SSID: ZCOM
Password: u6qQ]Zcom[8a

Register:

http://bit.ly/wwcodemanila

Github Project:

https://github.com/wwcodemanila/WWCodeManila-ML.AI

Gitter:

https://gitter.im/WWCodeManila/Machine-Learning-AI

WOMEN WHO CODE MANILA

Artificial Intelligence Study Group

Twitter: @wwcodemanila
FB: fb.com/wwcodemanila

#WWCodeManila
#AI
#StudyGroup

Issa Tingzon

Research Fellow

PCARI

Our Awesome Mentors

- **Brian Baquiran** – Managing Director for Engineering, Pez AI
- **Marylette Roa** – Researcher at the Philippine Genome Center (PGC)

New Member's Introduction

I am <name>

<your current profession>

<why did you join this study group>

<what’s your favorite horror movie/series>

OUR MISSION

Inspiring women to excel in technology careers.

WOMEN WHO CODE
MANILA

OUR VISION

A world where women are representative as technical executives, founders, VCs, board members and software engineers.

WOMEN WHO CODE MANILA

STUDY GROUP

Study groups are events where women can come together and help each other learn and understand a specific programming language, technology, or anything related to coding or engineering.

GUIDELINES

- If you have a question, just **ask**
- If you have an idea, **share it**
- **Make friends** and learn from your study groupmates
- **Do not** recruit or promote your business

ANNOUNCEMENTS

- Today will be our last study group for the year. ☹

ANNOUNCEMENTS

- Today will be our last study group for the year. ☹
- **Women Who Code Hackathon!**

ANNOUNCEMENTS

- **Coming up: R Study Group**
  - To be led by our awesome mentor **Brian Baquiran**!
  - Every 2nd week of the month

ANNOUNCEMENTS

- **Coming up: R Study Group**
  - To be led by our awesome mentor **Brian Baquiran**!
  - Every 2nd week of the month
- **In-depth study of ML algorithms/ ML with Python**
  - Review Math, Statistics, Linear Algebra, Calculus
  - Every 4th week of the month

Fun with Artificial Intelligence ☺

TOPIC FOR TODAY

DECISION TREES

Session Resource:

Decision Trees Lecture by Victor Lavrenko (Youtube)

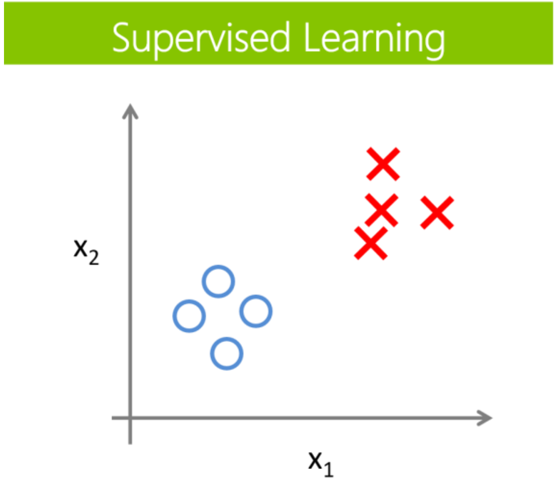
PREREQUISITES

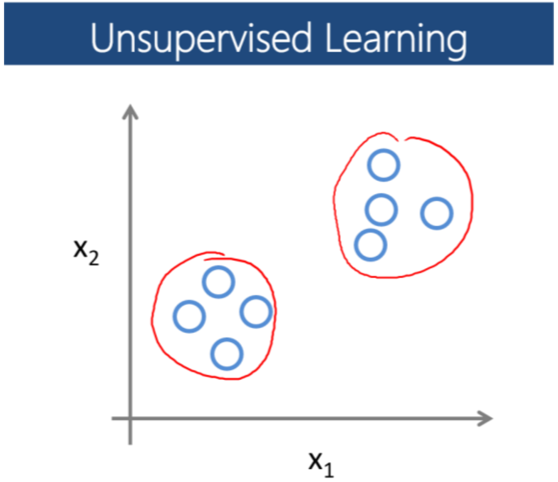
- Knowledge of Python basics
- Accomplished Introduction To Machine Learning
- Understanding of Basic Math Notations

REVIEW

Two types of ML Algorithms:

- **Supervised**
    - Data is labelled
    - Goal: Predict or classify data
- **Unsupervised**
    - Data is unlabelled
    - Goal: Uncover patterns or structure in data





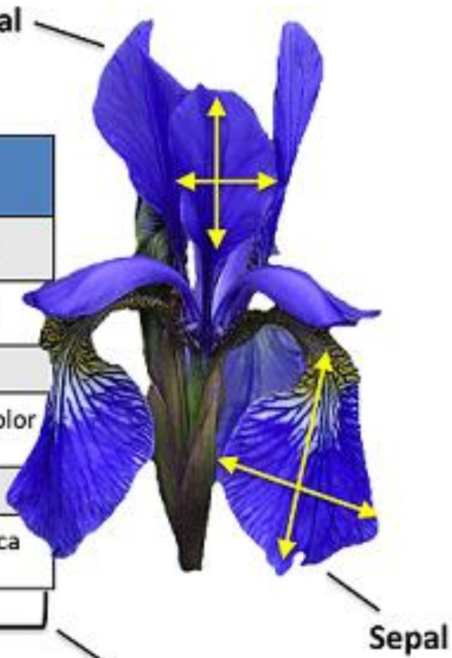
IRIS PLANT CLASSIFICATION

Samples
(instances, observations)

