Learning Basics

Dr. Xiaowei Huang

https://cgi.csc.liv.ac.uk/~xiaowei/

In the last lecture,

- What is machine learning?
- A few applications of machine learning
- consider how to represent instances as fixed-length feature vectors

Topics

- Learning basics:
  - Before learning: data collection
  - Learning tasks: supervised and unsupervised learning
  - Learning schemes

Before learning: data collection

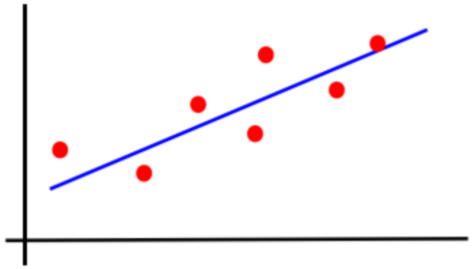
Independent and identically distributed (i.i.d.)

- we often assume that training instances are *independent and identically distributed* (i.i.d.) – sampled independently from the same unknown distribution
- there are also cases where this assumption does not hold
  - cases where sets of instances have dependencies
    - instances sampled from the same medical image
    - instances from time series
    - etc.

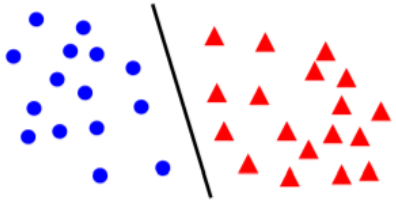
Learning tasks: supervised and unsupervised learning

