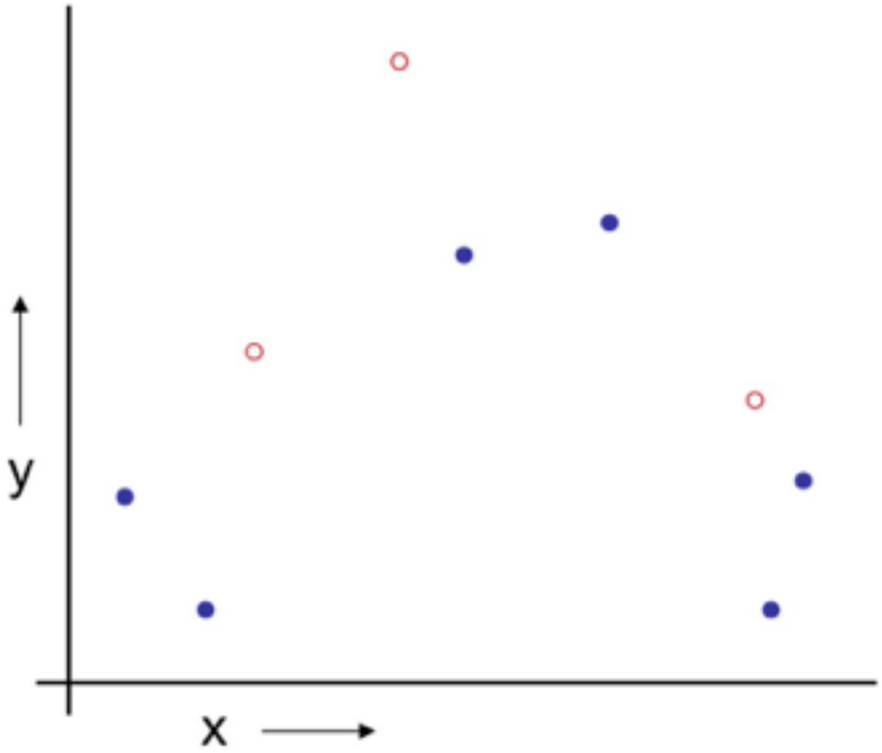
Note: this is parametric, but not based on the normal distribution so 'alternative-parametric' or non-normal parametric

Which to choose?



adapted from Brad Voytek

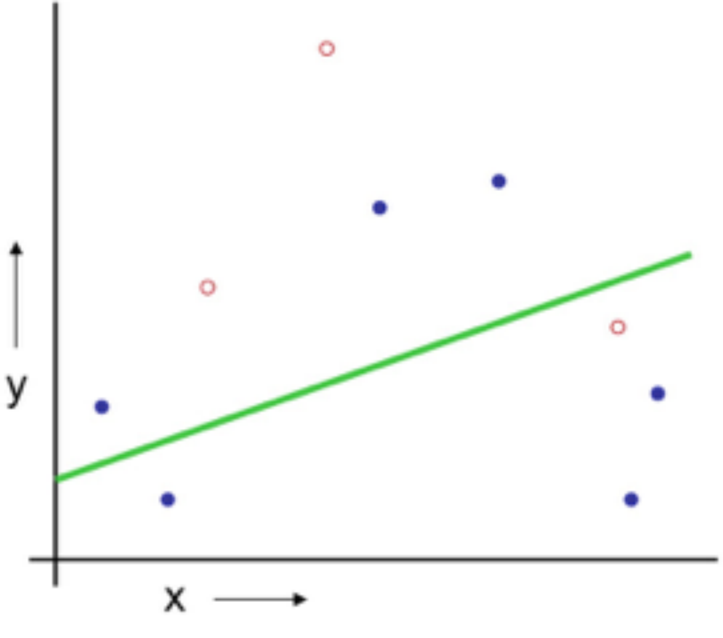
The data partition method



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



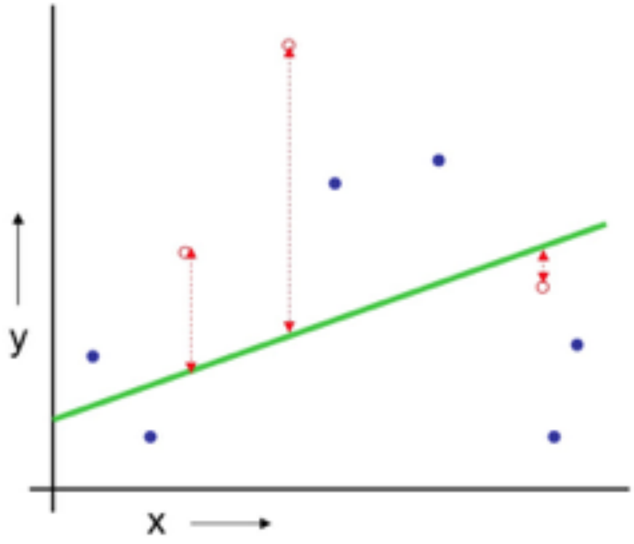
(Linear regression example)

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

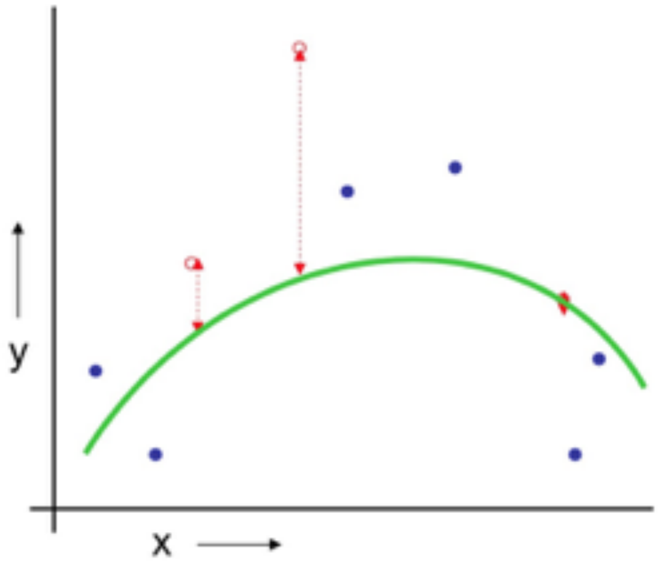
1. Randomly choose 30% of the data to be in a test set

