

# Course Announcements

Due Sunday (11:59 PM):

- D7
- Q8
- Weekly Project Survey (*optional*)

Notes:

- A4 will be posted tomorrow
- I will catch up on Piazza/email today and tomorrow

# Feb Fridays: Valerie Thomas (1943-)

Data Scientist (Mathematician & Data Analyst)

- Developed the digital media formats for image processing systems used by NASA
- Led teams of up to 50 people at NASA
- Invented the illusion transmitter (holds patent)
- Has mentored students from elementary through university; judged science fairs for decades
- Recipient of the Goddard Space Flight Center Award of Merit and the NASA Equal Opportunity Medal

Also see: Mary Jackson, Katherine Johnson and Dorothy Vaughan (computers behind NASA's early space missions; depicted in Hidden Figures)



# Machine Learning I



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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 make a prediction on future data

Classic Statistics  
(parametric & nonparametric)

Text Analysis

Are they trying to predict measurement(s) for individuals?

**Causal**

**STOP!**  
Not a data analysis

**No** Are the data a corpus of text?

**No** Are the observations spatially related?

**Inferential**

**Predictive**

Supervised Machine Learning

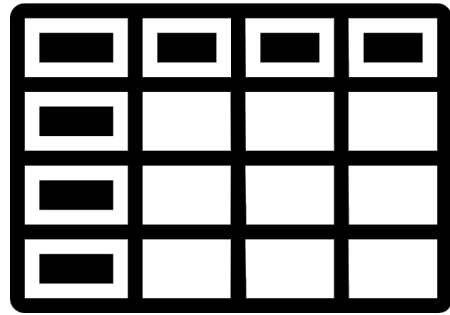
Unsupervised Machine Learning

Did the computer decide the features of your model?

Geospatial Statistics

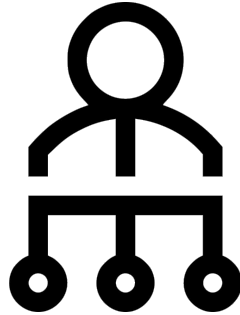
**predictive analysis** uses data  
you have now to make  
predictions in the future

**machine learning** approaches  
are used for predictive analysis!



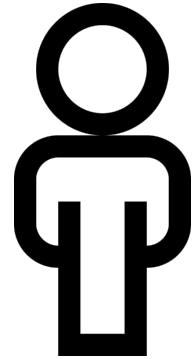
data

train →



model

→ predict



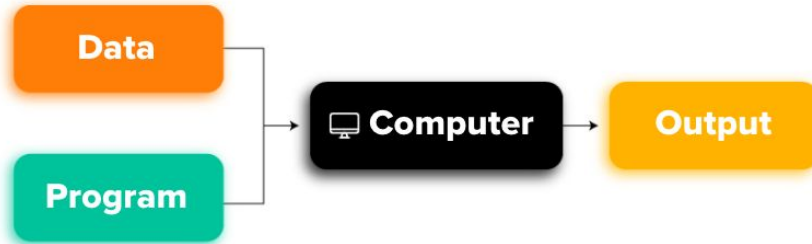
# What is machine learning?

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

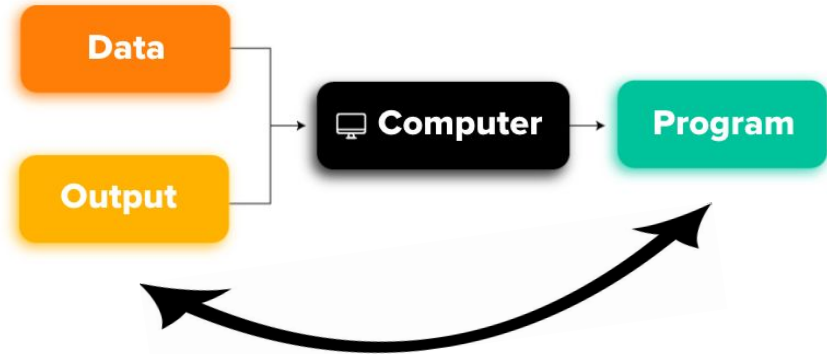
- Andrew Ng, Stanford, ex-Google, chief scientist at Baidu, Coursera founder, Stanford Adjunct Faculty

# A Shift in Programming Paradigm

## TRADITIONAL PROGRAMMING



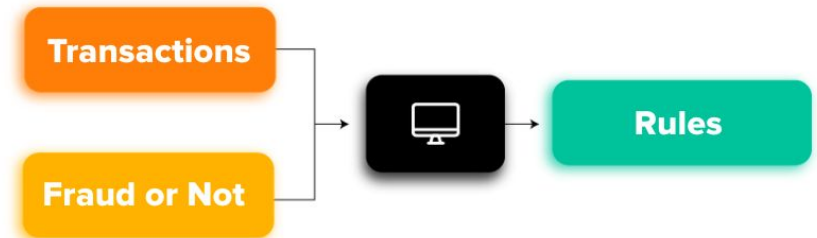
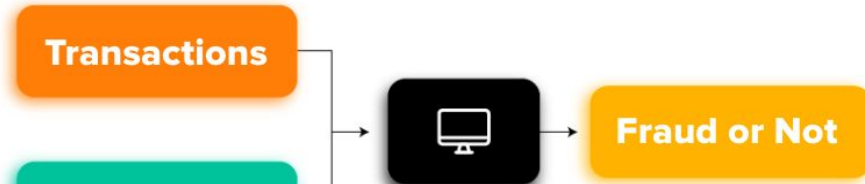
## MACHINE LEARNING



- **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







- Rule1. Claim time - Submit time < 1 h
- Rule2. Agreement review time > 5 m
- Rule3. ...

# 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

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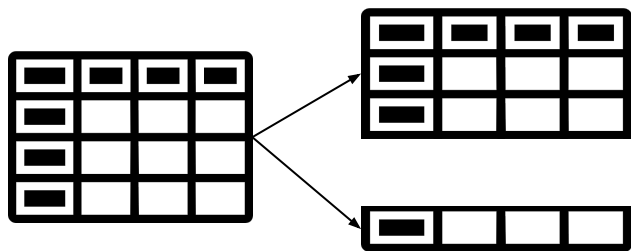
*All models are wrong  
but some are useful*



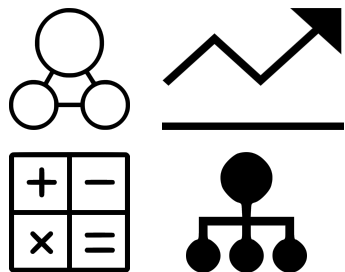
George E.P. Box

**The goal of all models is to simplify, not replicate**

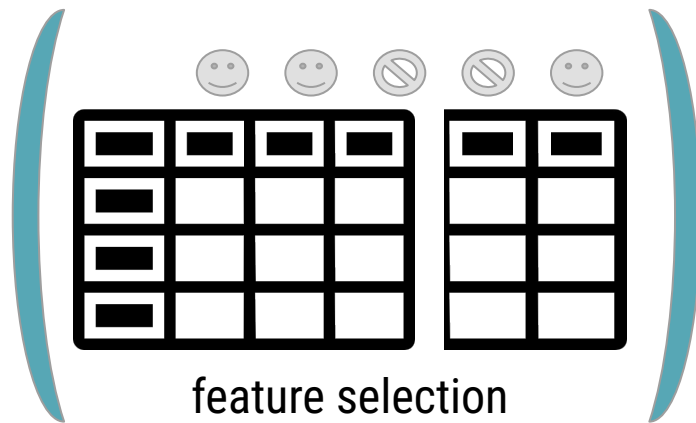
# Basic Steps to Prediction



data  
partitioning



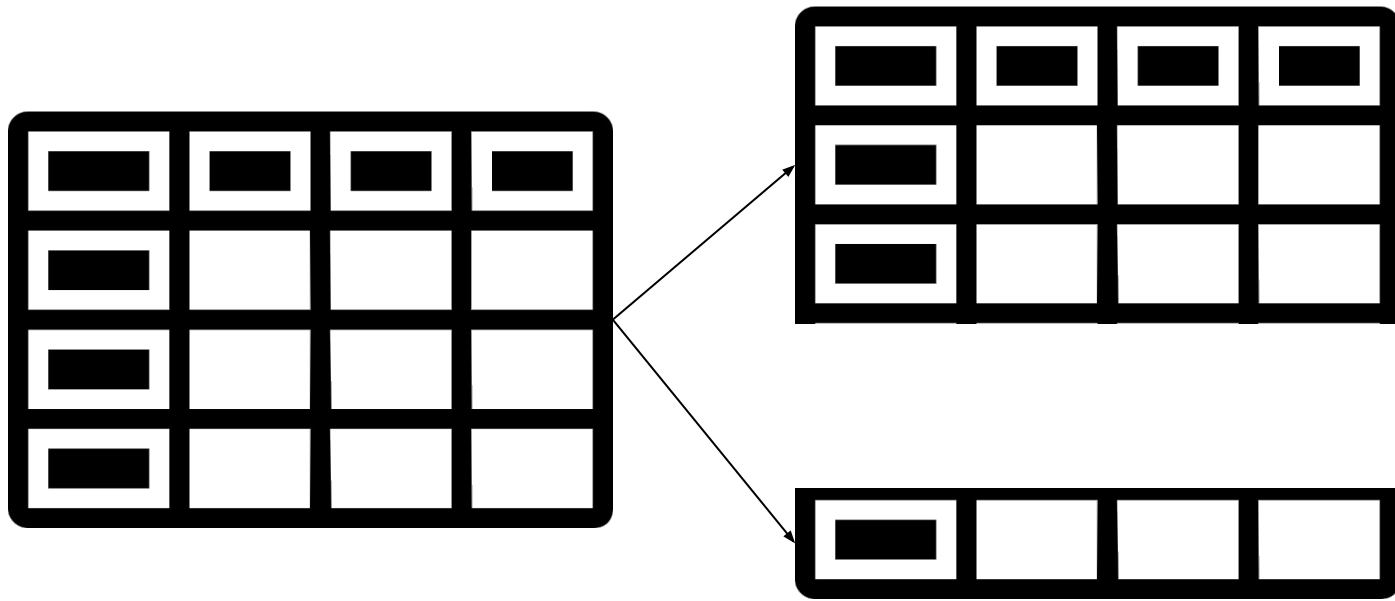
model selection



feature selection



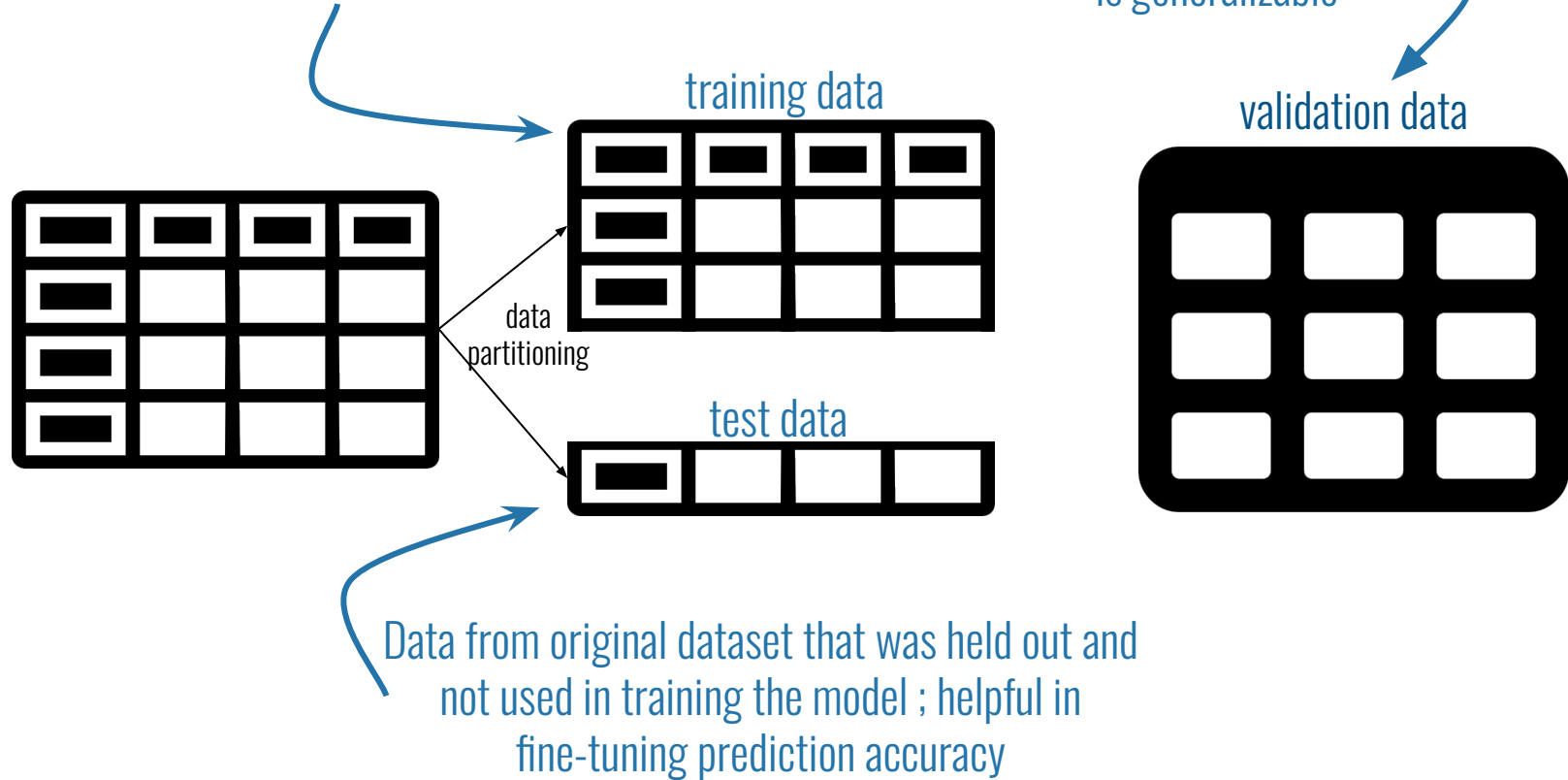
model assessment



data partitioning

the data used to build  
your predictive model

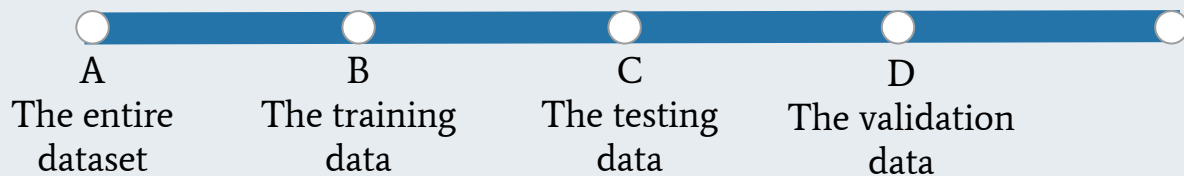
new and independent data set  
used to assess if prediction model  
is generalizable