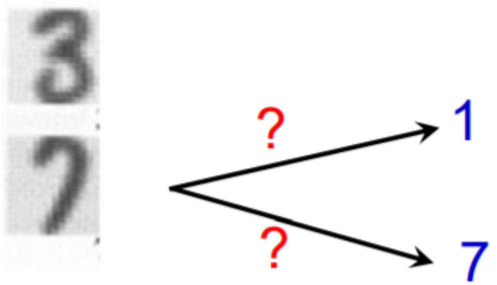
Three canonical learning problems

1. Regression - supervised
   - estimate parameters, e.g. of weight vs height

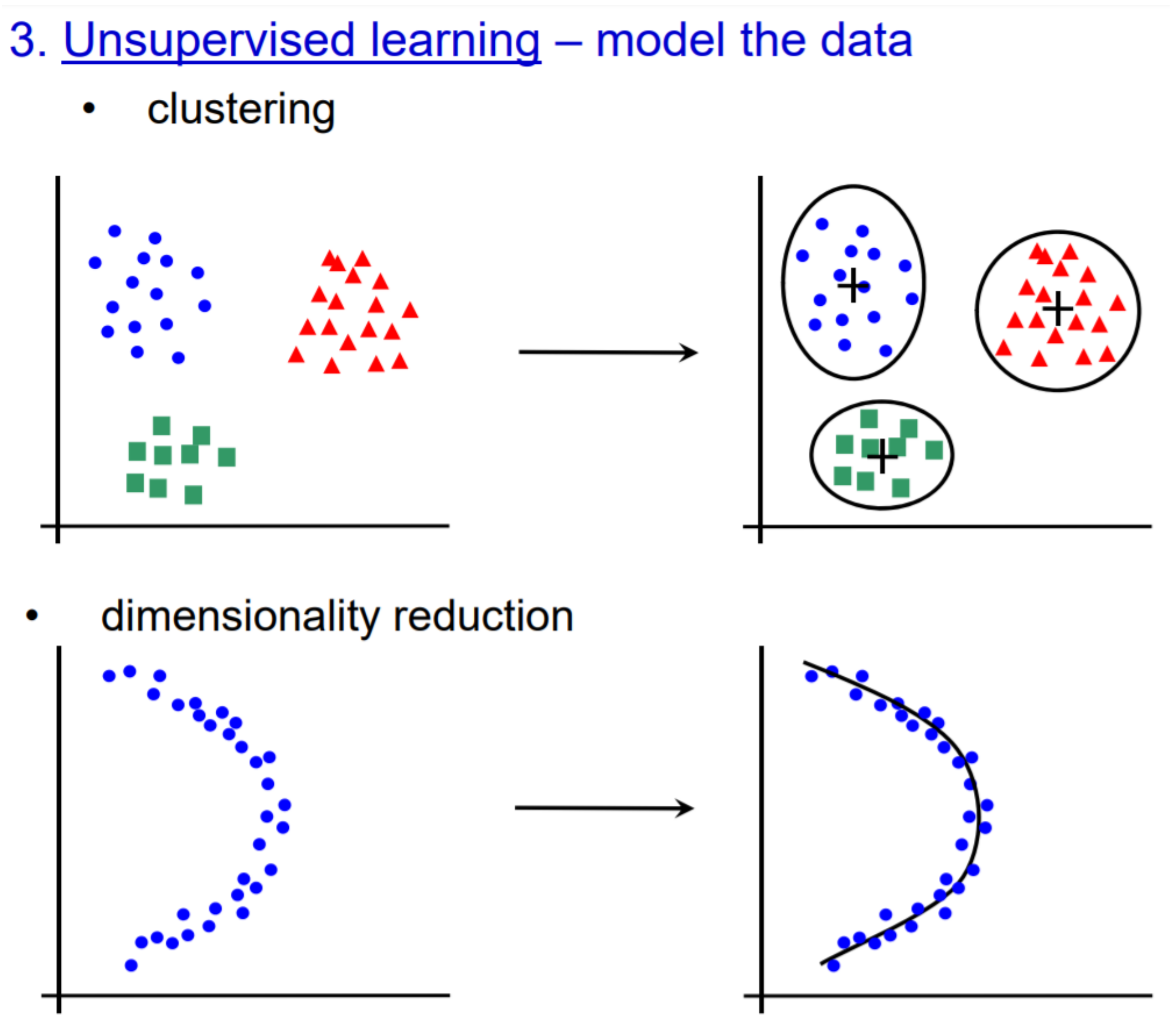


2. Classification - supervised
   - estimate class, e.g. handwritten digit classification





Three canonical learning problems



3. Unsupervised learning – model the data

- clustering

- dimensionality reduction

The supervised learning task

- problem setting
  - set of possible instances: *X*
  - unknown *target function:* $f : X \rightarrow Y$
  - set of *models* (a.k.a. *hypotheses*): $H = \{h \mid h : X \rightarrow Y\}$

- given *training set* of instances of unknown target function f

$$\left(\mathbf{x}^{(1)}, y^{(1)}\right), \left(\mathbf{x}^{(2)}, y^{(2)}\right) \ldots \left(\mathbf{x}^{(m)}, y^{(m)}\right)$$

- Output
  - model $h \in H$ that best approximates target function

The supervised learning task

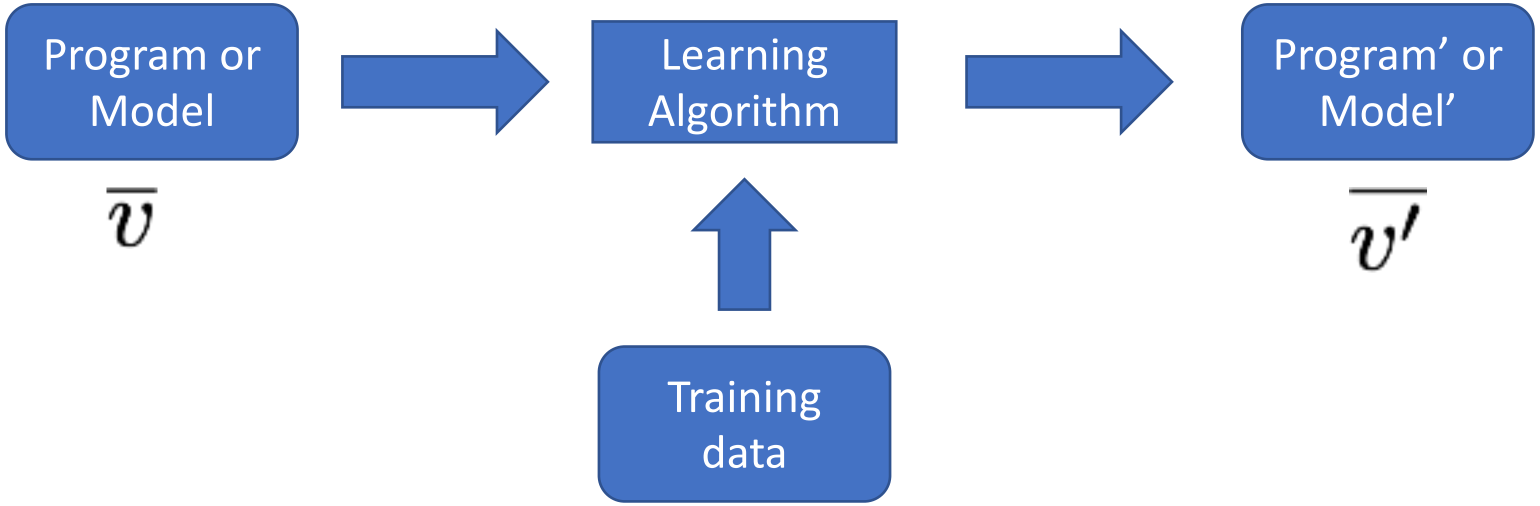
- when y is discrete, we term this a *classification* task (or *concept learning*)

- when y is continuous, it is a *regression* task

- there are also tasks in which each y is more structured object like a *sequence* of discrete labels (as in e.g. image segmentation, machine translation)

Model representations

- throughout the semester, we will consider a broad range of representations for learned models, including
  - decision trees
  - neural networks
  - support vector machines
  - Bayesian networks
  - etc.



