Predictive Analysis of Text:
Concepts, Features, and Instances

Jaime Arguello
jarguell@email.unc.edu

Concepts from Domingo's Paper

1. Representation + Parameter Optimization + Evaluation
2. Bias/Variance Trade-off + Overfitting

Predictive Analysis of Text

- Objective: developing and evaluating computer programs that automatically detect a particular concept in natural language text

Predictive Analysis

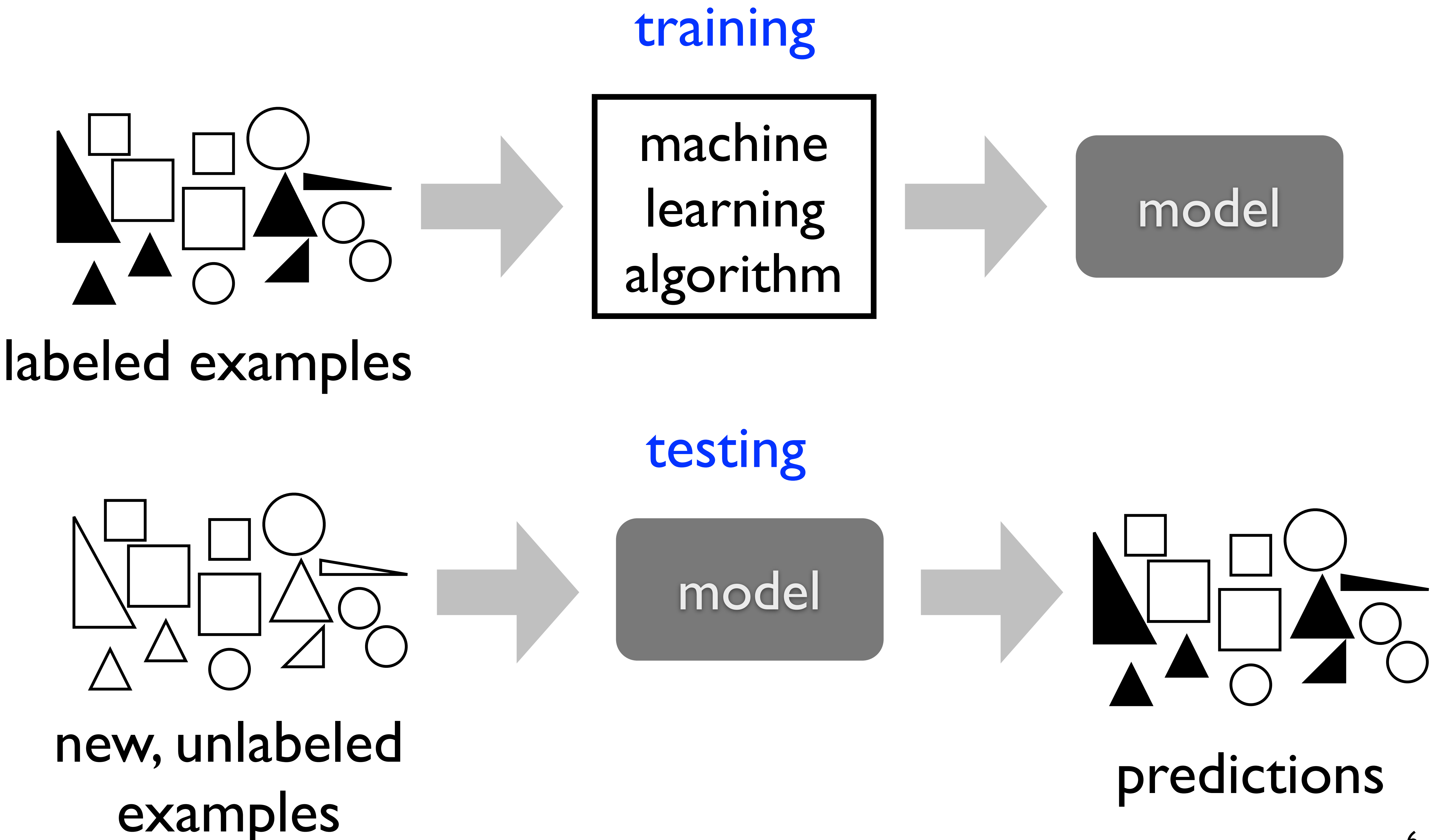
basic ingredients

1. Training data: a set of positive and negative examples of the concept we want to automatically recognize
2. Representation: a set of features that we believe are useful in recognizing the desired concept
3. Learning algorithm: a computer program that uses the training data to learn a predictive model of the concept

Predictive Analysis
basic ingredients

4. Model: a function that describes a predictive relationship between feature values and the presence of the concept
5. Test data: a set of previously unseen examples used to estimate the model's effectiveness
6. Performance metrics: a set of statistics used to measure the predictive effectiveness of the model

Predictive Analysis
training and testing



Predictive Analysis

concept, instances, and features

features **concept**

instances

color	size	# sides	equal sides	...	label
red	big	3	no	...	yes
green	big	3	yes	...	yes
blue	small	inf	yes	...	no
blue	small	4	yes	...	no
⋮	⋮	⋮	⋮	⋮	⋮
red	big	3	yes	...	yes

Predictive Analysis

training and testing

training

color	size	sides	equal sides	...	label
red	big	3	no	...	yes
green	big	3	yes	...	yes
blue	small	inf	yes	...	no
blue	small	4	yes	...	no
⋮	⋮	⋮	⋮	⋮	⋮
red	big	3	yes	...	yes

labeled examples

machine learning algorithm

model

testing

color	size	sides	equal sides	...	label
red	big	3	no	...	???
green	big	3	yes	...	???
blue	small	inf	yes	...	???
blue	small	4	yes	...	???
⋮	⋮	⋮	⋮	⋮	???
red	big	3	yes	...	???

new, unlabeled examples

model

color	size	sides	equal sides	...	label
red	big	3	no	...	yes
green	big	3	yes	...	yes
blue	small	inf	yes	...	no
blue	small	4	yes	...	no
⋮	⋮	⋮	⋮	⋮	⋮
red	big	3	yes	...	yes

predictions

Predictive Analysis

questions

- Is a particular concept appropriate for predictive analysis?
- What should the unit of analysis be?
- How should I divide the data into training and test sets?
- What is a good feature representation for this task?
- What type of learning algorithm should I use?

Predictive Analysis

concepts

- Learning algorithms can recognize some concepts better than others
- What are some properties of concepts that are easier to recognize?

Predictive Analysis

concepts

- Option 1: can a human recognize the concept?

Predictive Analysis
concepts

- Option 1: can a human recognize the concept?
- Option 2: can two or more humans recognize the concept independently and do they agree?

Predictive Analysis
concepts

- Option 1: can a human recognize the concept?
- Option 2: can two or more humans recognize the concept independently and do they agree?
- Option 2 is better.
- In fact, models are sometimes evaluated as an independent assessor
- How does the model's performance compare to the performance of one assessor with respect to another?
  - One assessor produces the "ground truth" and the other produces the "predictions"

Predictive Analysis

measures agreement: percent agreement

- Percent agreement: percentage of instances for which both assessors agree that the concept occurs or does not occur

	yes	no
yes	A	B
no	C	D

$$\frac{(? + ?)}{(? + ? + ? + ?)}$$

Predictive Analysis

measures agreement: percent agreement

- Percent agreement: percentage of instances for which both assessors agree that the concept occurs or does not occur

	yes	no
yes	A	B
no	C	D

$$\frac{(A + D)}{(A + B + C + D)}$$

Predictive Analysis

measures agreement: percent agreement

- Percent agreement: percentage of instances for which both assessors agree that the concept occurs or does not occur

	yes	no	
yes	5	5	10
no	15	75	90
	20	80	

% agreement = ???

Predictive Analysis

measures agreement: percent agreement

- Percent agreement: percentage of instances for which both assessors agree that the concept occurs or does not occur

	yes	no	
yes	5	5	10
no	15	75	90
	20	80	

% agreement = (5 + 75) / 100 = 80%

Predictive Analysis

measures agreement: percent agreement

- Problem: percent agreement does not account for agreement due to random chance.
- How can we compute the expected agreement due to random chance?
  - Option 1: assume unbiased assessors
  - Option 2: assume biased assessors

Predictive Analysis

kappa agreement: chance-corrected % agreement

- Option 1: unbiased assessors

	yes	no	
yes	??	??	50
no	??	??	50
	50	50	

Predictive Analysis

kappa agreement: chance-corrected % agreement

- Option 1: unbiased assessors

	yes	no	
yes	25	25	50
no	25	25	50
	50	50	

Predictive Analysis

kappa agreement: chance-corrected % agreement

- Option 1: unbiased assessors

	yes	no	
yes	25	25	50
no	25	25	50
	50	50	

random chance % agreement = ???