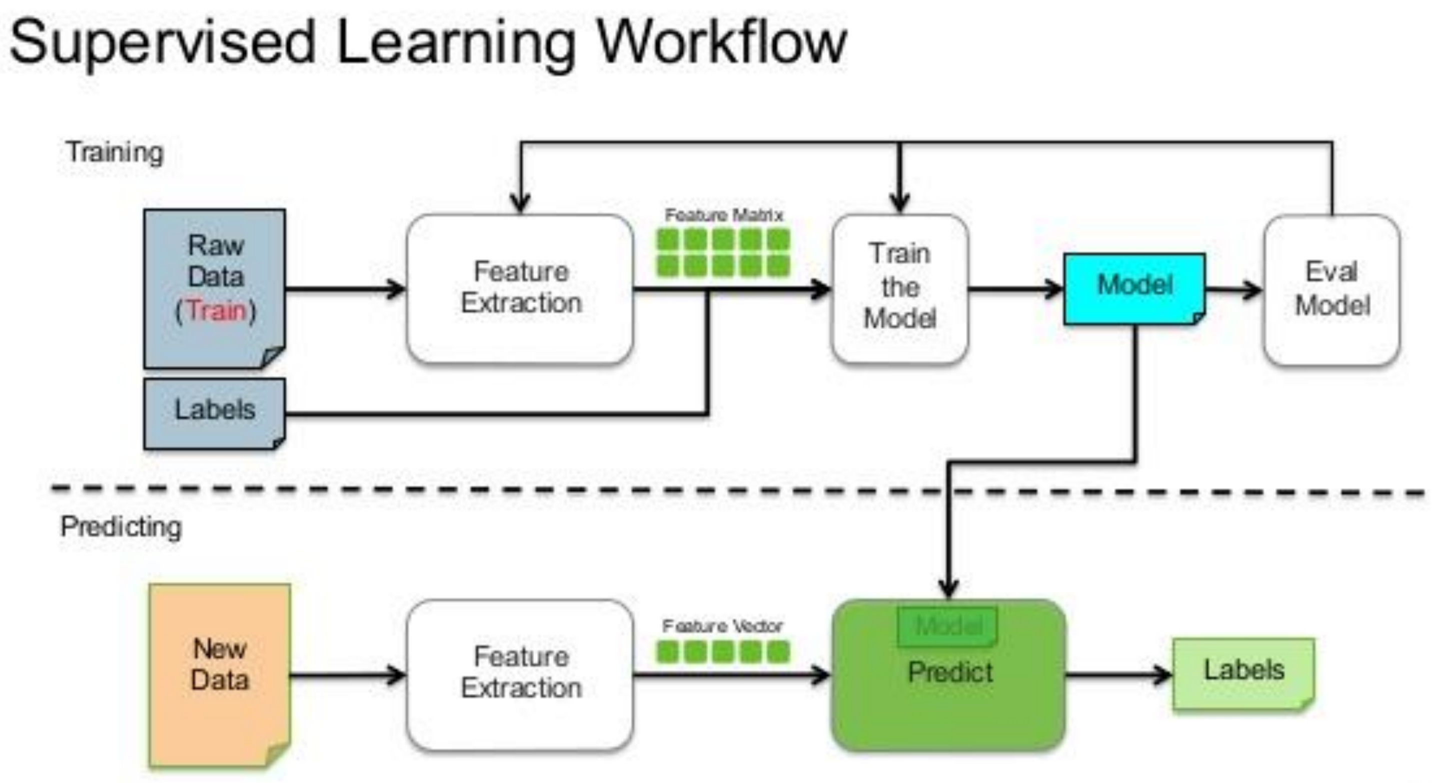
	Sepal length	Sepal width	Petal length	Petal width	Class label
1	5.1	3.5	1.4	0.2	Setosa
2	4.9	3.0	1.4	0.2	Setosa
...					
50	6.4	3.5	4.5	1.2	Versicolor
...					
150	5.9	3.0	5.0	1.8	Virginica

Features
(attributes, measurements, dimensions)

Class labels
(targets)

