Text Data Mining:
Predictive and Exploratory Analysis of Text

Jaime Arguello
jarguell@email.unc.edu

Outline

Introductions

What is Text Data Mining?

Predictive Analysis of Text: The Big Picture

Exploratory Analysis of Text: The Big Picture

Applications

Introductions

- Hello, my name is ______.
- I'm in the ______ program.
- I'm taking this course because I'd like to learn how to ______.

What is Text Data Mining?

- The science and practice of <u>building</u> and <u>evaluating</u> computer programs that automatically <u>detect</u> or <u>discover</u> <u>interesting</u> and <u>useful</u> things in collections of <u>natural language text</u>

Related Fields

- Machine Learning: developing computer programs that improve their performance with "experience"
- Data Mining: developing methods that discover patterns within large structured datasets
- Statistics: developing methods for the interpretation of data and experimental outcomes in reaching conclusions with a certain degree of confidence

Text Data Mining in this Course

- Predictive Analysis of Text
  - developing computer programs that automatically <u>recognize</u> or <u>detect</u> a particular concept within a span of text
- Exploratory Analysis of Text:
  - developing computer programs that automatically <u>discover</u> interesting and useful patterns or trends in text collections

Outline

Introductions

What is Text Data Mining?

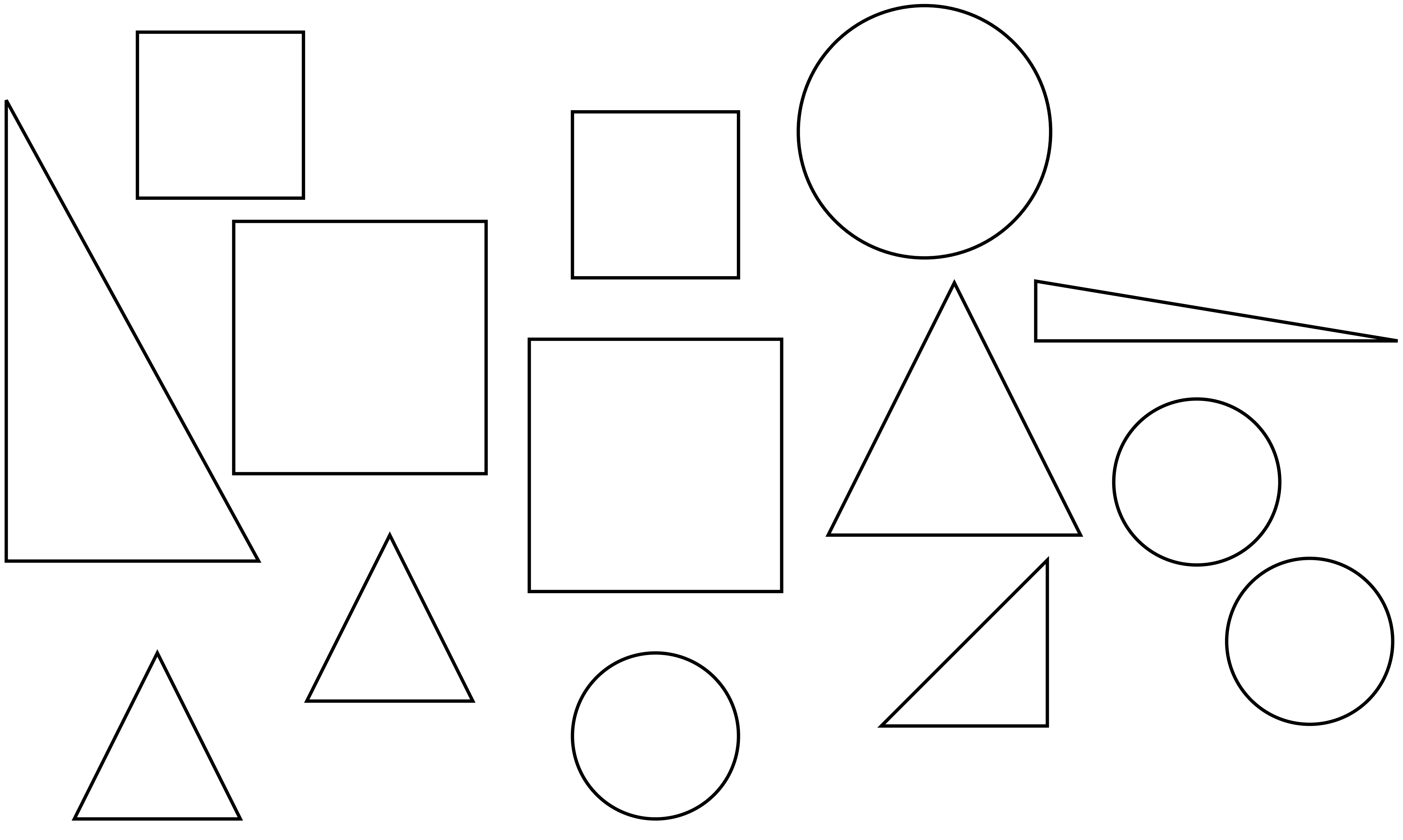
Predictive Analysis of Text: The Big Picture

Exploratory Analysis of Text: The Big Picture

Applications

Predictive Analysis

example: recognizing triangles



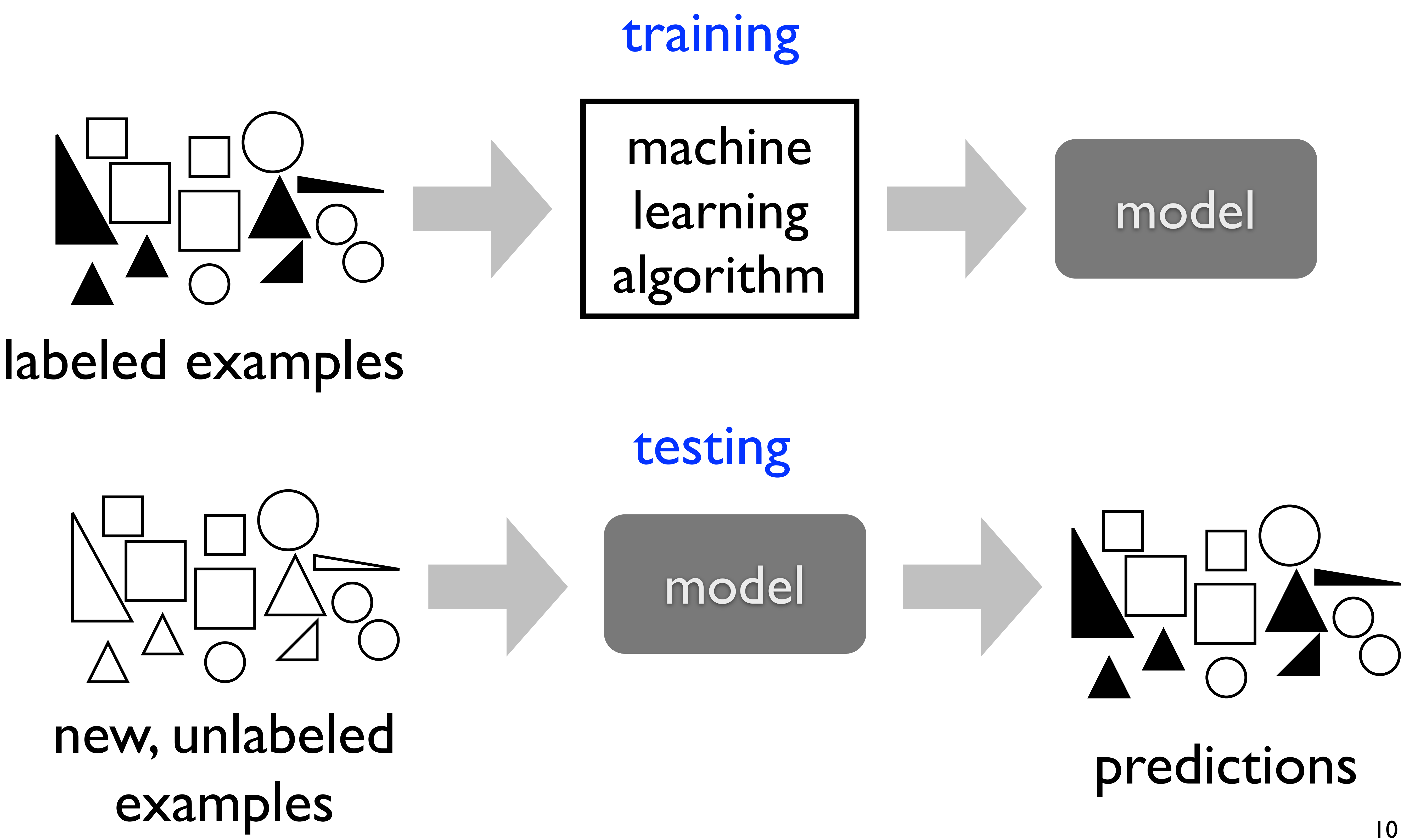
Predictive Analysis

example: recognizing triangles

- We could imagine writing a “triangle detector” by hand:
  - if shape has three sides, then shape = triangle.
  - otherwise, shape = other
- Alternatively, we could use supervised machine learning!