Program or Model

$\overline{v}$

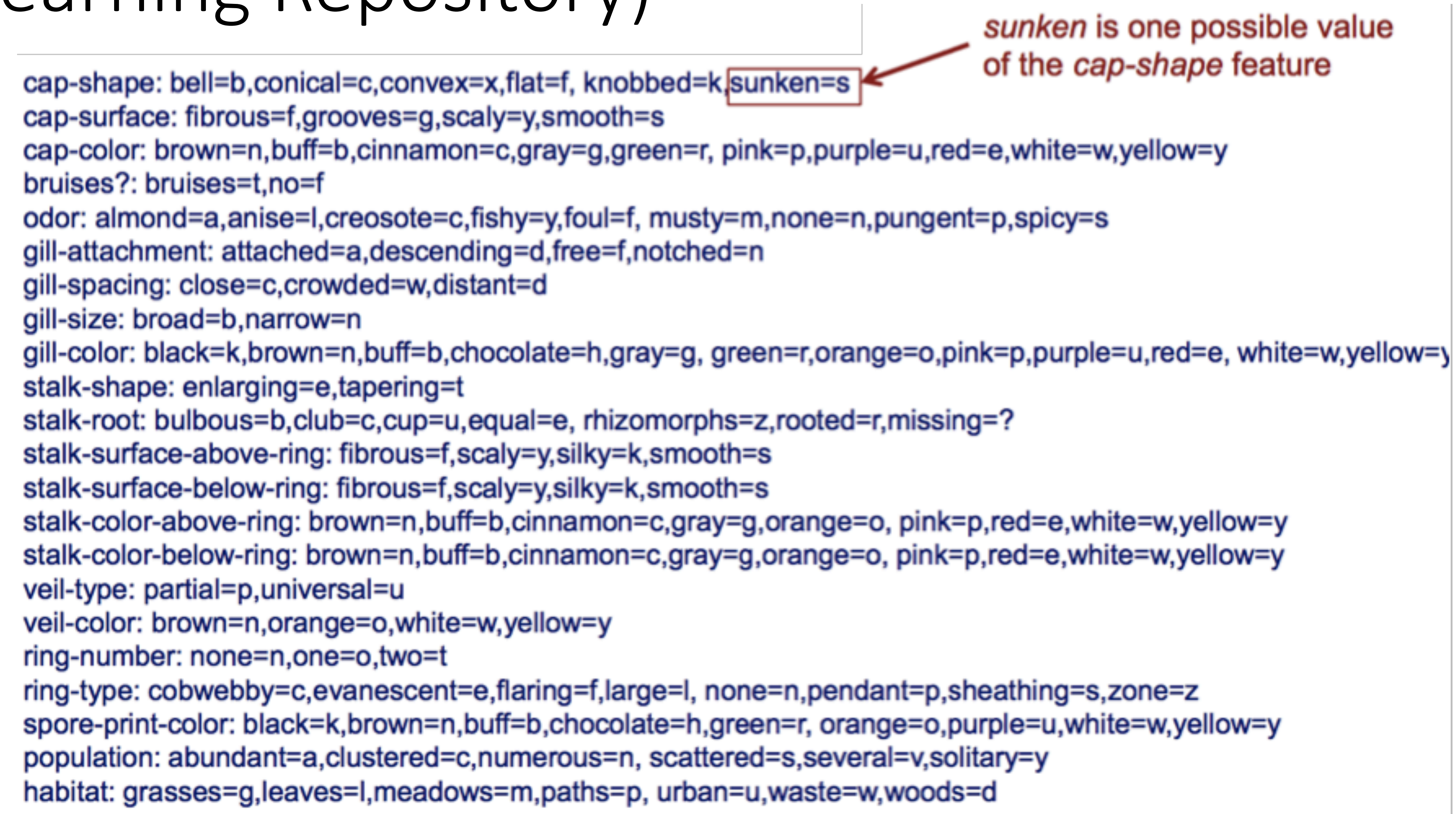
Learning Algorithm

Training data

Program’ or Model’

$\overline{v'}$

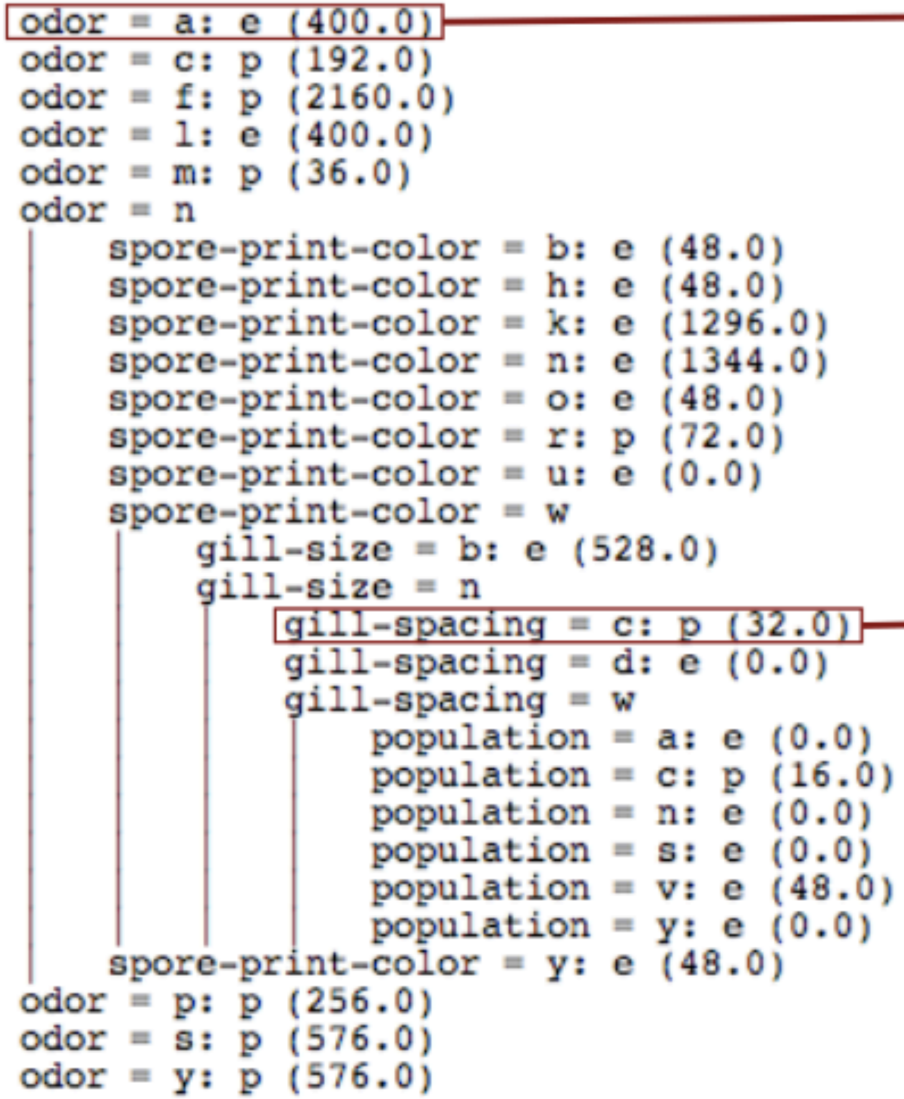
Mushroom features (from the UCI Machine Learning Repository)