Predictive Analysis

kappa agreement: chance-corrected % agreement

- Option 1: unbiased assessors

	yes	no	
yes	25	25	50
no	25	25	50
	50	50	

random chance % agreement = (25 + 25)/100 = 50%

Predictive Analysis

kappa agreement: chance-corrected % agreement

- Kappa agreement: percent agreement after correcting for the expected agreement due to random chance

$$\mathcal{K} = \frac{P(a) - P(e)}{1 - P(e)}$$

- P(a) = percent of observed agreement
- P(e) = percent of agreement due to random chance

Predictive Analysis

kappa agreement: chance-corrected % agreement

- **Kappa agreement:** percent agreement after correcting for the expected agreement due to <u>unbiased</u> chance

	yes	no	
yes	5	5	10
no	15	75	90
	20	80	

	yes	no	
yes	25	25	50
no	25	25	50
	50	50	

$$P(a) = \frac{5+75}{100} = 0.80$$

$$P(e) = \frac{25+25}{100} = 0.50$$

$$\mathcal{K} = \frac{P(a) - P(e)}{1 - P(e)} = \frac{0.80 - 0.50}{1 - 0.50} = 0.60$$

Predictive Analysis

kappa agreement: chance-corrected % agreement

- Option 2: biased assessors

	yes	no	
yes	5	5	10
no	15	75	90
	20	80	

biased chance % agreement = ???

Predictive Analysis

kappa agreement: chance-corrected % agreement

- Kappa agreement: percent agreement after correcting for the expected agreement due to <u>biased</u> chance

	yes	no	
yes	**5**	5	**10**
no	15	**75**	**90**
	20	**80**	

$$P(a) = \boxed{\frac{5+75}{100}} = 0.80 \qquad P(e) = \left(\boxed{\frac{10}{100}} \times \boxed{\frac{20}{100}}\right) + \left(\boxed{\frac{90}{100}} \times \boxed{\frac{80}{100}}\right) = 0.74$$

$$\mathcal{K} = \frac{P(a) - P(e)}{1 - P(e)} = \frac{0.80 - 0.74}{1 - 0.74} = 0.23$$

Predictive Analysis
data annotation process

- **INPUT**: unlabeled data, annotators, coding manual
- **OUTPUT**: labeled data

1. using the latest coding manual, have <u>all</u> annotators label some previously unseen portion of the data (~10%)
2. measure inter-annotator agreement (Kappa)
3. **IF** agreement < X, **THEN**:
   - refine coding manual using disagreements to resolve inconsistencies and clarify definitions
   - return to 1

   ELSE

   - have annotators label the remainder of the data

Predictive Analysis

data annotation process

- What is good (Kappa) agreement?
- It depends on who you ask
- According to Landis and Koch, 1977:
  - 0.81 - 1.00: almost perfect
  - 0.61 - 0.70: substantial
  - 0.41 - 0.60: moderate
  - 0.21 - 0.40: fair
  - 0.00 - 0.20: slight
  - < 0.00: no agreement

Predictive Analysis
questions

- Is a particular concept appropriate for predictive analysis?
- What should the unit of analysis be?
- How should I divide the data into training and test sets?
- What is a good feature representation for this task?
- What type of learning algorithm should I use?

Predictive Analysis

turning data into (training and test) instances

- For many text-mining applications, turning the data into instances for training and testing is fairly straightforward
- Easy case: instances are self-contained, independent units of analysis
  - topic categorization: instances = documents
  - opinion mining: instances = product reviews
  - bias detection: instances = political blog posts
  - emotion detection: instances = support group posts

Topic Categorization

predicting health-related documents

features | concept

instances

w_1	w_2	w_3	...	w_n	label
1	1	0	...	0	health
0	0	0	...	0	other
0	0	0	...	0	other
0	1	0	...	1	other
⋮	⋮	⋮	...	0	⋮
1	0	0	...	1	health

Opinion Mining

predicting positive/negative movie reviews

features **concept**

instances

w_1	w_2	w_3	...	w_n	label
1	1	0	...	0	positive
0	0	0	...	0	negative
0	0	0	...	0	negative
0	1	0	...	1	negative
⋮	⋮	⋮	...	0	⋮
1	0	0	...	1	positive

Bias Detection

predicting liberal/conservative blog posts

features

concept

instances

w_1	w_2	w_3	...	w_n	label
1	1	0	...	0	liberal
0	0	0	...	0	conservative
0	0	0	...	0	conservative
0	1	0	...	1	conservative
⋮	⋮	⋮	...	0	⋮
1	0	0	...	1	liberal

Predictive Analysis

turning data into (training and test) instances

- A not-so-easy case: relational data
- The concept to be learned is a relation between sets of objects
- May require features that characterize properties of the set
- May require ML algorithms that do not make independent predictions

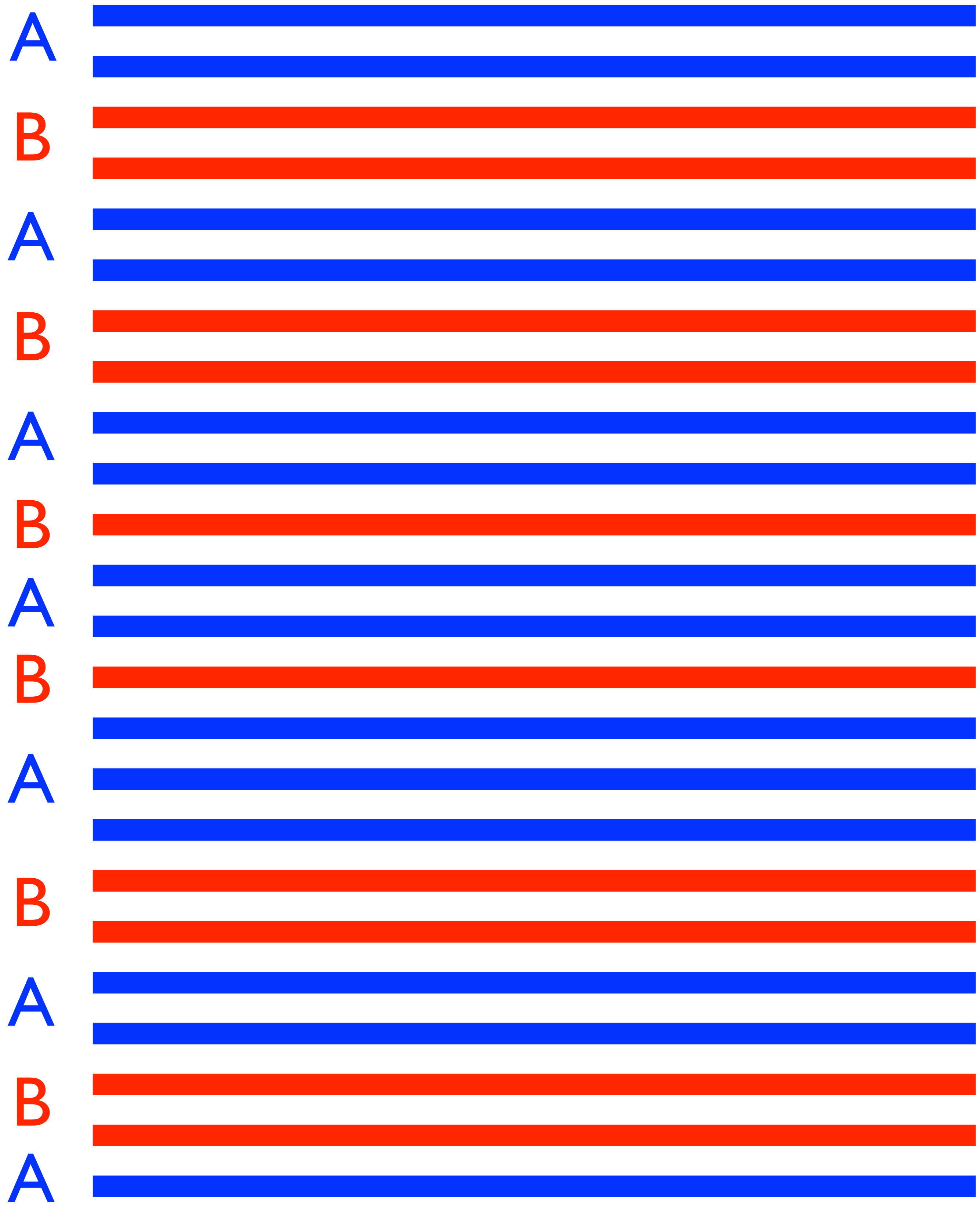
Predictive Analysis

turning data into (training and test) instances

- Example of relational data in text-mining:
  - topic segmentation: segmenting discourse into topically coherent chunks