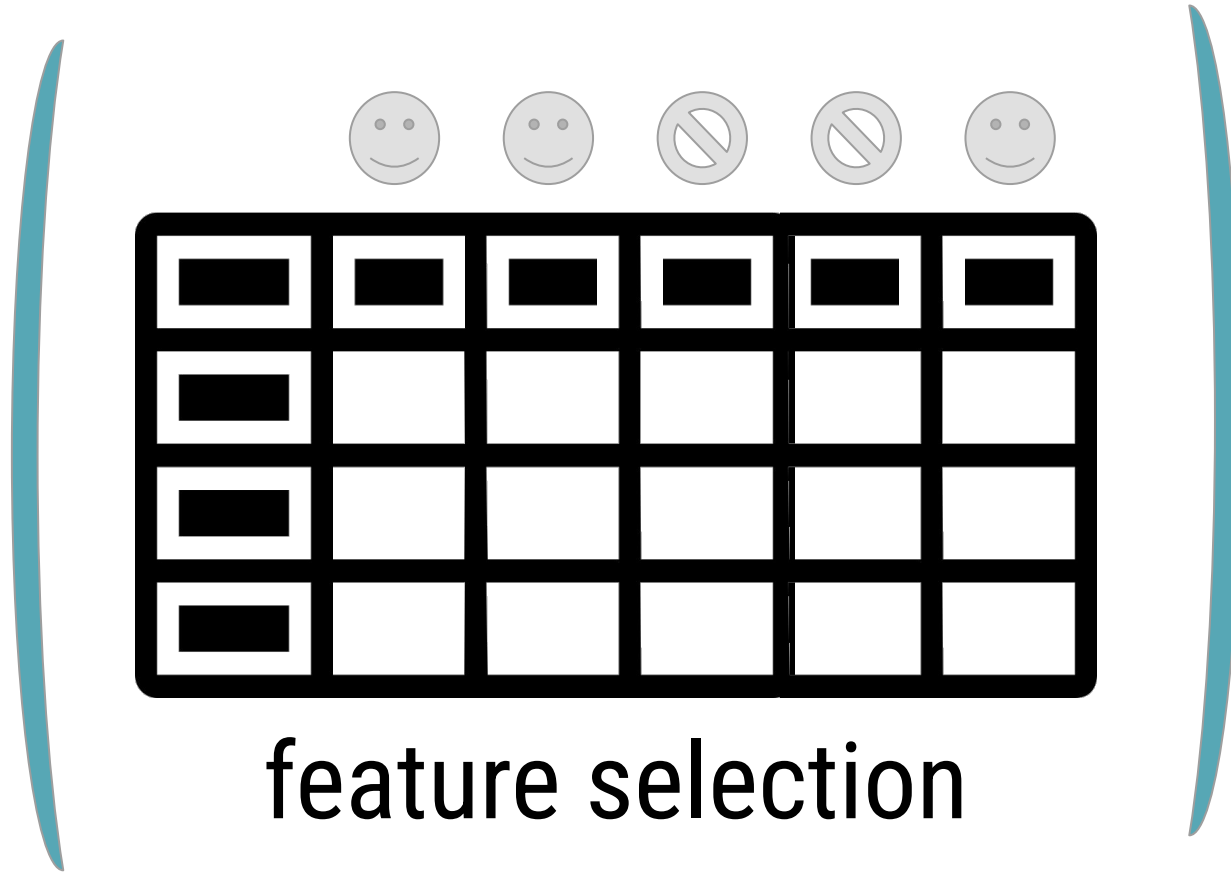
# Data Partitioning



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

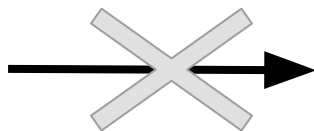
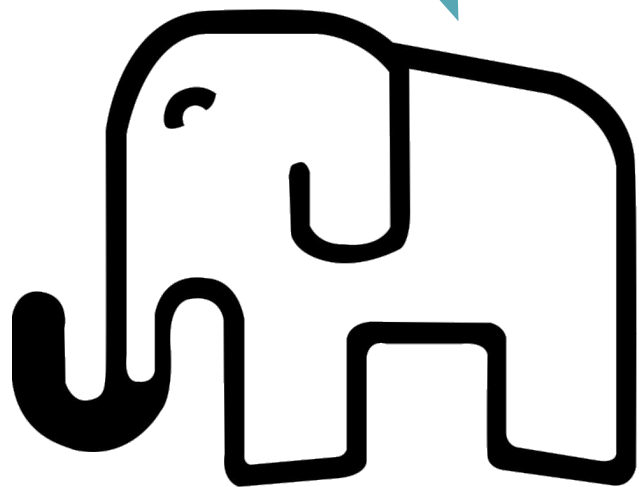


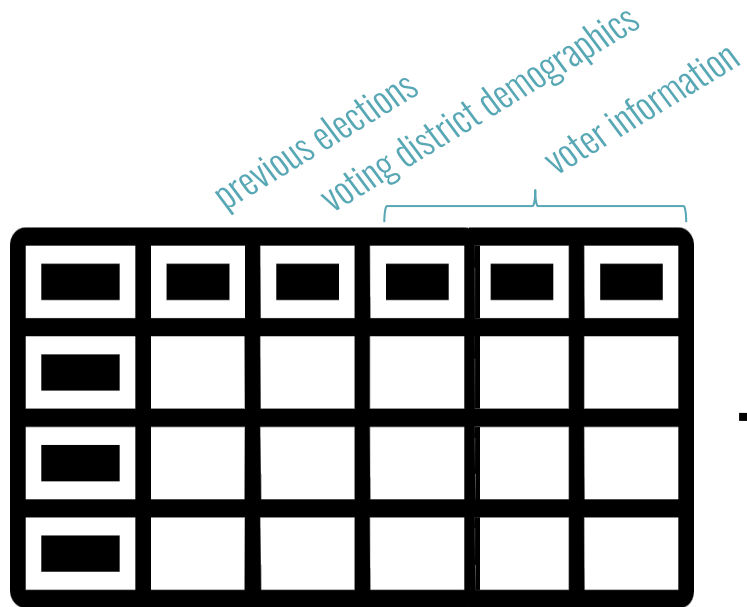




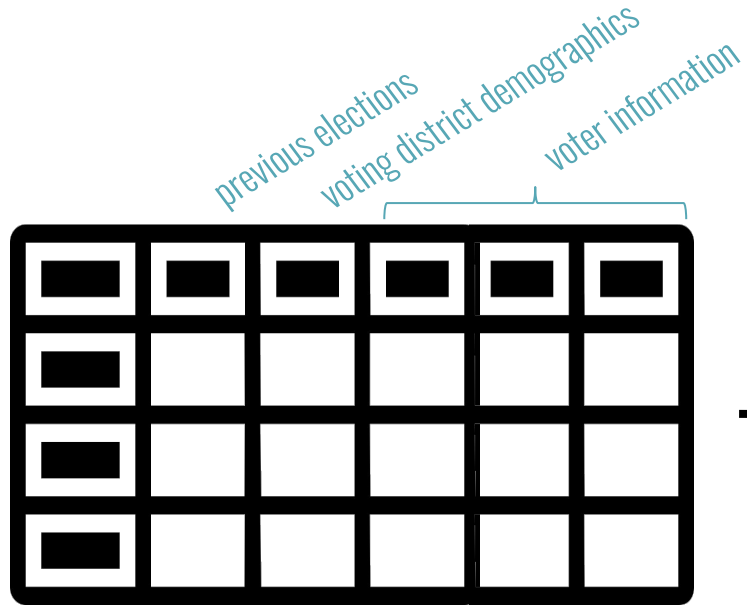
feature selection

elephant height data are likely  
not predictive of US elections

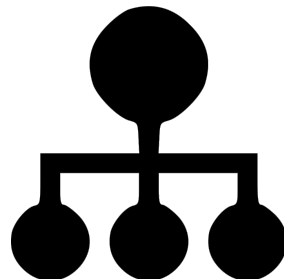
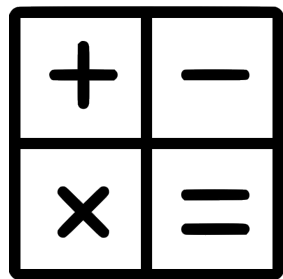
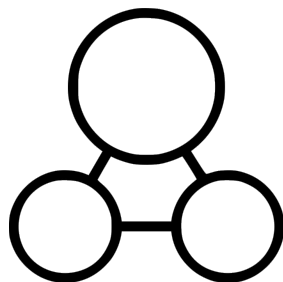




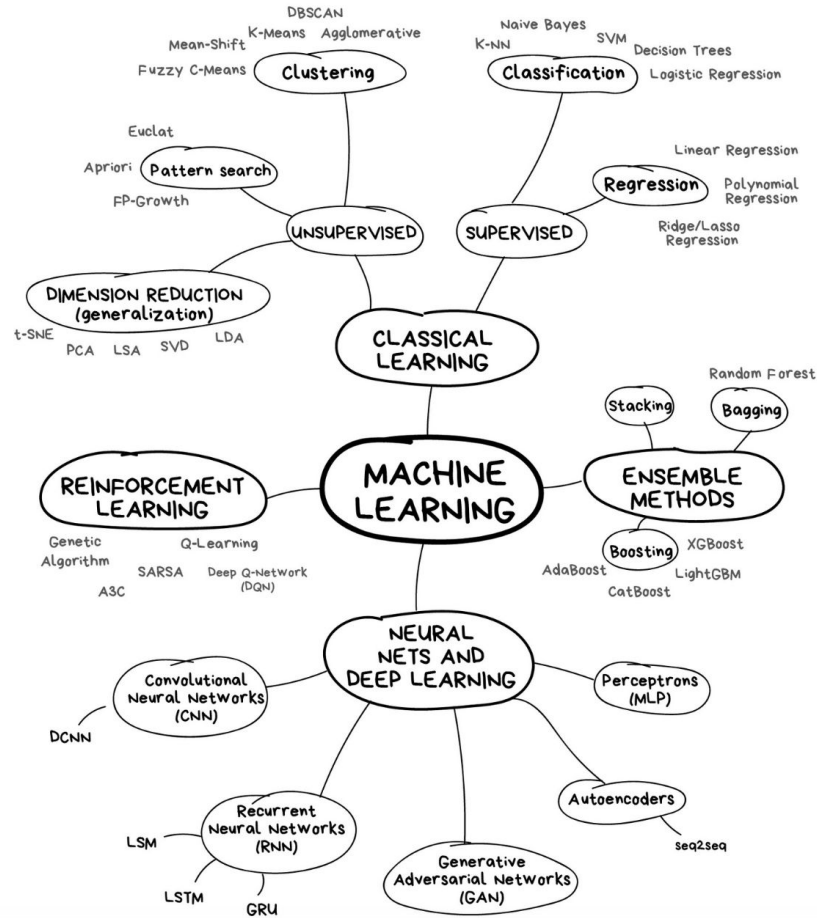
these data are likely predictive  
of US election outcomes