sunken is one possible value of the *cap-shape* feature

cap-shape: bell=b,conical=c,convex=x,flat=f, knobbed=k,sunken=s
cap-surface: fibrous=f,grooves=g,scaly=y,smooth=s
cap-color: brown=n,buff=b,cinnamon=c,gray=g,green=r, pink=p,purple=u,red=e,white=w,yellow=y
bruises?: bruises=t,no=f
odor: almond=a,anise=l,creosote=c,fishy=y,foul=f, musty=m,none=n,pungent=p,spicy=s
gill-attachment: attached=a,descending=d,free=f,notched=n
gill-spacing: close=c,crowded=w,distant=d
gill-size: broad=b,narrow=n
gill-color: black=k,brown=n,buff=b,chocolate=h,gray=g, green=r,orange=o,pink=p,purple=u,red=e, white=w,yellow=y
stalk-shape: enlarging=e,tapering=t
stalk-root: bulbous=b,club=c,cup=u,equal=e, rhizomorphs=z,rooted=r,missing=?
stalk-surface-above-ring: fibrous=f,scaly=y,silky=k,smooth=s
stalk-surface-below-ring: fibrous=f,scaly=y,silky=k,smooth=s
stalk-color-above-ring: brown=n,buff=b,cinnamon=c,gray=g,orange=o, pink=p,red=e,white=w,yellow=y
stalk-color-below-ring: brown=n,buff=b,cinnamon=c,gray=g,orange=o, pink=p,red=e,white=w,yellow=y
veil-type: partial=p,universal=u
veil-color: brown=n,orange=o,white=w,yellow=y
ring-number: none=n,one=o,two=t
ring-type: cobwebby=c,evanescent=e,flaring=f,large=l, none=n,pendant=p,sheathing=s,zone=z
spore-print-color: black=k,brown=n,buff=b,chocolate=h,green=r, orange=o,purple=u,white=w,yellow=y
population: abundant=a,clustered=c,numerous=n, scattered=s,several=v,solitary=y
habitat: grasses=g,leaves=l,meadows=m,paths=p, urban=u,waste=w,woods=d

A learned decision tree



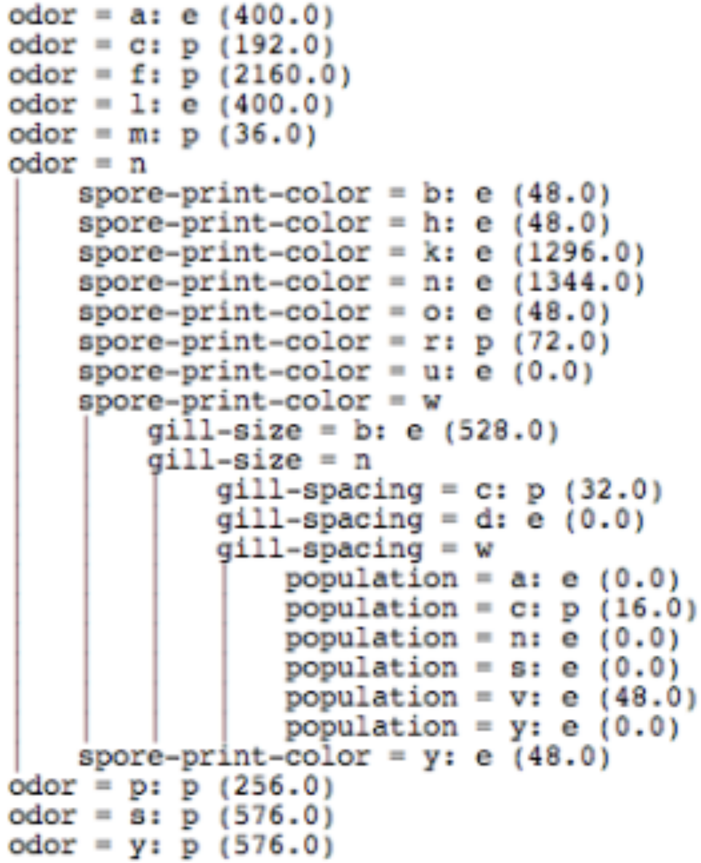
```
odor = a: e (400.0)
odor = c: p (192.0)
odor = f: p (2160.0)
odor = l: e (400.0)
odor = m: p (36.0)
odor = n
|   spore-print-color = b: e (48.0)
|   spore-print-color = h: e (48.0)
|   spore-print-color = k: e (1296.0)
|   spore-print-color = n: e (1344.0)
|   spore-print-color = o: e (48.0)
|   spore-print-color = r: p (72.0)
|   spore-print-color = u: e (0.0)
|   spore-print-color = w
|   |   gill-size = b: e (528.0)
|   |   gill-size = n
|   |   |   gill-spacing = c: p (32.0)
|   |   |   gill-spacing = d: e (0.0)
|   |   |   gill-spacing = w
|   |   |   |   population = a: e (0.0)
|   |   |   |   population = c: p (16.0)
|   |   |   |   population = n: e (0.0)
|   |   |   |   population = s: e (0.0)
|   |   |   |   population = v: e (48.0)
|   |   |   |   population = y: e (0.0)
|   spore-print-color = y: e (48.0)
odor = p: p (256.0)
odor = s: p (576.0)
odor = y: p (576.0)
```