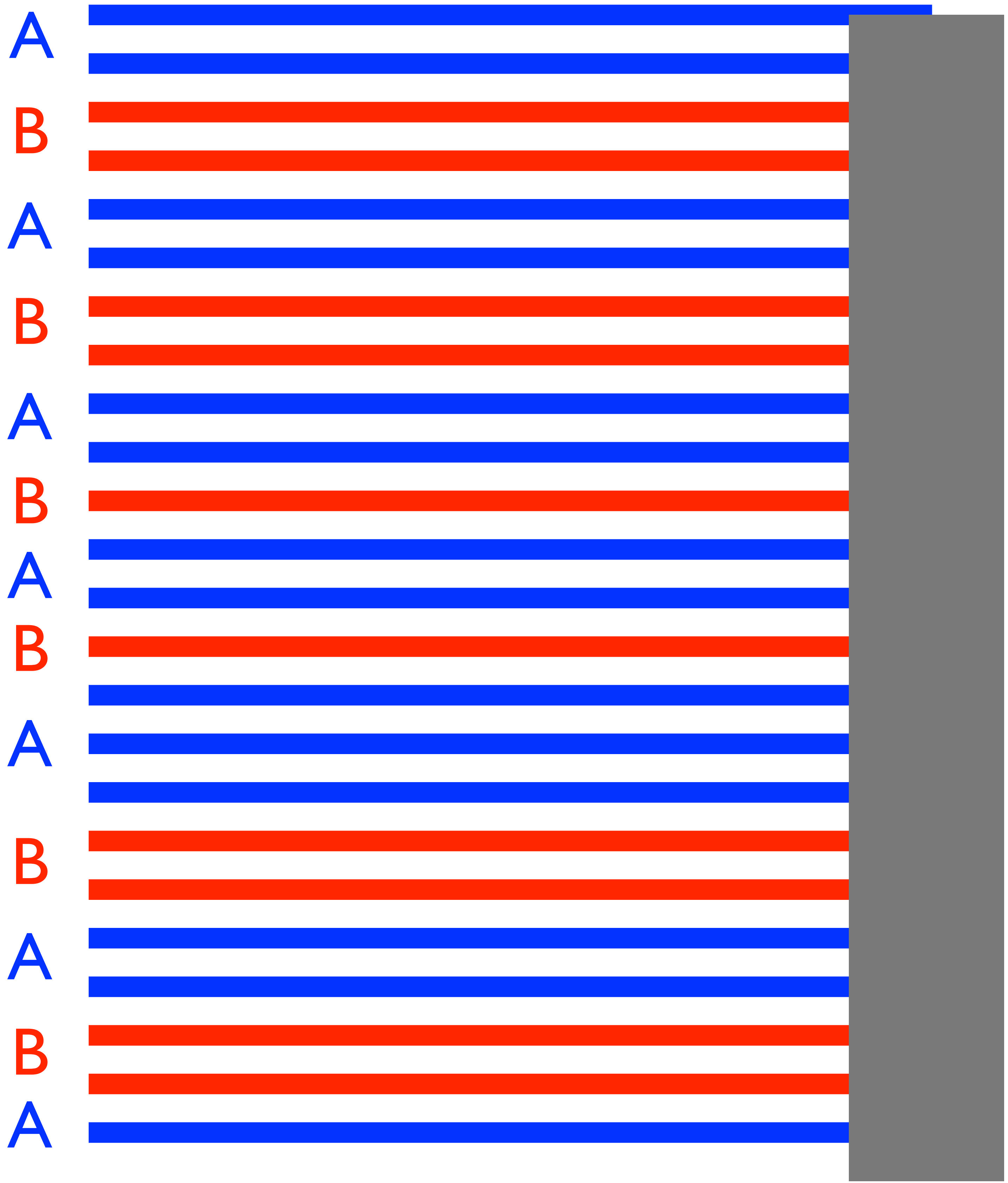
Predictive Analysis

topic segmentation example



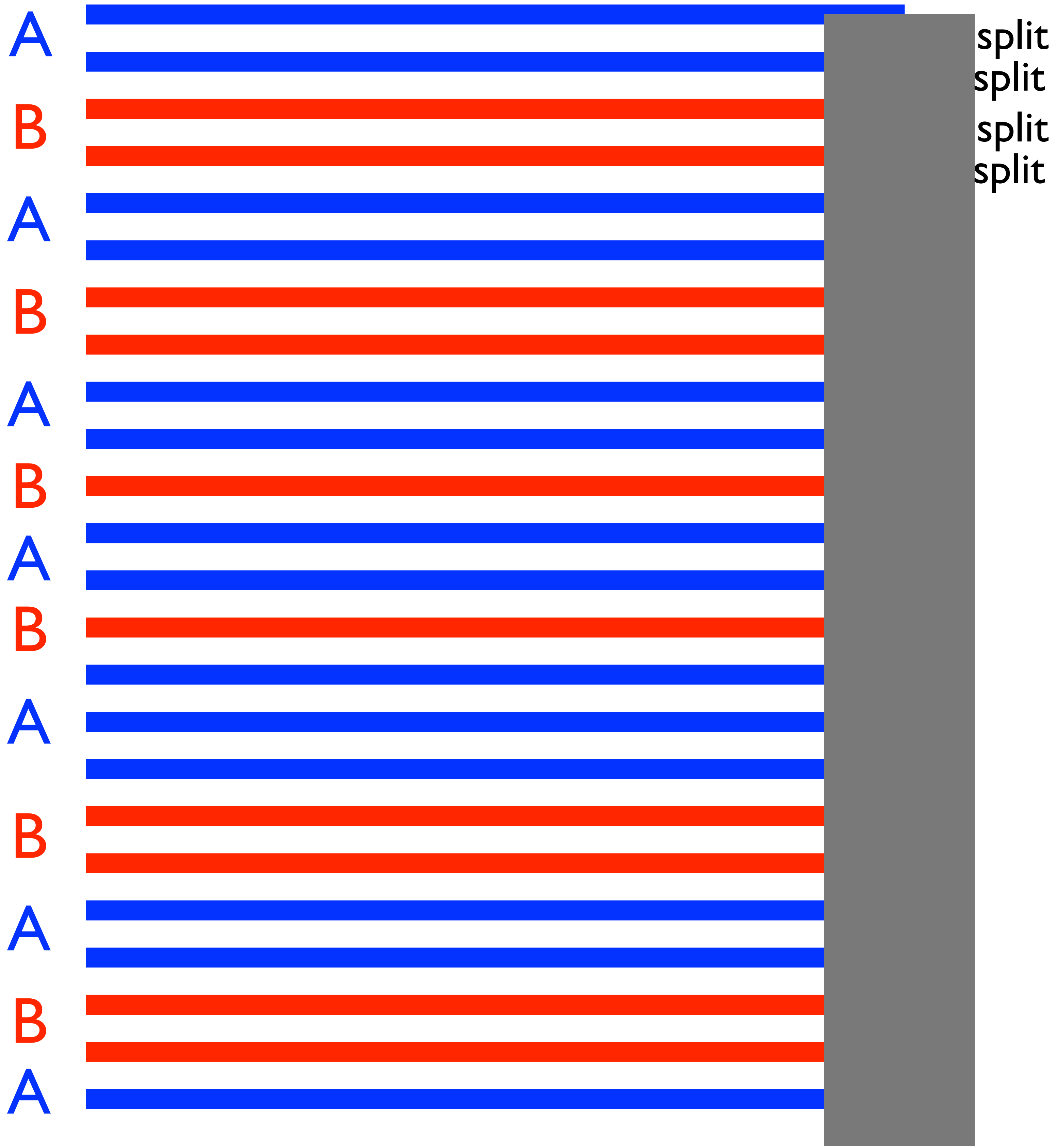
Predictive Analysis

topic segmentation example: instances



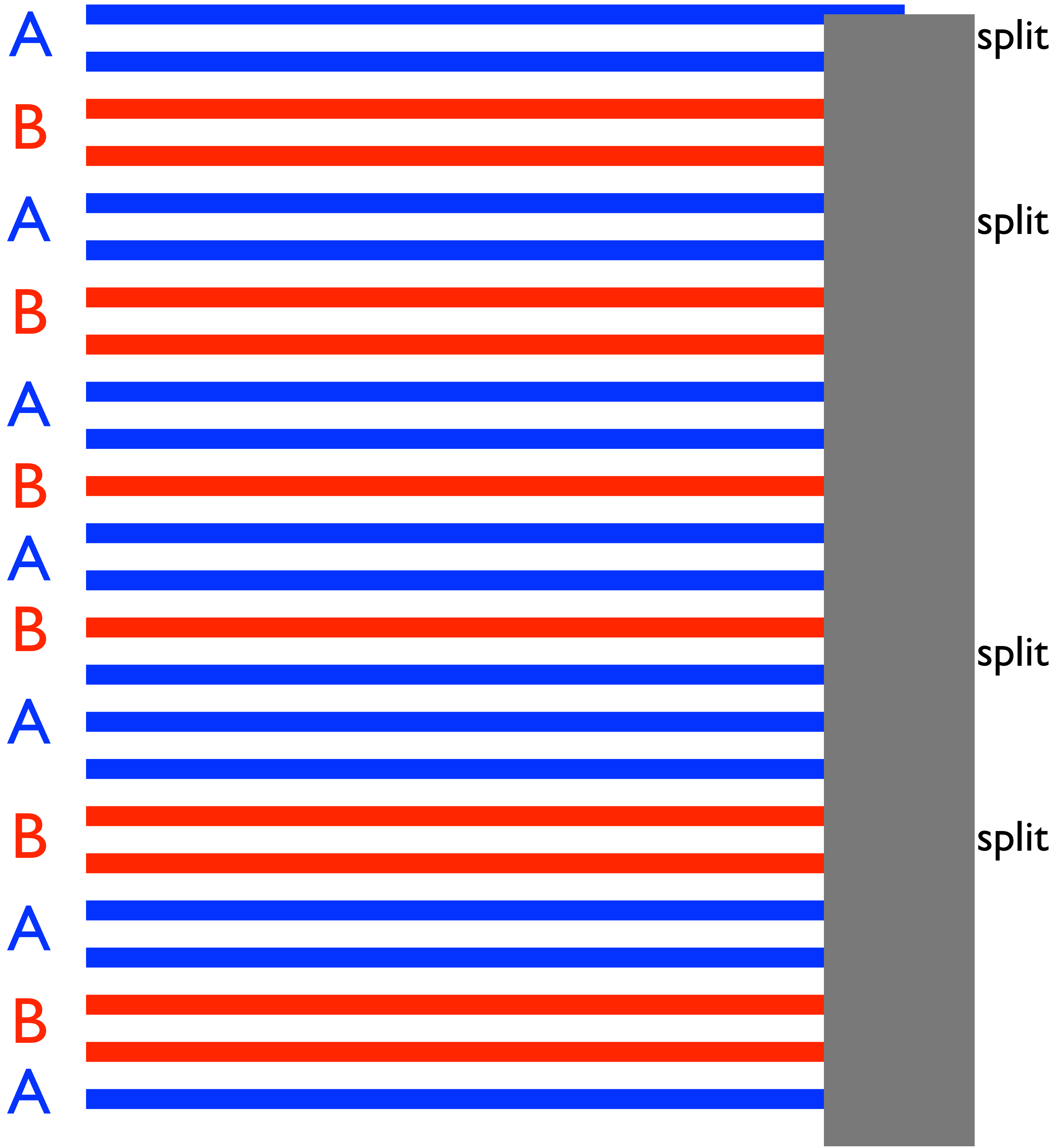
Predictive Analysis

topic segmentation example: independent instances?



Predictive Analysis

topic segmentation example: independent instances?



Predictive Analysis

discourse analysis in MOOCs: independent instances?

- Question: requests information about the course content
- Answer: contributes information in response to a question
- Issue: expresses a problem with the course management
- Issue Resolution: attempts to resolve a previously raised issue
- Positive Ack: positive sentiment about a previous post
- Negative Ack: negative sentiment about a previous post
- Other: serves a different purpose

Predictive Analysis

turning data into (training and test) instances

- There are learning algorithms that incorporate relational constraints between predictions
- However, they are beyond the scope of this class
- We'll be covering algorithms that make independent predictions on instances
- That said, many algorithms output prediction confidence values
- Heuristics can be used to favor certain types of joint outcomes more than others