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



model selection

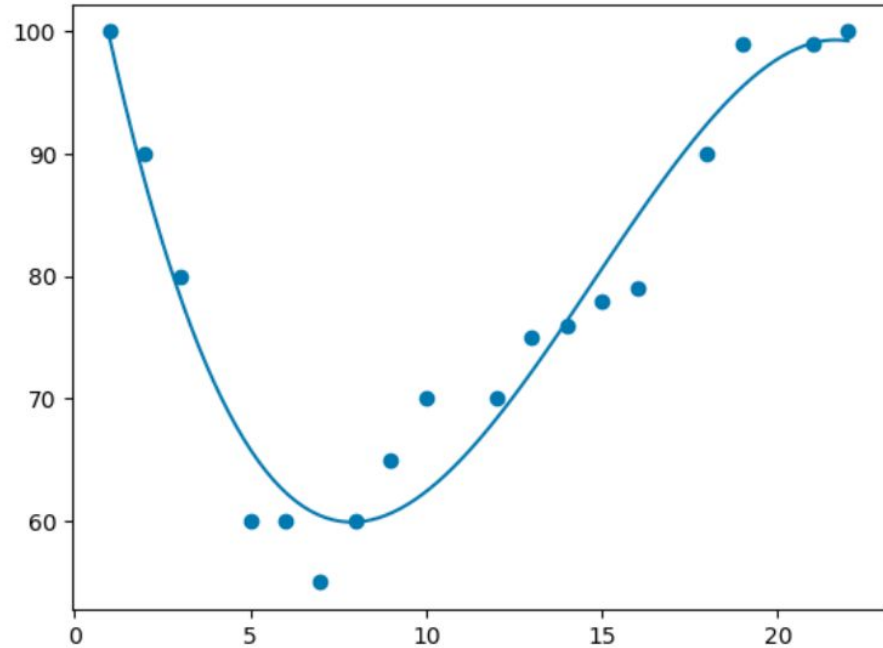


# Selecting the Right Model

**A** - Thought about it and have a thought

**B** - Thought about it and have no thought

**C** - I'm confused

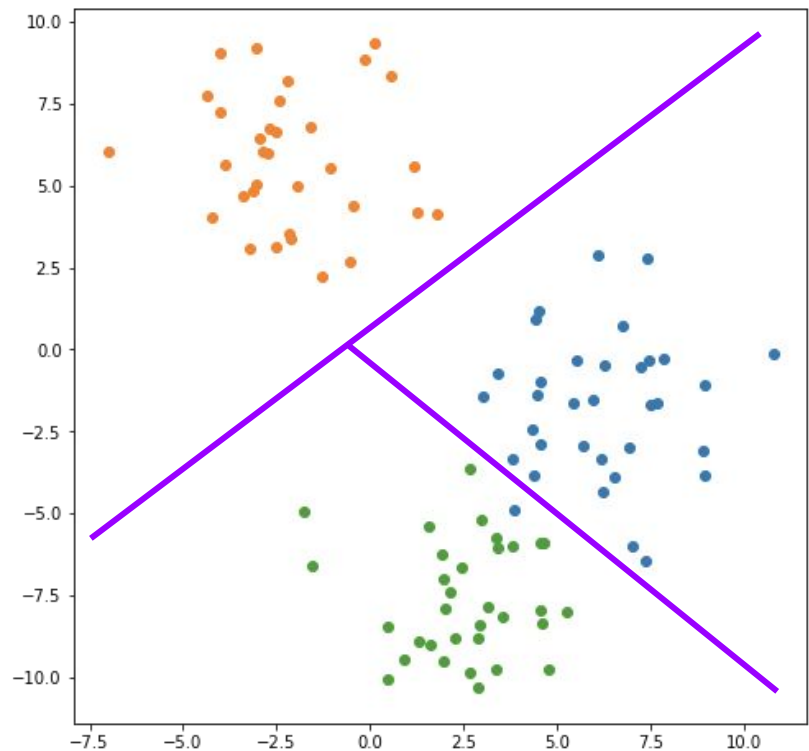


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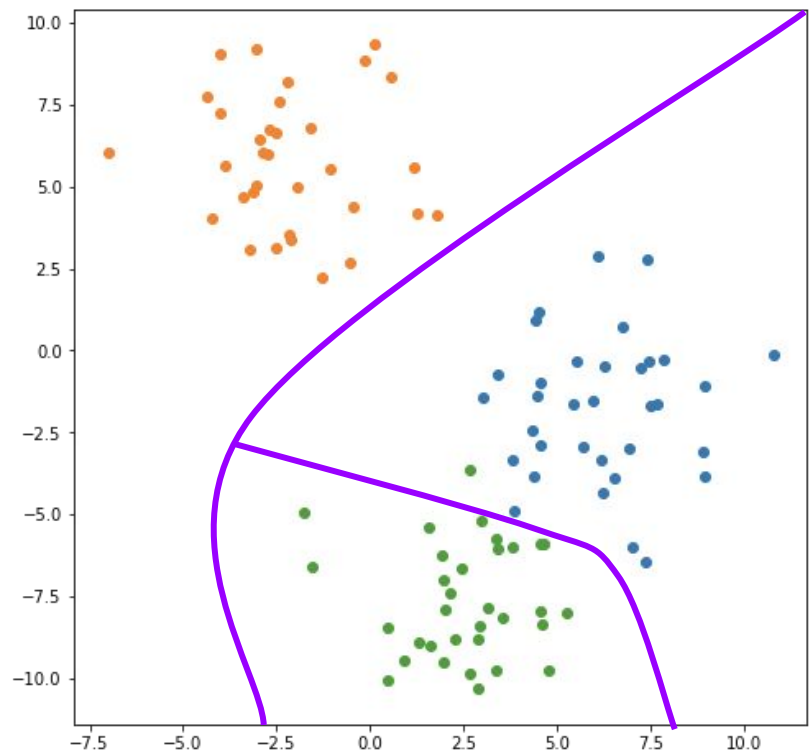


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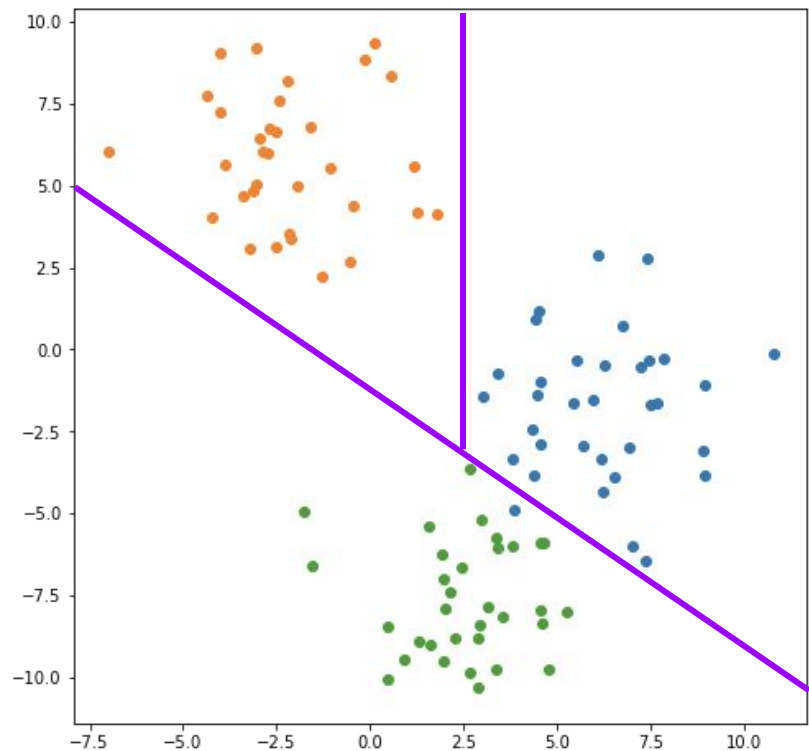


# Selecting the Right Model

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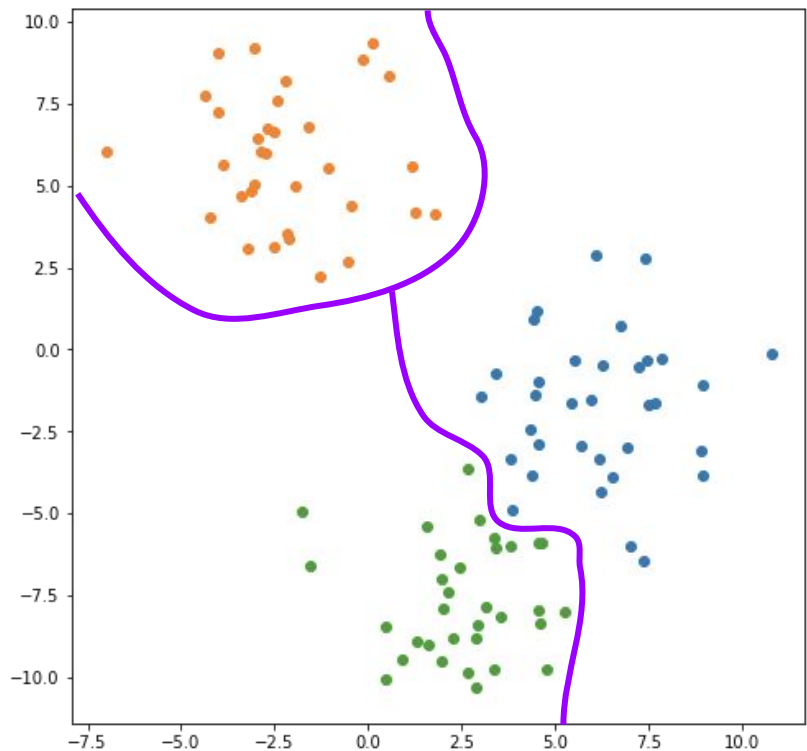


# Selecting the Right Model

**A** - Thought about it and have a thought

**B** - Thought about it and have no thought

**C** - I'm confused



# Cross-Validation

In reality, our eyeball meter won't (and sometimes can't) cut it

Real data are messy and live in dimensions we cannot even comprehend (let alone visualize)

**Cross-validation** offers a systematic way of assessing various models and determine which ones meet our requirements the closest

- Validation Set
- Leave-one-out
- K-Fold



model assessment

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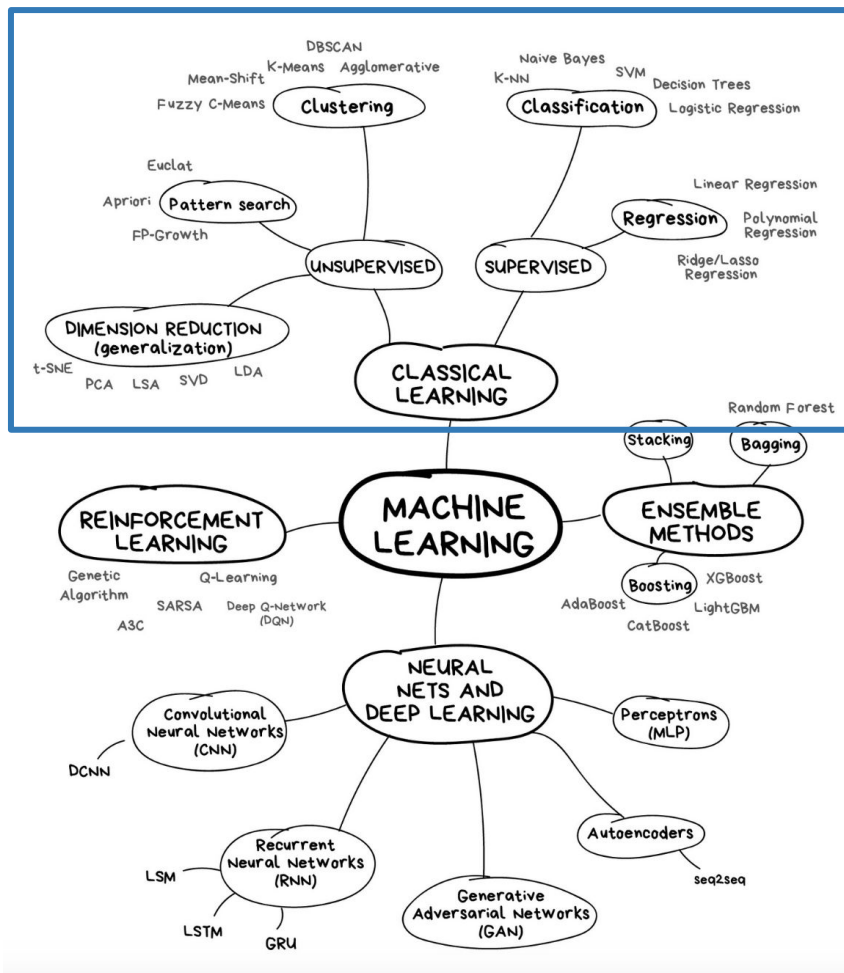
# Many Metrics!

Assessing machine learning models involves gauging its performance on novel data

- Novel data come from the testing partition we left out earlier!
  - Training data was the study guide
  - Validation data was the practice exam
  - Testing data are the actual exam
- Performance assessments depend on the specific problem/question
- Different metrics measure different aspects of models
  - e.g. RMSE, MAE, accuracy, specificity/sensitivity, etc.

