

# CS 260: Foundations of Data Science

Prof. Sara Mathieson

Fall 2023



**HVERFORD**  
COLLEGE

# Admin

- Lab 5 due **Wednesday** (tomorrow)
- Lab 6 posted tomorrow
- **Midterm 1** returned today
- **Lab today**: Lab 5 implementation advice and check-ins
  - If you're *\*completely\** finished, don't need to attend, but please email me
  - Otherwise will check in about Lab 5

# Lab 5 implementation

Partition contains:

- Features dictionary F:

F = {**age**: [Senior, Middle-age, Mid-adult, Young-adult, Child], **workclass**: [Private, Local-gov...] ... }

- List of Examples

– Each example contains

features = {**age**: Senior, **workclass**: Private ... }

label = 1 (Female)

# Outline for October 24

- Entropy and Shannon encoding
- Information gain for selecting features
- Go over Midterm 1
- Continuous features (if time)

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# Decision Trees use entropy to select best features

## Examples

- Medical diagnostics



Journal of  
**MEDICAL  
SYSTEMS**  
Editor: Azeez Ehrenfeld

[Journal of Medical Systems](#)  
October 2002, Volume 26, [Issue 5](#), pp 445–463 | [Cite as](#)

### Decision Trees: An Overview and Their Use in Medicine

Authors [Authors and affiliations](#)

Vili Podgorelec , Peter Kokol, Bruno Stiglic, Ivan Rozman

- Credit risk analysis



Computational  
**Economics**  
Volume 15, No. 1, January 2000

[Computational Economics](#)  
April 2000, Volume 15, [Issue 1-2](#), pp 107–143 | [Cite as](#)

### Credit Risk Assessment Using Statistical and Machine Learning: Basic Methodology and Risk Modeling Applications

Authors [Authors and affiliations](#)

J. Galindo, P. Tamayo

- Modeling calendar scheduling preferences

# Decision Trees in Chemistry reactions

- Example of decision trees in practice
- Use decision trees to interpret another ML algorithm (SVMs)

## Machine-learning-assisted materials discovery using failed experiments

Paul Raccuglia, Katherine C. Elbert, Philip D. F. Adler, Casey Falk, Malia B. Wenny, Aurelio Mollo, Matthias Zeller, Sorelle A. Friedler , Joshua Schrier  & Alexander J. Norquist 

*Nature* **533**, 73–76 (05 May 2016) | [Download Citation](#) 

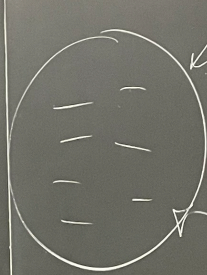
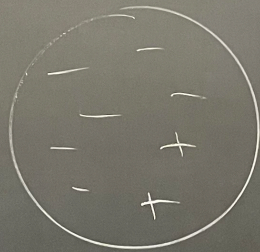
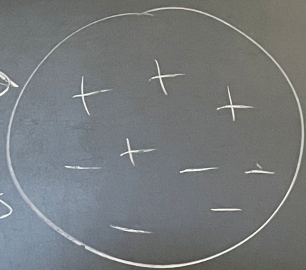
# How do we choose the best feature?

- Single feature model + evaluate with a ROC curve **(Lab 4)**
- What feature gives us the most information about the label? **(Lab 6)**



Idea of Entropy : avg # of bits needed to send one datapoint

poisonous  
+  
edible  
mushrooms



(1 bit)

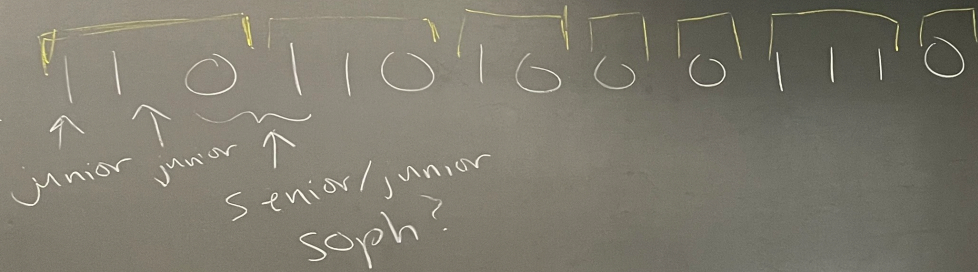
high entropy

low entropy  
(what we want)