if odor=almond, predict edible

if odor=none ∧
spore-print-color=white ∧
gill-size=narrow ∧
gill-spacing=crowded,
predict poisonous

Classification with a learned decision tree

x = <bell,fibrous,brown,false, foul,...>



```
odor = a: e (400.0)
odor = c: p (192.0)
odor = f: p (2160.0)
odor = l: e (400.0)
odor = m: p (36.0)
odor = n
|   spore-print-color = b: e (48.0)
|   spore-print-color = h: e (48.0)
|   spore-print-color = k: e (1296.0)
|   spore-print-color = n: e (1344.0)
|   spore-print-color = o: e (48.0)
|   spore-print-color = r: p (72.0)
|   spore-print-color = u: e (0.0)
|   spore-print-color = w
|   |   gill-size = b: e (528.0)
|   |   gill-size = n
|   |   |   gill-spacing = c: p (32.0)
|   |   |   gill-spacing = d: e (0.0)
|   |   |   gill-spacing = w
|   |   |   |   population = a: e (0.0)
|   |   |   |   population = c: p (16.0)
|   |   |   |   population = n: e (0.0)
|   |   |   |   population = s: e (0.0)
|   |   |   |   population = v: e (48.0)
|   |   |   |   population = y: e (0.0)
|   spore-print-color = y: e (48.0)
odor = p: p (256.0)
odor = s: p (576.0)
odor = y: p (576.0)
```

y = ?

Unsupervised learning

- in unsupervised learning, we're given a set of instances, without y's

$$\mathbf{x}^{(1)},\mathbf{x}^{(2)} \ldots \mathbf{x}^{(m)}$$

goal: discover interesting regularities/structures/patterns that characterize the instances

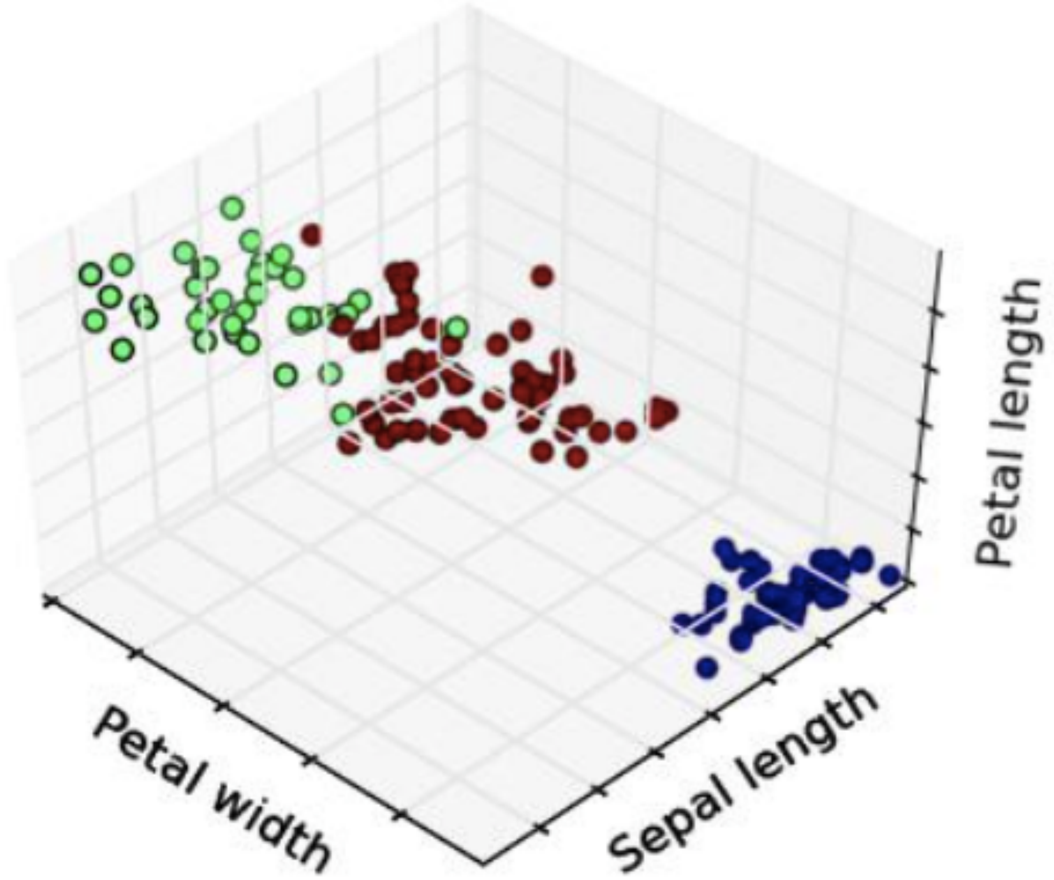
- common unsupervised learning tasks
    - *clustering*
    - *anomaly detection*
    - *dimensionality reduction*