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



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

2. The remainder is a training set

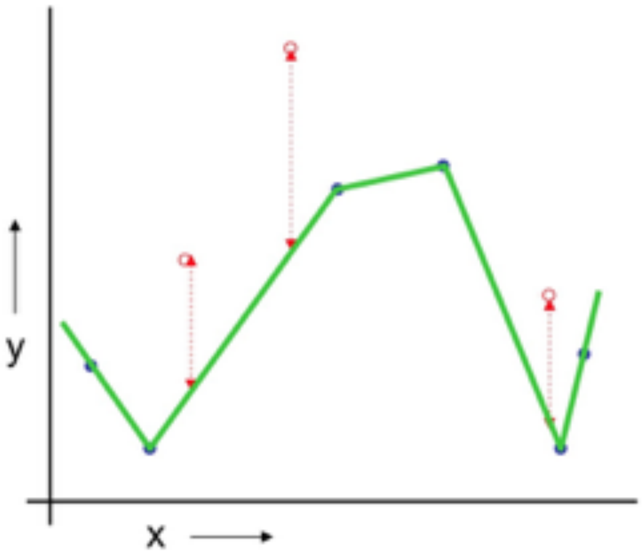
3. Perform your regression on the training set

4. Estimate your future performance with the test set

(Quadratic regression example)

Mean Squared Error = 0.9

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

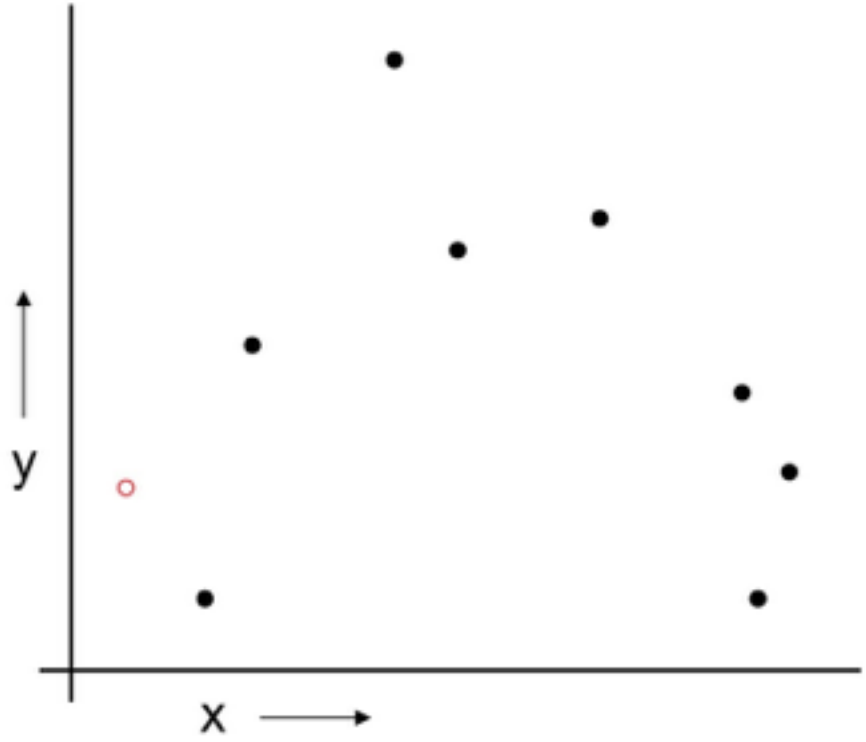
Pros:

- 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

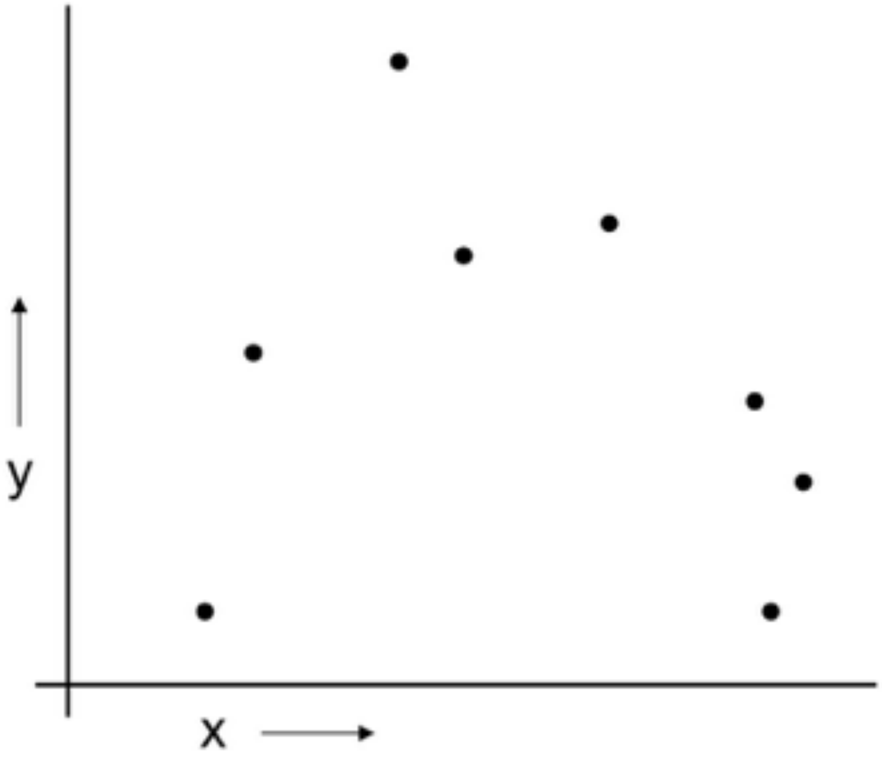
Leave one out cross validation (LOOCV)