Predictive Analysis

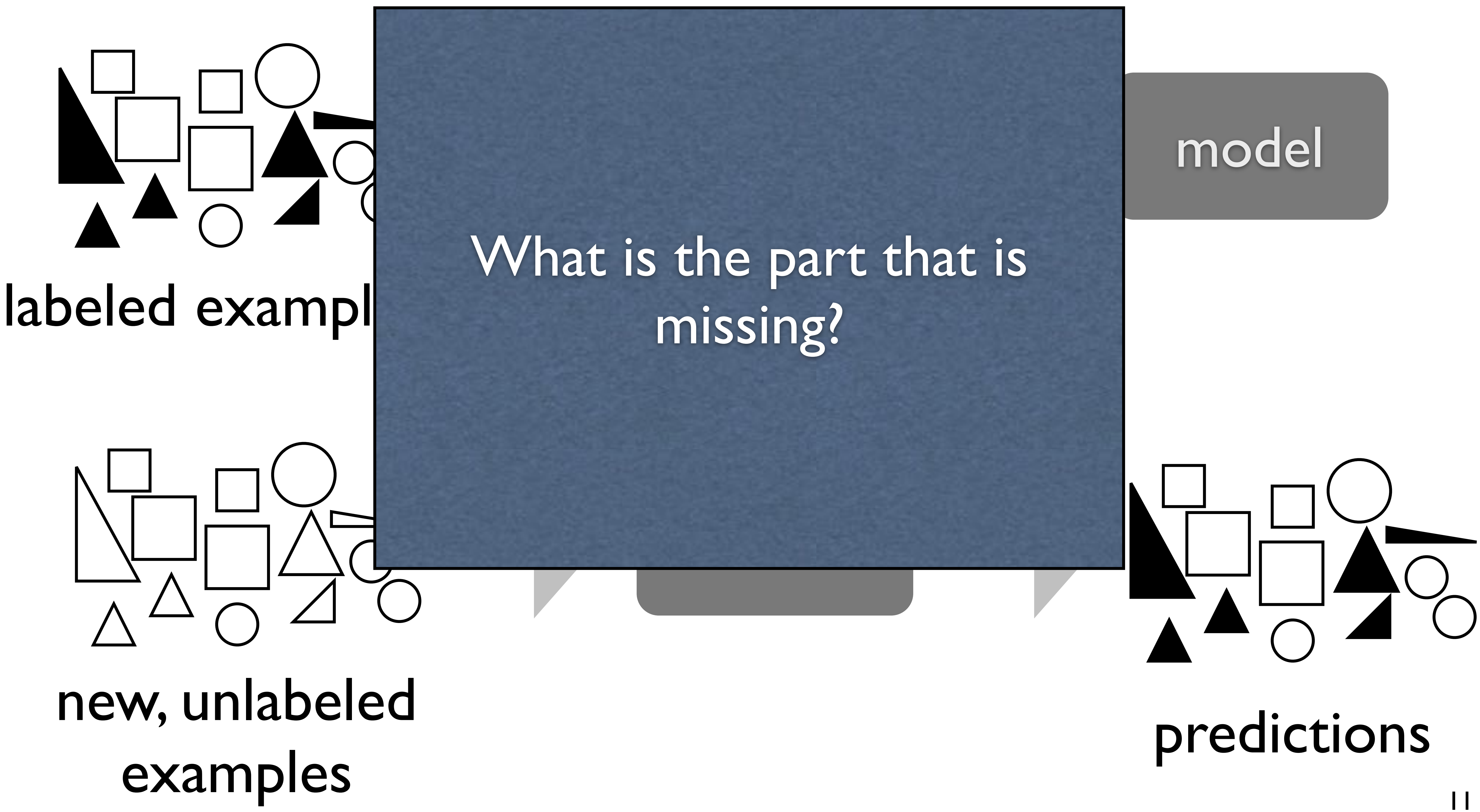
example: recognizing triangles



Predictive Analysis

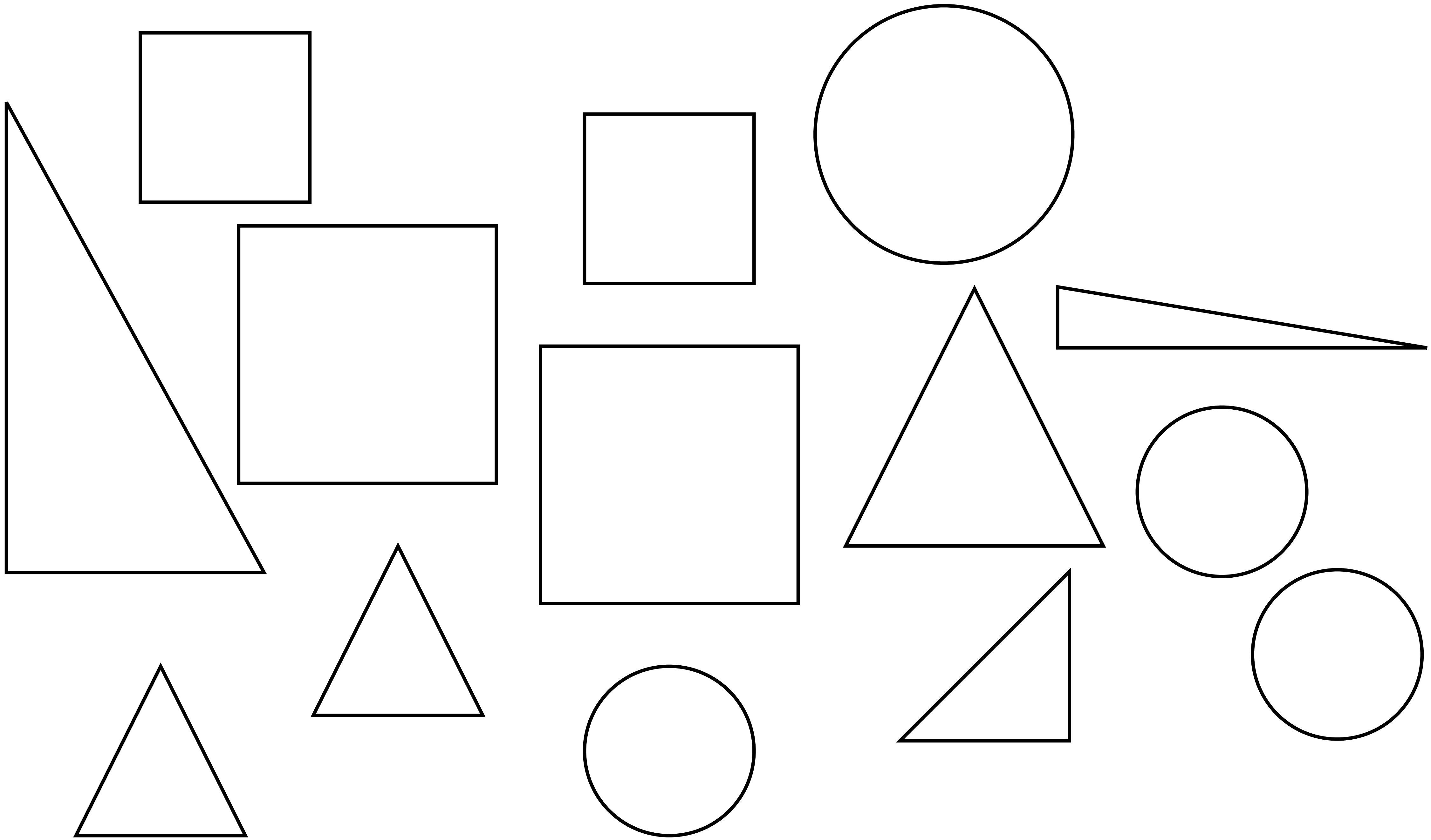
example: recognizing triangles

training



Predictive Analysis

raw data



Predictive Analysis

representation: features

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

example: recognizing triangles

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

basic ingredients

1. Training data: a set of 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

Highly influential!

1. Training data: 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 (mathematical) function that describes a predictive relationship between the feature values and the presence/absence 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

basic ingredients: the focus in this course

1. Training data: a set of 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: uses the training data to learn a predictive model of the "concept"

Predictive Analysis

basic ingredients: the focus in this course

4. Model: describes a predictive relationship between feature values and the presence/absence 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

applications

- Topic categorization
- Opinion mining
- Sentiment analysis
- Bias or viewpoint detection
- Discourse analysis
- Forecasting and nowcasting
- Any other ideas?

Predictive Analysis

example: recognizing triangles

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

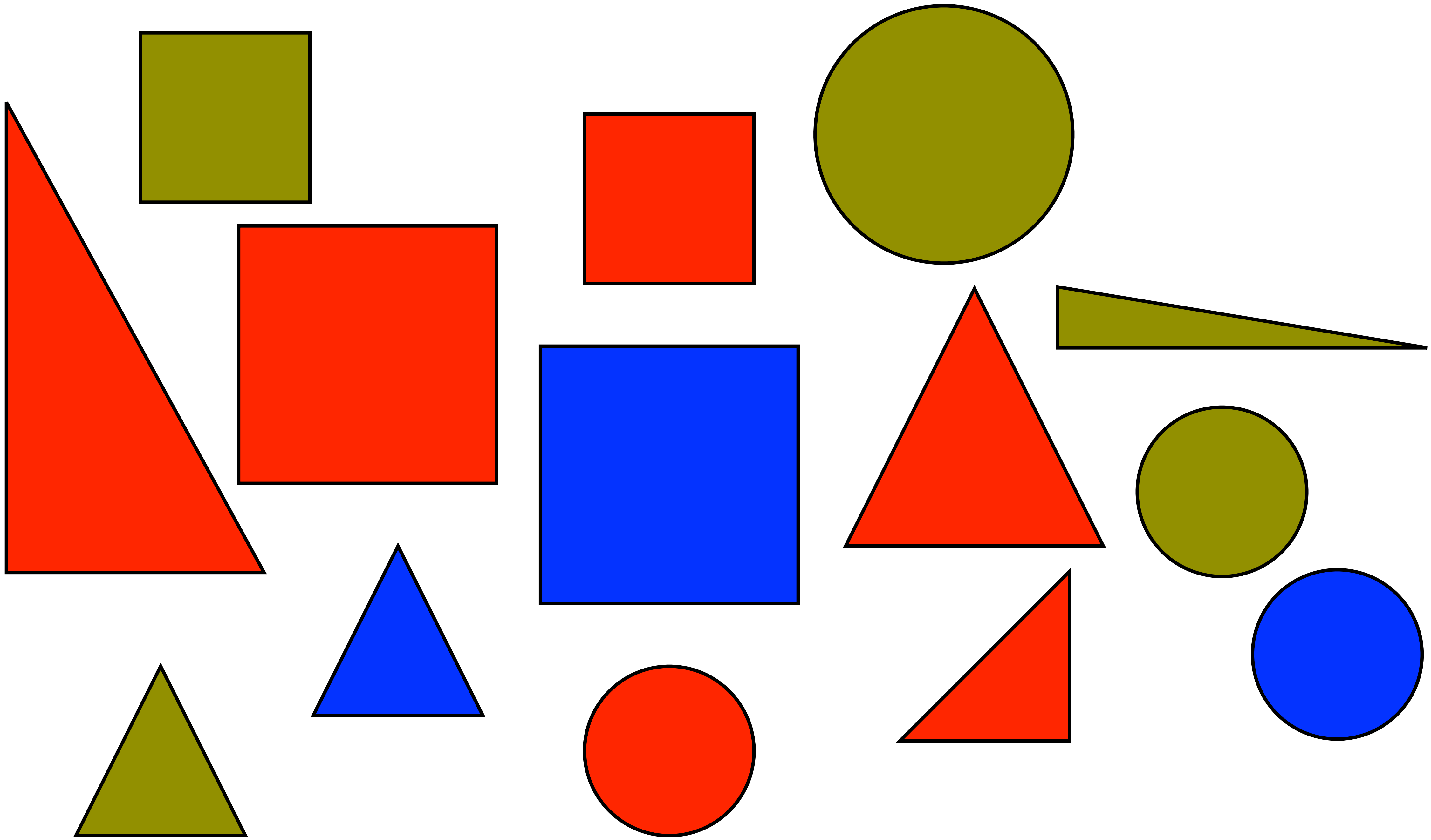
predictions

What Could Possibly Go Wrong?

1. Bad feature representation
2. Bad data + misleading correlations
3. Noisy labels for training and testing
4. Bad learning algorithm
5. Misleading evaluation metric

Training data + Representation

what could possibly go wrong?