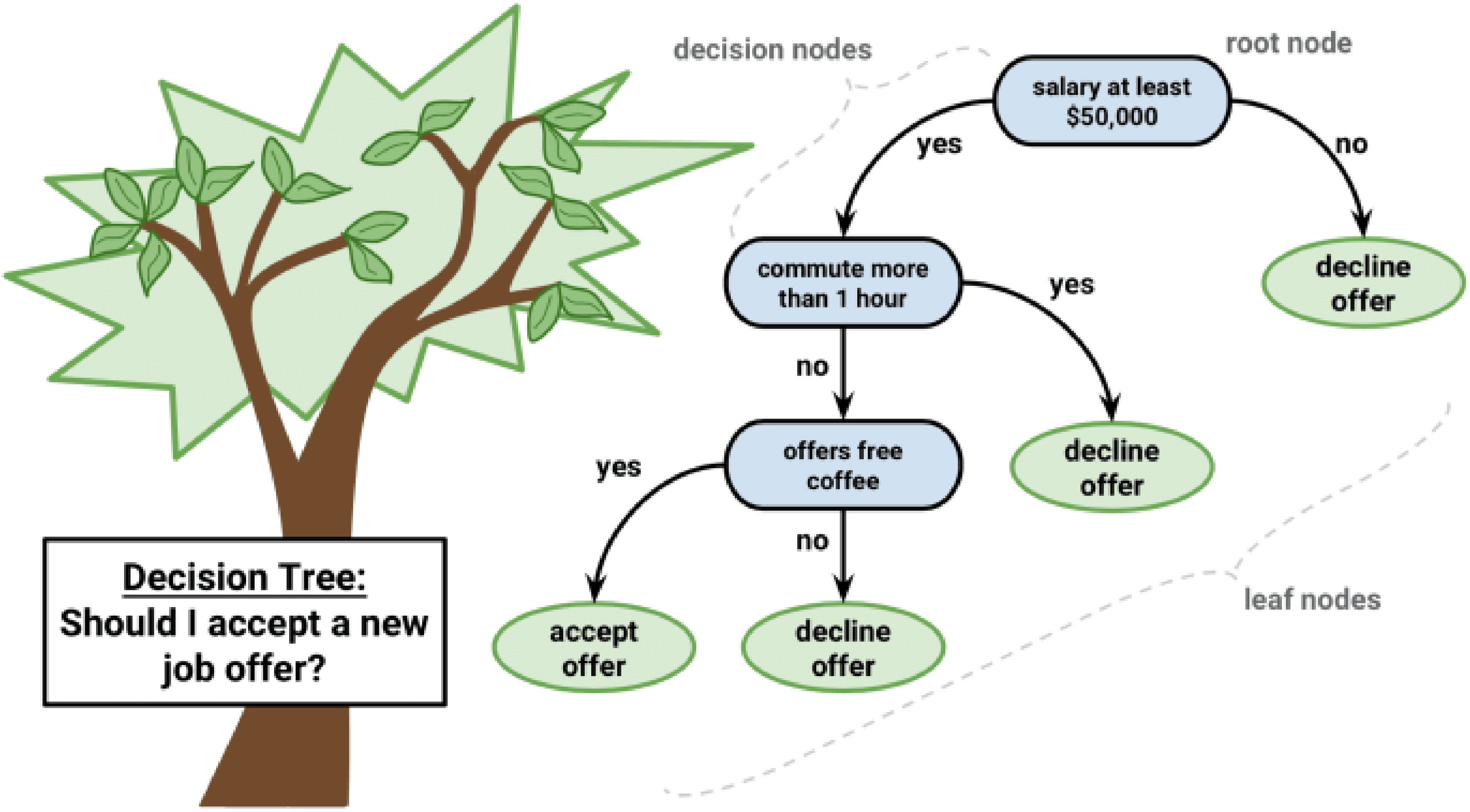


Supervised Learning Workflow



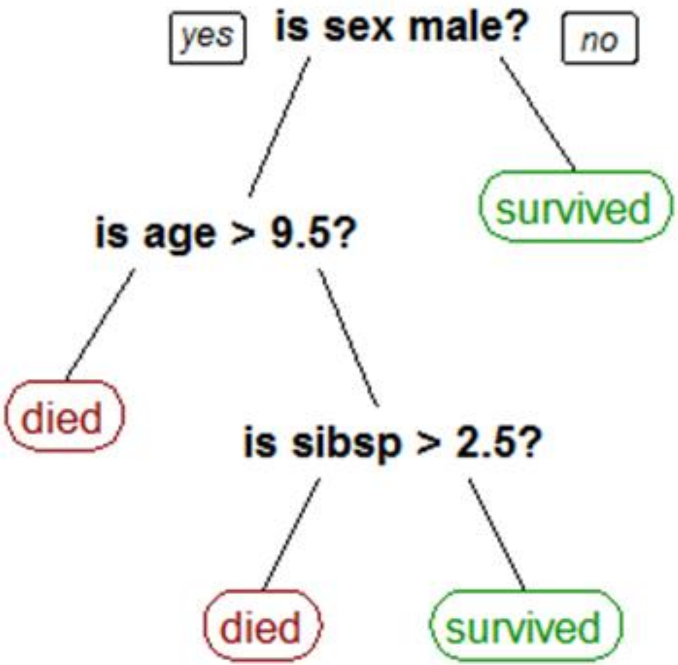
DECISION TREES

- A type of supervised learning algorithm
- Interpretable; mimics human decision making



If Salary > $50,000 **and** commute is not more than 1 hour **and** offers free coffee, **then** accept offer!

Would you survive the sinking of the Titanic?



TERMINOLOGY

- **Root Node:** represents the entire training set
- **Splitting**: process of dividing a node into two or more subsets/nodes
- **Internal/Decision Node**: corresponds to an attribute
- **Leaf/Terminal Node:** corresponds to a class label

Predict if John will play tennis

Training examples: **9 yes / 5 no**

Day	Outlook	Humidity	Wind	Play
D1	Sunny	High	Weak	No
D2	Sunny	High	Strong	No
D3	Overcast	High	Weak	Yes
D4	Rain	High	Weak	Yes
D5	Rain	Normal	Weak	Yes
D6	Rain	Normal	Strong	No
D7	Overcast	Normal	Strong	Yes
D8	Sunny	High	Weak	No
D9	Sunny	Normal	Weak	Yes
D10	Rain	Normal	Weak	Yes
D11	Sunny	Normal	Strong	Yes
D12	Overcast	High	Strong	Yes
D13	Overcast	Normal	Weak	Yes
D14	Rain	High	Strong	No

Predict if John will play tennis

Training examples: **9 yes / 5 no**

Day	Outlook	Humidity	Wind	Play
D1	Sunny	High	Weak	No
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D3	Overcast	High	Weak	Yes
D4	Rain	High	Weak	Yes
D5	Rain	Normal	Weak	Yes
D6	Rain	Normal	Strong	No
D7	Overcast	Normal	Strong	Yes
D8	Sunny	High	Weak	No
D9	Sunny	Normal	Weak	Yes
D10	Rain	Normal	Weak	Yes
D11	Sunny	Normal	Strong	Yes
D12	Overcast	High	Strong	Yes
D13	Overcast	Normal	Weak	Yes
D14	Rain	High	Strong	No

New data:

D15	Rain	High	Weak	?

Predict if John will play tennis

Training examples: **9 yes / 5 no**

Day	Outlook	Humidity	Wind	Play
D1	Sunny	High	Weak	No
D2	Sunny	High	Strong	No
D3	Overcast	High	Weak	Yes
D4	Rain	High	Weak	Yes
D5	Rain	Normal	Weak	Yes
D6	Rain	Normal	Strong	No
D7	Overcast	Normal	Strong	Yes
D8	Sunny	High	Weak	No
D9	Sunny	Normal	Weak	Yes
D10	Rain	Normal	Weak	Yes
D11	Sunny	Normal	Strong	Yes
D12	Overcast	High	Strong	Yes
D13	Overcast	Normal	Weak	Yes
D14	Rain	High	Strong	No

New data:

D15	Rain	High	Weak	?

- Hard to guess
- Try to understand *when* John plays tennis

Predict if John will play tennis

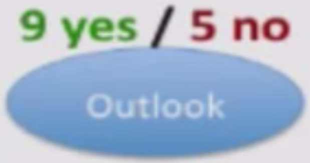
Training examples: **9 yes / 5 no**

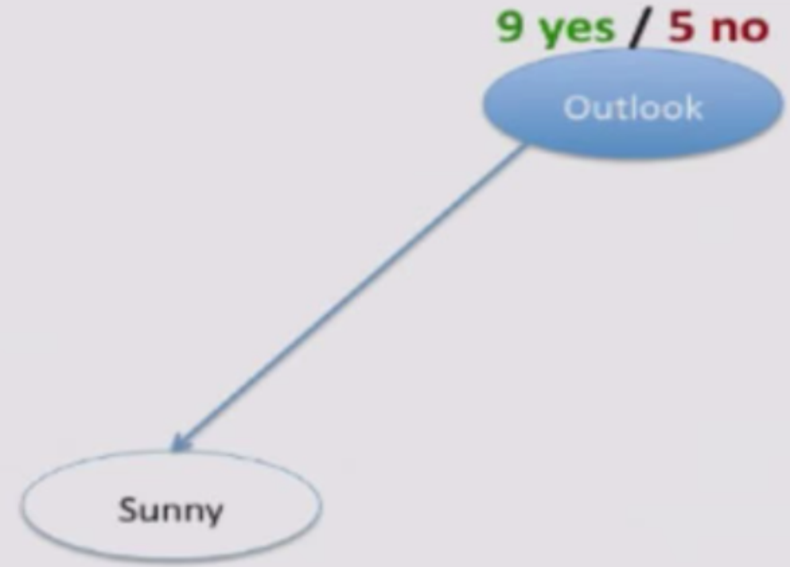
Day	Outlook	Humidity	Wind	Play
D1	Sunny	High	Weak	No
D2	Sunny	High	Strong	No
D3	Overcast	High	Weak	Yes
D4	Rain	High	Weak	Yes
D5	Rain	Normal	Weak	Yes
D6	Rain	Normal	Strong	No
D7	Overcast	Normal	Strong	Yes
D8	Sunny	High	Weak	No
D9	Sunny	Normal	Weak	Yes
D10	Rain	Normal	Weak	Yes
D11	Sunny	Normal	Strong	Yes
D12	Overcast	High	Strong	Yes
D13	Overcast	Normal	Weak	Yes
D14	Rain	High	Strong	No