For k=1 to R

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

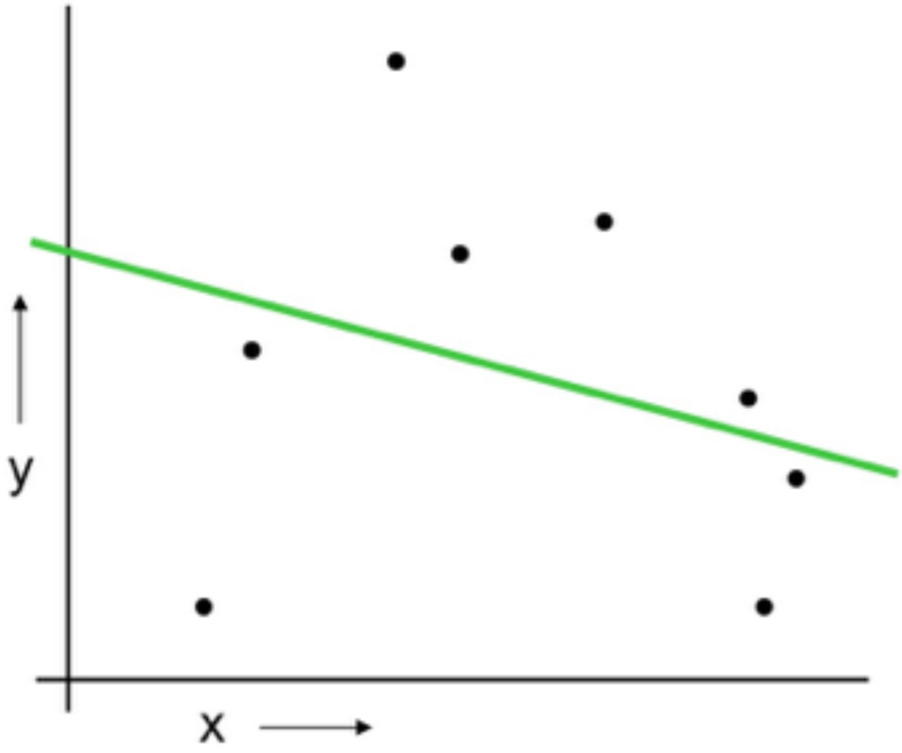
Leave one out cross validation (LOOCV)



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

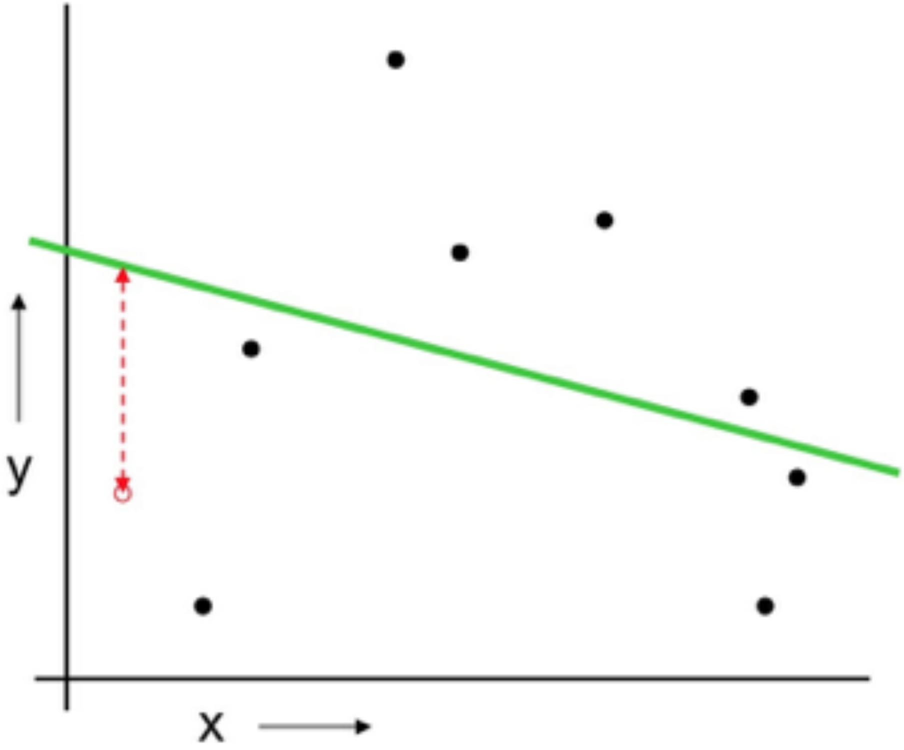
Leave one out cross validation (LOOCV)



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

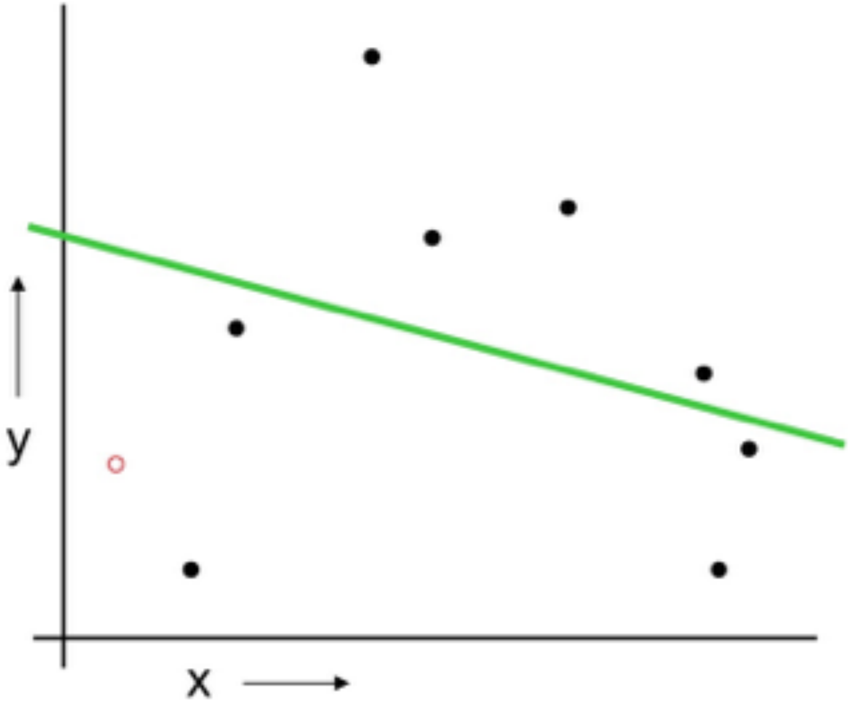
Leave one out cross validation (LOOCV)



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)