Training data + Representation

what could possibly go wrong?

color	size	90 deg. angle	equal sides	label
red	big	yes	no	yes
green	big	no	yes	yes
blue	small	no	yes	no
blue	small	yes	yes	no
⋮	⋮	⋮	⋮	⋮
red	big	no	yes	yes

Training data + Representation

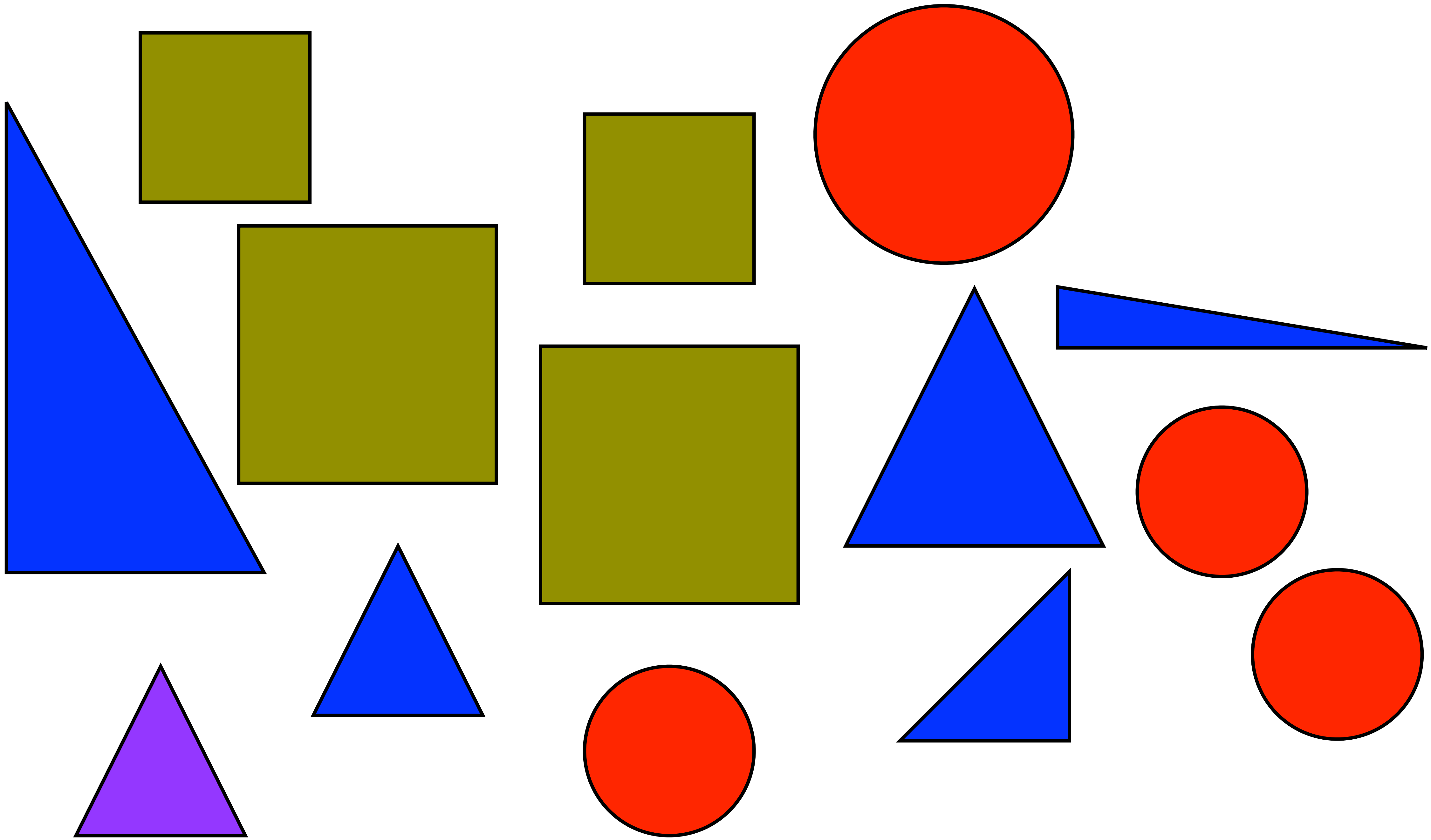
what could possibly go wrong?

color	size	90 deg. angle	equal sides	label
red	big	yes	no	yes
green	big	no	yes	yes
blue	small	no	yes	no
blue	small	yes	yes	no
⋮	⋮	⋮	⋮	⋮
red	big	no	yes	yes

1. bad feature representation!

Training data + Representation

what could possibly go wrong?



Training data + Representation

what could possibly go wrong?

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

Training data + Representation

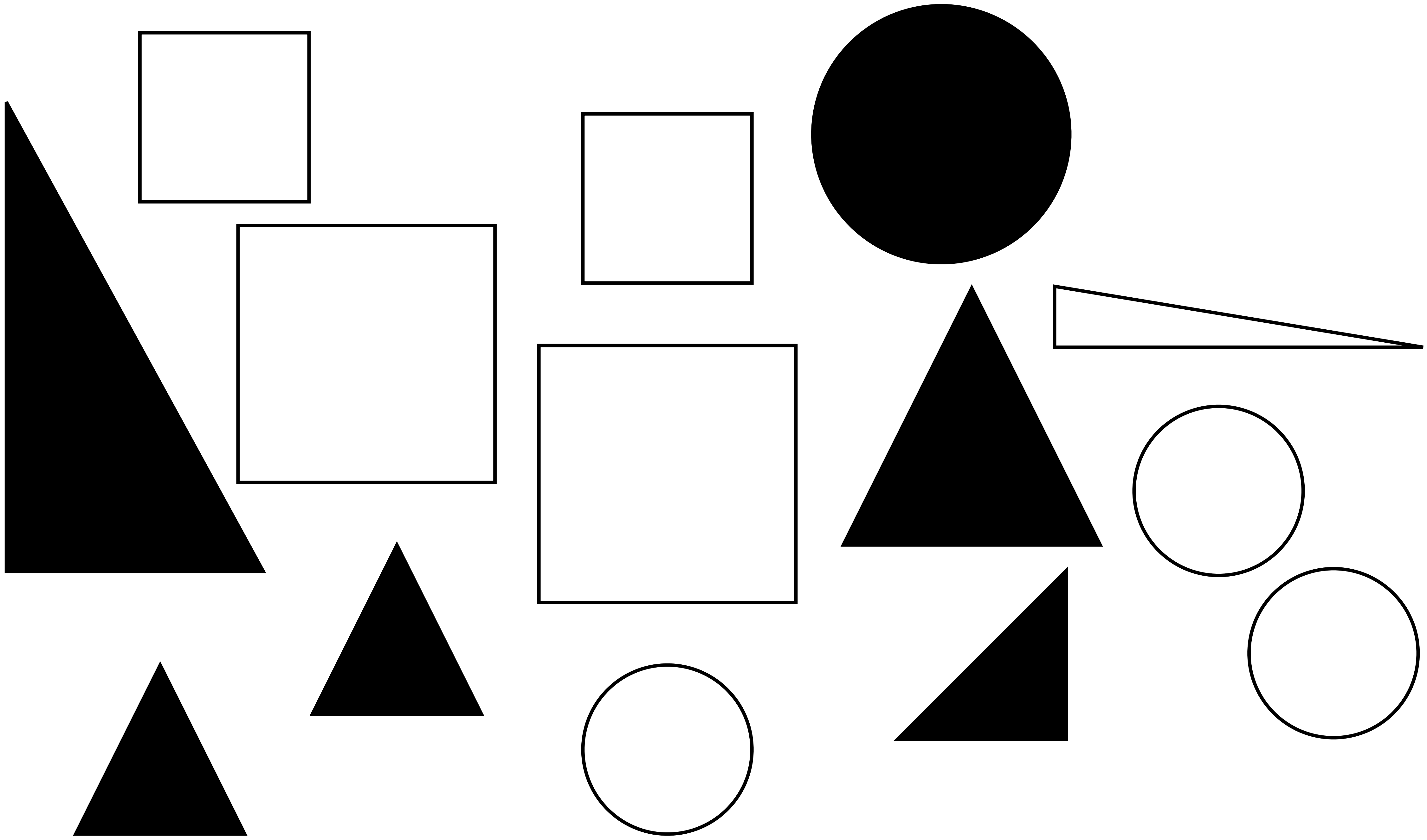
what could possibly go wrong?

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

2. bad data + misleading correlations

Training data + Representation

what could possibly go wrong?



Training data + Representation

what could possibly go wrong?

color	size	# sides	equal sides	...	label
white	big	3	no	...	yes
white	big	3	no	...	no
white	small	inf	yes	...	yes
white	small	4	yes	...	no
⋮	⋮	⋮	⋮	⋮	⋮
white	big	3	yes	...	yes

3. noisy training data!

What Could Possibly Go Wrong?

1. Bad feature representation
2. Bad data + misleading correlations
3. Noisy labels for training and testing
4. Bad learning algorithm
5. Misleading evaluation metric

Learning Algorithm + Model
what could possibly go wrong?

- Linear classifier

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

Learning Algorithm + Model
what could possibly go wrong?

- Linear classifier

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

parameters learned by the model

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

Learning Algorithm + Model

what could possibly go wrong?

test instance

f_1	f_2	f_3
0.5	1	0.2

model parameters

w_0	w_1	w_2	w_3
2	-5	2	1

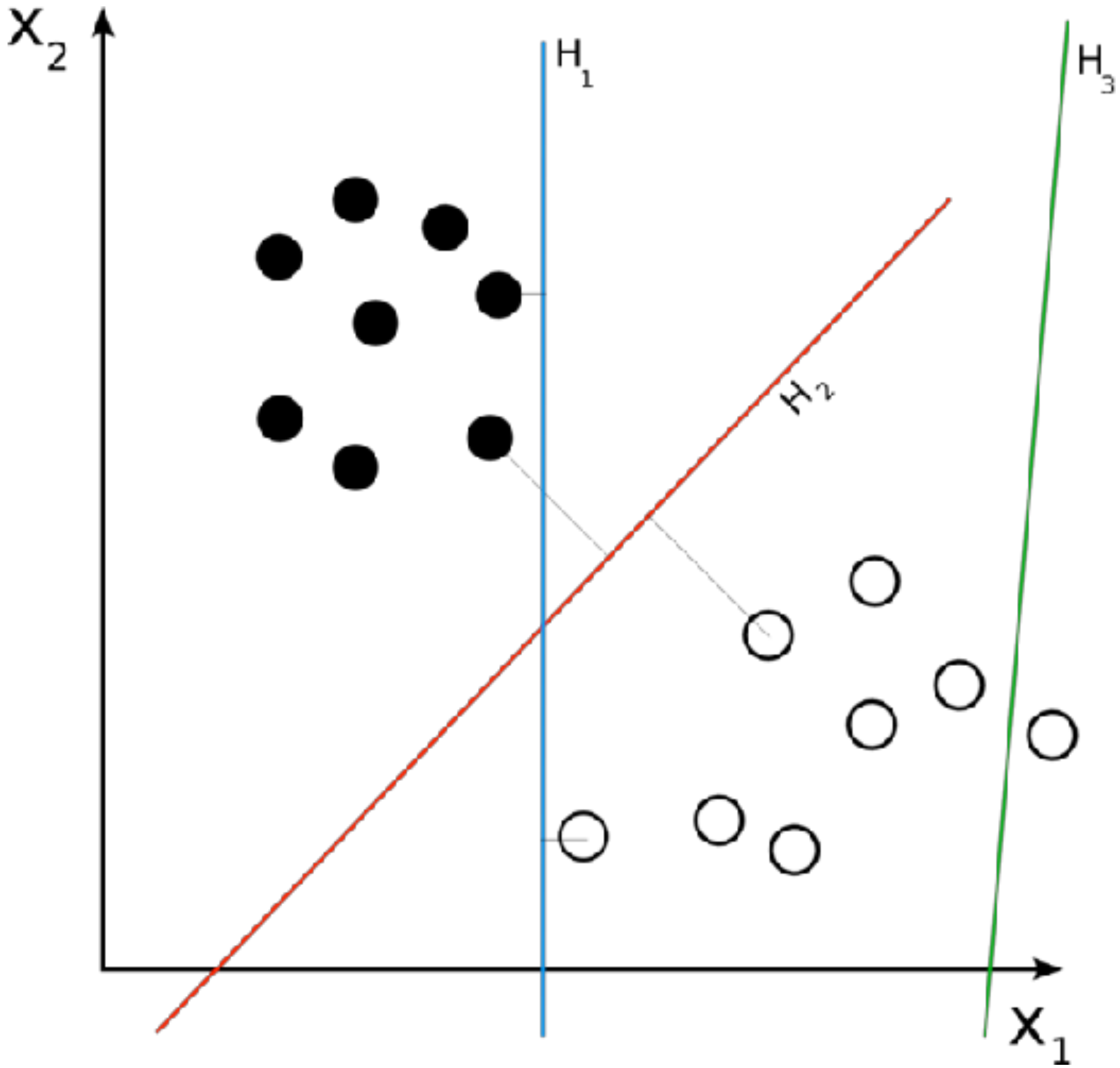
output = 2.0 + (0.50 x -5) + (1 x 2) + (0.2 x 1)