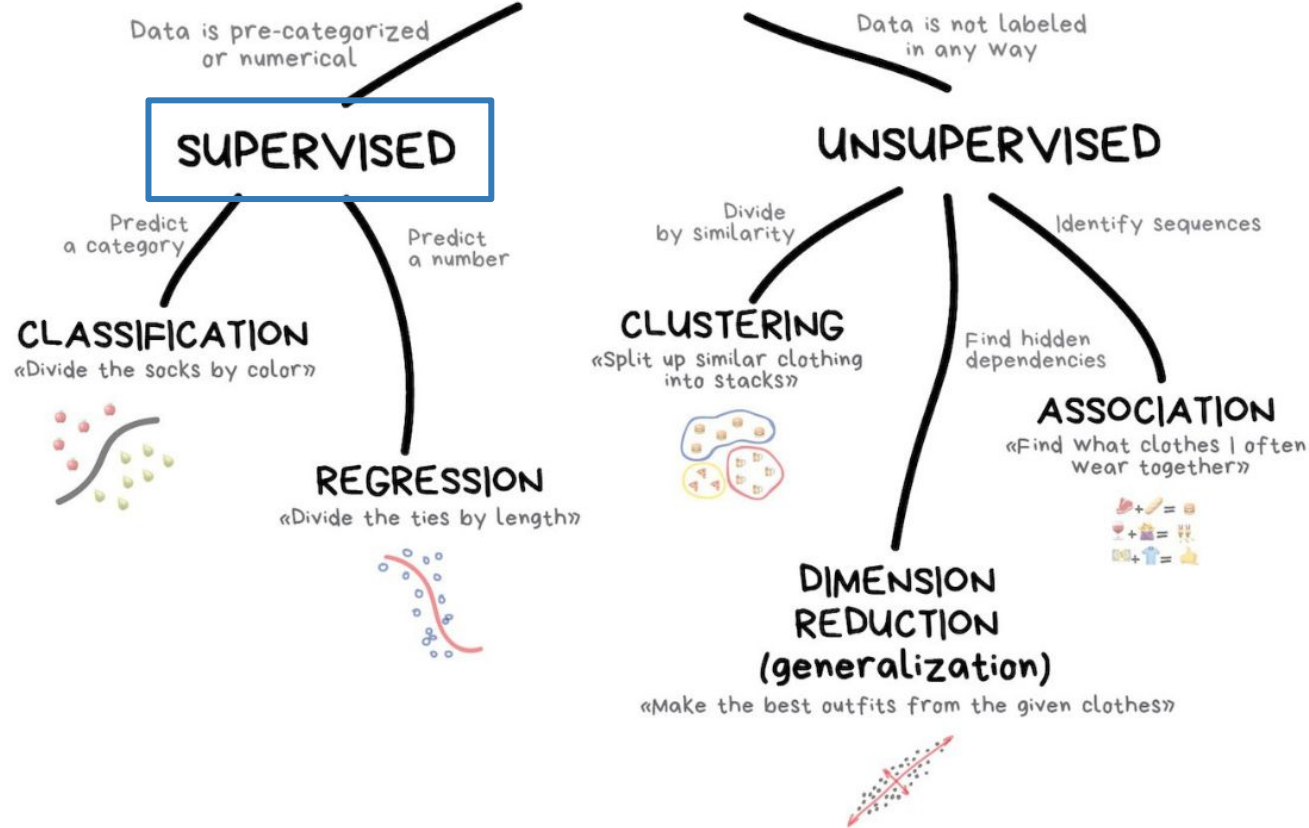
# Classical Machine Learning

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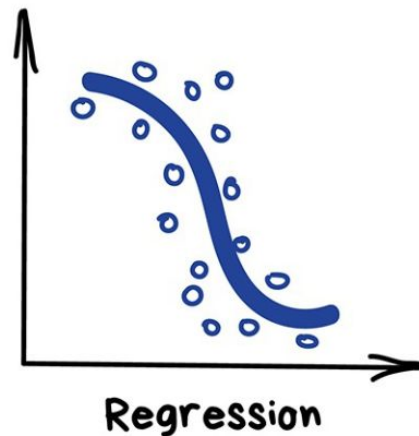


# CLASSICAL MACHINE LEARNING

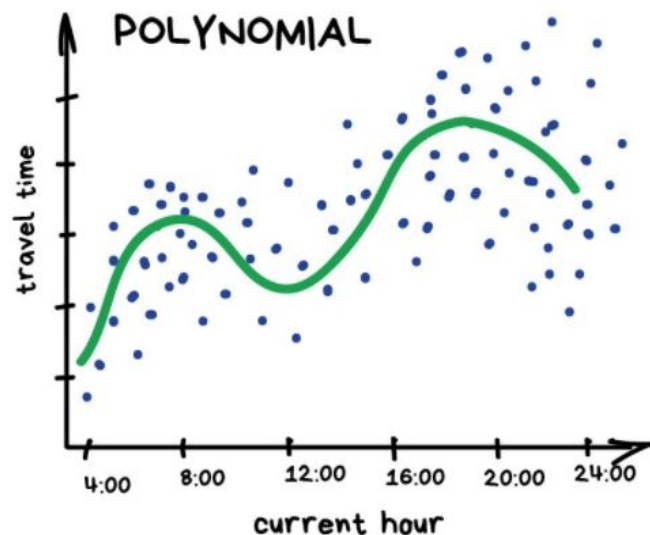
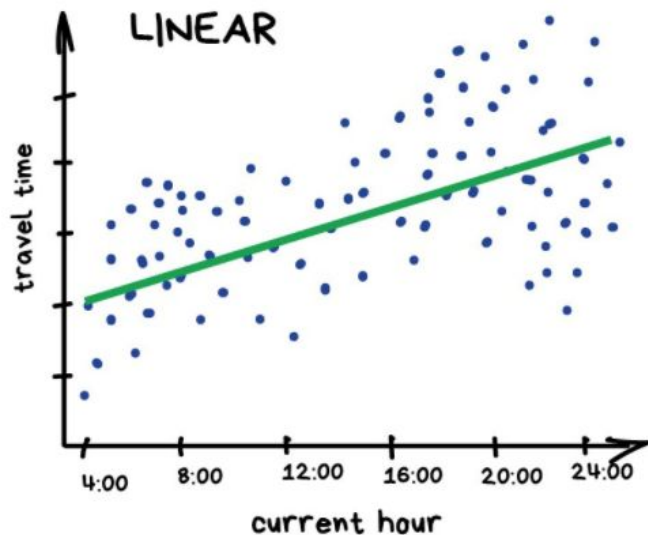


# Regression

- Predicting a **continuous** outcome by finding a relationship between inputs and outputs
- Makes predictions on new data based on the learned patterns from the training set
- Used for:
  - Stock price forecasts
  - Demand and sales volume analysis
  - Number-time correlations
- Popular regression models include:
  - Linear regression
  - Polynomial regression



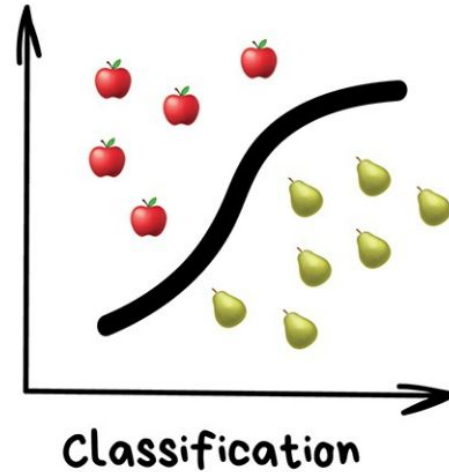
## PREDICT TRAFFIC JAMS



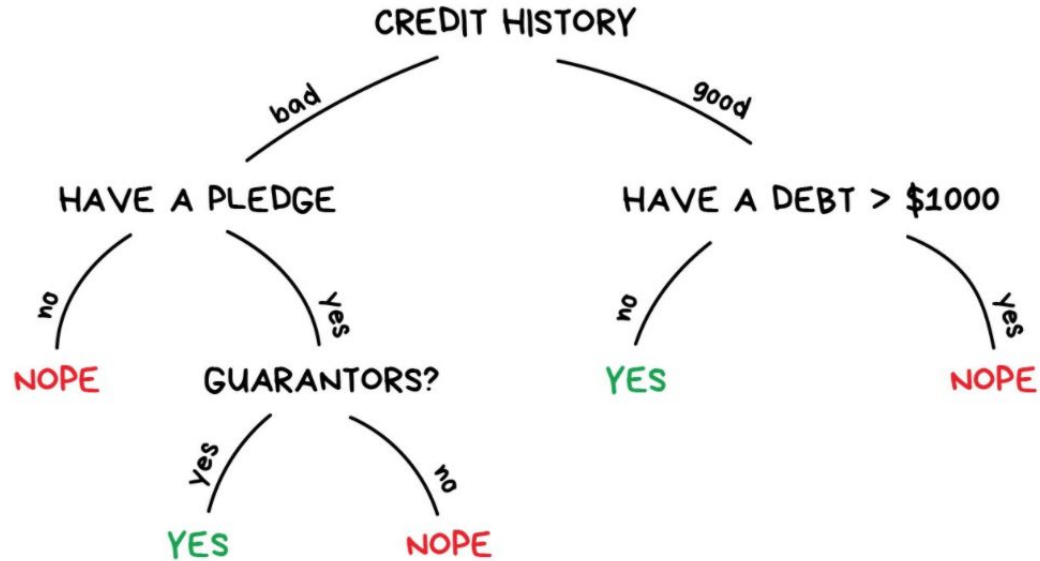
REGRESSION

# Classification

- Predicting a **categorical** outcome by finding boundaries between classes of data points
- Makes predictions on new data based on where within the decision boundary it falls
- Used for:
  - Spam filtering
  - Fraud detection
  - Language detection
- Popular classification models include:
  - Logistic regression
  - Support Vector Machine
  - Decision Tree

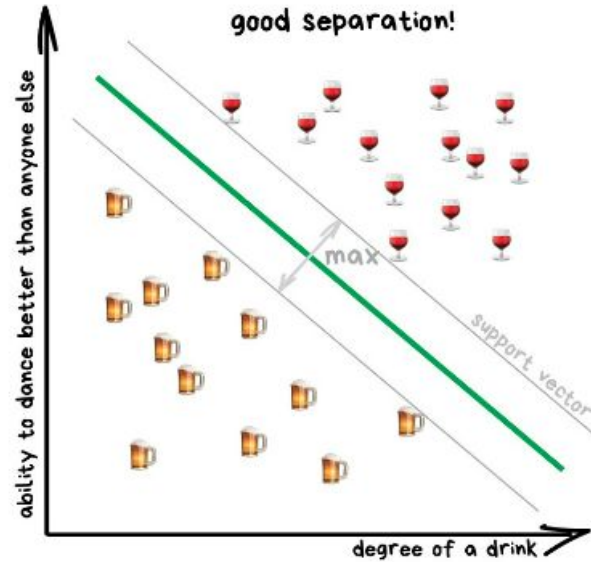


# GIVE A LOAN?



DECISION TREE

## SEPARATE TYPES OF ALCOHOL



SUPPORT VECTOR MACHINE

# Supervised vs. Unsupervised

Supervised algorithms use labeled data → Checks answers and improves over time

- Learning relationships between inputs and outputs to make predictions
- Goal is to minimize error or maximize accuracy in predictions

Unsupervised algorithms use unlabeled data → No “correct” answers

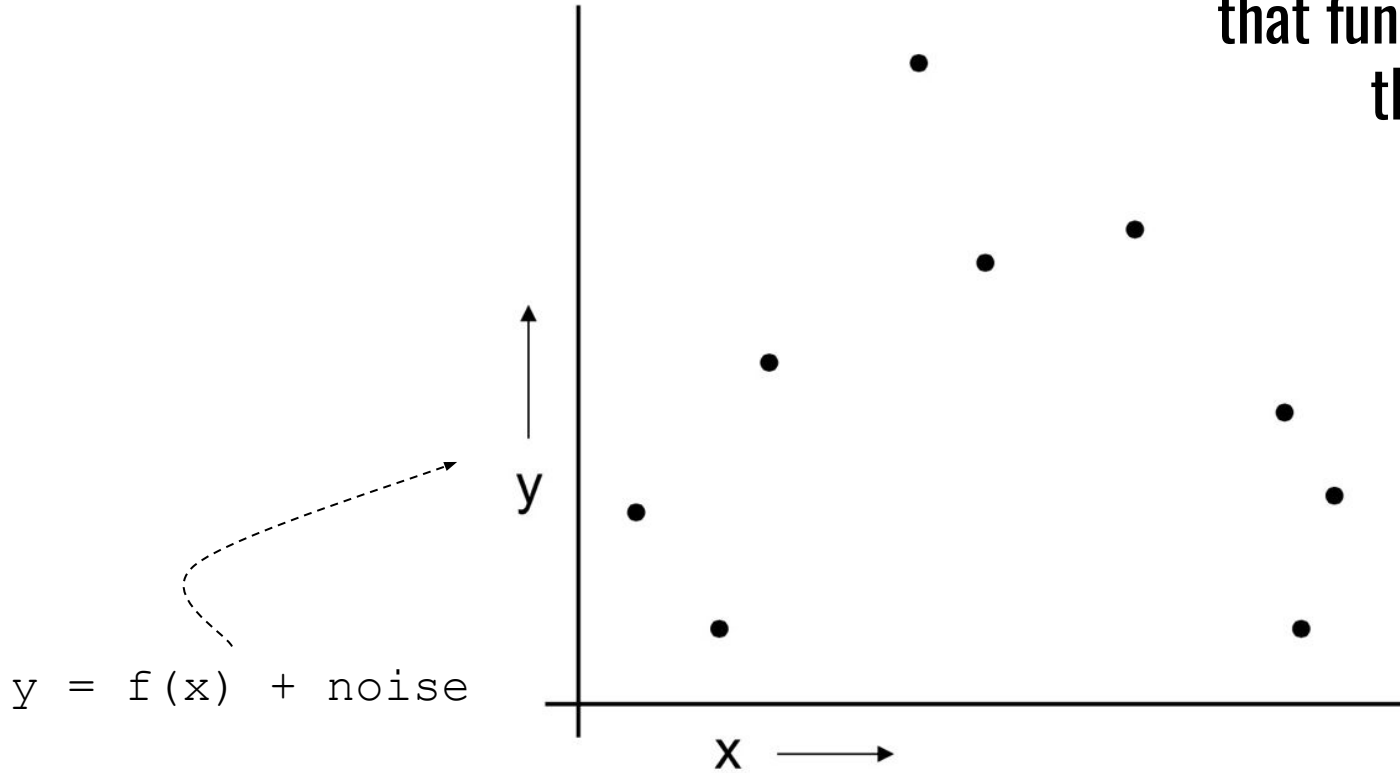
- Commonly used to discover new patterns where they are unknown → research!!
- Verifies itself with similarity/stability scores