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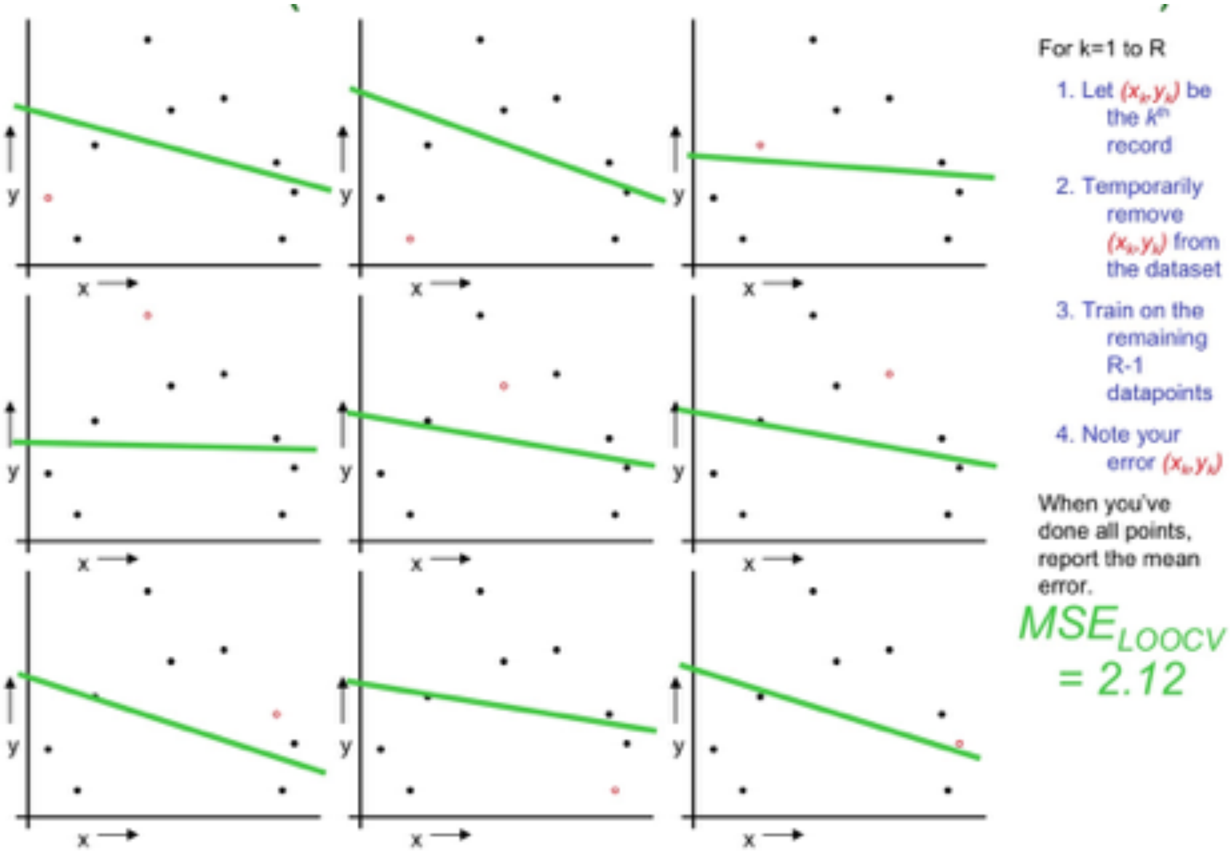
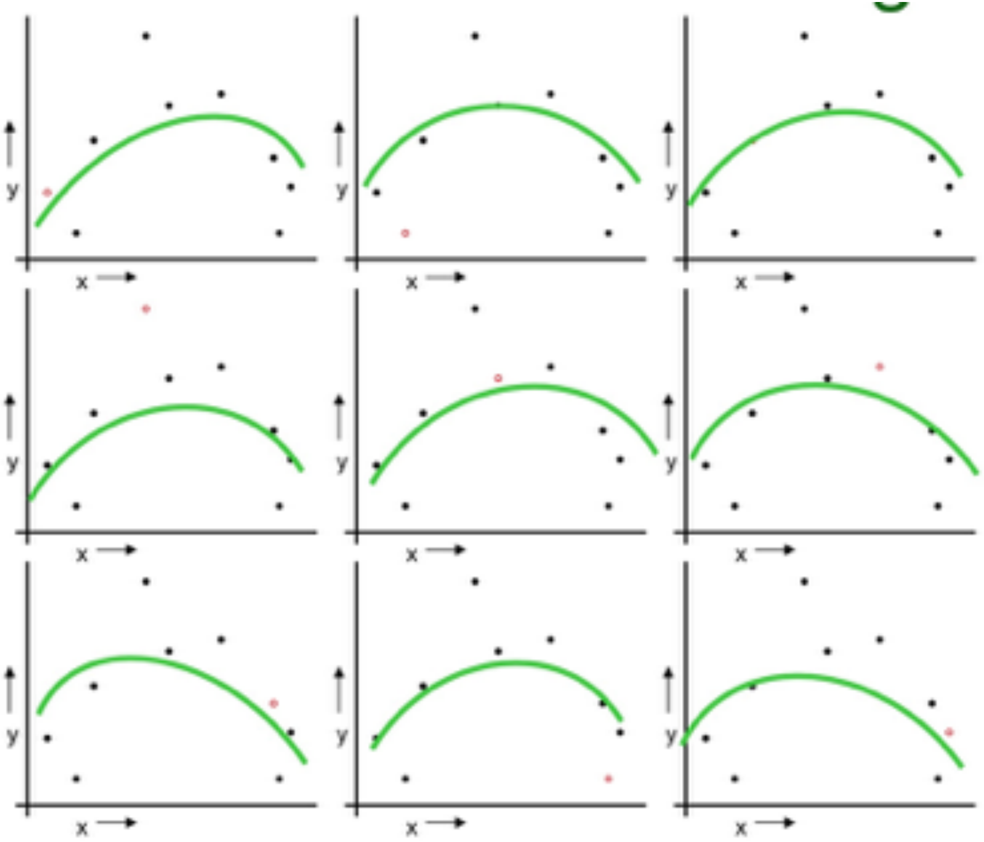
When you've done all points, report the mean error.

Leave one out cross validation (LOOCV)



adapted from Brad Voytek

Leave one out cross validation (LOOCV)