output = 1.7

output prediction = positive

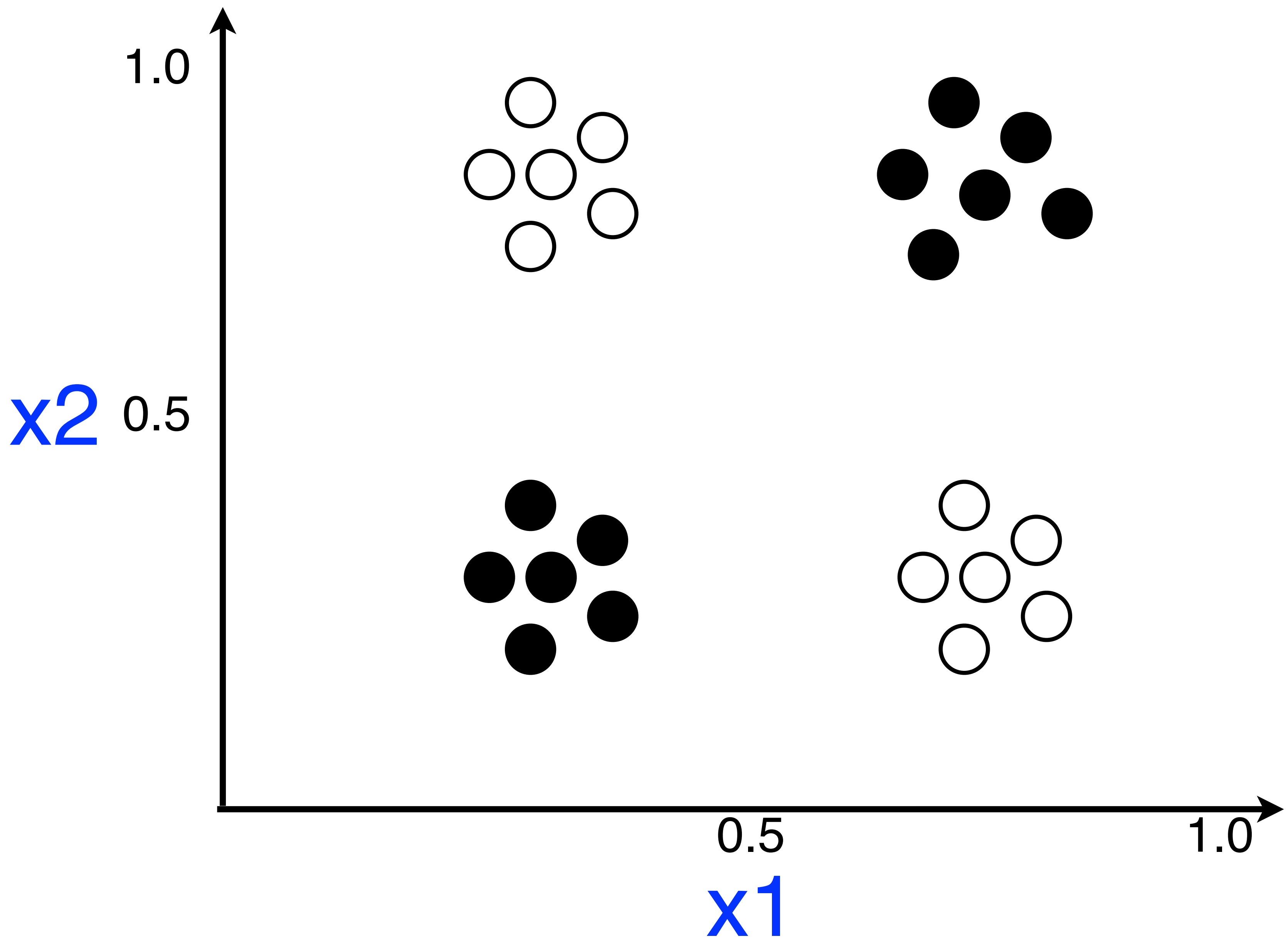
Learning Algorithm + Model

what could possibly go wrong?



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

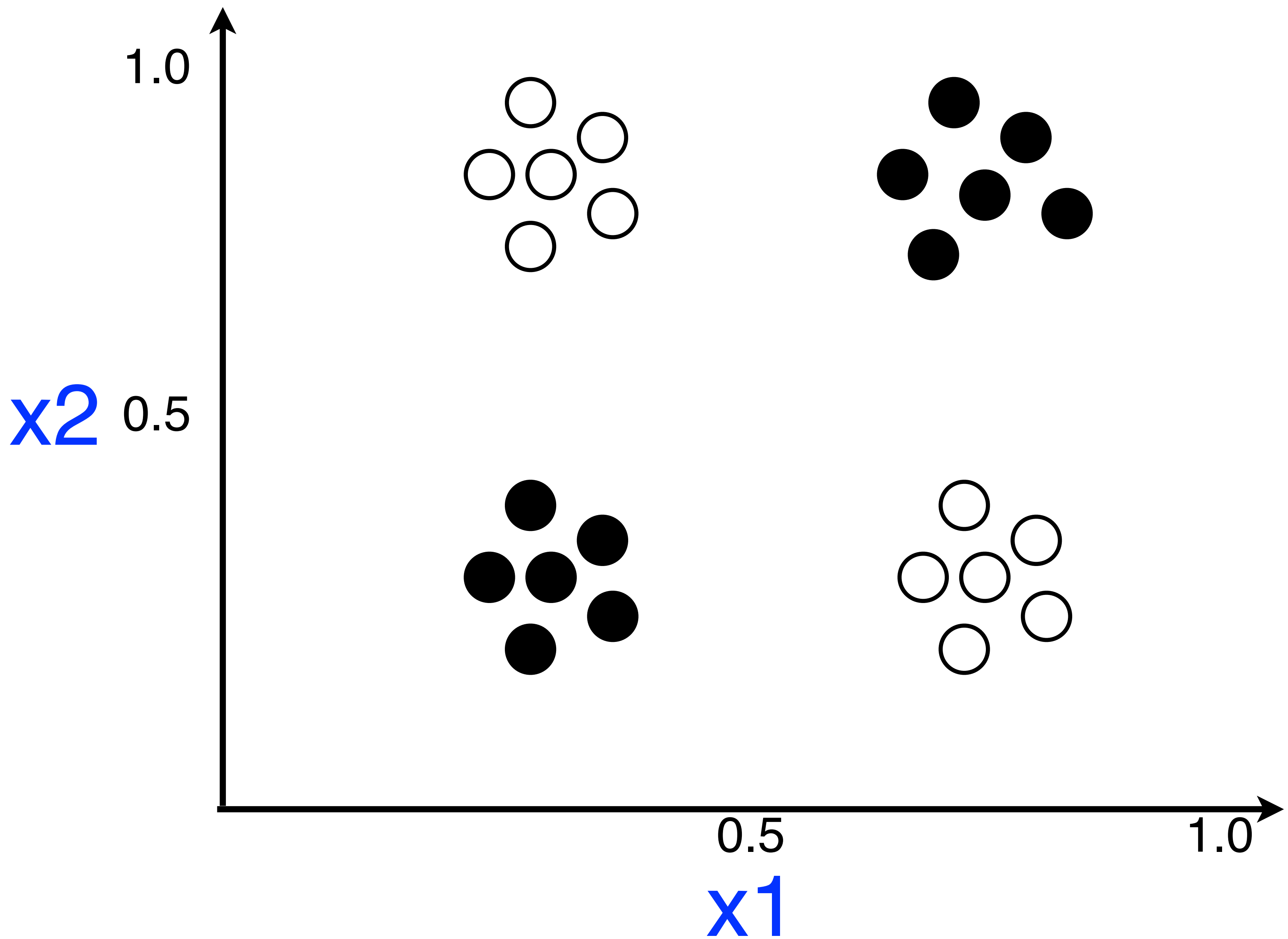
Learning Algorithm + Model
what could possibly go wrong?



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

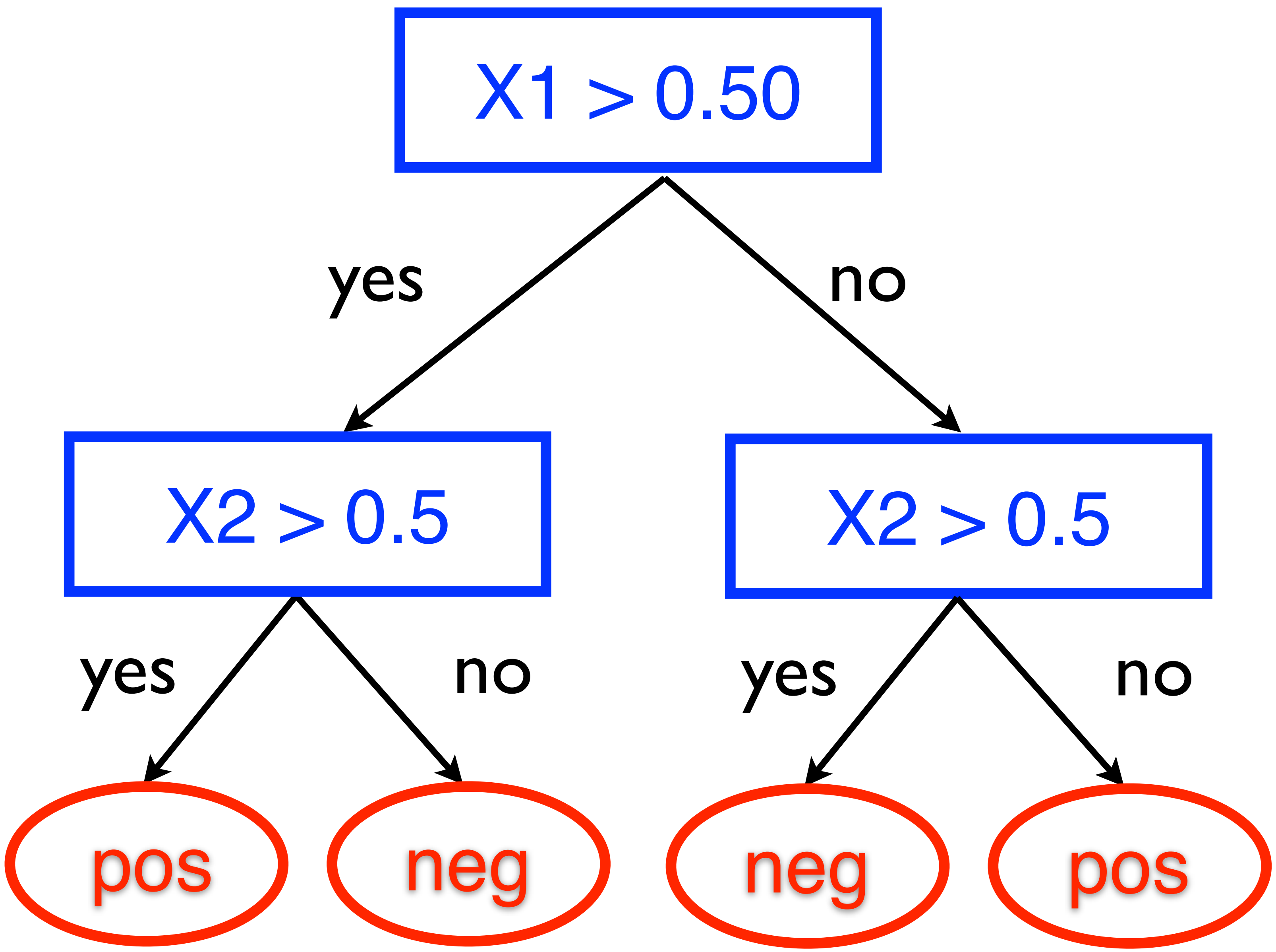
Learning Algorithm + Model

what could possibly go wrong?