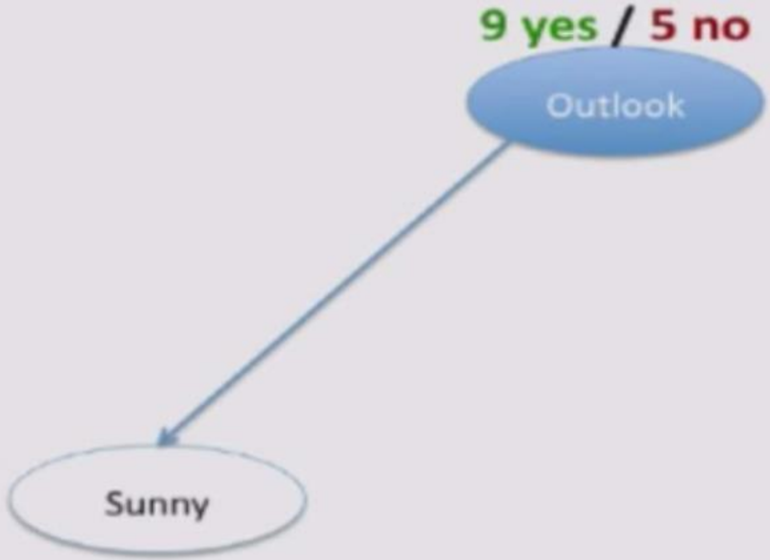
New data:

D15	Rain	High	Weak	?

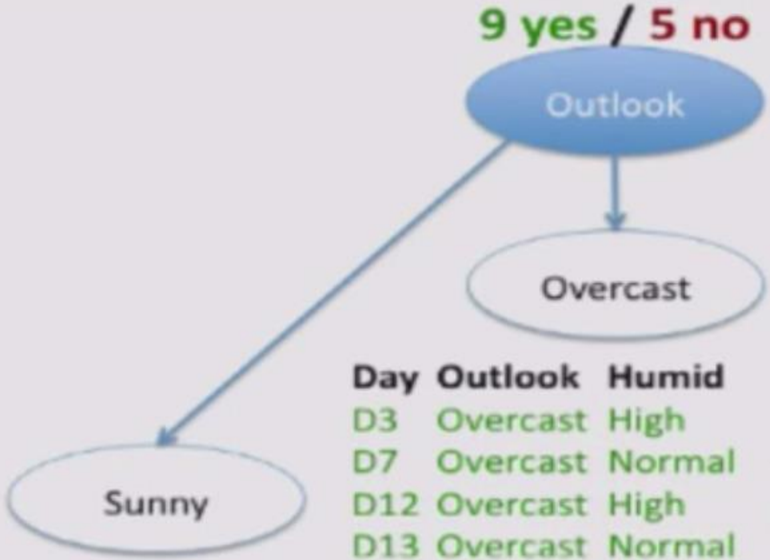
- **Divide and Conquer**
  - Split into subsets
  - Are they all “pure”?
  - If yes: stop
  - If not: repeat
- See which subset new data falls into


9 yes / 5 no
Outlook


9 yes / 5 no
Outlook
Sunny



Day	Outlook	Humid	Wind
D1	Sunny	High	Weak
D2	Sunny	High	Strong
D8	Sunny	High	Weak
D9	Sunny	Normal	Weak
D11	Sunny	Normal	Strong



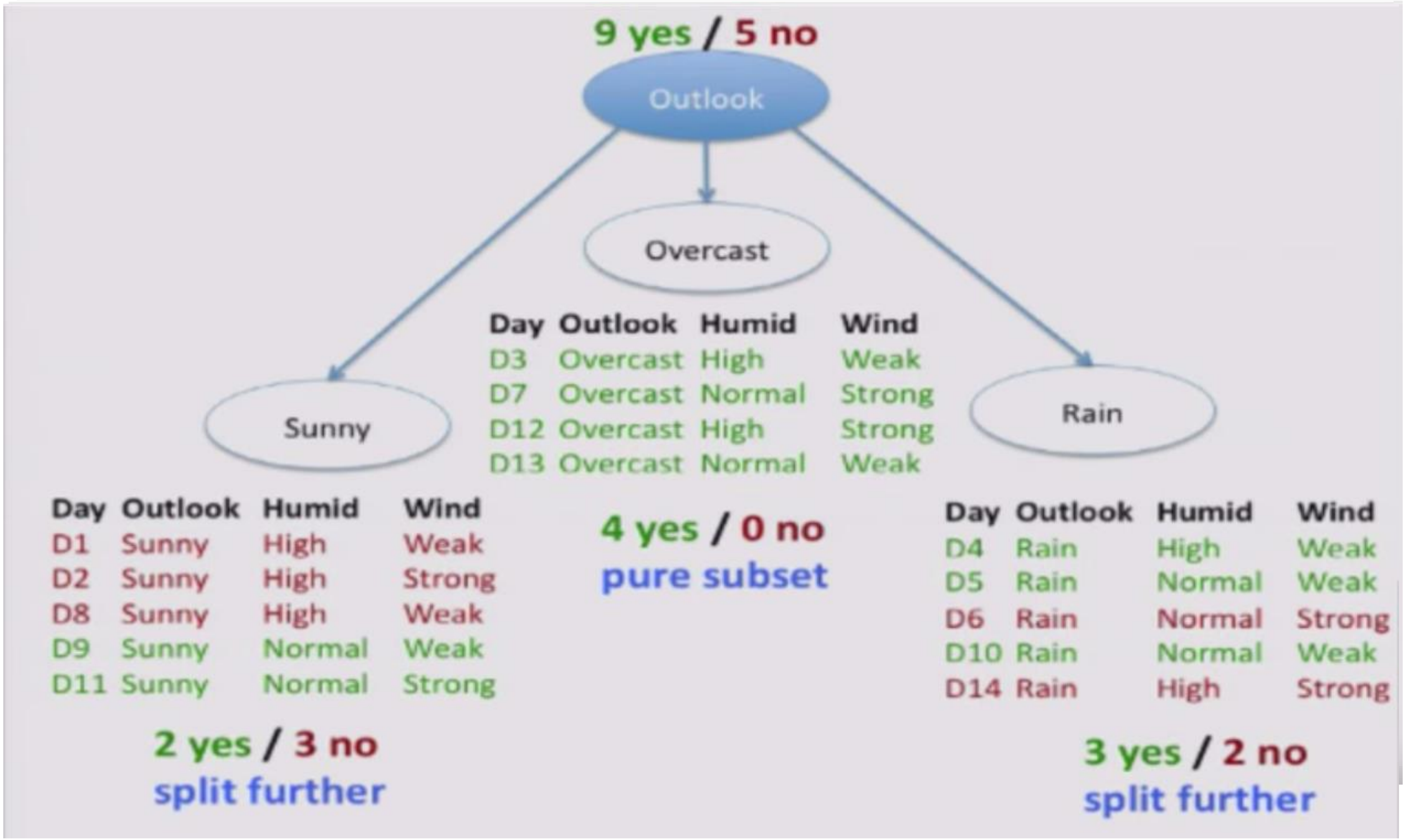
Day	Outlook	Humid	Wind
D3	Overcast	High	Weak
D7	Overcast	Normal	Strong
D12	Overcast	High	Strong
D13	Overcast	Normal	Weak