Predictive Analysis

questions

Predictive Analysis
training and test data

- We want our model to “learn” to recognize a concept
- So, what does it mean to <u>learn</u>?

Predictive Analysis
training and test data

- The machine learning definition of “learning:”

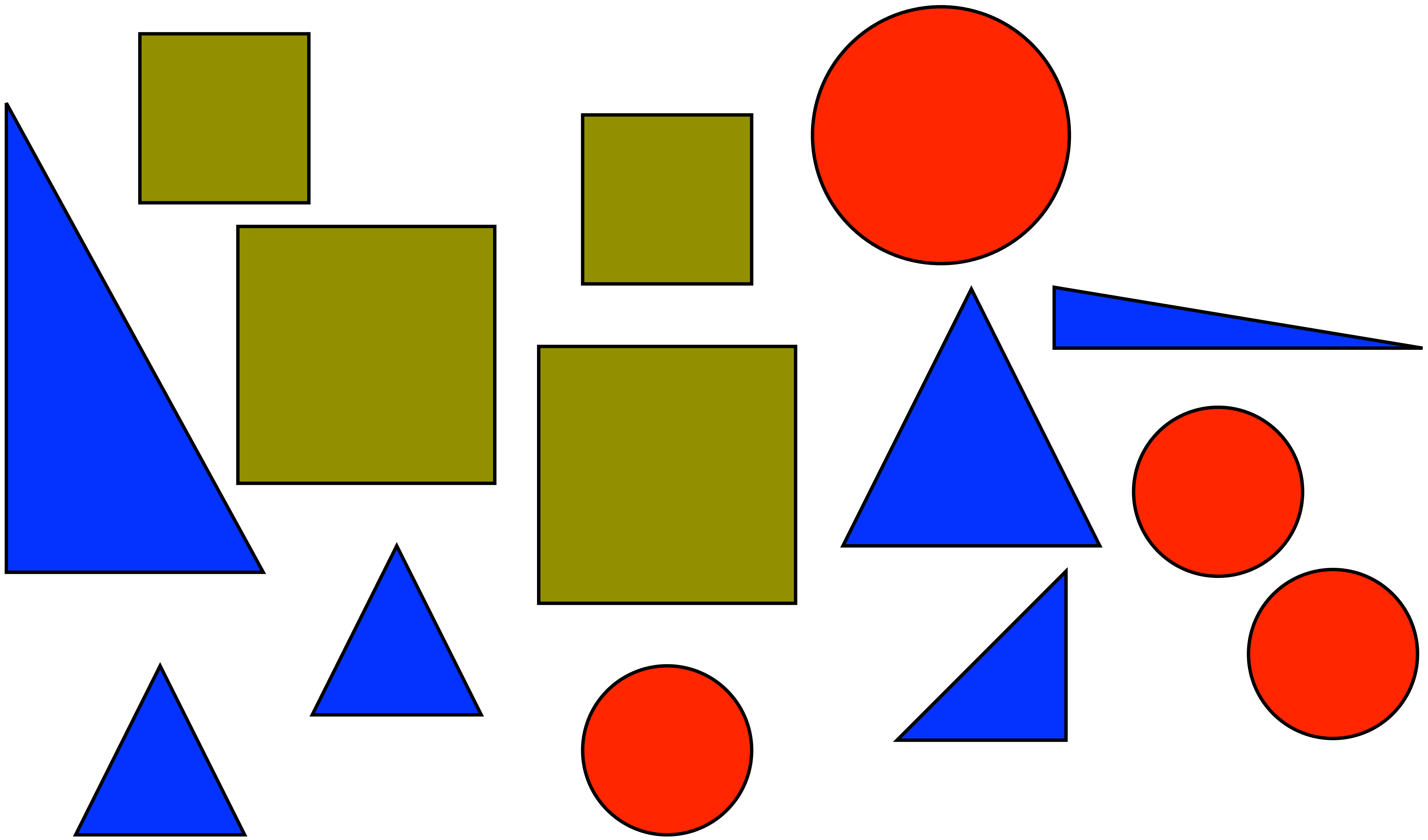
  A machine “learns” with respect to a particular task T, performance metric P, and experience E, if the system improves its performance P at task T (on new data) following experience E. -- Tom Mitchell

Predictive Analysis
training and test data

- We want our model to improve its <u>generalization performance</u>!
- That is, its performance on previously unseen data!
- Generalize: to derive or induce a general conception or principle from particulars. -- Merriam-Webster
- In order to test generalization performance, the training and test data cannot be the same.
- Why?

Training data + Representation

what could possibly go wrong?



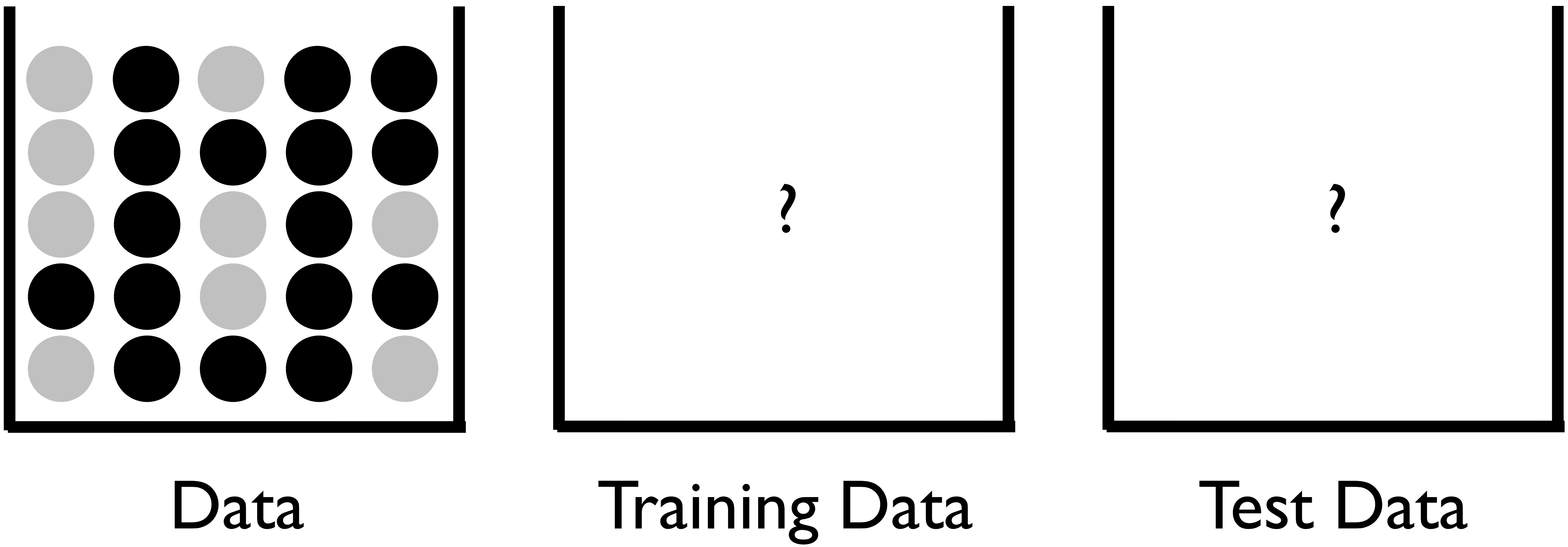
Predictive Analysis

training and test data

- While we don’t want to test on training data, models usually perform the best when the training and test set are derived from the same “probability distribution”.
- What does that mean?