4. Bad learning algorithm!

Learning Algorithm + Model
what could possibly go wrong?



Predictive Analysis

example: recognizing triangles

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

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Evaluation Metric

what could possibly go wrong?

- Most evaluation metrics can be understood using a <u>contingency table</u>

		true	
		triangle	other
predicted	triangle	A	B
	other	C	D

- What number(s) do we want to maximize?
- What number(s) do we want to minimize?

Evaluation Metric

what could possibly go wrong?

- True positives (A): number of triangles correctly predicted as triangles
- False positives (B): number of "other" incorrectly predicted as triangles
- False negatives (C): number of triangles incorrectly predicted as "other"
- True negatives (D): number of "other" correctly predicted as "other"

		true	
		triangle	other
predicted	triangle	A	B
	other	C	D

Evaluation Metric

what could possibly go wrong?

- Accuracy: percentage of predictions that are correct (i.e., true positives and true negatives)

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

		true	
		triangle	other
predicted	triangle	A	B
	other	C	D

Evaluation Metric

what could possibly go wrong?

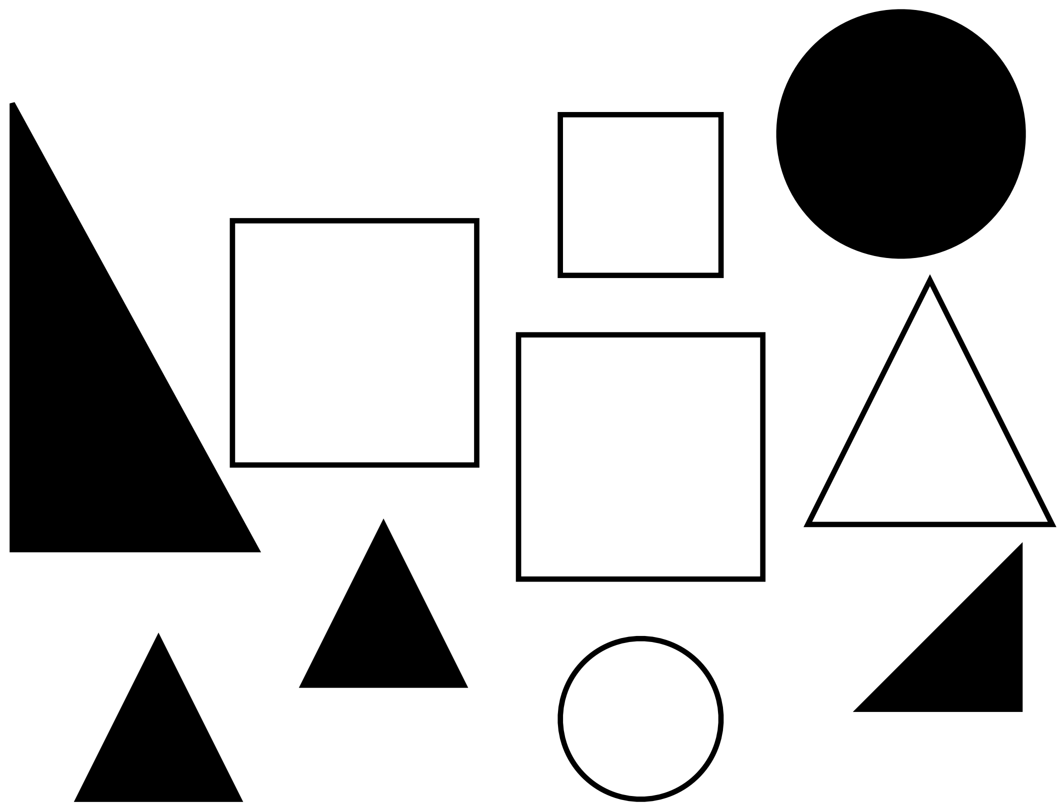
- Accuracy: percentage of predictions that are correct (i.e., true positives <u>and</u> true negatives)

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

		true	
		triangle	other
predicted	triangle	A	B
	other	C	D

Evaluation Metric
what could possibly go wrong?

- Accuracy: percentage of predictions that are correct (i.e., true positives <u>and</u> true negatives)

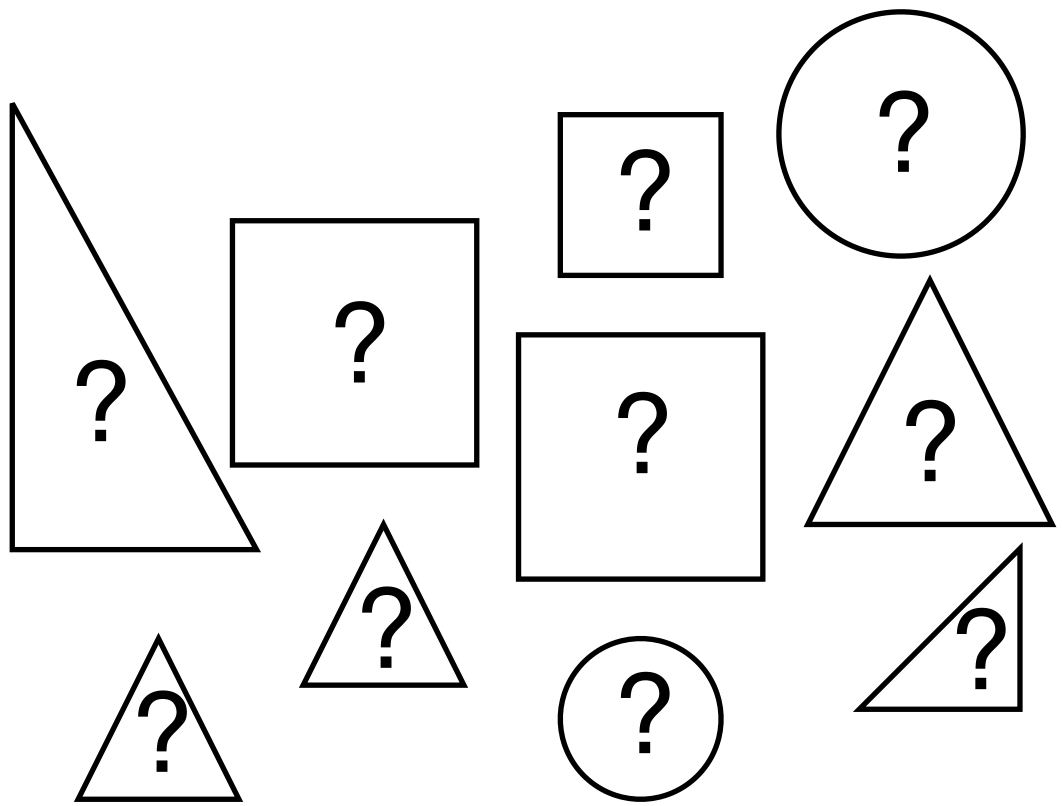


- What is the accuracy of this model?

Evaluation Metric

what could possibly go wrong?

- Interpreting the value of a metric on a particular data set requires some thinking ...

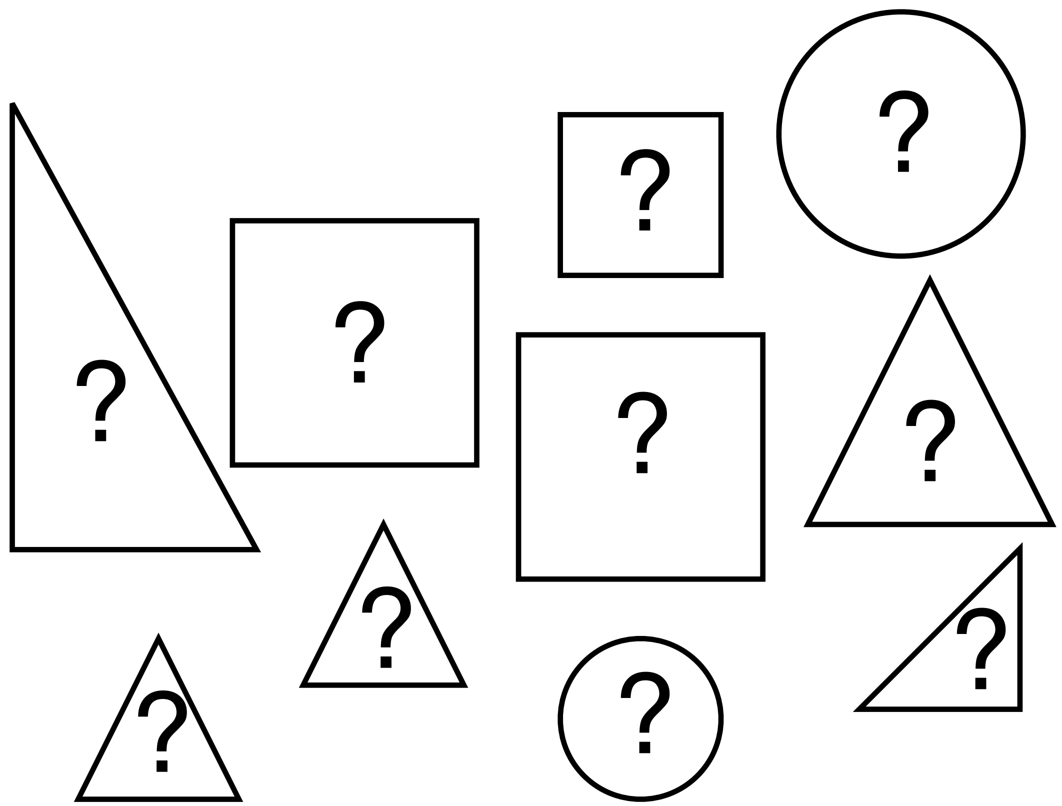


- On this dataset, what would be the expected accuracy of a model that does NO learning (degenerate baseline)?

Evaluation Metric

what could possibly go wrong?

- Interpreting the value of a metric on a particular data set requires some thinking ...



5. Misleading interpretation of a metric value!

What Could Possibly Go Wrong?