# Regression Walkthrough

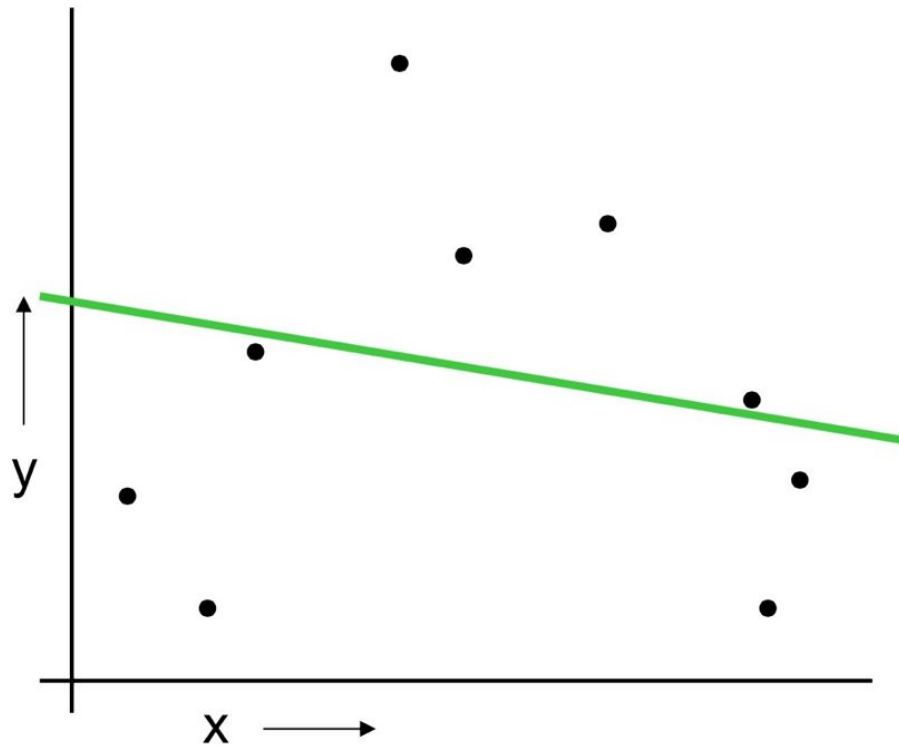
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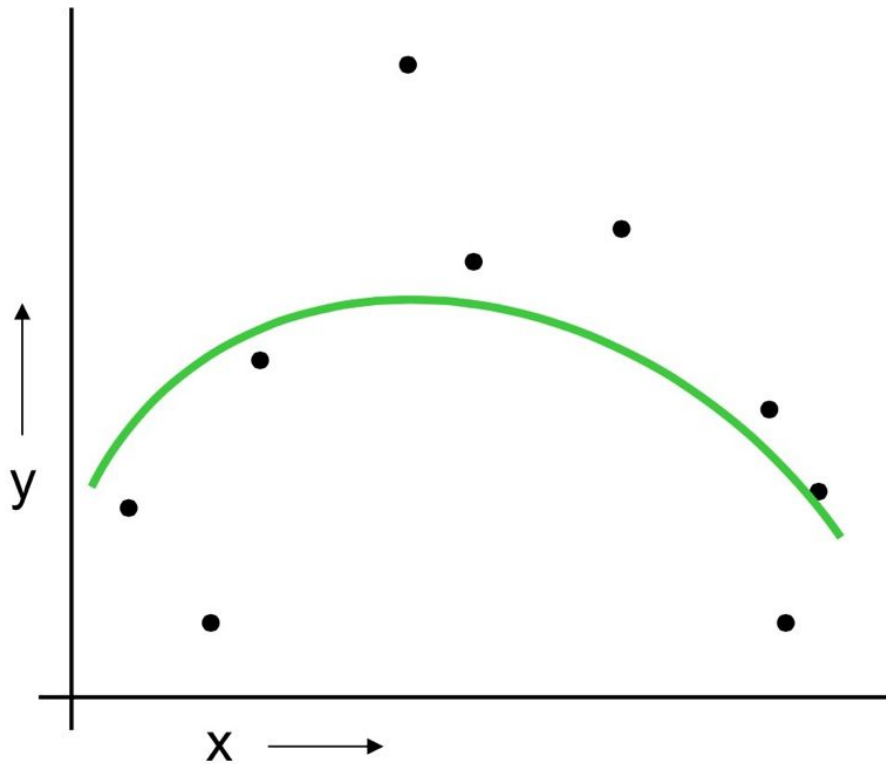
Can we determine what  
that function ( $f$ ) is using  
these data?



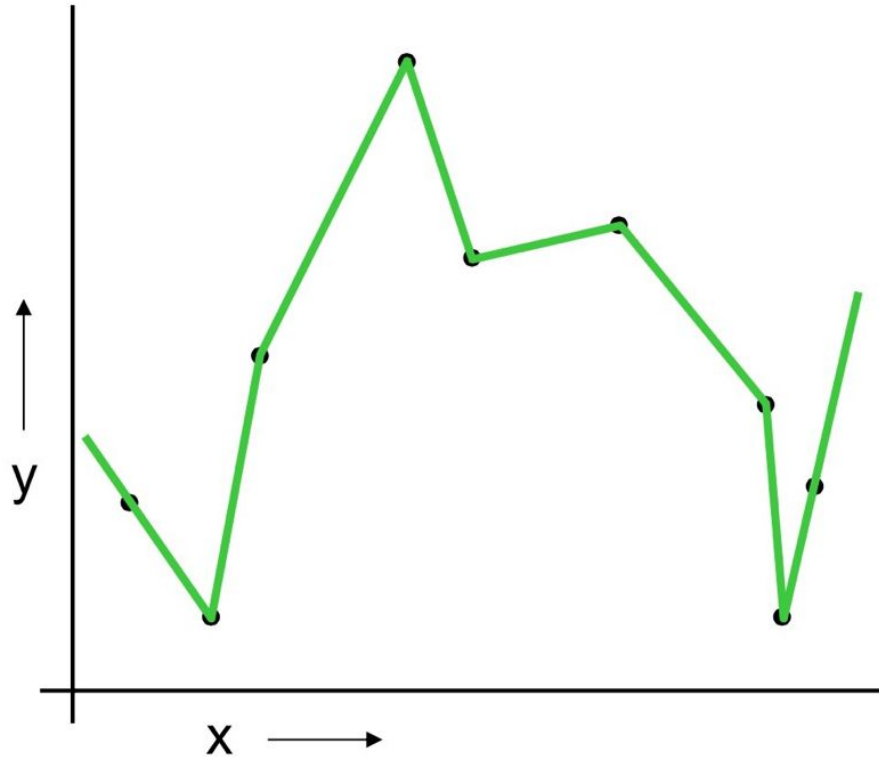
# Linear regression



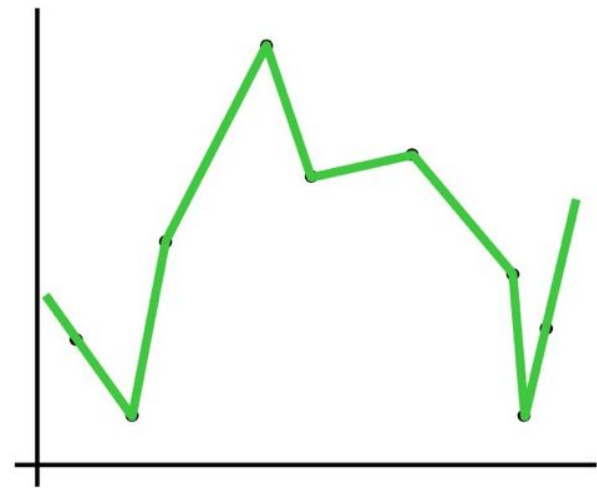
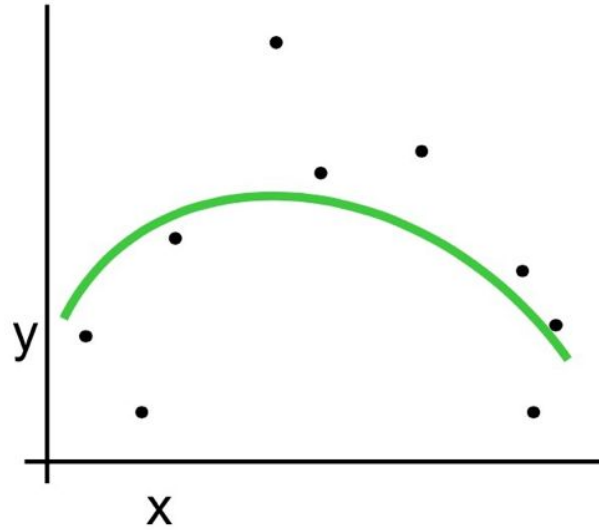
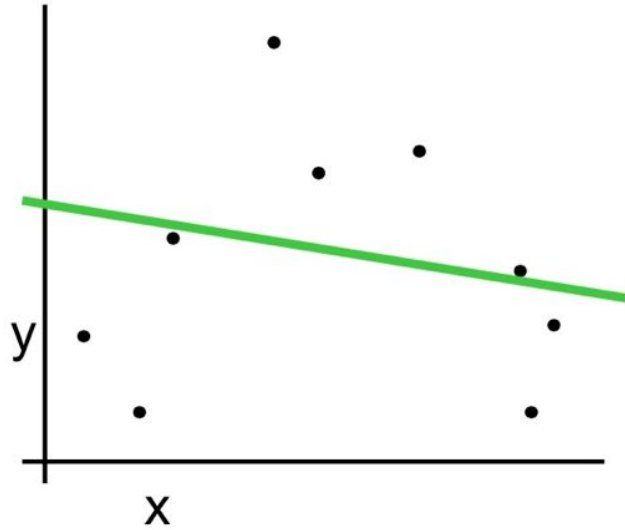
# Quadratic regression



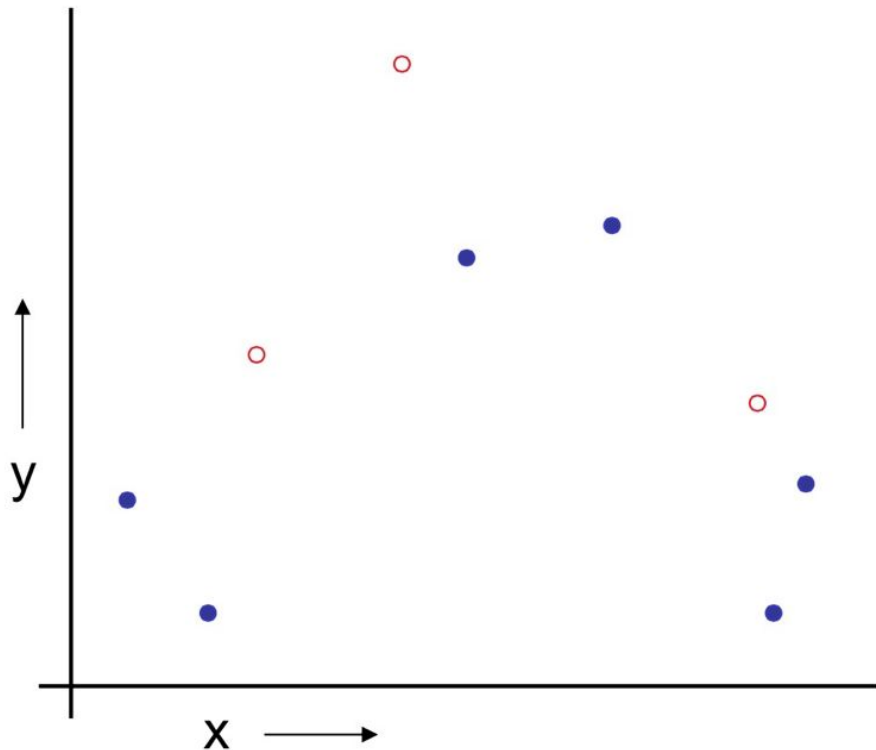
# Piecewise linear nonparametric regression