Predictive Analysis

training and test data



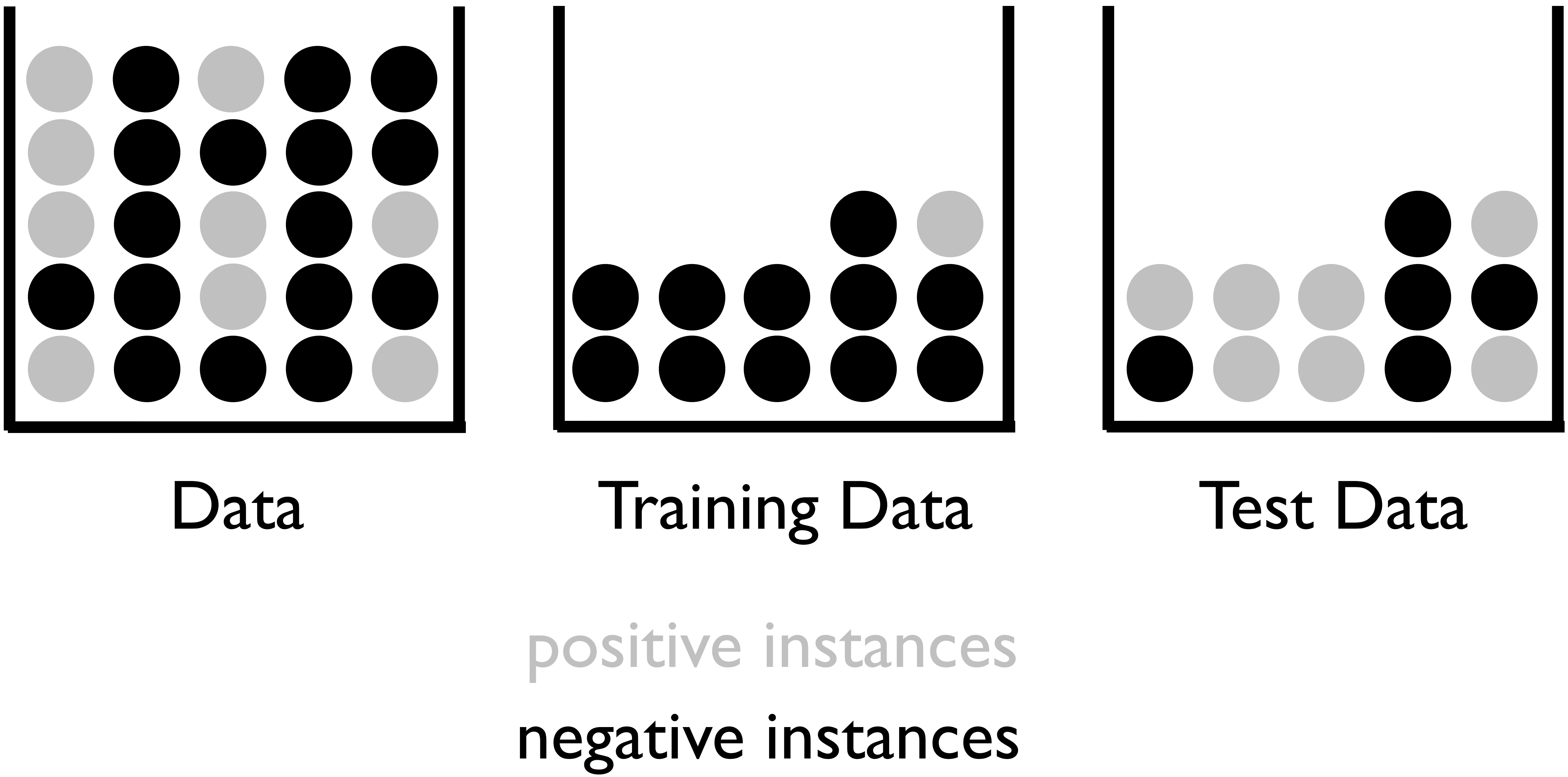
positive instances

negative instances

Predictive Analysis

training and test data

- Is this a good partitioning? Why or why not?



Predictive Analysis

training and test data

Data Training Data Test Data

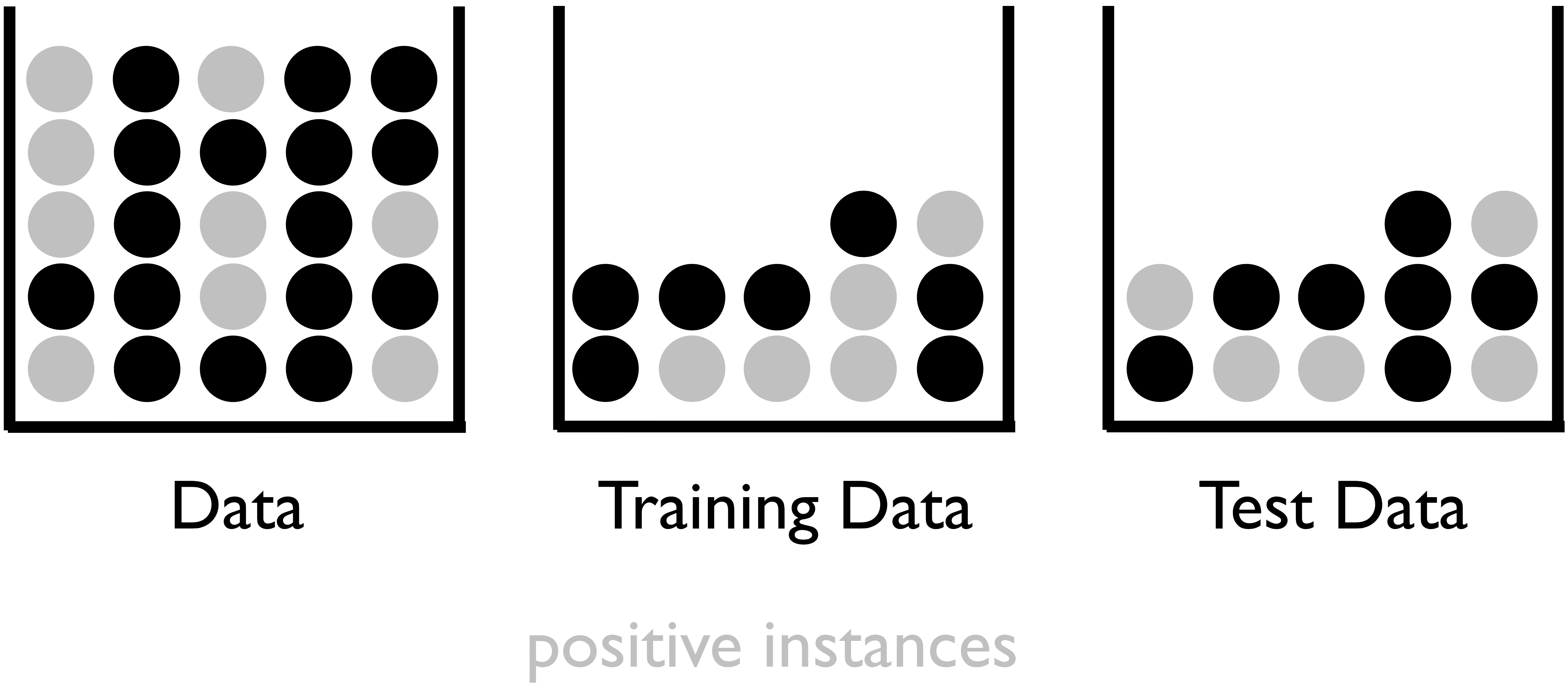
positive instances

negative instances

Predictive Analysis

training and test data

- Usually, random sampling should produce comparable (but not equal) data for training and testing



Predictive Analysis
training and test data

- Models usually perform the best when the training and test set have:
  - a similar proportion of positive and negative examples
  - a similar co-occurrence of feature-values and each target class value

Predictive Analysis
training and test data

- Caution: in some situations, partitioning the data randomly might inflate performance in an unrealistic way!
- How the data is split into training and test sets determines what we can claim about generalization performance
- The appropriate split between training and test sets is usually determined on a case-by-case basis

Predictive Analysis

Email Span Detection

- Suppose we want to train an email spam classifier
- Obviously, we want it to generalize to new emails (i.e., not in the training set)
- But, what are some other "things" we might want to classifier to generalize beyond?