Day	Outlook	Humid	Wind
D1	Sunny	High	Weak
D2	Sunny	High	Strong
D8	Sunny	High	Weak
D9	Sunny	Normal	Weak
D11	Sunny	Normal	Strong

Day	Outlook	Humid	Wind
D3	Overcast	High	Weak
D7	Overcast	Normal	Strong
D12	Overcast	High	Strong
D13	Overcast	Normal	Weak

Day	Outlook	Humid	Wind
D1	Sunny	High	Weak
D2	Sunny	High	Strong
D8	Sunny	High	Weak
D9	Sunny	Normal	Weak
D11	Sunny	Normal	Strong

Day	Outlook	Humid	Wind
D4	Rain	High	Weak
D5	Rain	Normal	Weak
D6	Rain	Normal	Strong
D10	Rain	Normal	Weak
D14	Rain	High	Strong



Day	Outlook	Humid	Wind
D3	Overcast	High	Weak
D7	Overcast	Normal	Strong
D12	Overcast	High	Strong
D13	Overcast	Normal	Weak

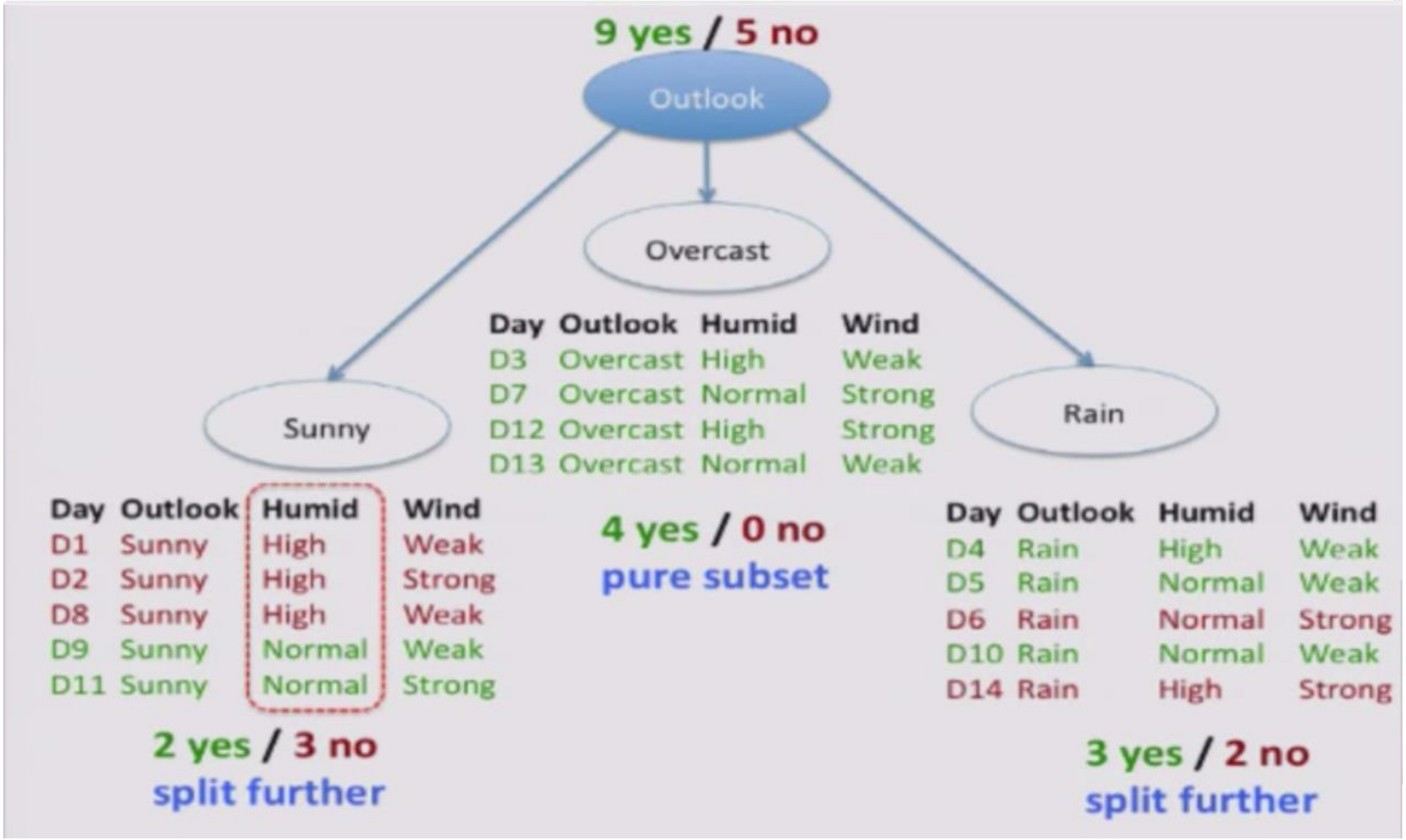
4 yes / 0 no
pure subset

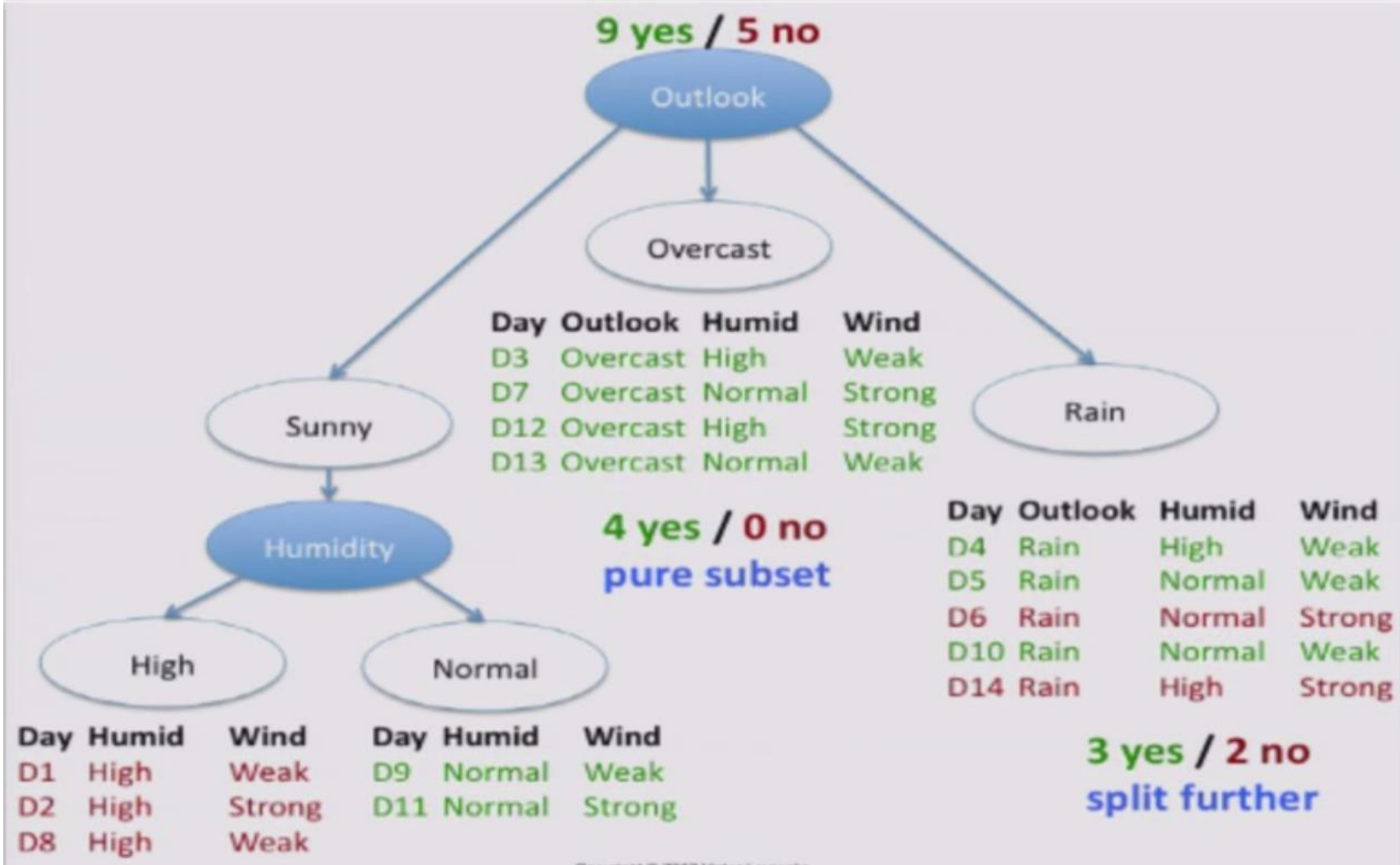
Day	Outlook	Humid	Wind
D1	Sunny	High	Weak
D2	Sunny	High	Strong
D8	Sunny	High	Weak
D9	Sunny	Normal	Weak
D11	Sunny	Normal	Strong

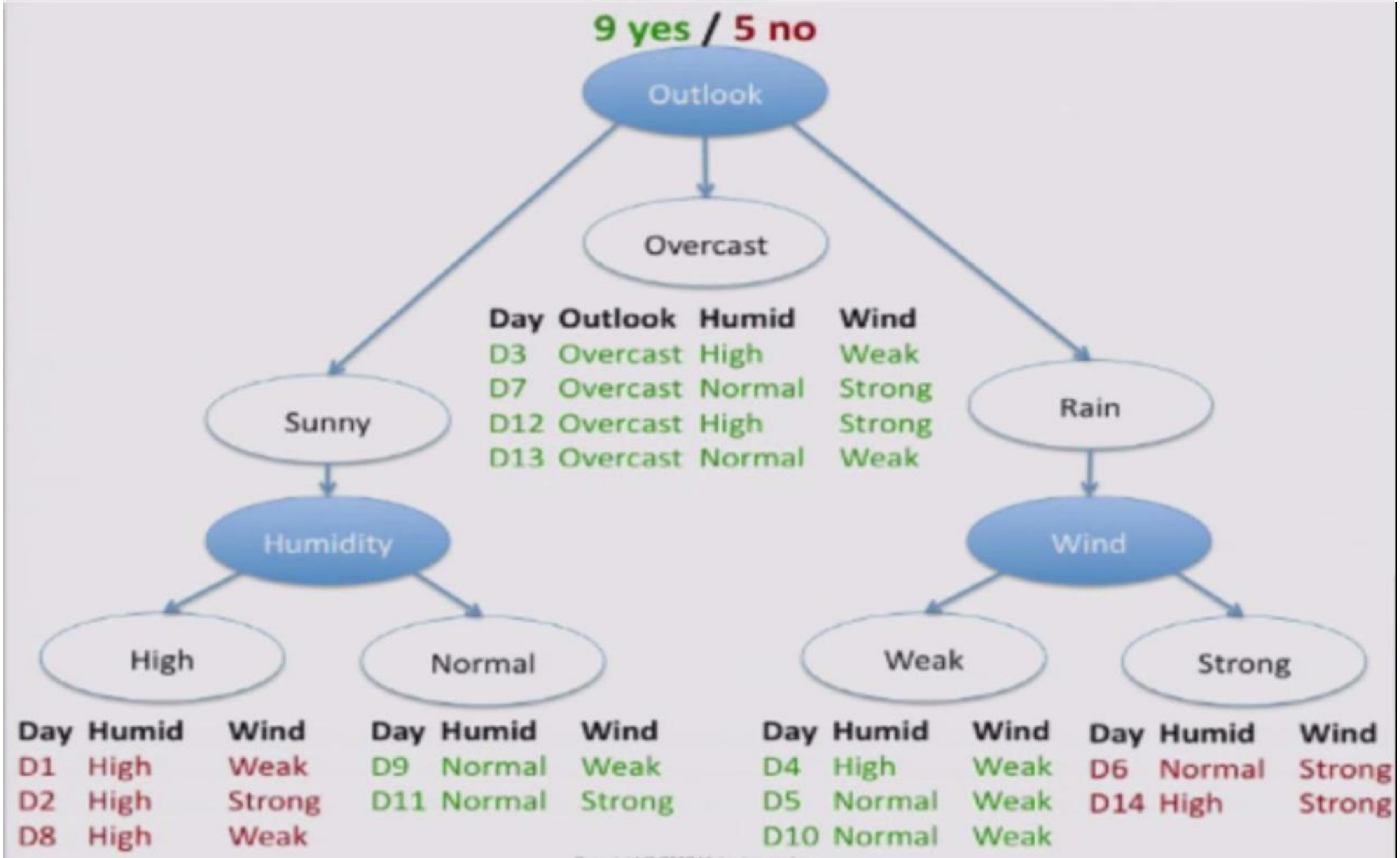
2 yes / 3 no
split further

Day	Outlook	Humid	Wind
D4	Rain	High	Weak
D5	Rain	Normal	Weak
D6	Rain	Normal	Strong
D10	Rain	Normal	Weak
D14	Rain	High	Strong