For k=1 to R

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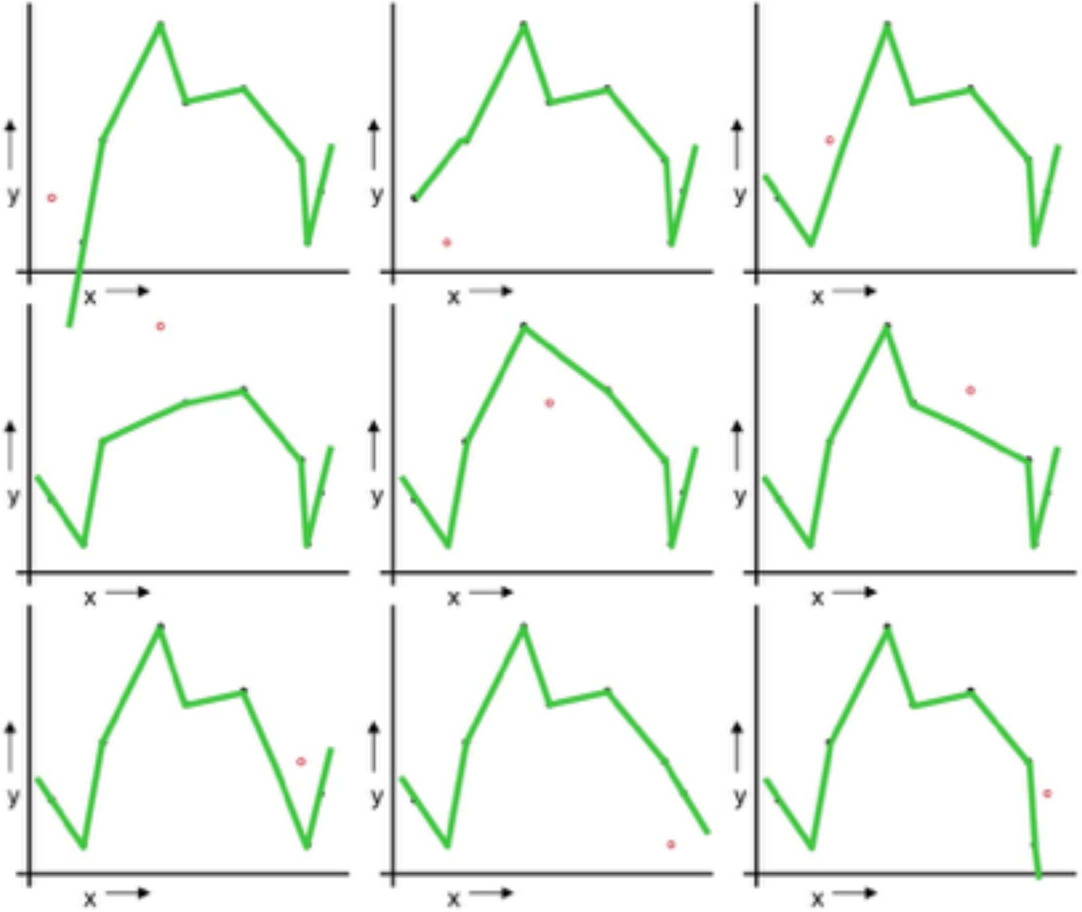
3. Train on the remaining R-1 datapoints
4. Note your error (x_k, y_k)

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.

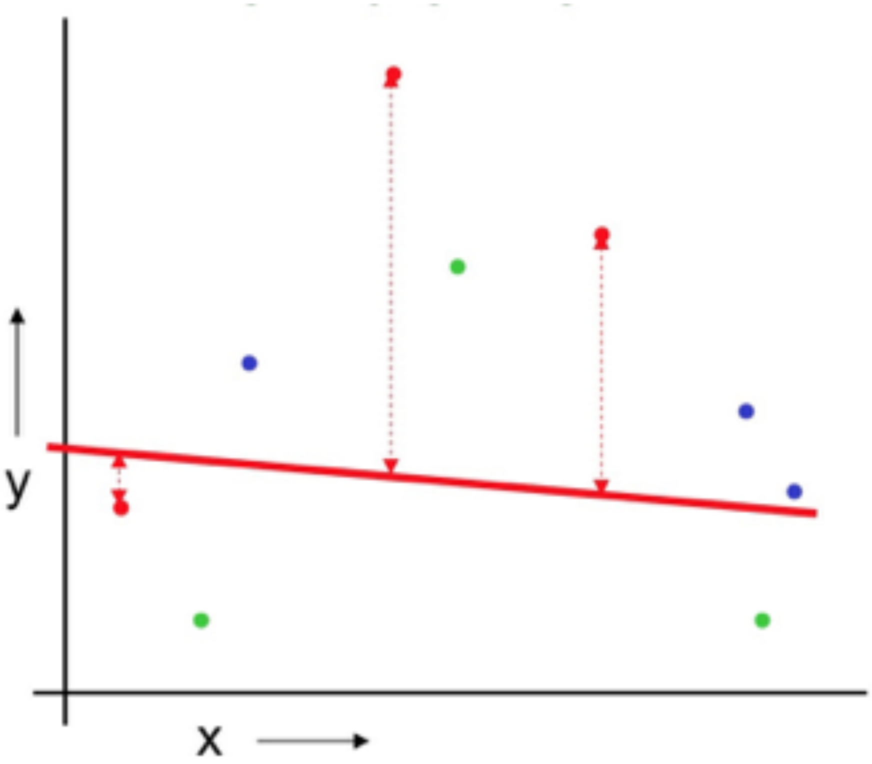
MSE_{LOOCV} =3.33

adapted from Brad Voytek

Method Comparison

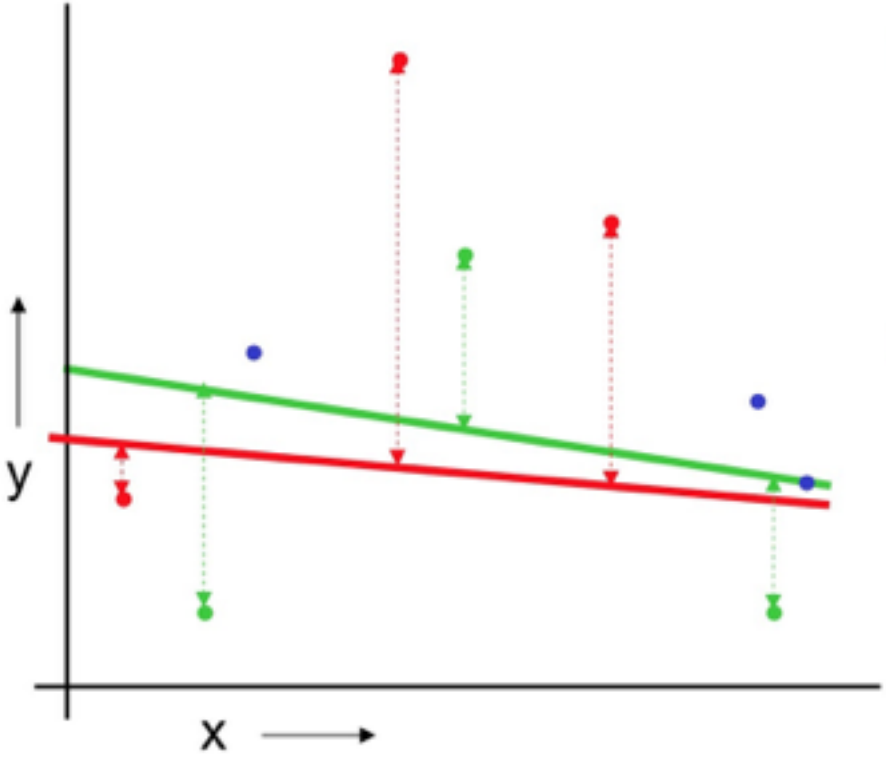
	Cons	Pros
Data partitioning	Variance: unreliable estimate of future performance	Cheap
LOOCV	Computationally expensive; has weird behavior	Uses all your data

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.