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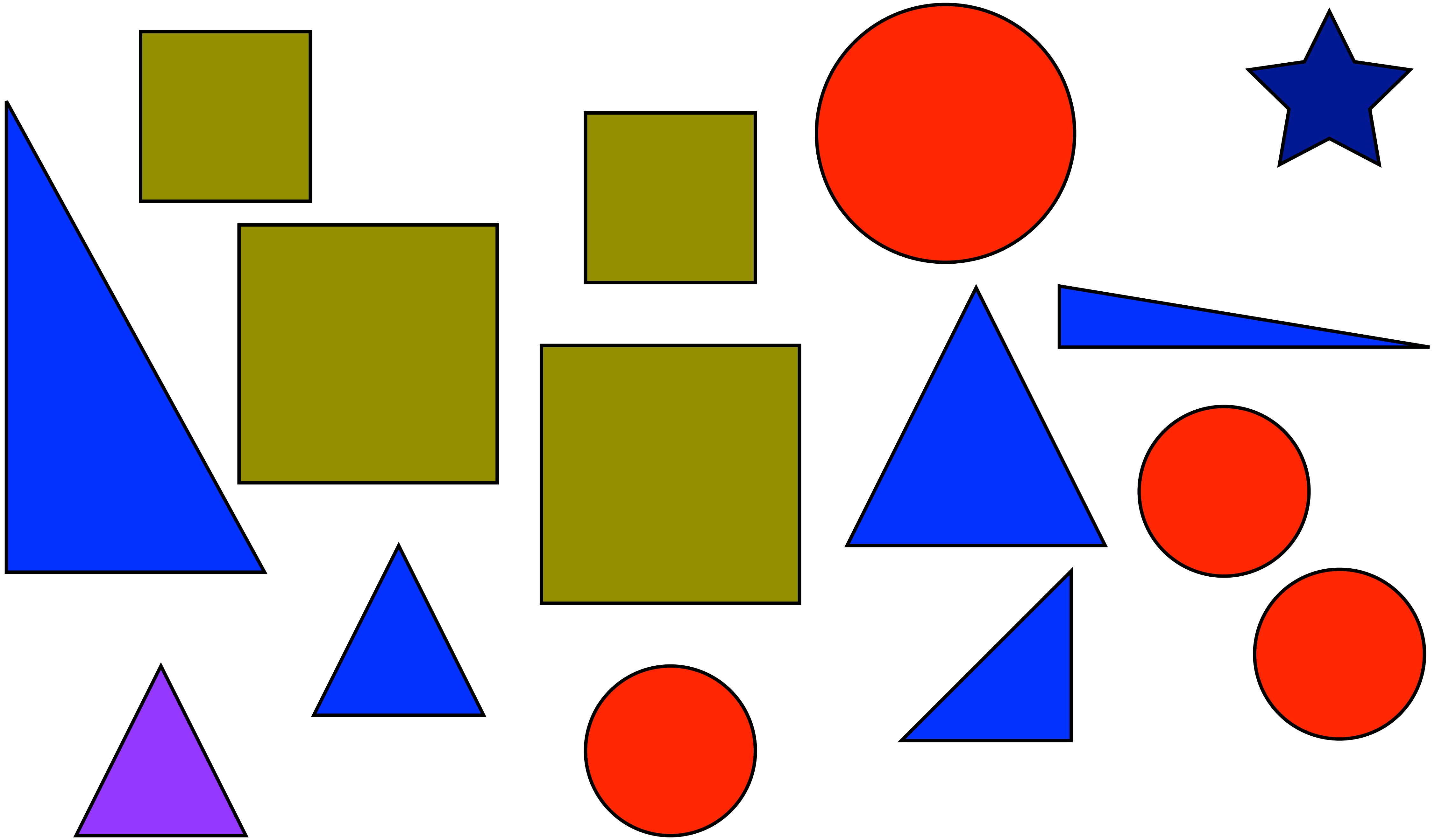
Text Data Mining in this Course

- Predictive Analysis of Text
  - developing computer programs that automatically recognize a particular concept within a span of text
- Exploratory Analysis of Text:
  - developing computer programs that automatically discover useful patterns or trends in text collections

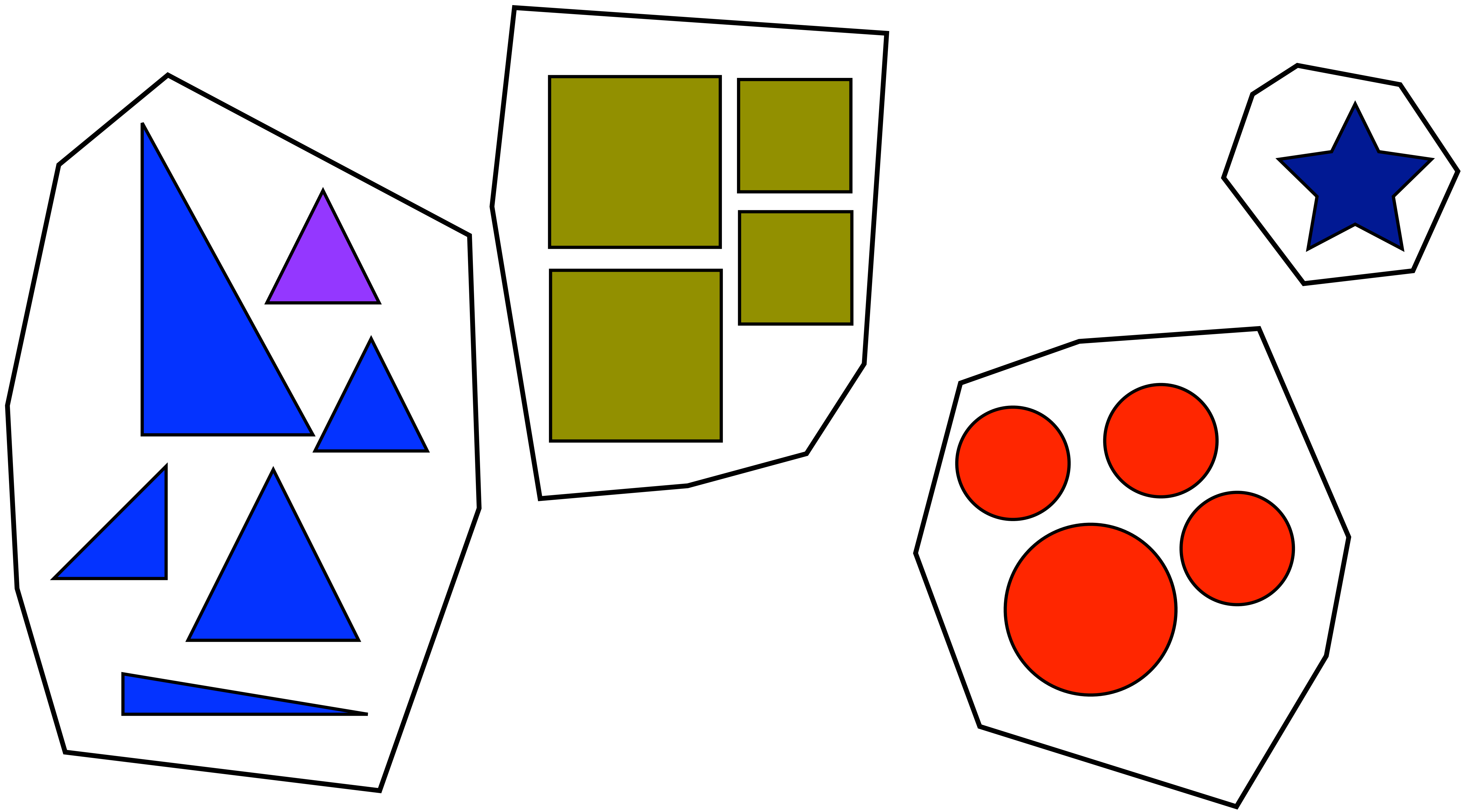
Exploratory Analysis

example: clustering shapes



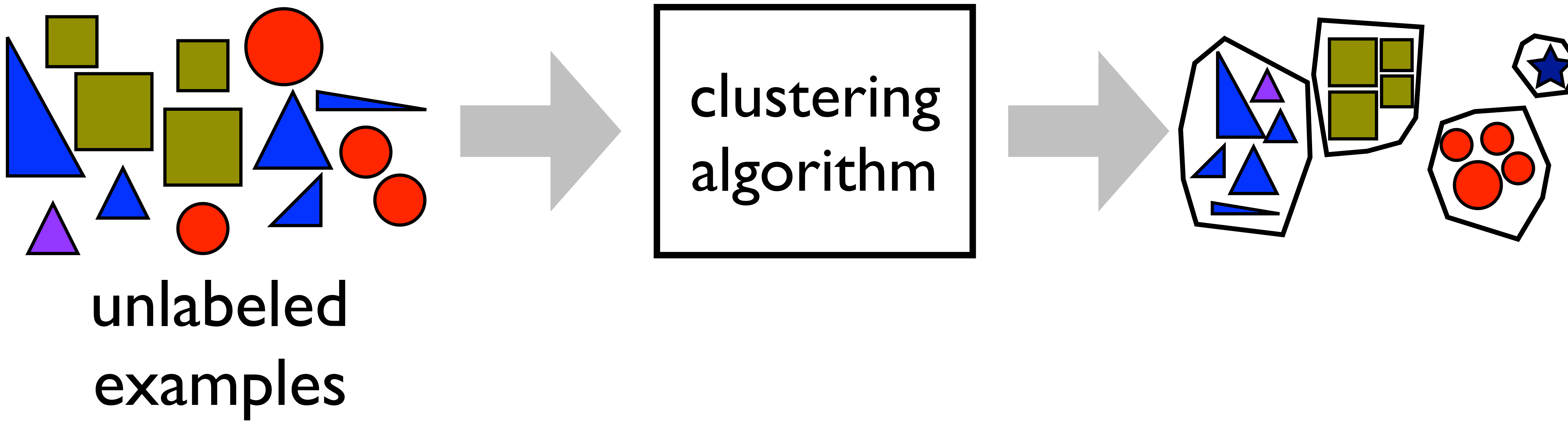
Exploratory Analysis

example: clustering shapes



Exploratory Analysis

example: clustering shapes



Exploratory Analysis

representation: features

color	size	# sides	equal sides	...	shape
blue	big	3	no	...	triangle
blue	big	3	yes	...	triangle
red	small	inf	yes	...	circle
green	small	4	yes	...	square
⋮	⋮	⋮	⋮	⋮	⋮
blue	big	3	yes	...	triangle