Predictive Analysis

discussion

- Spam detection: should the training and test sets contain email messages from the same sender, same recipient, and/or same timeframe?
- Topic segmentation: should the training and test sets contain potential boundaries from the same discourse?
- Opinion mining for movie reviews: should the training and test sets contain reviews for the same movie?
- Sentiment analysis: should the training and test sets contain blog posts from the same discussion thread?

Predictive Analysis

questions

- Is a particular concept appropriate for predictive analysis?
- What should the unit of analysis be?
- How should I divide the data into training and test sets?
- What is a good feature representation for this task?
- What type of learning algorithm should I use?

Predictive Analysis
three types of classifiers

- Linear classifiers
- Decision tree classifiers
- Instance-based classifiers

Predictive Analysis
three types of classifiers

- All types of classifiers learn to make predictions based on the input feature values
- However, different types of classifiers combine the input feature values in different ways
- Chapter 3 in the book refers to a trained model as knowledge representation

Predictive Analysis

linear classifiers: perceptron algorithm

$$y = \begin{cases} 1 & \text{if } w_0 + \sum_{j=1}^{n} w_j x_j > 0 \\ 0 & \text{otherwise} \end{cases}$$

Predictive Analysis

linear classifiers: perceptron algorithm

$$y = \begin{cases} \boxed{1} & \text{if } \boxed{w_0} + \sum_{j=1}^{n} \boxed{w_j} x_j > 0 \\ \boxed{0} & \text{otherwise} \end{cases}$$

parameters learned by the model

predicted value (e.g., 1 = positive, 0 = negative)

Predictive Analysis

linear classifiers: perceptron algorithm

test instance

f_1	f_2	f_3
0.5	1	0.2

model weights

w_0	w_1	w_2	w_3
2	-5	2	1

output = 2 + (0.50 x -5) + (1.0 x 2) + (0.2 x 1)

output = 1.7

output prediction = positive

Predictive Analysis

linear classifiers: perceptron algorithm

test instance

f_1	f_2	f_3
0.5	1	0.2

model weights

w_0	w_1	w_2	w_3
2	-5	2	1

output = 2 + $\boxed{(0.50 \times -5)}$ + (1.0 x 2) + (0.2 x 1)

tput = 1.7

diction = positive

According to this model, f_1 has an inverse relation with "positive"

Predictive Analysis

linear classifiers: perceptron algorithm

test instance

f_1	f_2	f_3
0.5	1	0.2

model weights

w_0	w_1	w_2	w_3
2	-5	2	1

$$\text{output} = 2 + (0.50 \times -5) + \boxed{(1.0 \times 2)} + (0.2 \times 1)$$

ou

output pre

According to this model, f_2 has a positive relation with "positive"

Predictive Analysis

linear classifiers: perceptron algorithm

test instance

f_1	f_2	f_3
0.5	1	0.2

model weights

w_0	w_1	w_2	w_3
2	-5	2	1

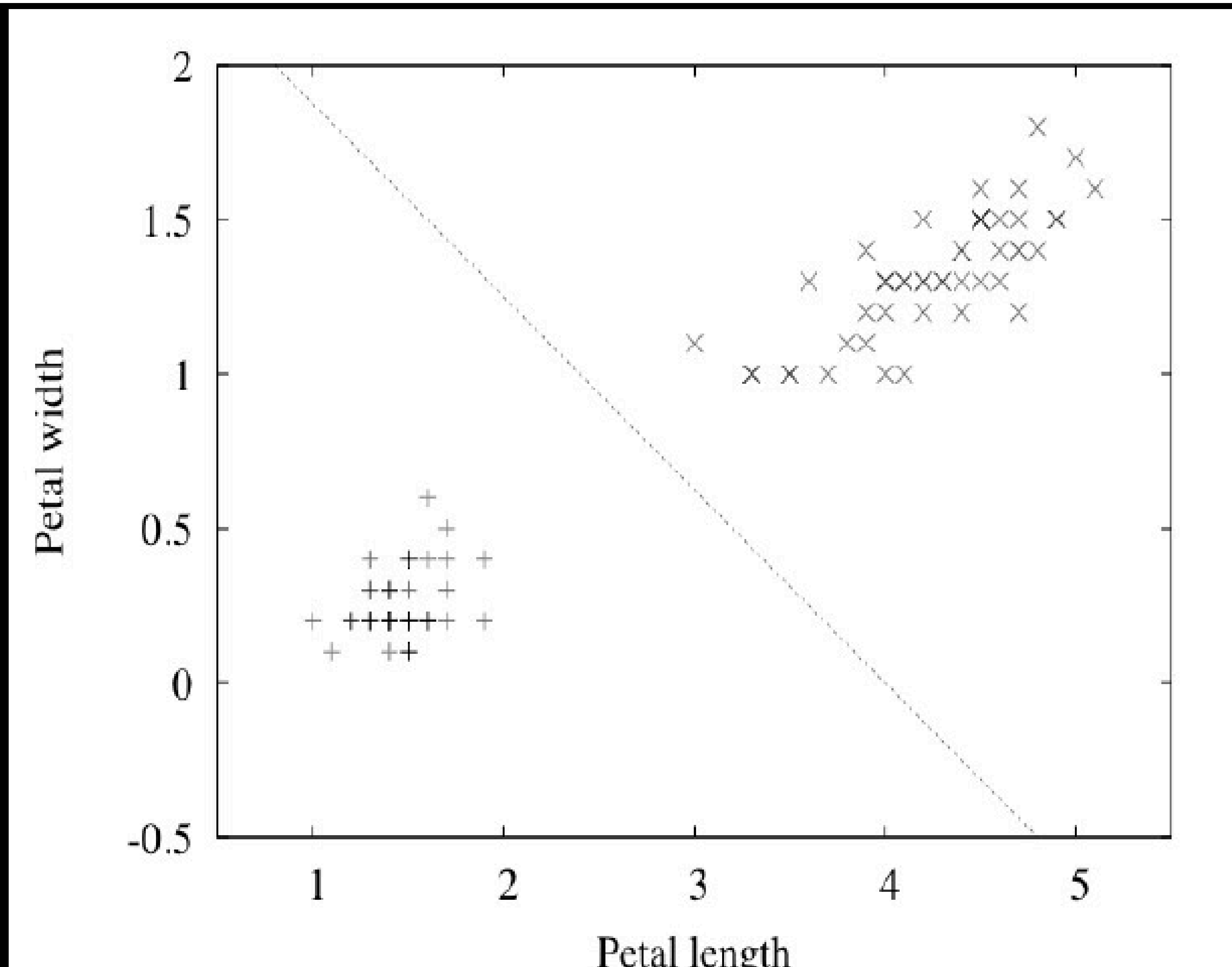
$$\text{output} = 2 + (0.50 \times -5) + (1.0 \times 2) + \boxed{(0.2 \times 1)}$$

output = 1.7

output prediction =

According to this model, f_3 has a positive, but weaker, relation with "positive"