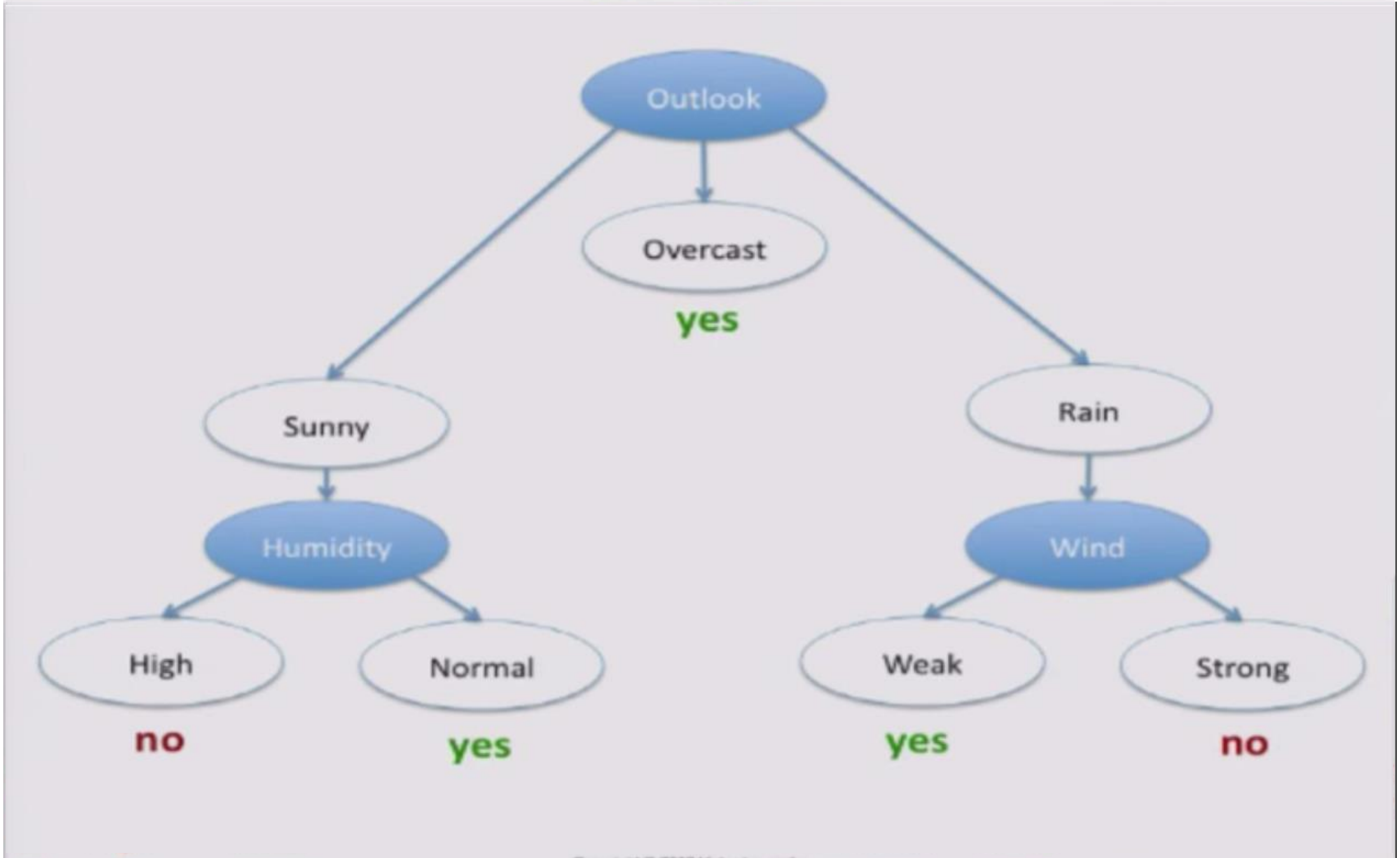
3 yes / 2 no
split further

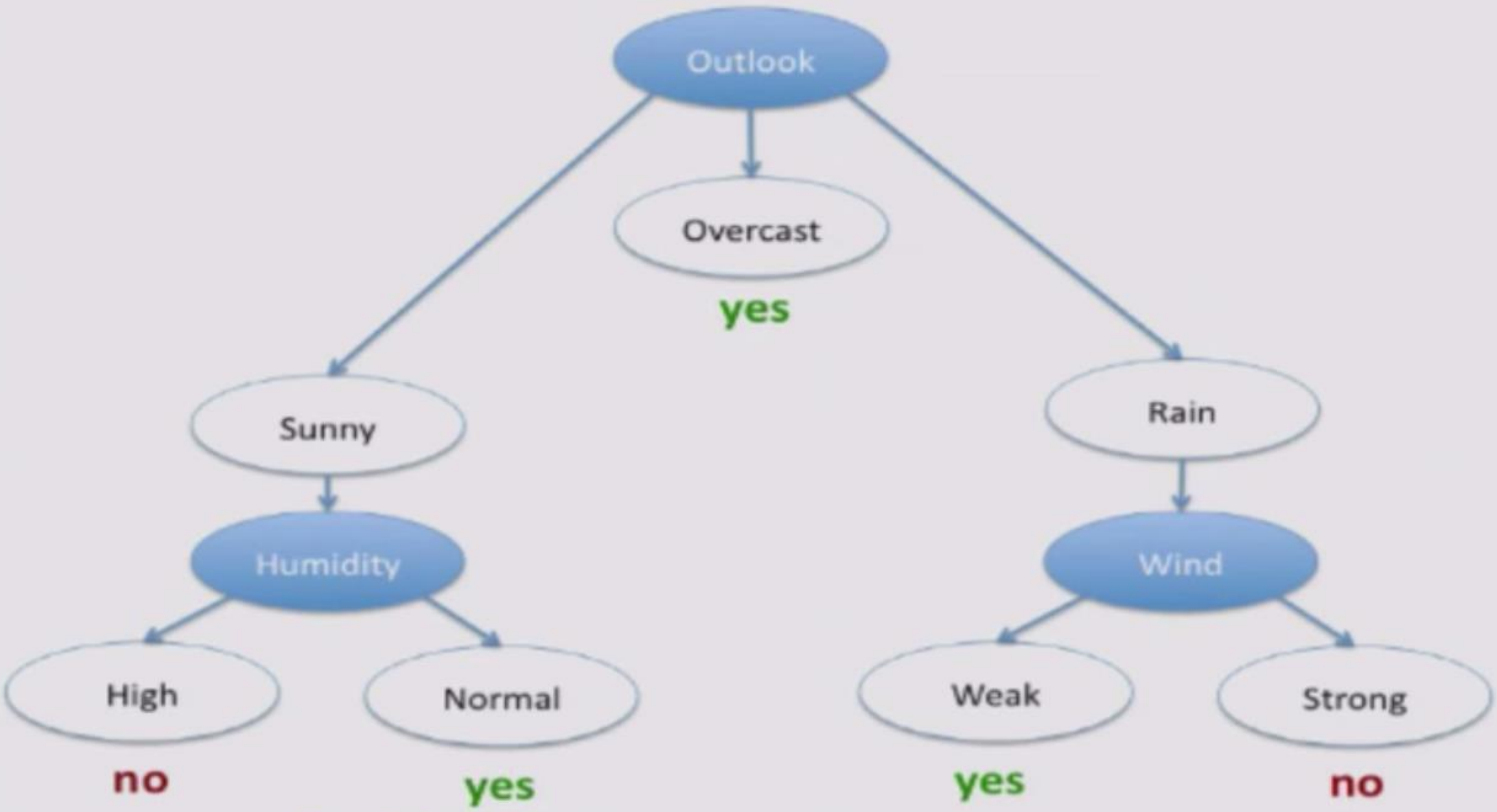

9 yes / 5 no
Outlook
Overcast
Sunny
Rain
Day Outlook Humid Wind
D3 Overcast High Weak
D7 Overcast Normal Strong
D12 Overcast High Strong
D13 Overcast Normal Weak
4 yes / 0 no
pure subset
Day Outlook Humid Wind
D1 Sunny High Weak
D2 Sunny High Strong
D8 Sunny High Weak
D9 Sunny Normal Weak
D11 Sunny Normal Strong
2 yes / 3 no
split further
Day Outlook Humid Wind
D4 Rain High Weak
D5 Rain Normal Weak
D6 Rain Normal Strong
D10 Rain Normal Weak
D14 Rain High Strong
3 yes / 2 no
split further


9 yes / 5 no
Outlook
Overcast
Day Outlook Humid Wind
D3 Overcast High Weak
D7 Overcast Normal Strong
D12 Overcast High Strong
D13 Overcast Normal Weak
4 yes / 0 no
pure subset
Sunny
Humidity
High