# Which to choose?

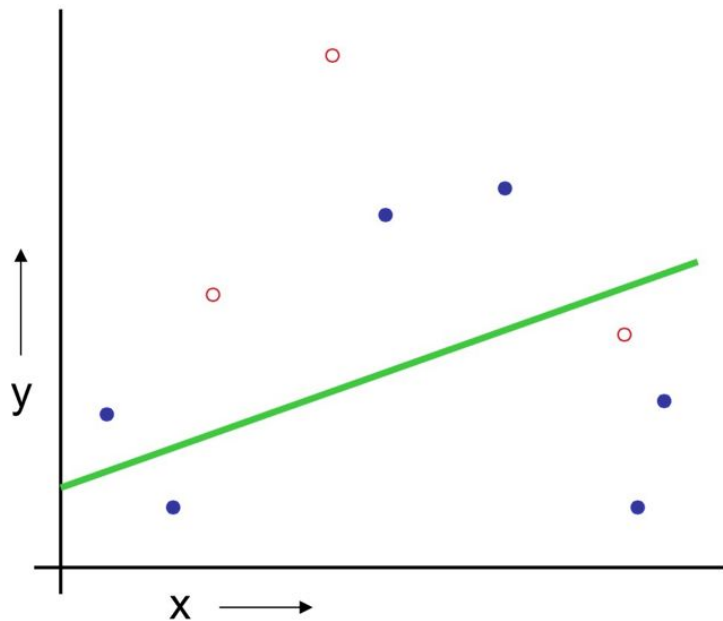


# The data partition method



1. Randomly choose 30% of the data to be in a **test set**
2. The remainder is a **training set**

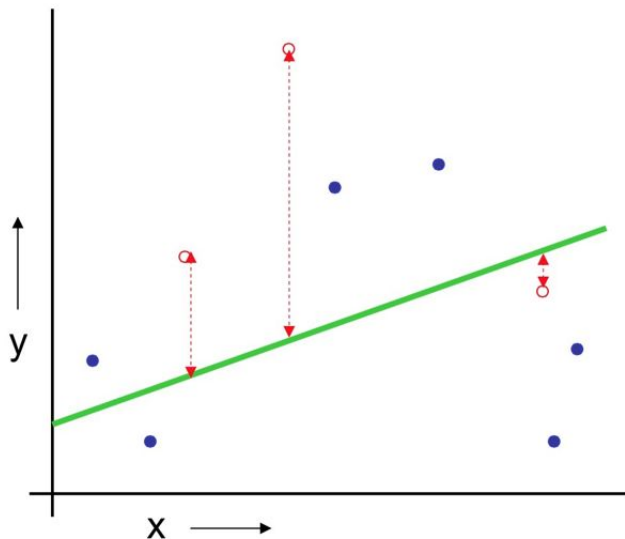
# Train the model on your **training set**



(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**

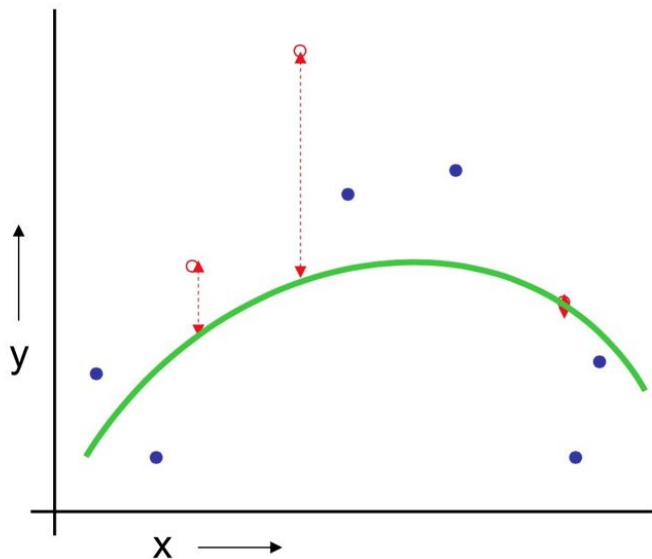
2. The remainder is a  
training set

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

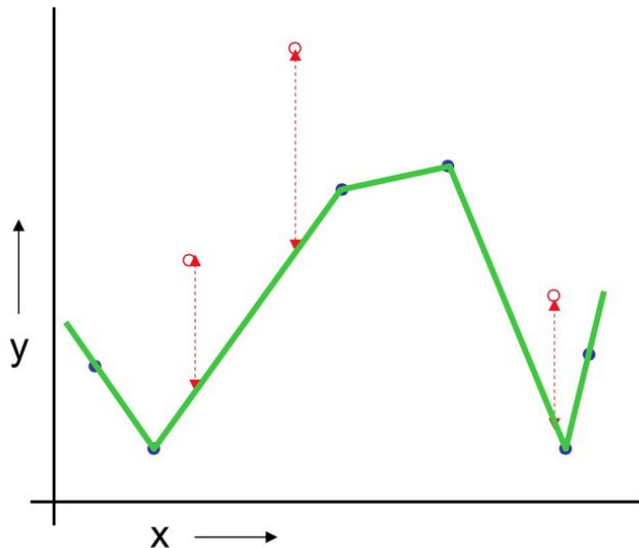
1. Randomly choose  
30% of the data to be in a  
**test set**

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

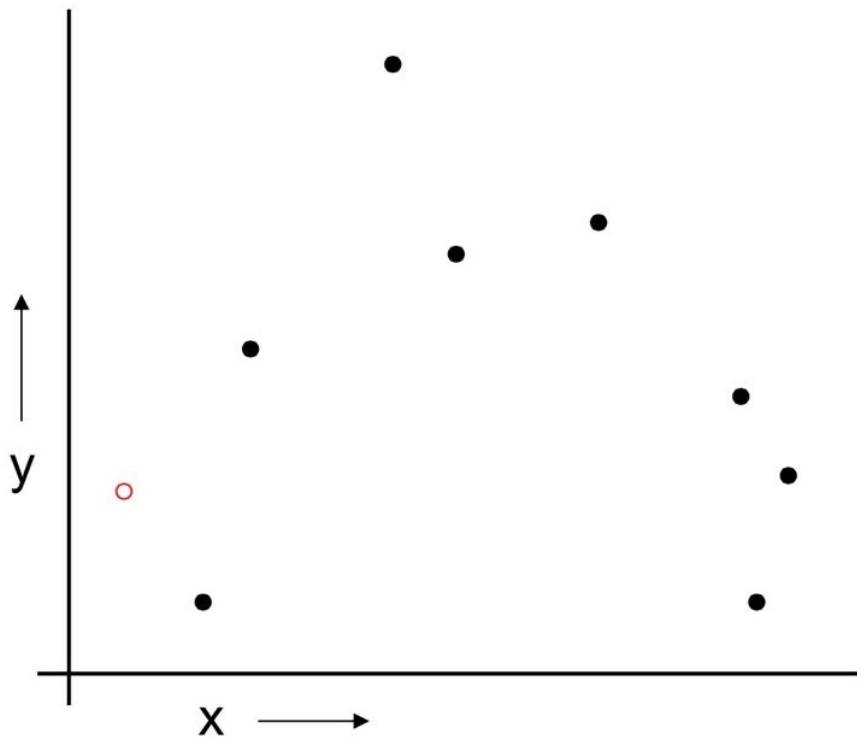
## Cons:

- 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  $R$

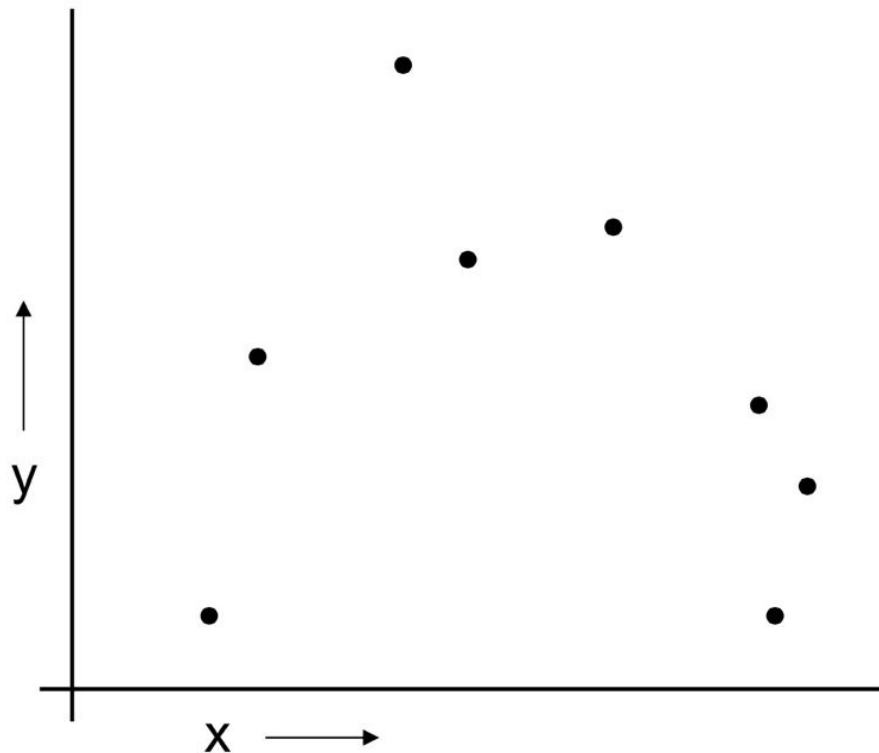
1. Let  $(x_k, y_k)$  be the  $k^{\text{th}}$  record



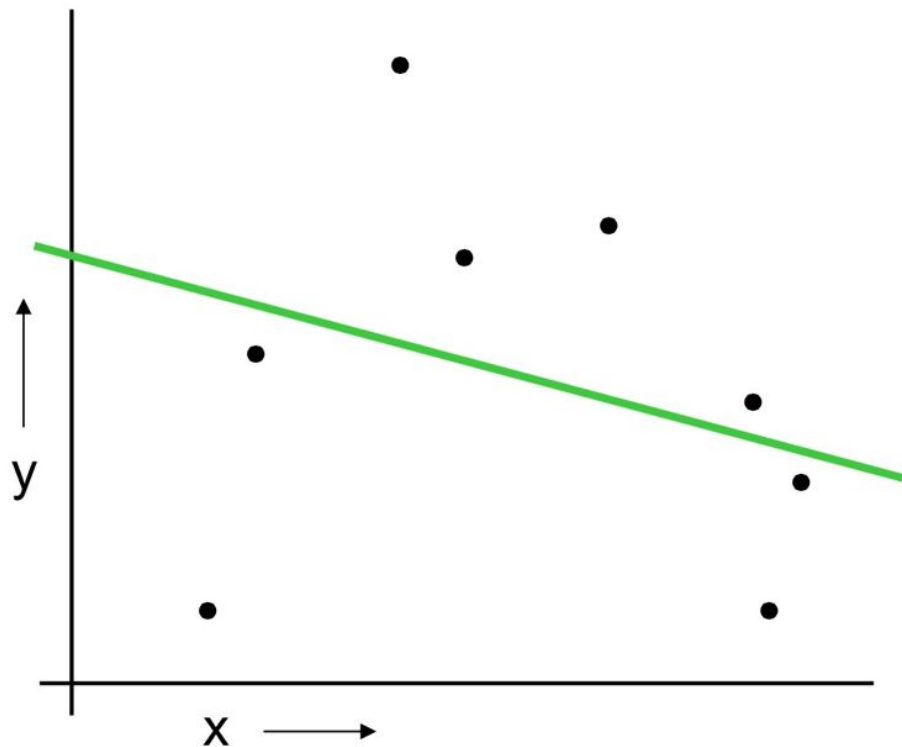
# Leave one out cross validation (LOOCV)

For  $k=1$  to  $R$

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



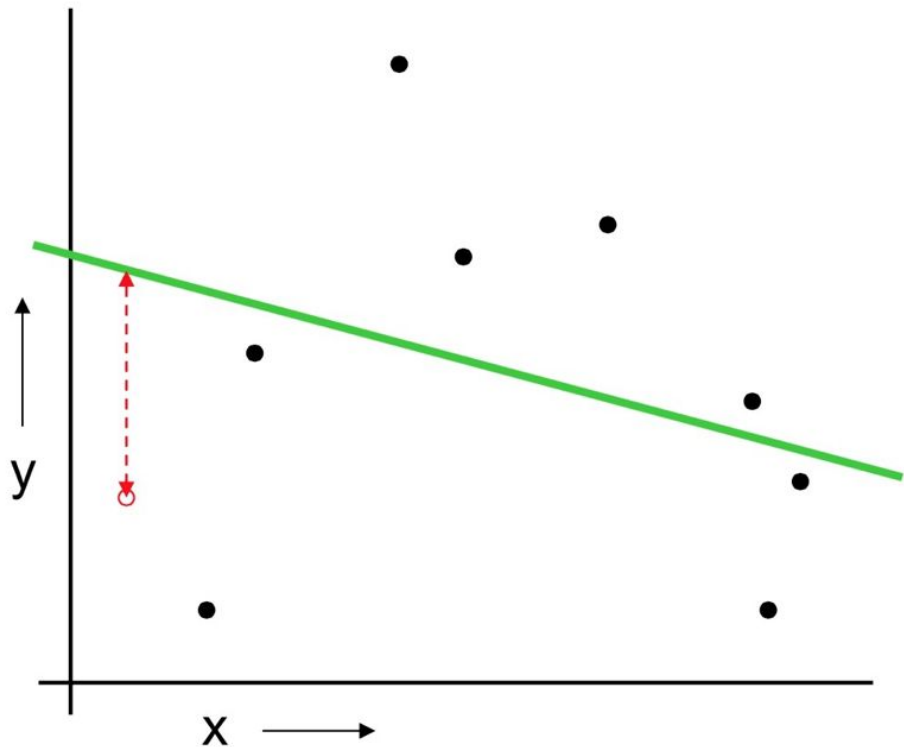
# Leave one out cross validation (LOOCV)