Predictive Analysis
linear classifiers: perceptron algorithm

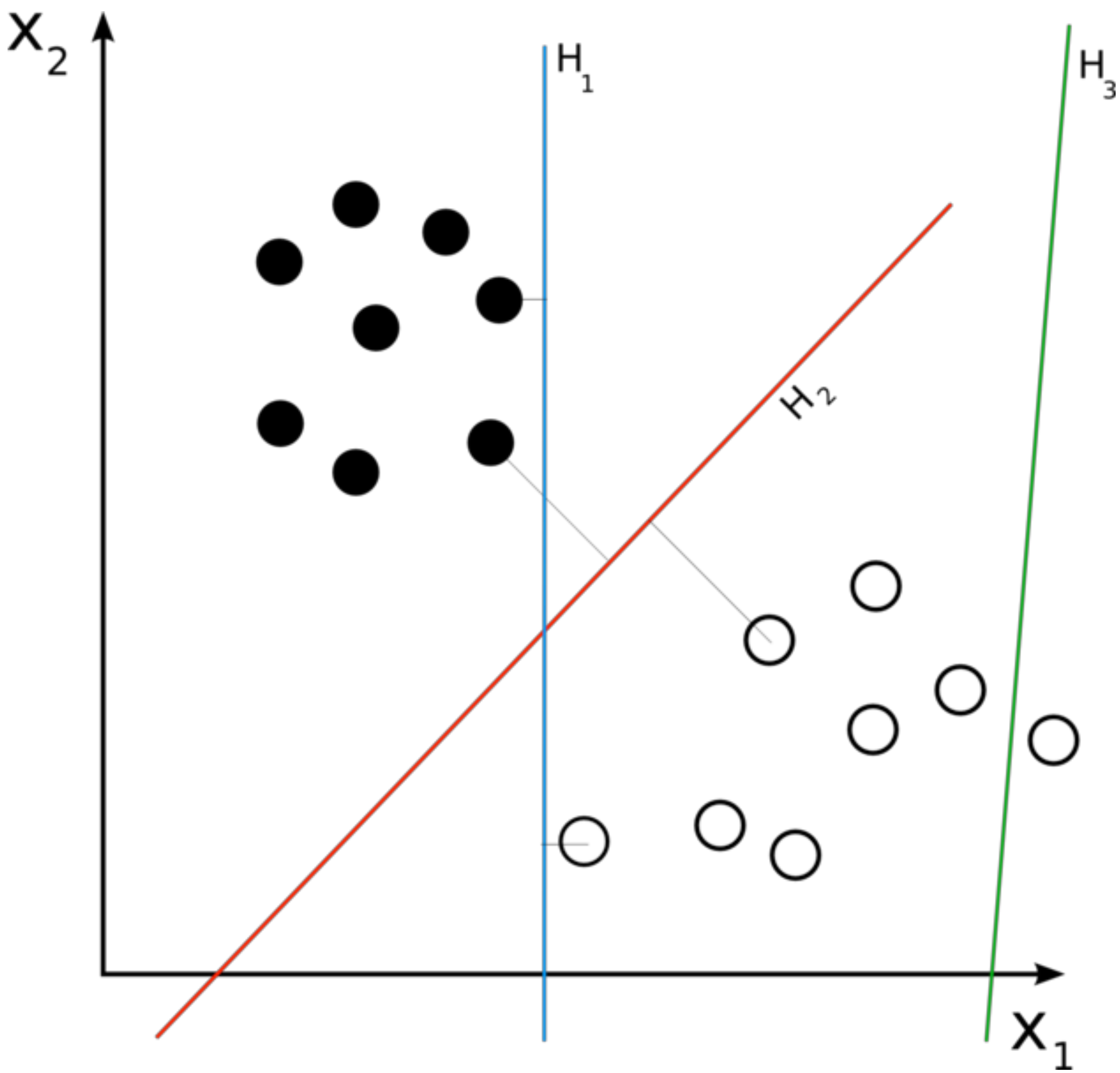


$$2.0 - 0.5\text{PETAL-LENGTH} - 0.8\text{PETAL-WIDTH} = 0$$

(two-feature example borrowed from Witten *et al.* textbook)

Predictive Analysis

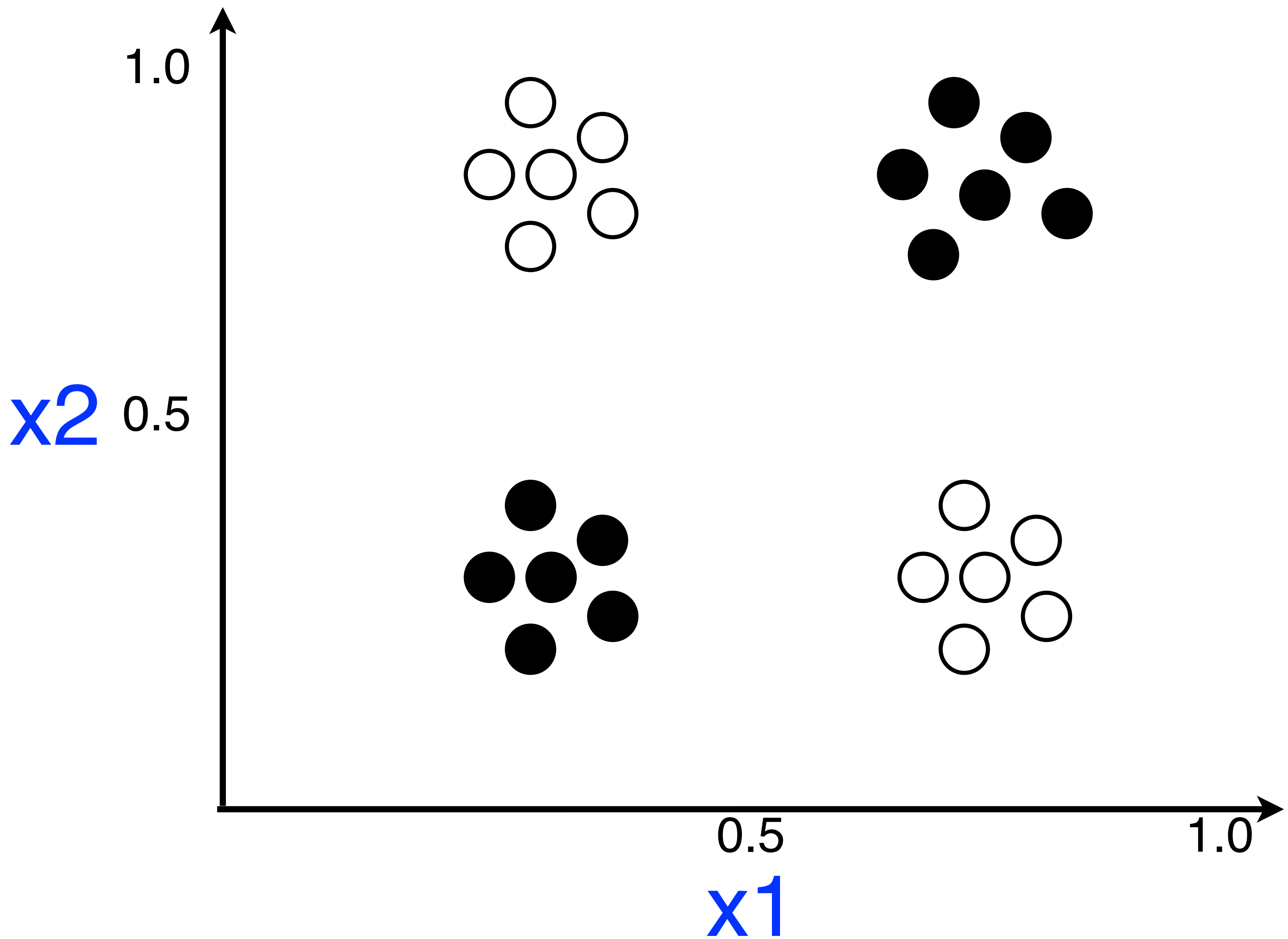
linear classifiers: perceptron algorithm



(source: http://en.wikipedia.org/wiki/File:Svm_separating_hyperplanes.png)

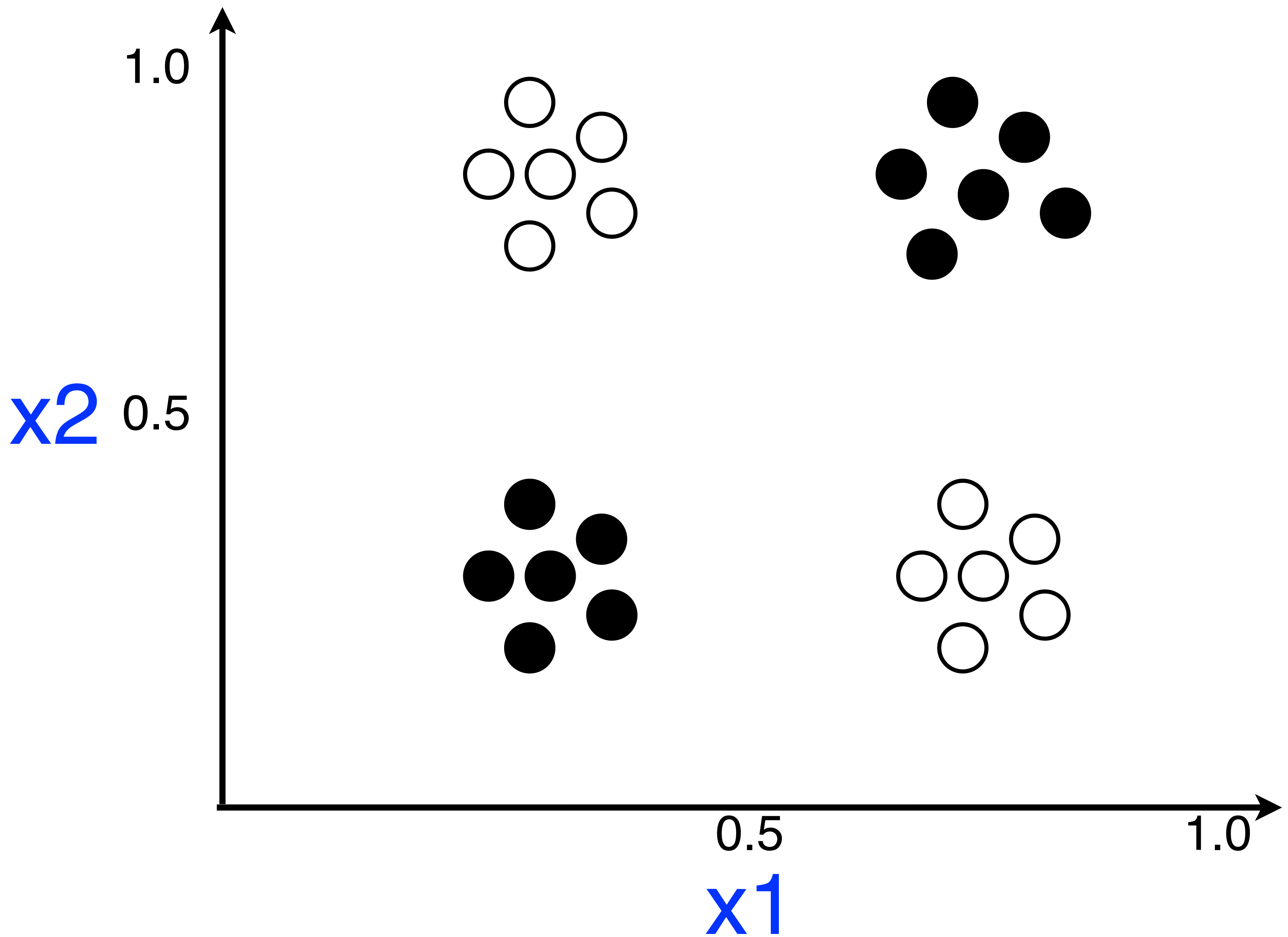
Predictive Analysis

linear classifiers: perceptron algorithm



- Would a linear classifier do well on positive (black) and negative (white) data that looks like this?