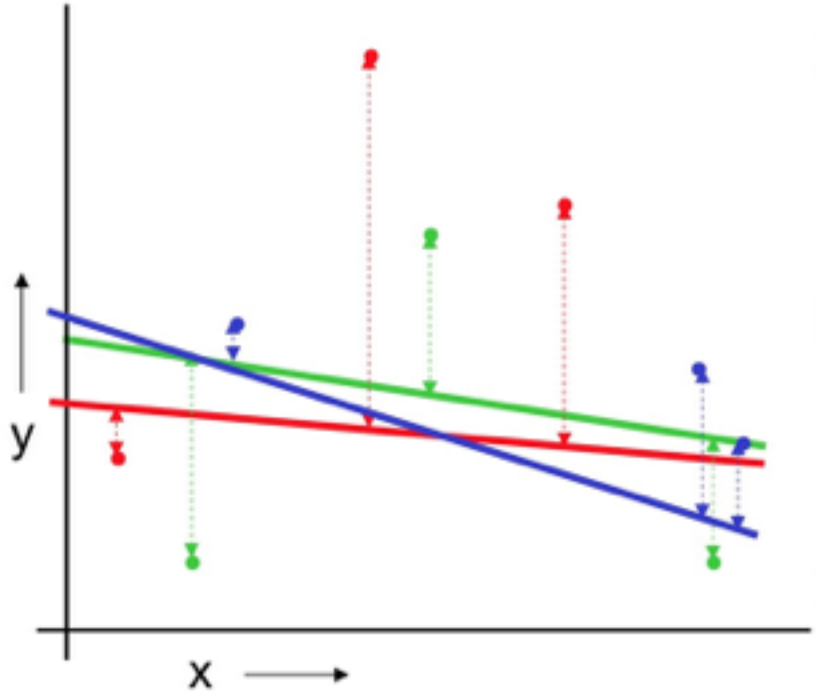
k-fold cross validation



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

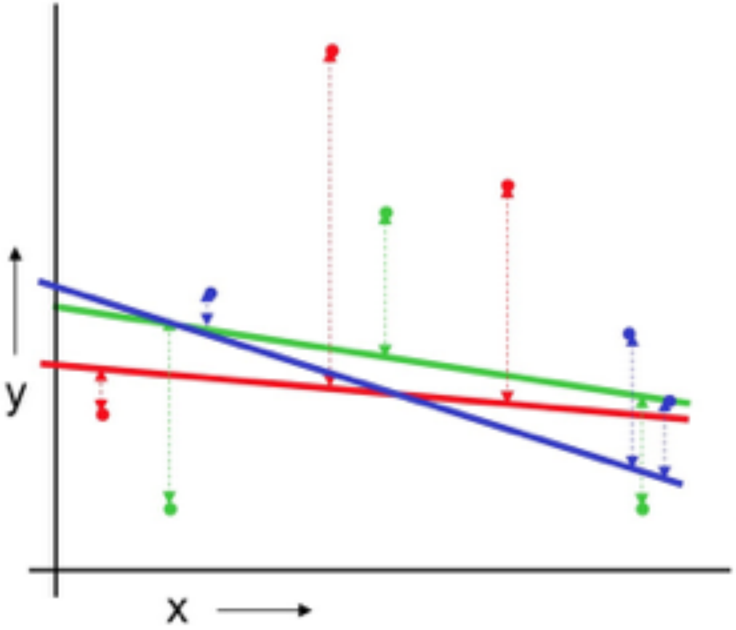


For the red partition: Train on all the points not in the red partition. Find the test-set sum of errors on the red points.

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

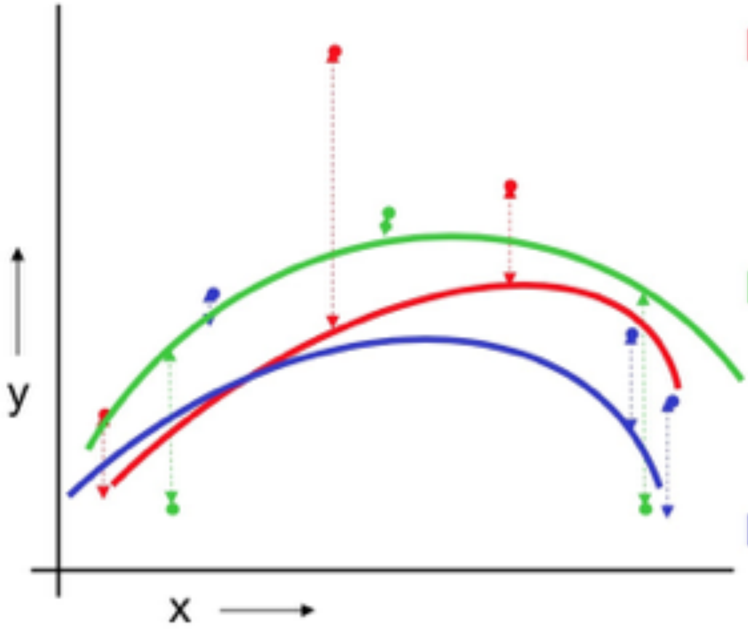
For the red partition: Train on all the points not in the red partition. Find the test-set sum of errors on the red points.

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.

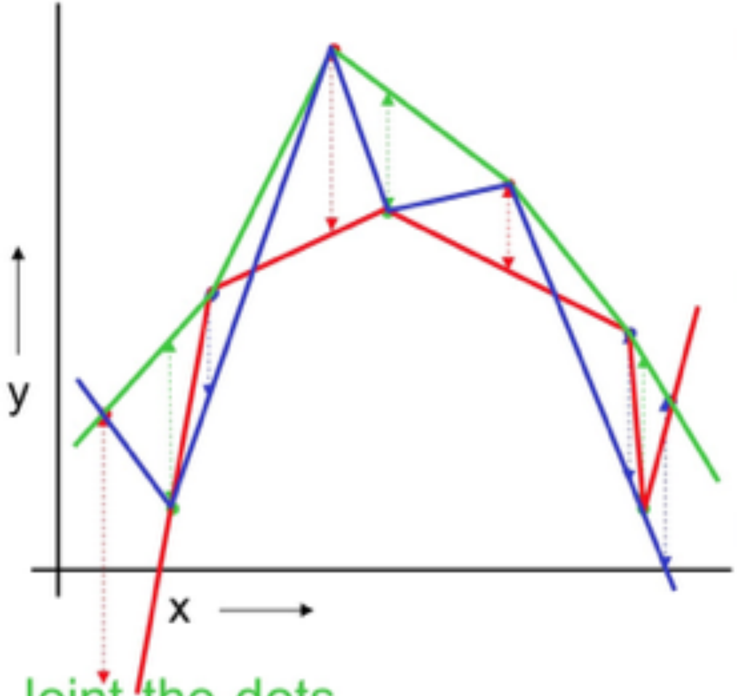
For the green partition: Train on all the points not in the green partition. Find the test-set sum of errors on the green points.