Clustering

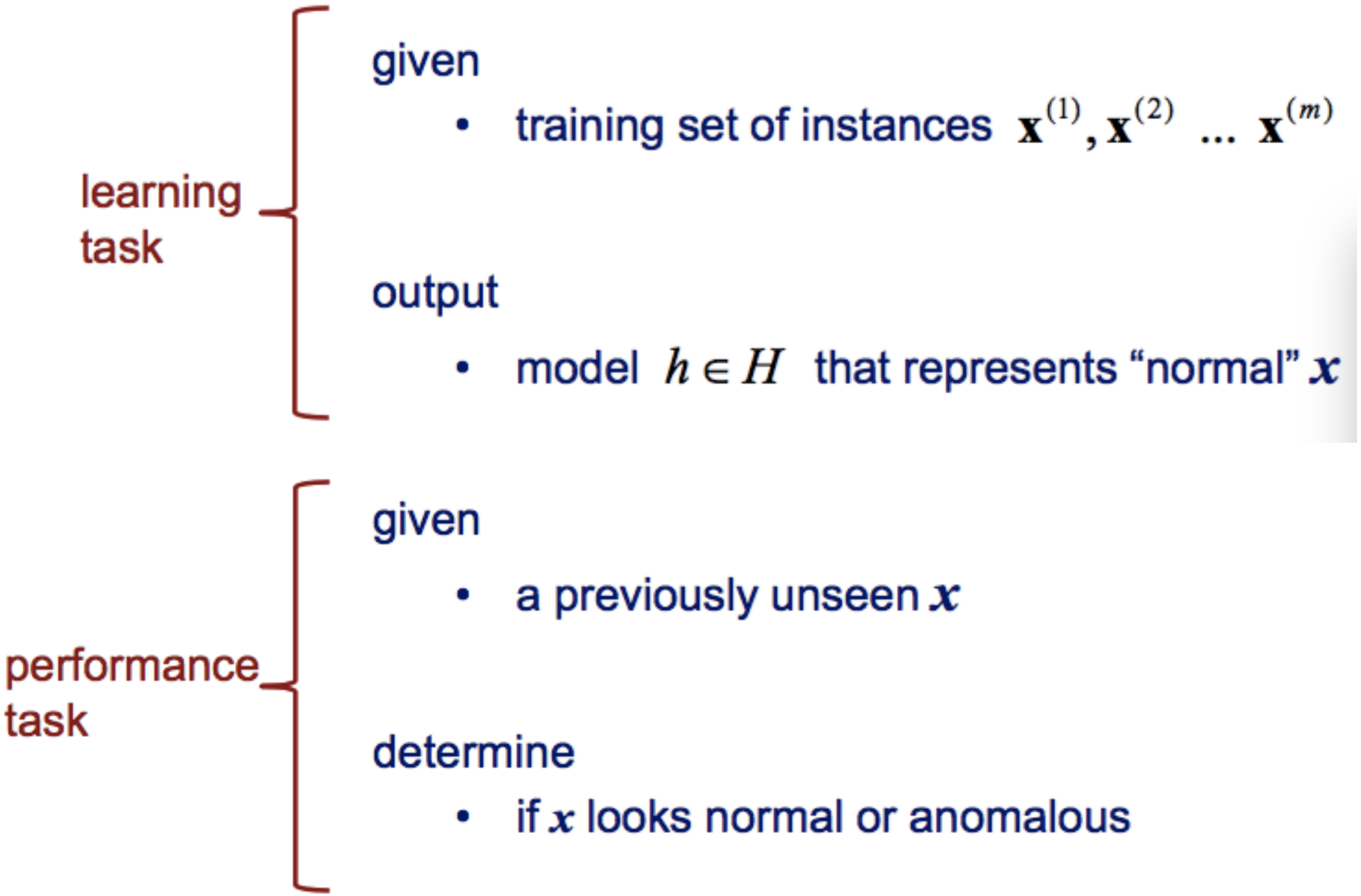
- given
  - training set of instances $\mathbf{x}^{(1)}$, $\mathbf{x}^{(2)}$ ... $\mathbf{x}^{(m)}$

- output
  - model $h \in H$ that divides the training set into clusters such that there is intra-cluster similarity and inter-cluster dissimilarity