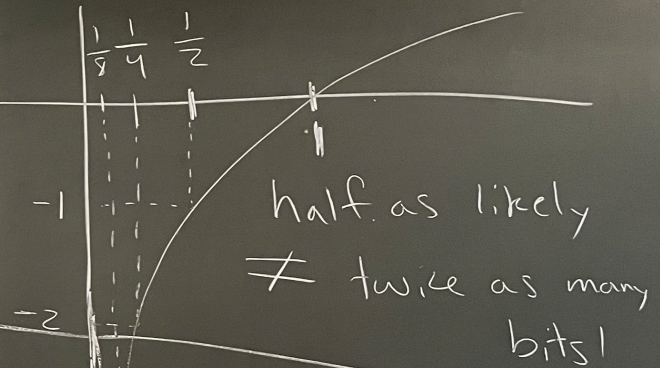
0 entropy  
(i.e. grocery store)

all edible

Send information



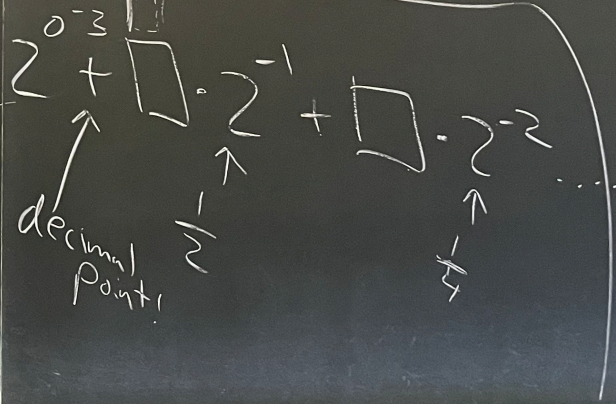
$$5.5 \Rightarrow \boxed{101.1}$$



binary

$$5 = 1 \cdot 2^2 + 0 \cdot 2^1 + 1 \cdot 2^0 + 1 \cdot 2^{-1} + 0 \cdot 2^{-2} + \dots$$

$\Rightarrow \boxed{101}$  in binary



fixed len encoding

00

01

10

11

works!

50%

first

year

Senior

Junior

Soph

first

Prob (p)

0.5

0.25

0.125

0.125

Sum to

1

idea

0

1

01

10

cumulative prob

0

0.5

0.75

0.875

in binary

0.000

0.100

0.110

0.1110

ceil round up  $\lceil -\log_2(p) \rceil$

1

2

3

3

# bits

Variable len Shannon encoding

0

10

110

111

no code is the prefix of another

# Entropy

$$H(Y) = \sum_{c \in \text{vals}(Y)} p(Y=c) \log_2 (p(Y=c))$$

↑  
label

$$H(\text{year}) = \frac{1}{2} \cdot 1 + \frac{1}{4} \cdot 2 + \frac{1}{8} \cdot 3 + \frac{1}{8} \cdot 3$$
$$= \boxed{1.75} \text{ bits}$$

~~$$\frac{1+2+3+3}{4} = 2.25$$~~

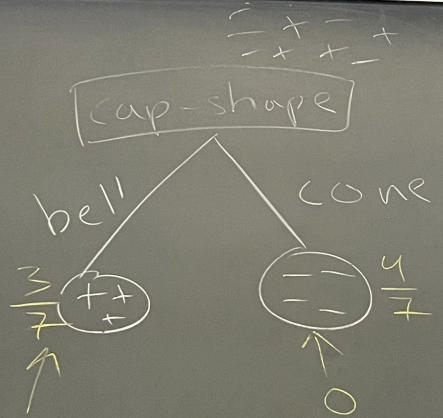
# bits

$$(p(Y=c))$$

H

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$$H(Y|X=\text{bell}) = -\left(0 \cdot \log_2 0 + 1 \cdot \log_2 1\right) = 0$$