For  $k=1$  to  $R$

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

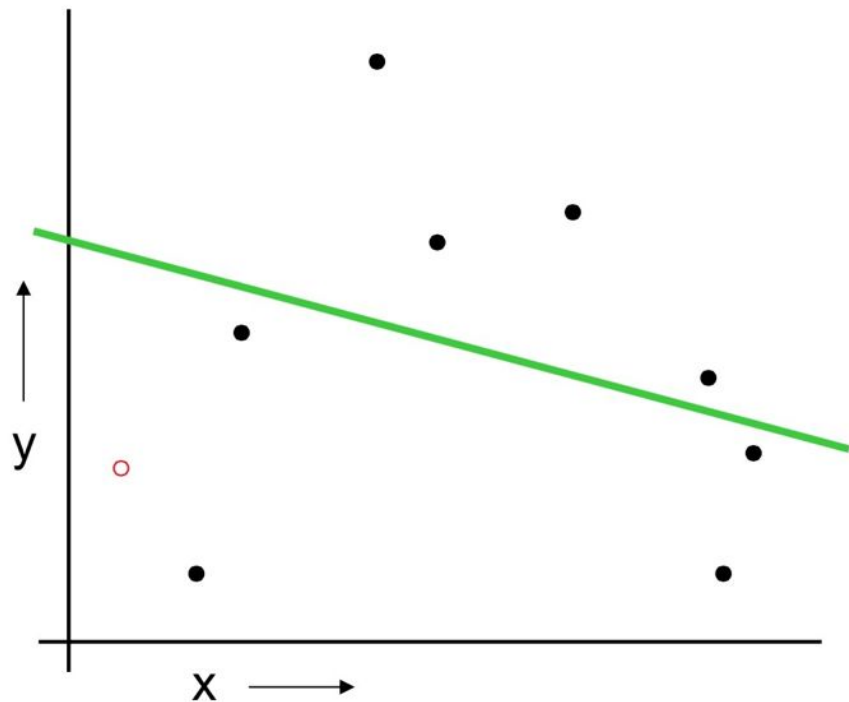
# Leave one out cross validation (LOOCV)



For  $k=1$  to  $R$

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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)



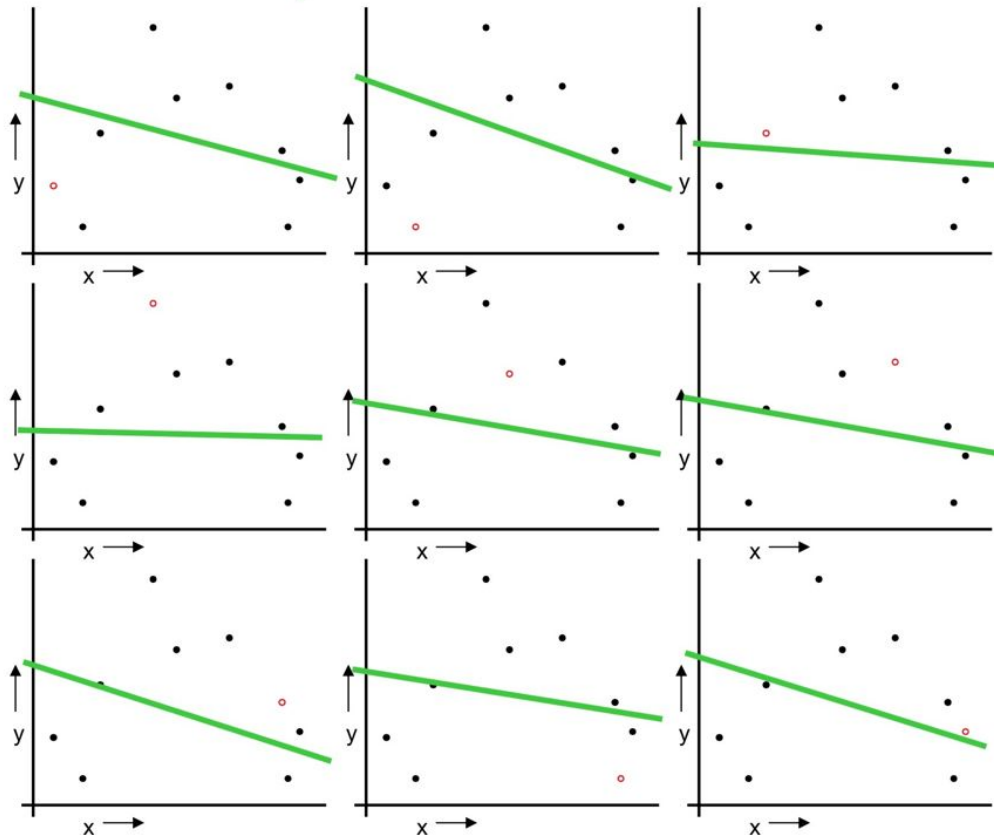
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When you've done all points, report the mean error.



# Leave one out cross validation (LOOCV)



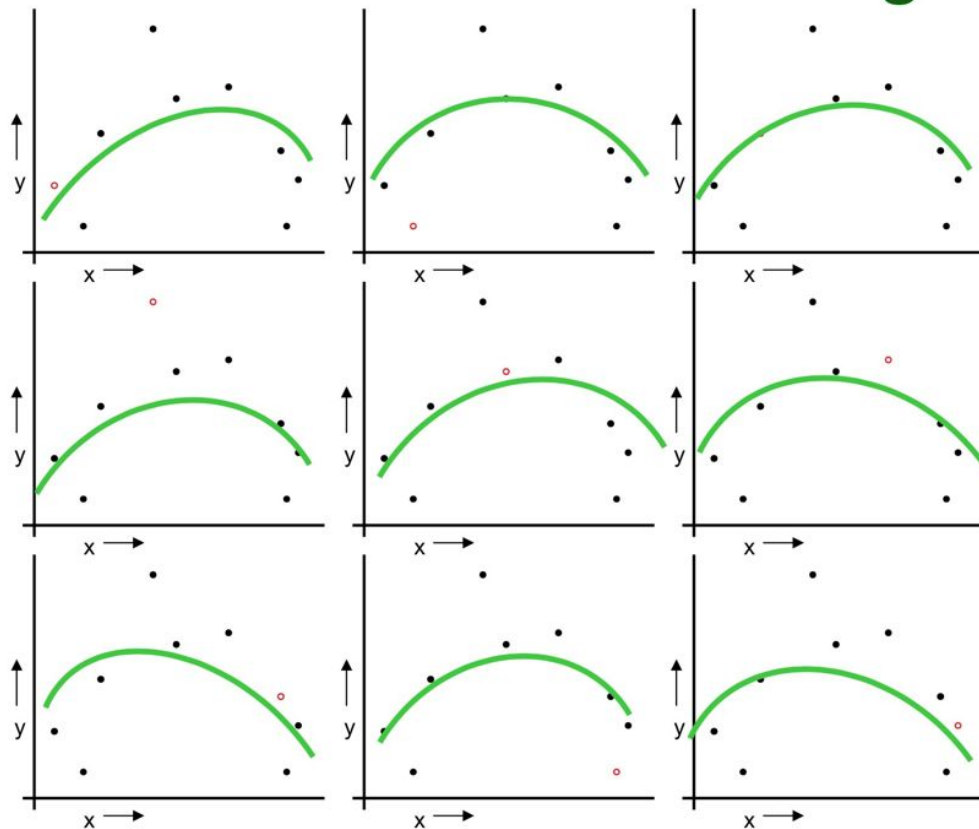
For  $k=1$  to  $R$

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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)



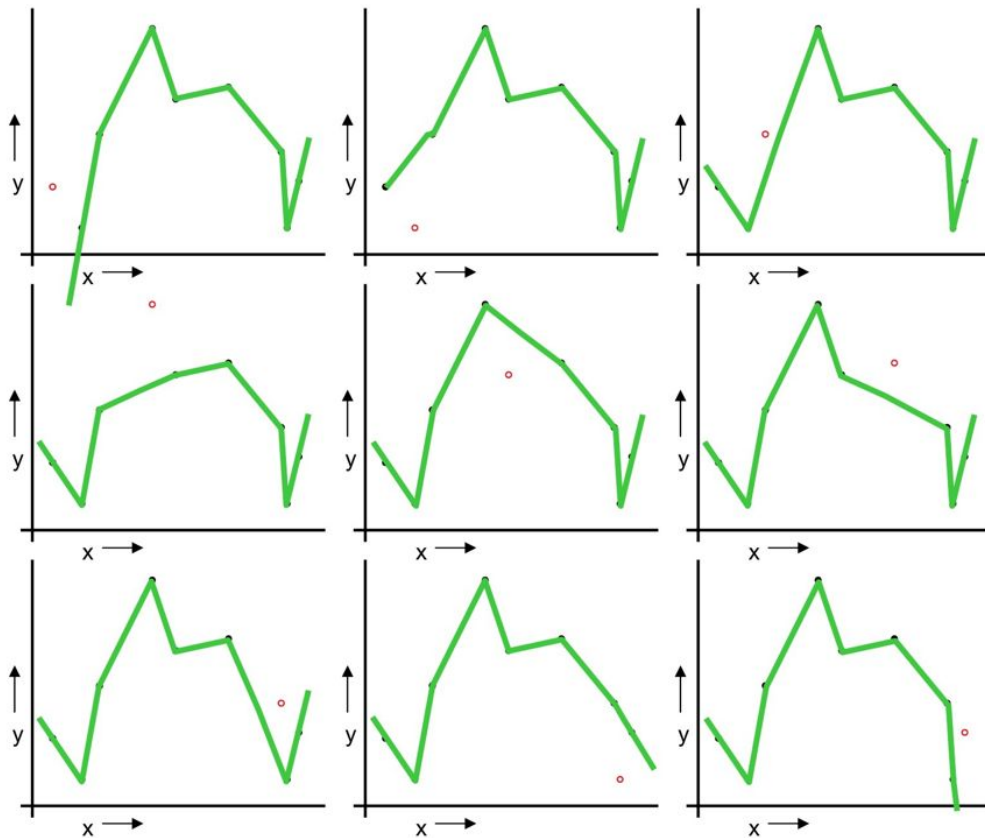
For  $k=1$  to  $R$

1. Let  $(x_k, y_k)$  be the  $k^{\text{th}}$  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  $k^{\text{th}}$  record
2. Temporarily remove  $(x_k, y_k)$  from the dataset
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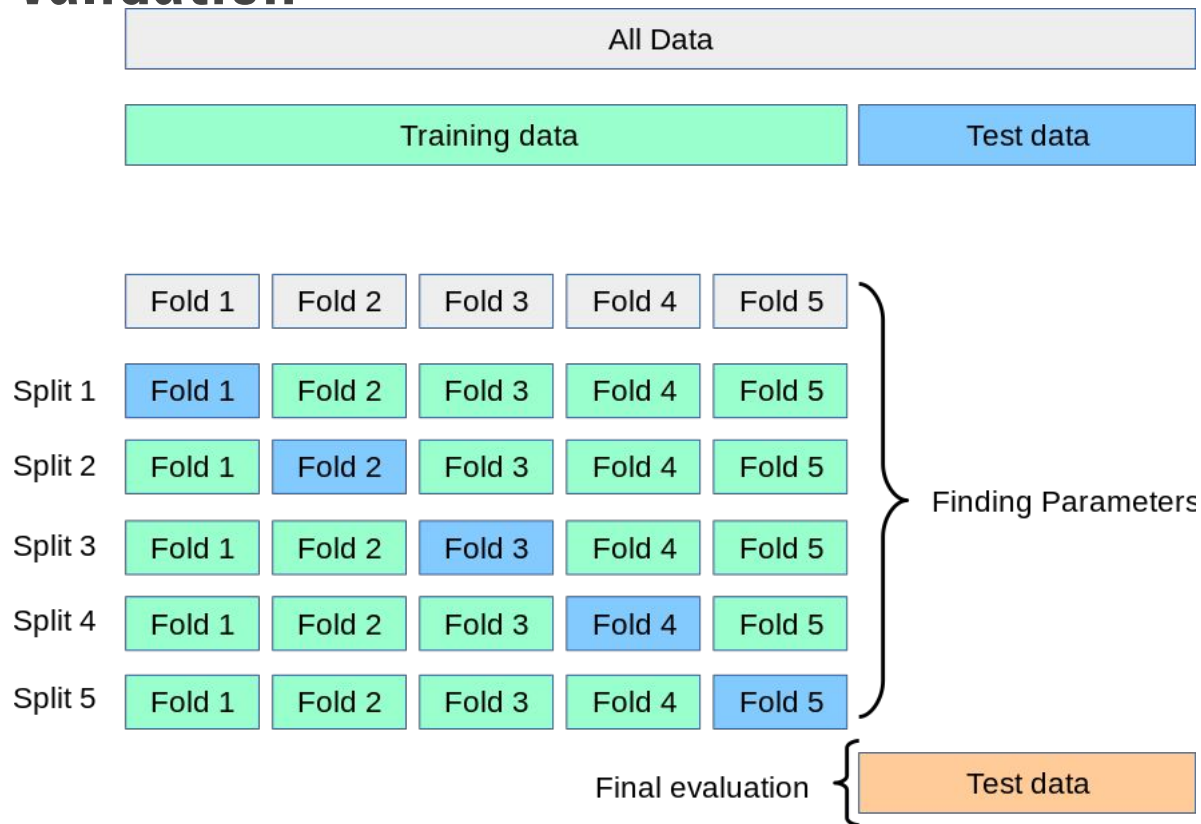
When you've done all points, report the mean error.