Clustering example



Anomaly detection



learning task

given

- training set of instances $\mathbf{x}^{(1)}, \mathbf{x}^{(2)}$ ... $\mathbf{x}^{(m)}$

output

- model $h \in H$ that represents “normal” $\boldsymbol{x}$

performance task

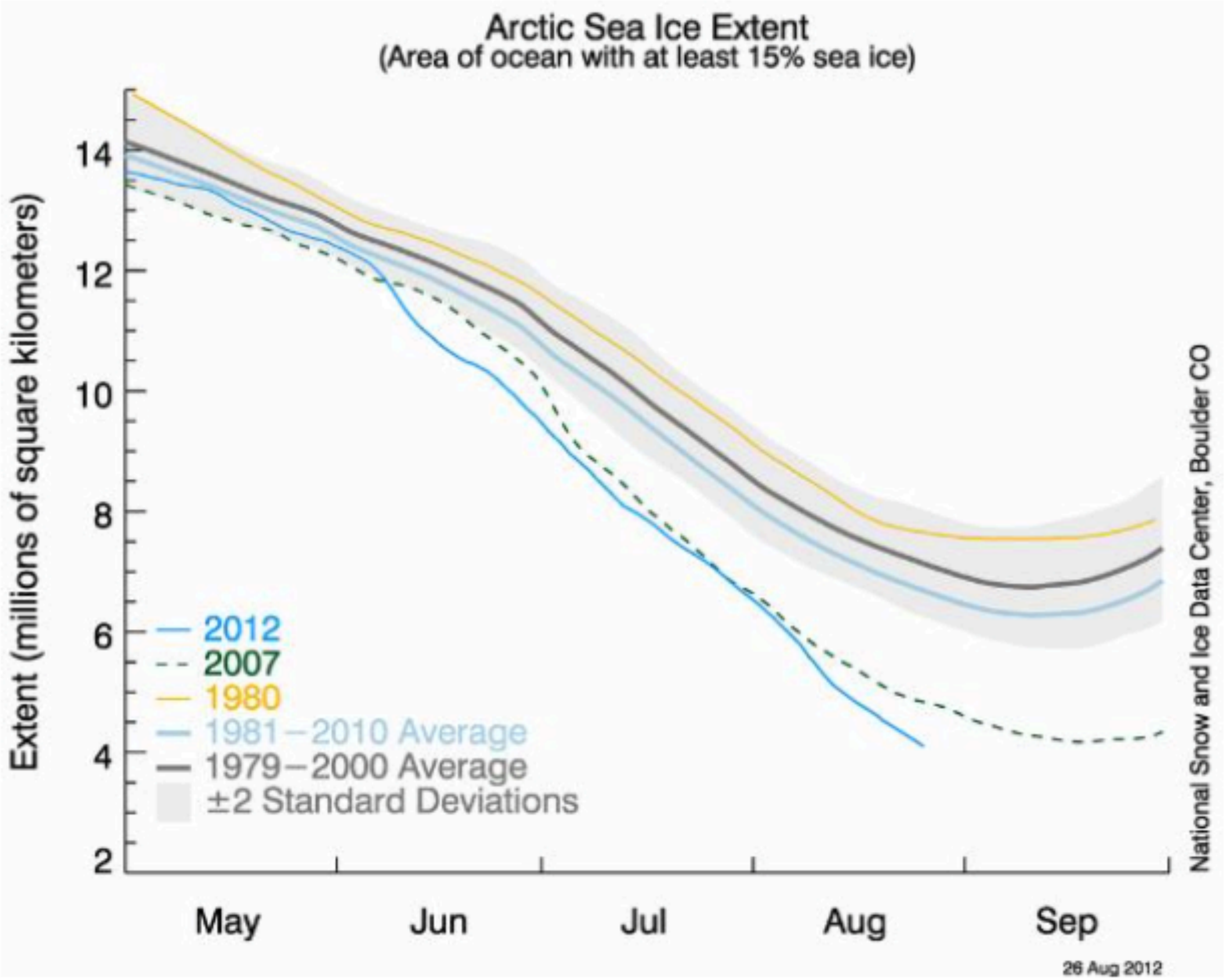
given

- a previously unseen $\boldsymbol{x}$

determine

- if x looks normal or anomalous

Anomaly detection example



Let's say our model is represented by: 1979-2000 average, ±2 stddev.

Does the data for 2012 look anomalous?