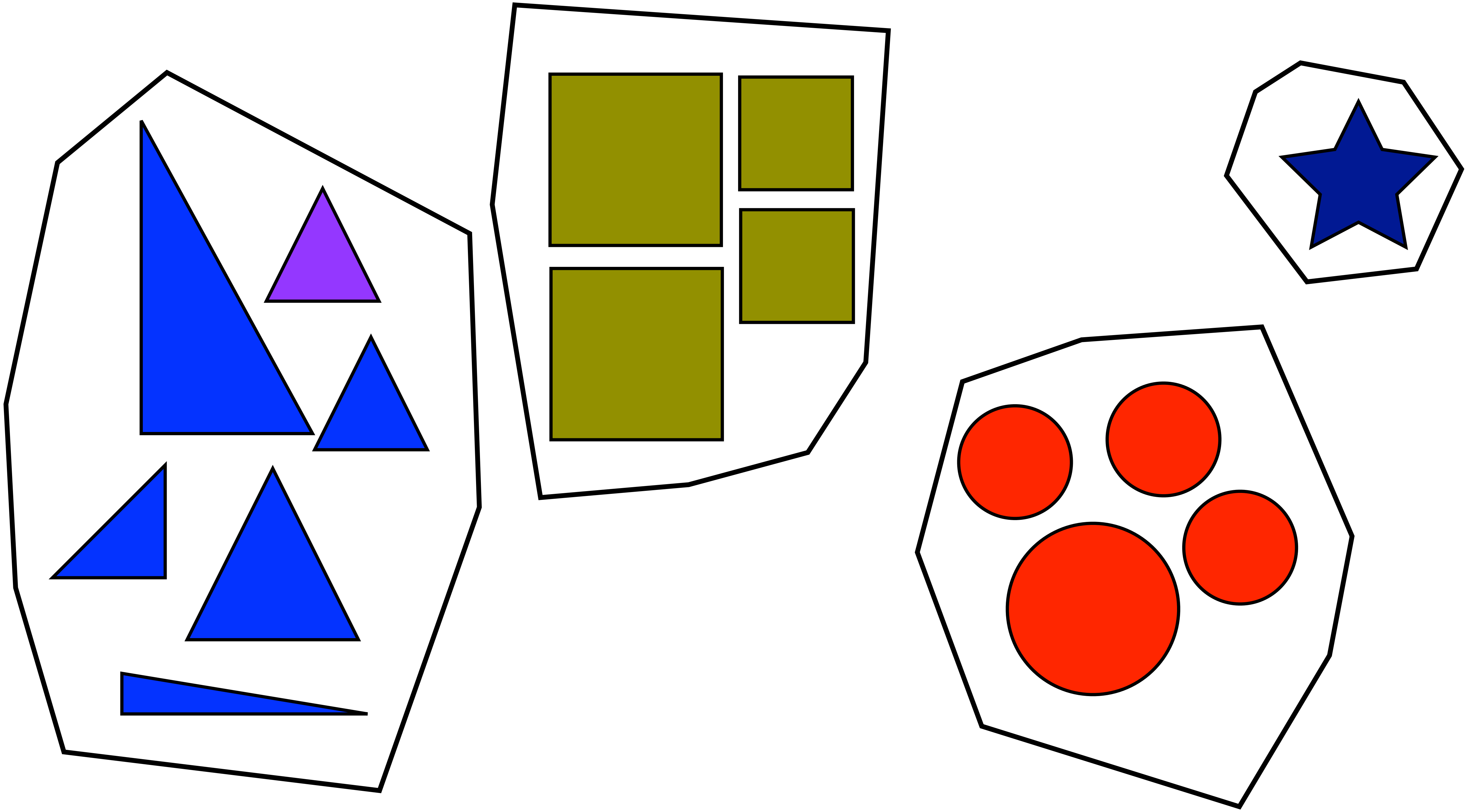
Exploratory Analysis

basic ingredients

1. Data: a set of examples that we want to automatically analyze in order to discover interesting trends
2. Representation: a set of features that we believe are useful in describing the data (i.e., important attributes)
3. Similarity Metric: a measure of similarity between two examples that is based on their feature values
4. Clustering algorithm: an algorithm that assigns items with similar feature values to the same group

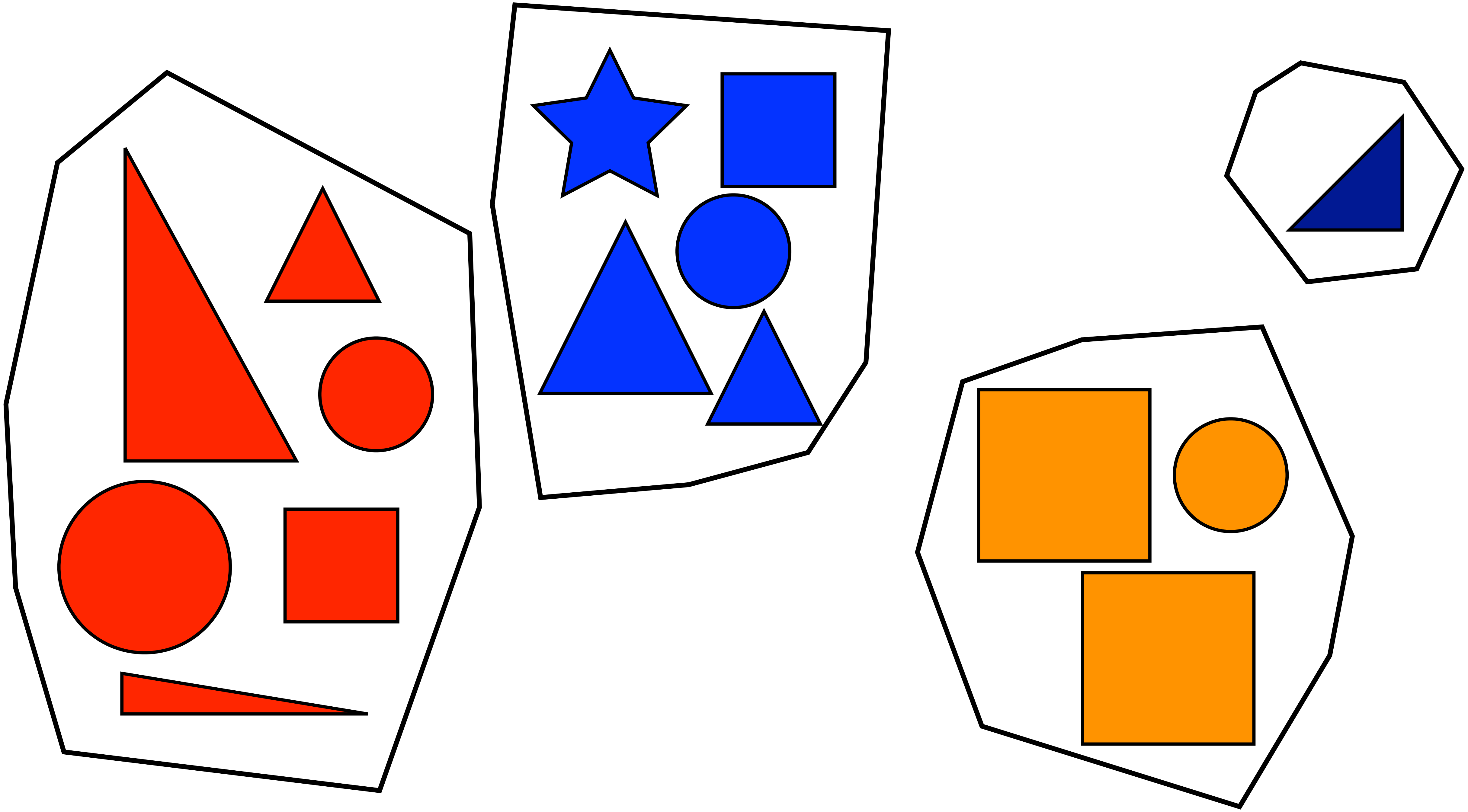
Representation

what could possibly go wrong?



Representation

what could possibly go wrong?



Exploratory Analysis

basic ingredients: the focus in this course

1. Data: a set of examples that we want to automatically analyze in order to discover interesting trends
2. Representation: a set of features that we believe are useful in describing the data
3. Similarity Metric: a measure of similarity between two examples that is based on their feature values
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Text Data Mining in this Course

- Predictive Analysis of Text
  - developing computer programs that automatically recognize or detect a particular concept within a span of text
- Exploratory Analysis of Text:
  - developing computer programs that automatically discover interesting and useful patterns or trends in text collections

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What is Text Data Mining?

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Applications

Predictive Analysis of Text

examples we'll cover in class

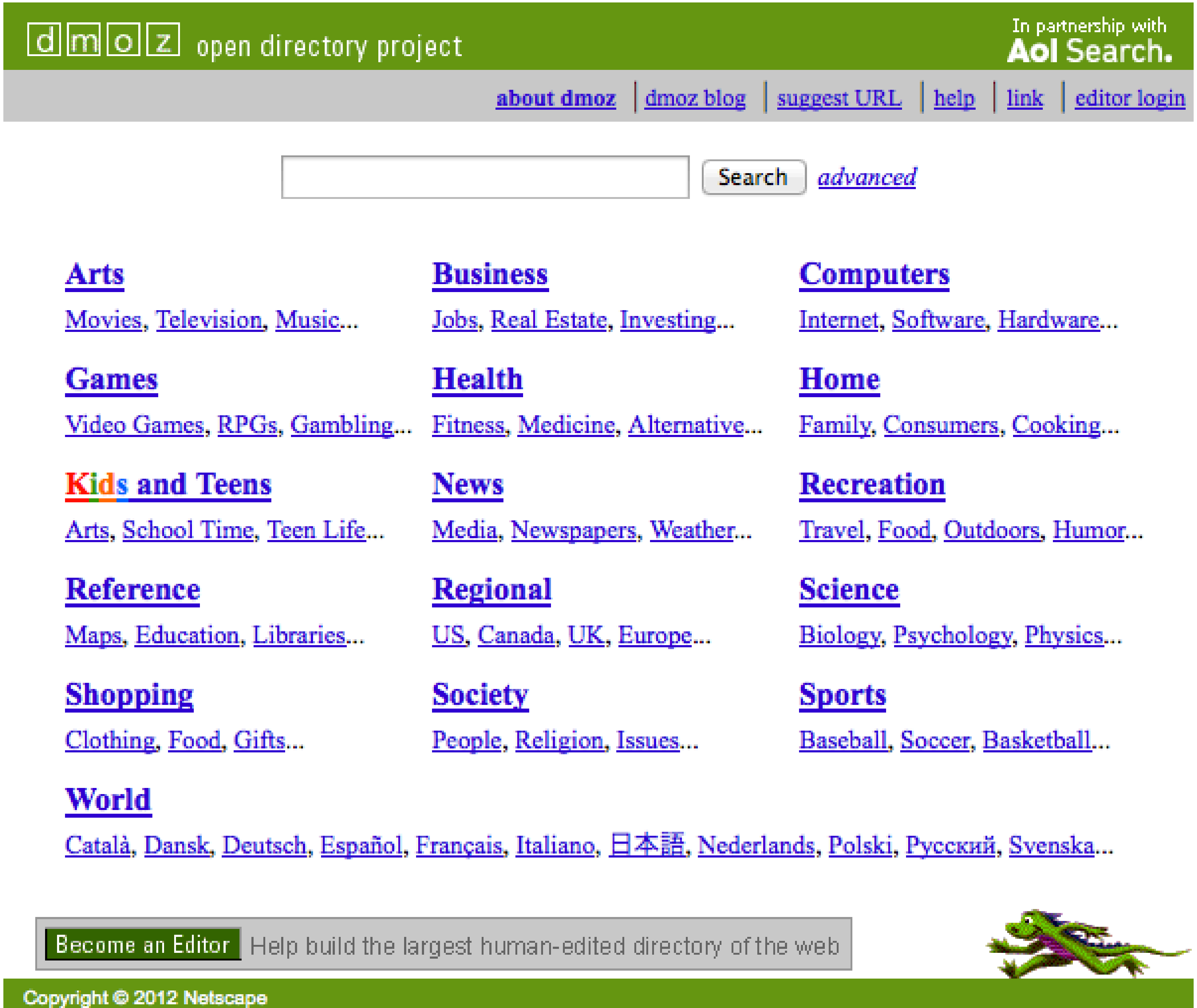
- Topic Categorization
- Opinion Mining
- Sentiment/Affect Analysis
- Bias Detection
- Information Extraction and Relation Learning
- Text-driven Forecasting
- Temporal Summarization

Predictive Analysis of Text

example applications

- Topic Categorization: automatically assigning documents to a set of pre-defined topical categories

Topic Categorization



Topic Categorization

Predictive Analysis of Text
example applications

- Opinion Mining: automatically detecting whether a span of opinionated text expresses a positive or negative opinion about the item being judged

Opinion Mining

movie reviews

- "Great movie! It kept me on the edge of my seat the whole time. I IMAX-ed it and have no regrets." — positive
- "Waste of time! It sucked!" — negative
- "This film should be brilliant. It sounds like a great plot, the actors are first grade, and the supporting cast is good as well, and Stallone is attempting to deliver a good performance. However, it can't hold up." — negative
- "Trust me, this movie is a masterpiece .... after you've seen it 4+ times." — ???