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

adapted from Brad Voytek

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?

A
linear regression

B
quadratic regression

C
pairwise linear nonparametric regression

Linear Regression
$MSE_{3FOLD}=2.05$

Quadratic Regression
$MSE_{3FOLD}=1.11$

Joint-the-dots
$MSE_{3FOLD}=2.93$

Validator

Which approach would *you* use to limit overfitting?

A
data
partitioning

B
LOOCV

C
k-fold CV

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

Predictive Analysis Ethics

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

{* ARTIFICIAL INTELLIGENCE *}

MIT apologizes, permanently pulls offline huge dataset that taught AI systems to use racist, misogynistic slurs

Top uni takes action after *El Reg* highlights concerns by academics

Katyanna Quach Wed 1 Jul 2020 // 10:55 UTC SHARE

https://www.theregister.com/2020/07/01/mit_dataset_removed/

https://github.com/oarriaga/face_classification

Chukwuemeka Afigbo
@nke_ise

Follow

If you have ever had a problem grasping the importance of diversity in tech and its impact on society, watch this video

5:48 AM - 16 Aug 2017

155,234 Retweets 215,762 Likes

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

Janice Wyatt-Ross, Ed.D
@JaniceWyattRoss

Daughter 1 was taking an exam today being proctored by some type of software that apparently was not tested on dark skin. She had to open her window, turn on the lights, and then shine a flashlight over her head to be detectable. 😡😡😡

6:01 PM · Feb 22, 2021 · Twitter for iPhone

7,030 Retweets **939** Quote Tweets **34.6K** Likes

https://twitter.com/JaniceWyattRoss/status/1364032597484056577

What to do about bias...

1. Anticipate and plan for potential biases before model generation. Check for bias after.
2. Have diverse teams.
3. Test test test! Test all possible situations and scenarios
4. Use machine learning to improve lives rather than for punitive purposes.
5. Revisit your models. Update your algorithms. Take feedback to improve the tech
    1. e.g. IR emitter-detector issues
6. 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?

A
Grade in COGS108

B
COGS108 Attendance

C
Marvel or DC?

D
Hair Color

E
Not Sure or Something Else

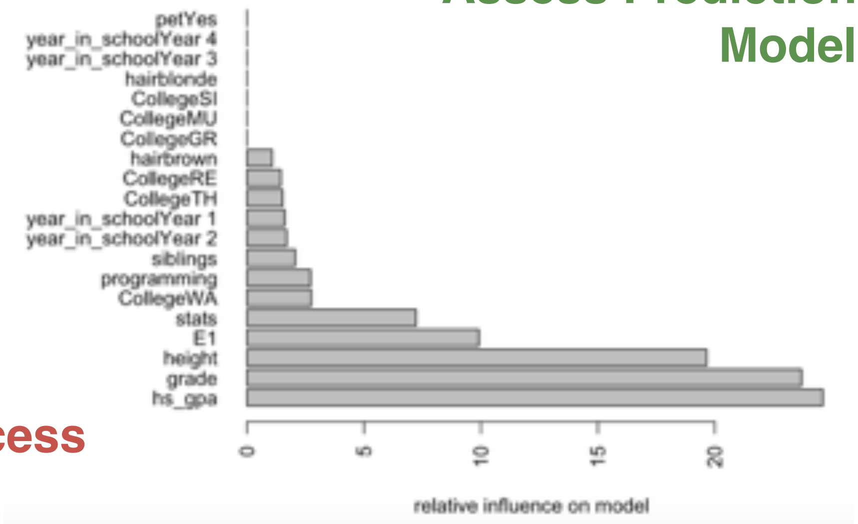
N = 254

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

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

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

Assess Prediction Model



train the model

predicted success in test set

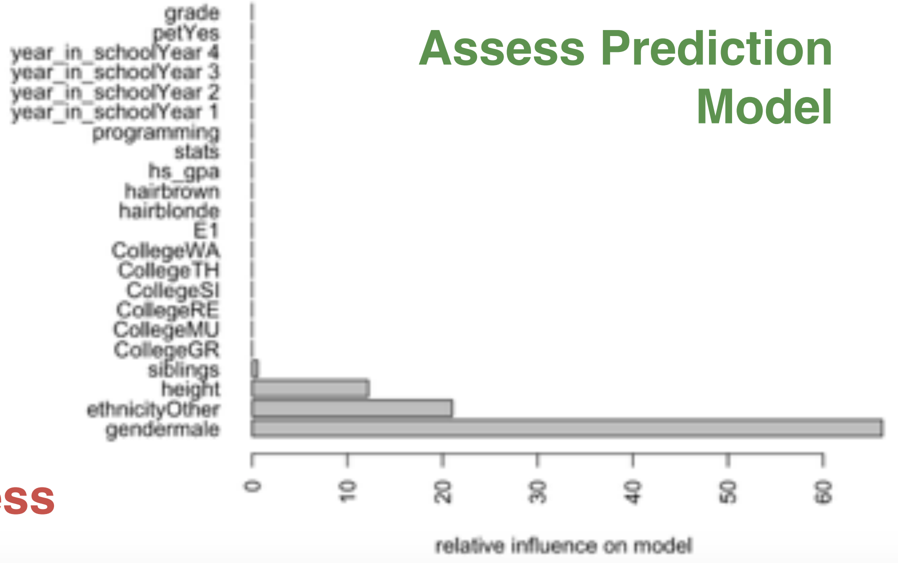
N = 254

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

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

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

Assess Prediction Model



train the model

predicted success in test set

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?