Conditional entropy

$$H(Y|X) = \sum_{v \in \text{vals}(X)} P(X=v) H(Y|X=v)$$

ex ↑  
cap-shape
weighted avg

$$= \frac{3}{7} \cdot 0 + \frac{4}{7} \cdot 0 = 0$$

$$H(Y|X=v) = -\sum_{c \in \text{vals}(Y)} P(Y=c|X=v) \log_2 P(Y=c|X=v)$$

Single feature value
Same
all

y=0
cap-shape = bell

= 0

Handout 13

all values / leaves

# Information gain

$$G(Y, X) = H(Y) - \underbrace{H(Y|X)}_{\text{want low}}$$

want high

Want the feature  
that maximizes info gain

# Handout 13



# Handout 13

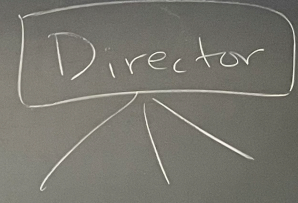
for Lab 6  
=> no rounding

$L_i =$

①  $P(\text{yes}) = \frac{6}{9} = \frac{2}{3}$

②  $H(L_i) = -\left(\frac{2}{3} \log_2 \frac{2}{3} + \frac{1}{3} \log_2 \frac{1}{3}\right) \approx 0.92$

③  $\text{Gain}(L_i, T) = 0.92 - 0.61 = 0.31$   
 $0.92 - 0.61 \dots$



# Handout 13

Movie	Type	Length	Director	Famous actors	Liked?
m1	Comedy	Short	Adamson	No	Yes
m2	Animated	Short	Lasseter	No	No
m3	Drama	Medium	Adamson	No	Yes
m4	Animated	Long	Lasseter	Yes	No
m5	Comedy	Long	Lasseter	Yes	No
m6	Drama	Medium	Singer	Yes	Yes
m7	Animated	Short	Singer	No	Yes
m8	Comedy	Long	Adamson	Yes	Yes
m9	Drama	Medium	Lasseter	No	Yes

$$P(Li = \text{yes}) = 2/3$$

$$H(Li) = 0.92$$

$$H(Li | T) = 0.61$$

$$H(Li | Le) = 0.61$$

$$H(Li | D) = 0.36 \quad \text{MIN ENTROPY}$$

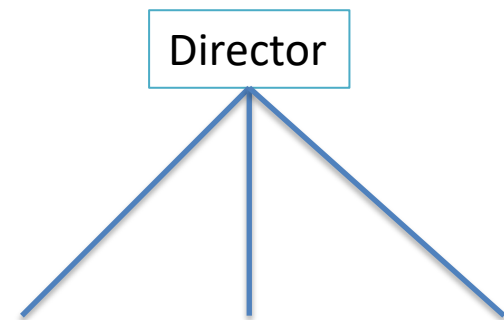
$$H(Li | F) = 0.85$$

$$\text{Gain}(Li, T) = 0.92 - 0.61 = 0.31$$

$$\text{Gain}(Li, Le) = 0.92 - 0.61 = 0.31$$

$$\text{Gain}(Li, D) = 0.92 - 0.36 = 0.56 \quad \text{MAX INFO GAIN}$$

$$\text{Gain}(Li, F) = 0.92 - 0.85 = 0.07$$



Start of the tree

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# Midterm 1 Grades

- 90-100%     A
- 80-89%     B
- 70-79%     C
- Below 70%: please meet with me
- Below 60%: not passing
  
- Any questions about the exam: bring to me within one week

Midterm solutions  
not posted online

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