Predictive Analysis of Text

example applications

- Sentiment/Affect Analysis: automatically detecting the emotional state of the author of a span of text (usually from a set of pre-defined emotional states).

Sentiment Analysis

support group posts

- “[I] also found out that the radiologist is doing the biopsy, not a breast surgeon. I am more scared now than when I ...” — fear
- “... My radiologist ‘assured’ me my scan was NOT going to be cancer...she was wrong.” — despair
- “ ... My radiologist did my core biopsy. Not a problem and he did a super job of it.” — hope
- “It's pretty standard for the radiologist to do the biopsy so I wouldn't be concerned on that score.” — hope

Predictive Analysis of Text

example applications

- Bias detection: automatically detecting whether the author of a span of text favors a particular viewpoint (usually from a set of pre-defined viewpoints)

Bias Detection

- "Coming [up] next, drug addicted pregnant women no longer have anything to fear from the authorities thanks to the Supreme Court. Both sides on this in a moment." -- Bill O'Reilly

pro-policy
(vs. anti-policy)

- "Nationalizing businesses, nationalizing banks, is not a solution for the democratic party, it's the objective." -- Rush Limbaugh

conservative
(vs. liberal)

- "If you're keeping score at home, so far our war in Iraq has created a police state in that country and socialism in Spain. So, no democracies yet, but we're really getting close." -- Jon Stewart

against war in iraq
(vs. in favor of)

Predictive Analysis of Text

example applications

- Information extraction: automatically detecting that a short sequence of words belongs to (or is an instance of) a particular entity type, for example:
  - Person(X)
  - Location(X)
  - TennisPlayer(X)
  - ...

Predictive Analysis of Text

example applications

- Relation Learning: automatically detecting pairs of entities that share a particular relation, for example:
  - CEO(<person>,<company>)
  - Capital(<city>,<country>)
  - Mother(<person>,<person>)
  - ConvictedFelon(<person>,<crime>)
  - ...

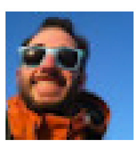
Relation Learning

CEO(<person>,<company>)

Marissa Mayer Yahoo

[Know **Yahoo's Marissa Mayer** in 11 facts - CNN.com](www.cnn.com/2012/07/17/...marissa-mayer/index.html)

www.cnn.com/2012/07/17/...**marissa-mayer**/index.html



by John D. Sutter - in 846,411 Google+ circles - More by John D. Sutter

Jul 19, 2012 – Here's a quick guide to some of the most interesting and water-cooler-worthy facts about **Marissa Mayer**, who was named CEO of **Yahoo** on ...

<person>, who was named CEO of <company>

Relation Learning

CEO(<person>,<company>)

",who was named CEO of"

[DailyTech - Fisker Appoints New CEO, Eliminates Battery/Engine ...]
www.dailytech.com/article.aspx?newsid=25412
4 days ago – Tom LaSorda, **who was named CEO of** Fisker back in February 2012 when founder Henrik Fisker stepped down, is leaving the company, but ...

CEO(Tom LaSorda, Fisker)

[**who was named CEO of** Yahoo on Monday. Christian Science Monitor]
gtp123.com/.../**who-was-named-ceo-of**-yahoo-on-monday-christian-...
Jul 17, 2012 – You are browsing the archive for **who was named CEO of** Yahoo on Monday. Christian Science Monitor. Avatar of Garland E. Harris ...

[CEO of renamed Sara Lee meat biz chooses Winnetka - Residential ...]
www.chicagorealestatedaily.com › Home › Residential News
Aug 7, 2012 – Sean Connolly, **who was named CEO of** Hillshire Brands Co. in January, declines to comment through a company spokesman. Records show ...

CEO(Sean Connolly, Hillshire Brands)

[Who is the woman **who was named CEO of** Gilt Groupe in Septemb...]
askville.amazon.com › Miscellaneous › Popular News
Askville Question: Who is the woman **who was named CEO of** Gilt Groupe in September? : Popular News.

CEO(woman, Gilt Groupe)

[Tom McKillop - Wikipedia, the free encyclopedia]
en.wikipedia.org/wiki/Tom_McKillop
Sir Thomas Fulton Wilson "Tom" McKillop, FRS (born 19 March 1943) is a Scottish chemist, **who was named CEO of** AstraZeneca PLC in 1999 (retired 1 January ...

CEO(scottish chemist, AztraZeneca)

[Harrison adjusts to view from top at First Hawaiian - Pacific Business ...]
www.bizjournals.com/.../harrison-adjusts-to-view-from-top-at.html?...
Jan 27, 2012 – Bob Harrison, **who was named CEO of** First Hawaiian Bank on Jan. 1, says he'll spend a lot of time focusing on his people and community ...

CEO(Bob Harrison, First Hawaiian Bank)

Predictive Analysis of Text

example applications

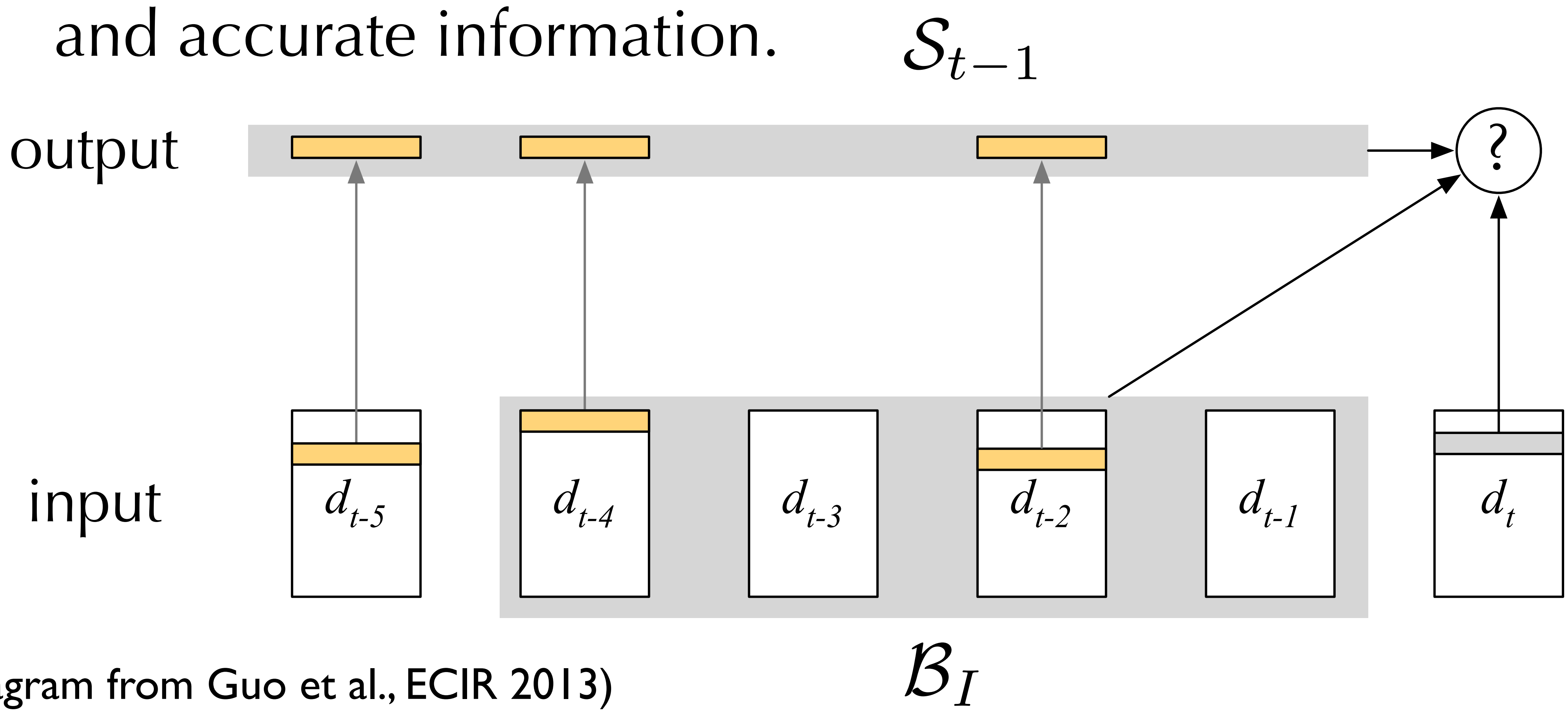
- Text-based Forecasting: monitoring incoming text (e.g., tweets) and making predictions about external, real-world events or trends, for example:
  - a presidential candidate's poll rating
  - a company's stock value change
  - a movie's box office earnings
  - side-effects for a particular drug
  - ...

Predictive Analysis of Text

example applications

- Temporal Summarization: monitoring incoming text (e.g., tweets) about a news event and predicting whether a sentence should be included in an on-going summary of the event

- Updates to the summary should contain relevant, novel, and accurate information.



(Diagram from Guo et al., ECIR 2013)

Predictive Analysis of Text

example applications

- Detecting other interesting properties of text: [insert your crazy idea here], for example, detecting humorous text:
  - "Beauty is in the eye of the beholder" not funny
  - "Beauty is in the eye of the beer holder" funny

(example from Mihalcea and Pulman, 2007)

Outline

Introductions

What is Text Data Mining?

Predictive Analysis of Text: The Big Picture

Exploratory Analysis of Text: The Big Picture

Applications

Course Overview

Road Map

first half of the semester

- Predictive Analysis of Text
  - Supervised machine learning principles
  - Text representation
  - Feature selection
  - Machine learning algorithms
  - Tools for predictive analysis of text
  - Experimentation and evaluation
- Exploratory Analysis of Text
  - Clustering

Road Map
second half of the semester

- Applications
  - Text classification
  - Opinion mining
  - Sentiment analysis
  - Discourse analysis
  - Bias detection
  - Text-based forecasting
- Is there anything that <u>you</u> would like to learn more about?

Grading

- 30% homework
  - 10% each
- 20% midterm
- 40% term project
  - 5% proposal
  - 10% presentation
  - 25% paper
- 10% participation

Participation

- Attendance **is not optional**
- Be “present” during class
- Avoid multi-tasking
- Ask questions
- Challenge the material
- You’re the most important part of the course, take ownership of it

Grading for Graduate Students

- H: 95-100%
- P: 80-94%
- L: 60-79%
- F: 0-59%

Grading for Undergraduate Students

- A+: 97-100%
- A: 94-96%
- A-: 90-93%
- B+: 87-89%
- B: 84-86%
- B-: 80-83%
- C+: 77-79%
- C: 74-76%
- C-: 70-73%
- D+: 67-69%
- D: 64-66%
- D-: 60-63%
- F: <= 59%

General Outline of Homework

- Given a dataset (i.e., a training and test set), run experiments where you try to predict the target class using different feature representations
- Do error analysis
- Report on what worked, what didn't, and why!
- Answer essay questions about the assignment
    - These will be associated with the course material

Course Tips

- Work hard
- Do the assigned readings
- Do <u>other</u> readings
- Be patient and have reasonable expectations
  - you're not supposed to understand everything we cover in class <u>during</u> class
- Seek help sooner rather than later
  - office hours: by appointment
  - questions via email
- Remember the golden rule: no pain, no gain

Questions?