$$MSE_{LOOCV} = 3.33$$

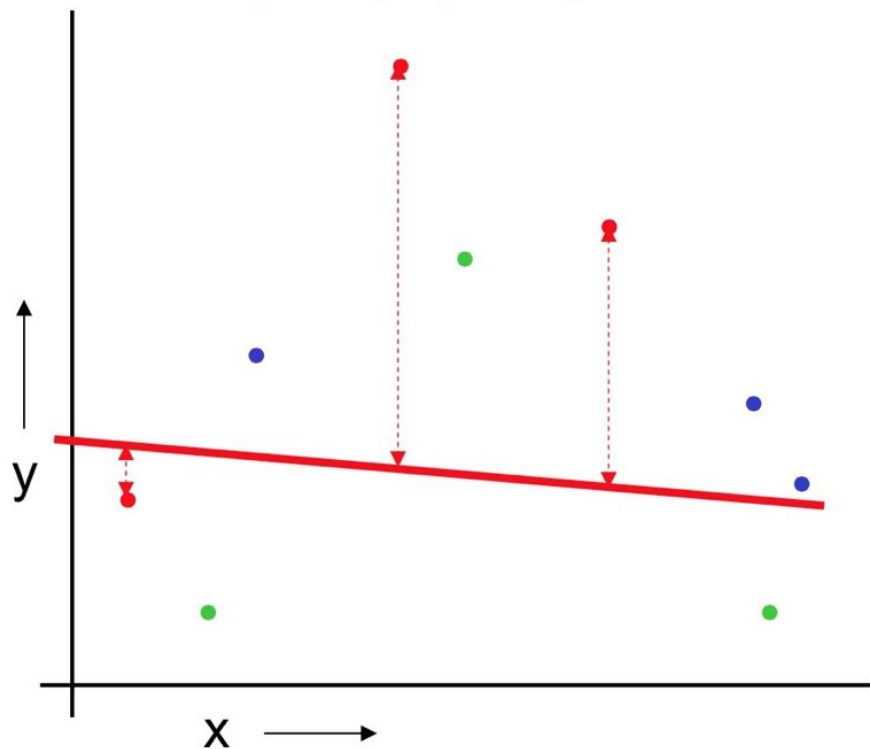
# Method Comparison

	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

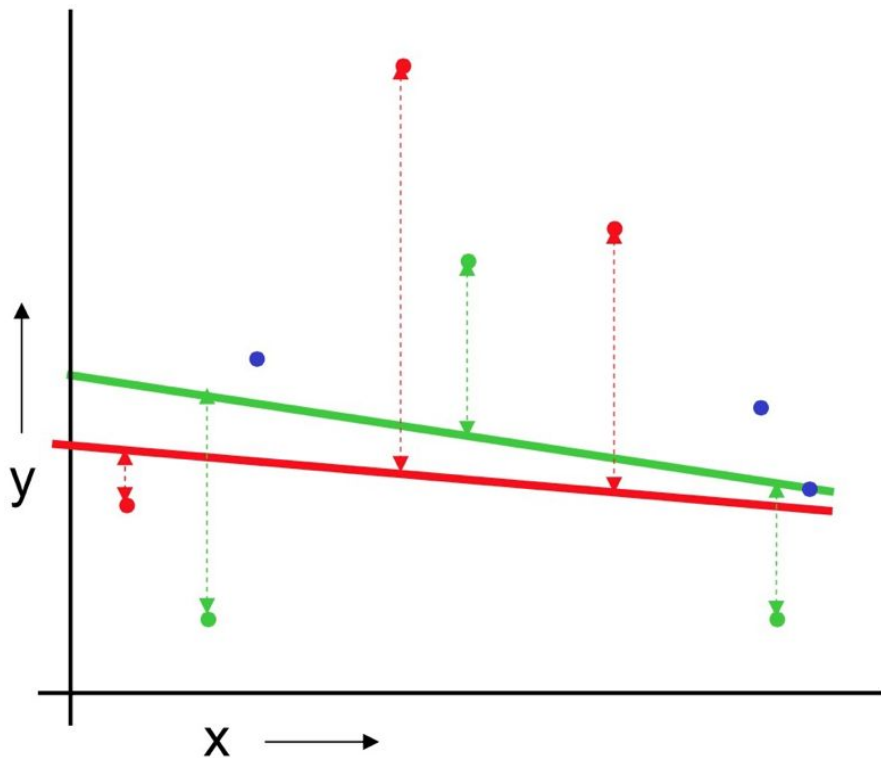


# $k$ -fold cross validation



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.

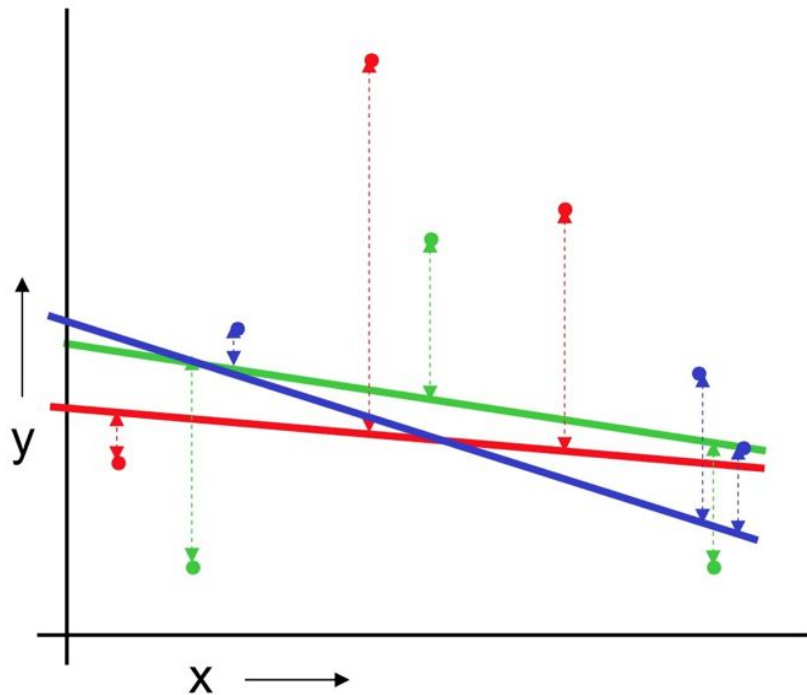
# $k$ -fold cross validation



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



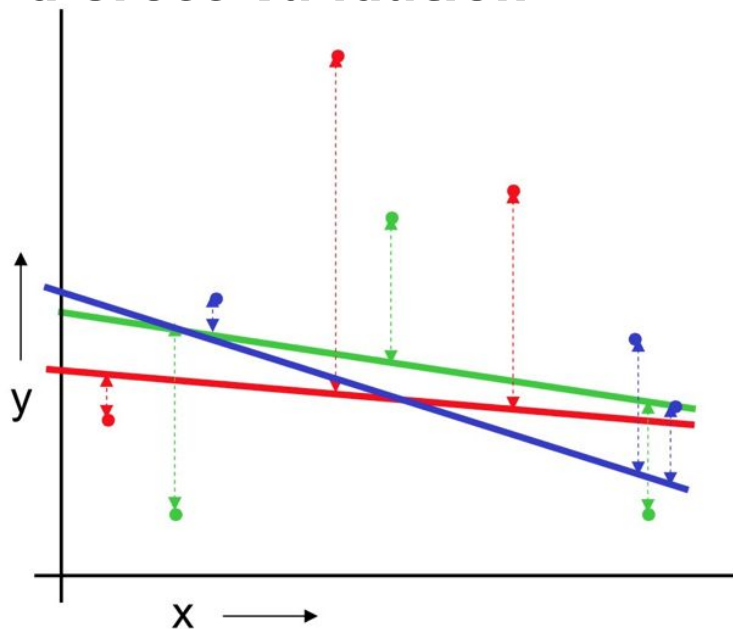
For the red partition: Train on all the points not in the red partition. Find the test-set sum of errors on the red points.

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

$$MSE_{3FOLD} = 2.05$$

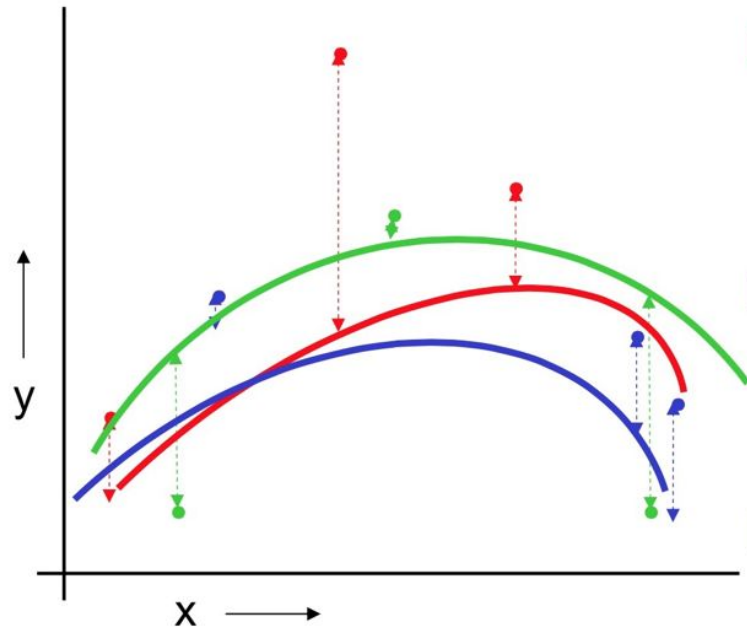
For the red partition: Train on all the points not in the red partition. Find the test-set sum of errors on the red points.

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

$$MSE_{3FOLD} = 1.11$$

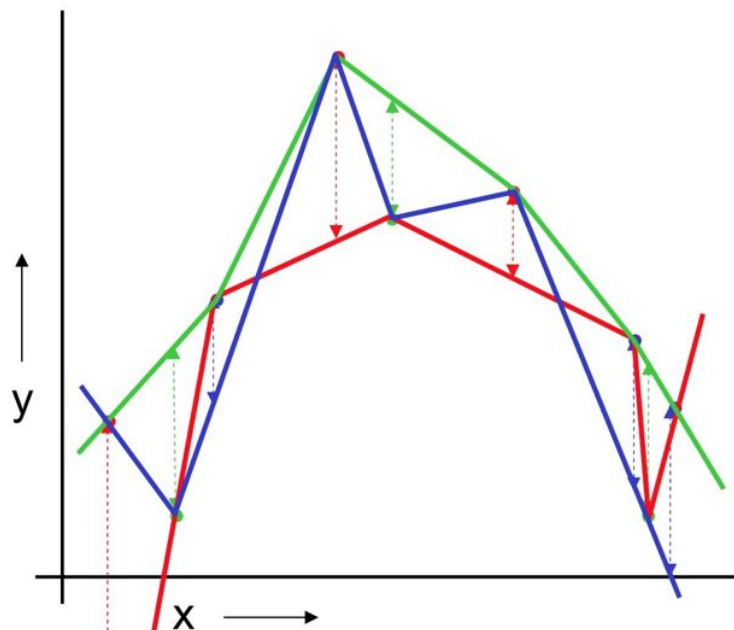
For the red partition: Train on all the points not in the red partition. Find the test-set sum of errors on the red points.

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.

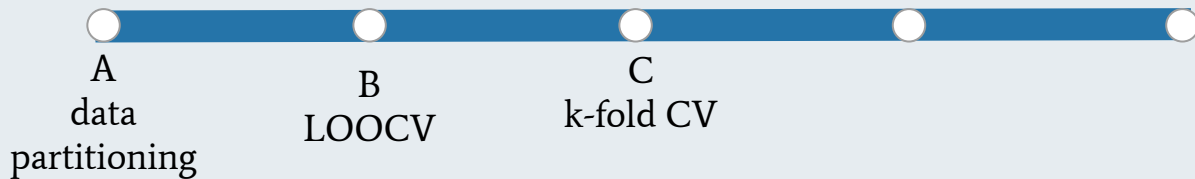
For the green partition: Train on all the points not in the green partition. Find the test-set sum of errors on the green points.

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



Which approach would *you* use to limit overfitting?





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