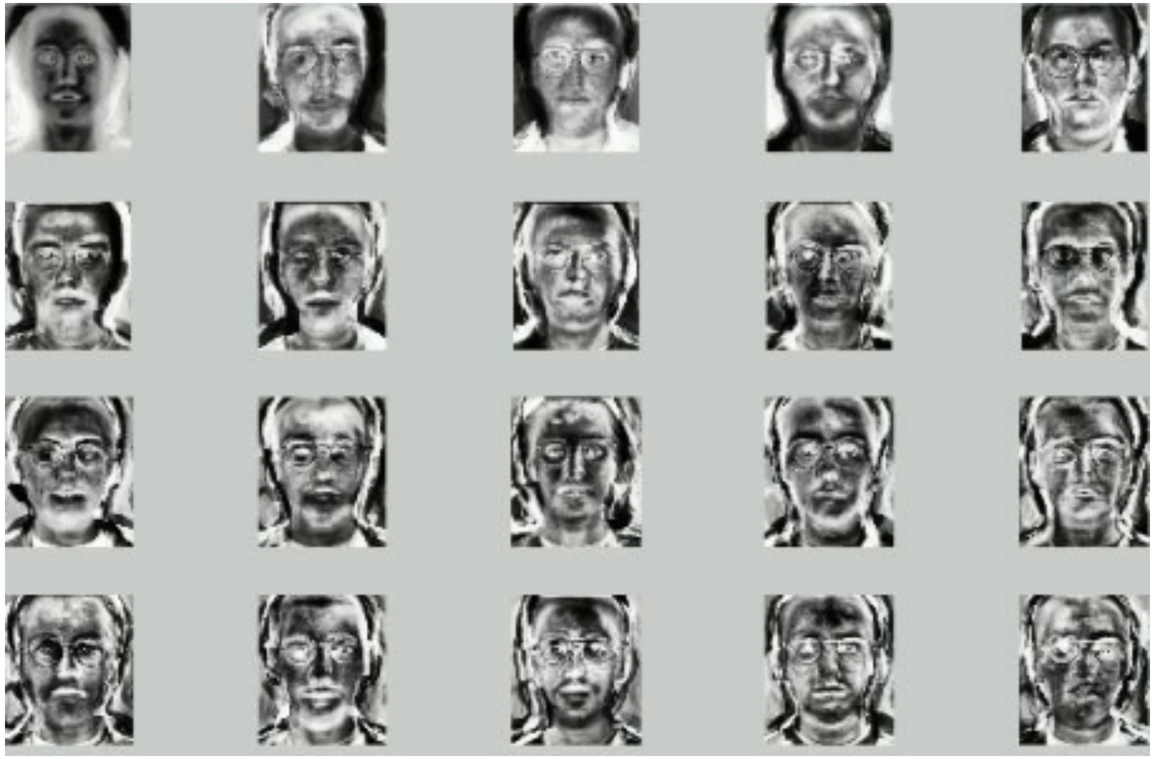
Dimensionality reduction

- given
  - training set of instances $\mathbf{x}^{(1)}$, $\mathbf{x}^{(2)}$ ... $\mathbf{x}^{(m)}$

- output
  - Model $h \in H$ that represents each x with a lower-dimension feature vector while still preserving key properties of the data

Dimensionality reduction example

We can represent a face using all of the pixels in a given image



More effective method (for many tasks): represent each face as a linear combination of *eigenfaces*

Dimensionality reduction example

- represent each face as a linear combination of *eigenfaces*

$= \alpha_1^{(1)} \times$ $+ \alpha_2^{(1)} \times$ $+ \ldots + \alpha_{20}^{(1)} \times$

$$\mathbf{x}^{(1)} = \left\langle \alpha_1^{(1)}, \alpha_2^{(1)}, \ldots, \alpha_{20}^{(1)} \right\rangle$$

$= a_1^{(2)}\,'$ $+ a_2^{(2)}\,'$ $+ \ldots + \alpha_{20}^{(2)} \times$

$$\mathbf{x}^{(2)} = \left\langle \alpha_1^{(2)}, \alpha_2^{(2)}, \ldots, \alpha_{20}^{(2)} \right\rangle$$

- # of features is now 20 instead of # of pixels in images

Other learning tasks

- later in the semester we'll cover other learning tasks that are not strictly supervised or unsupervised
    - *reinforcement learning*
    - *semi-supervised learning*
    - *etc.*

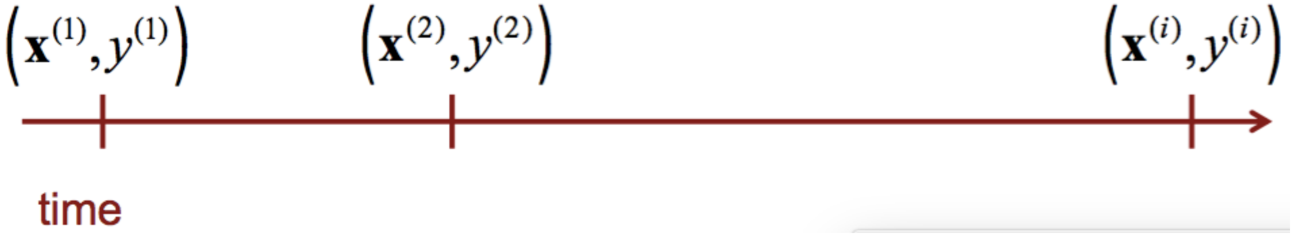
Learning Schemes

Batch vs. online learning

- In batch learning, the learner is given the training set as a batch (i.e. all at once)

$$\left(\mathbf{x}^{(1)}, y^{(1)}\right), \left(\mathbf{x}^{(2)}, y^{(2)}\right) \dots \left(\mathbf{x}^{(m)}, y^{(m)}\right)$$

- In online learning, the learner receives instances sequentially, and updates the model after each (for some tasks it might have to classify/make a prediction for each x(i) before seeing y(i))


$\left(\mathbf{x}^{(1)}, y^{(1)}\right)$
$\left(\mathbf{x}^{(2)}, y^{(2)}\right)$
$\left(\mathbf{x}^{(i)}, y^{(i)}\right)$
time

Active learning and concept drift

- *Active learning:* cases where the learner can select which instances for training
- the target function changes over time (*concept drift*)

Generalization

- The primary objective in supervised learning is to find a model that *generalizes*
  - one that accurately predicts y for previously unseen x

Can I eat this mushroom that **was not** in my training set?