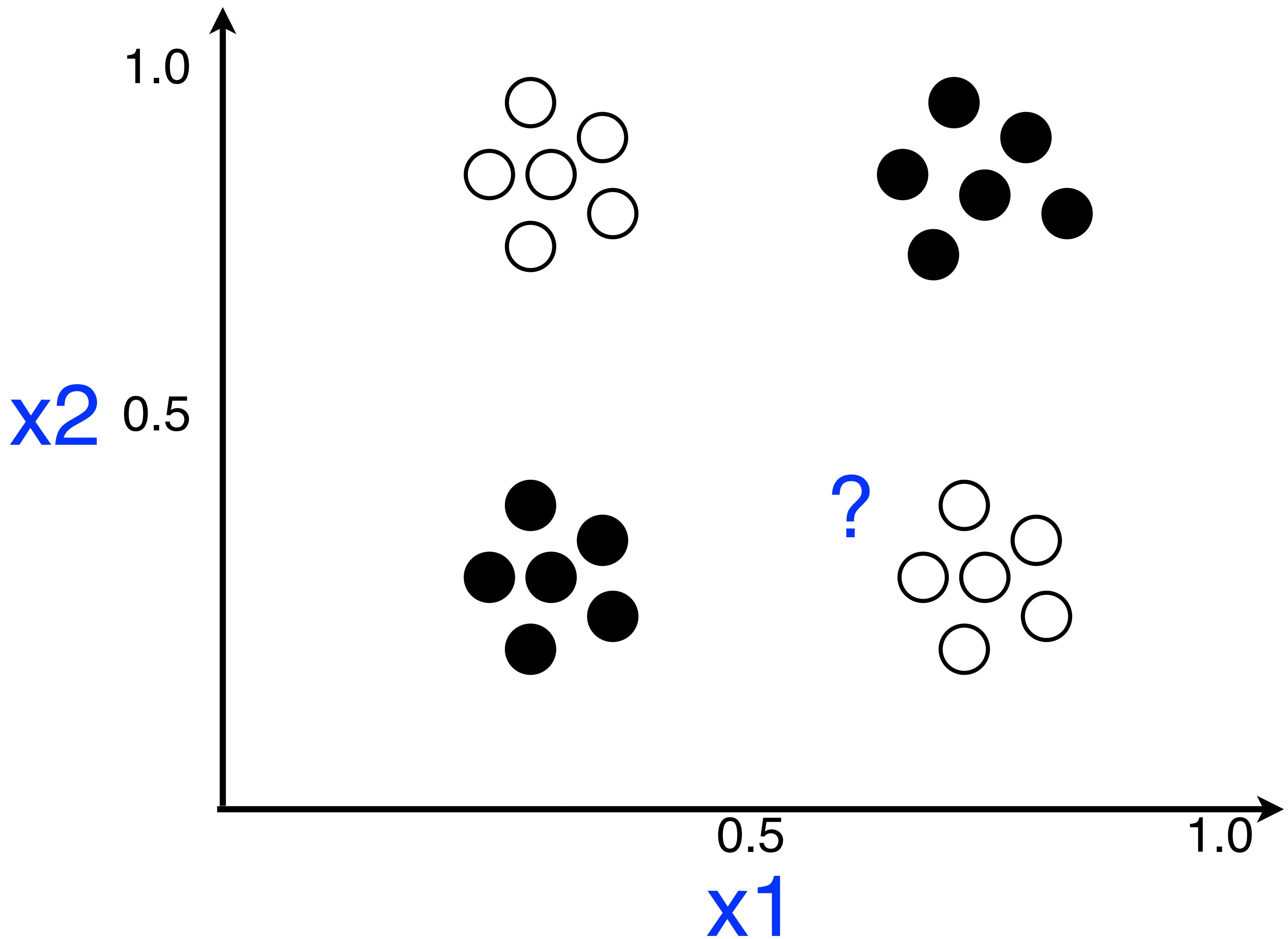
Predictive Analysis
decision tree classifiers



- Draw a decision tree that would perform perfectly on this training data!

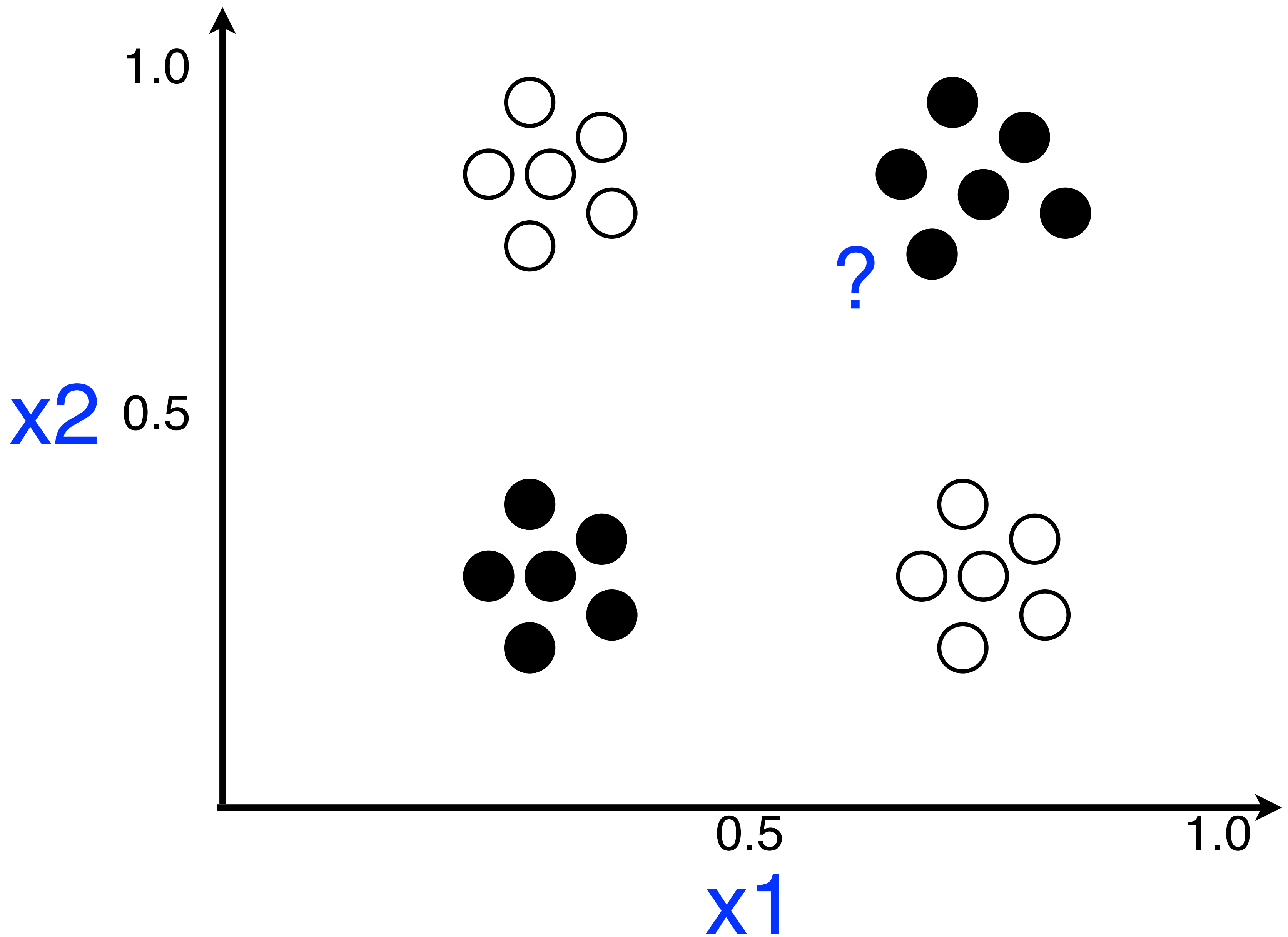
Predictive Analysis

instance-based classifiers



- predict the class associated with the most similar training examples

Predictive Analysis
instance-based classifiers



- predict the class associated with the most similar training examples

Predictive Analysis
instance-based classifiers

- Assumption: instances with similar feature values should have a similar label
- Given a test instance, predict the label associated with its nearest neighbors
- There are many different similarity metrics for computing distance between training/test instances
- There are many ways of combining labels from multiple training instances

Predictive Analysis
questions

- Is a particular concept appropriate for predictive analysis?
- What should the unit of analysis be?
- How should I divide the data into training and test sets?
- What is a good feature representation for this task?
- What type of learning algorithm should I use?