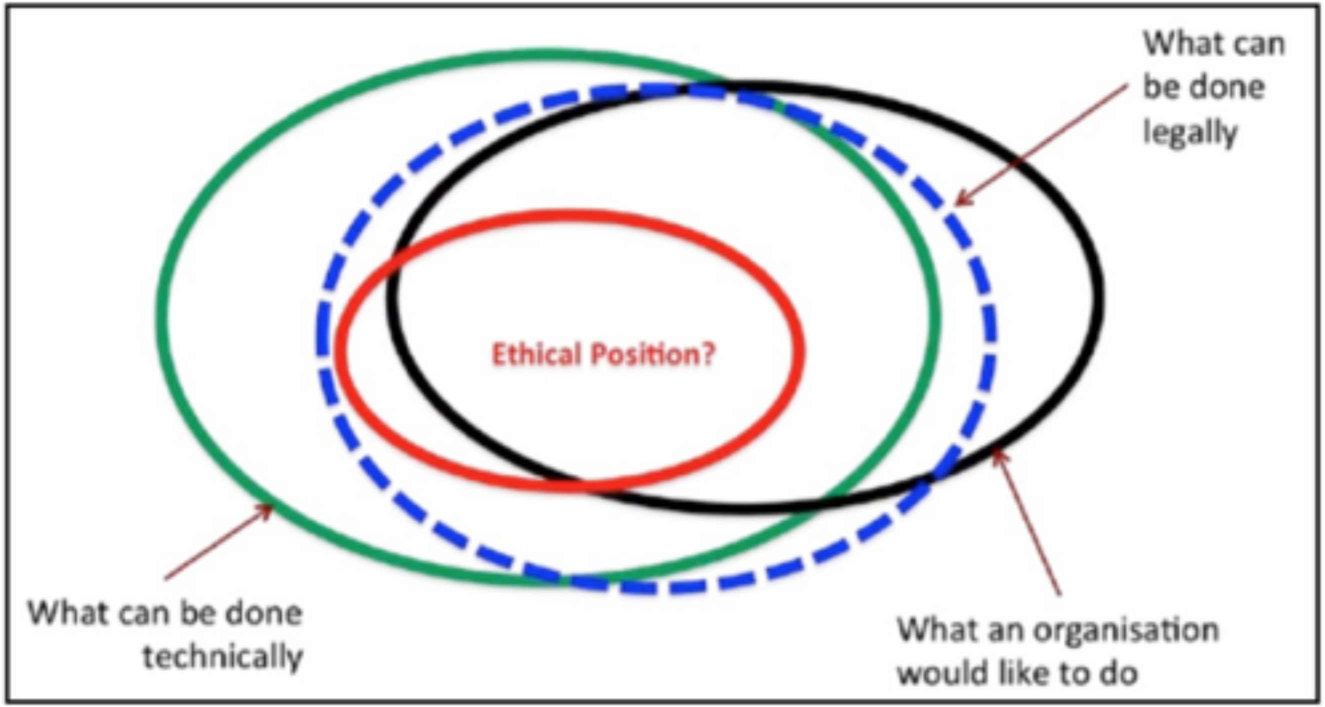
Or who UCSD allows to be data science majors?

What to do about bias...

1. Anticipate and plan for potential biases before model generation. Check for bias after.
2. Have diverse teams.
3. Test test test! Test all possible situations and scenarios
4. Use machine learning to improve lives rather than for punitive purposes.
5. Revisit your models. Update your algorithms. Take feedback to improve the tech
    1. e.g. IR emitter-detector issues
6. 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



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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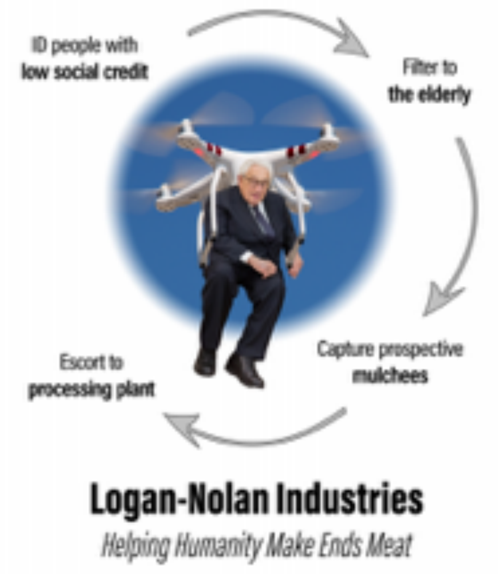

Figure 1: A publicity image for the project, produced by Logan-Nolan Industries

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

Prediction Thoughts

We should start using this algorithm to mulch up the elderly

A
Strongly Agree

B
Somewhat Agree

C
Neutral

D
Somewhat Disagree

E
Strongly Disagree

A Mulching Proposal

FAIR - equally considers all elderly individuals

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

TRANSPARENT - website with all features; testable

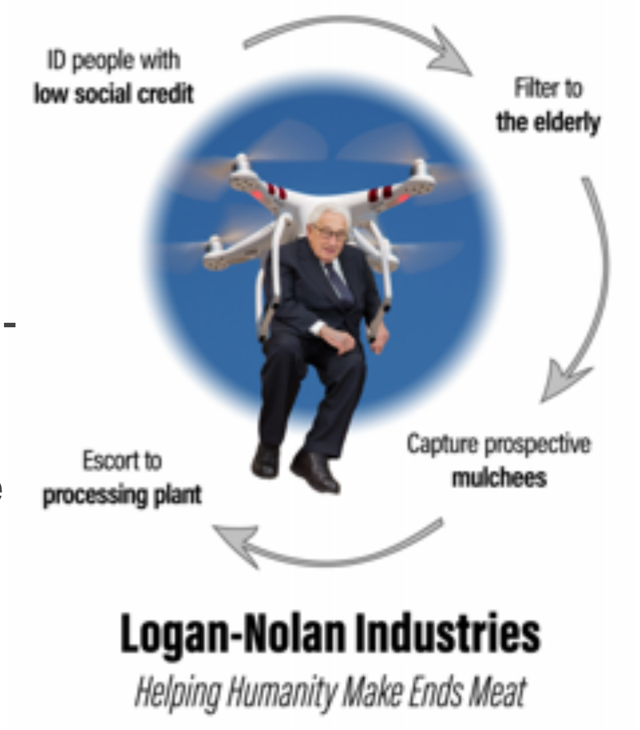

Figure 1: A publicity image for the project, produced by Logan-Nolan Industries

- Checklists are helpful, but they’re not and excuse for thoughtlessness.
- Ultimately you have to keep in mind that science and engineering are about ***increasing human knowledge and improving the human condition***
- Beware of de-humanizing people with technology
- Consider the big picture, take a step back periodically