Day Humid Wind
D1 High Weak
D2 High Strong
D8 High Weak
Normal
Day Humid Wind
D9 Normal Weak
D11 Normal Strong
Rain
Day Outlook Humid Wind
D4 Rain High Weak
D5 Rain Normal Weak
D6 Rain Normal Strong
D10 Rain Normal Weak
D14 Rain High Strong
3 yes / 2 no
split further



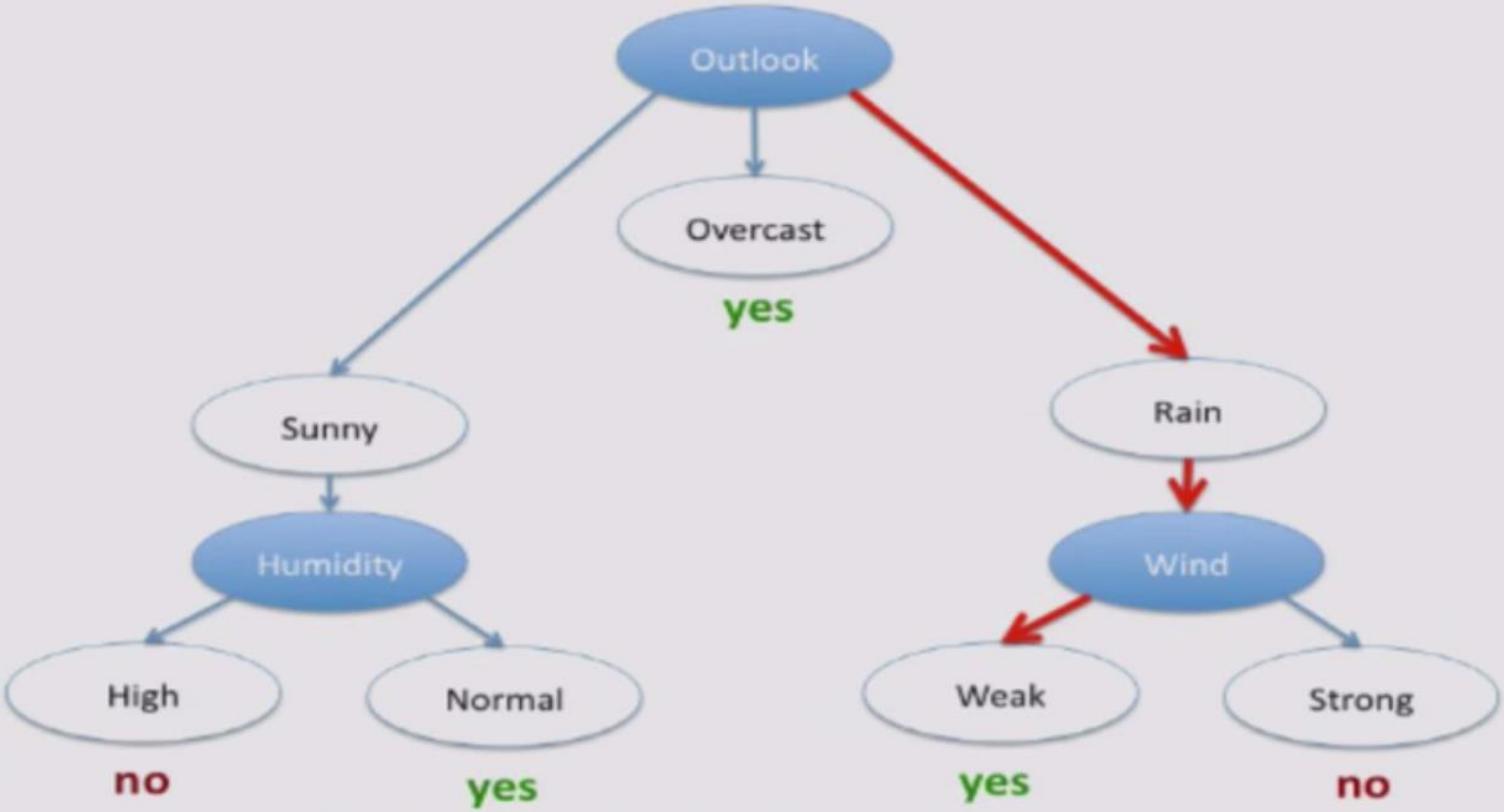
9 yes / 5 no
Outlook
Overcast
Day Outlook Humid Wind
D3 Overcast High Weak
D7 Overcast Normal Strong
D12 Overcast High Strong
D13 Overcast Normal Weak
Sunny
Rain
Humidity
Wind
High
Normal
Weak
Strong
Day Humid Wind
D1 High Weak
D2 High Strong
D8 High Weak
Day Humid Wind
D9 Normal Weak
D11 Normal Strong
Day Humid Wind
D4 High Weak
D5 Normal Weak
D10 Normal Weak
Day Humid Wind
D6 Normal Strong
D14 High Strong


Outlook
Overcast
yes
Sunny
Rain
Humidity
Wind
High
Normal
Weak
Strong
no
yes
yes
no



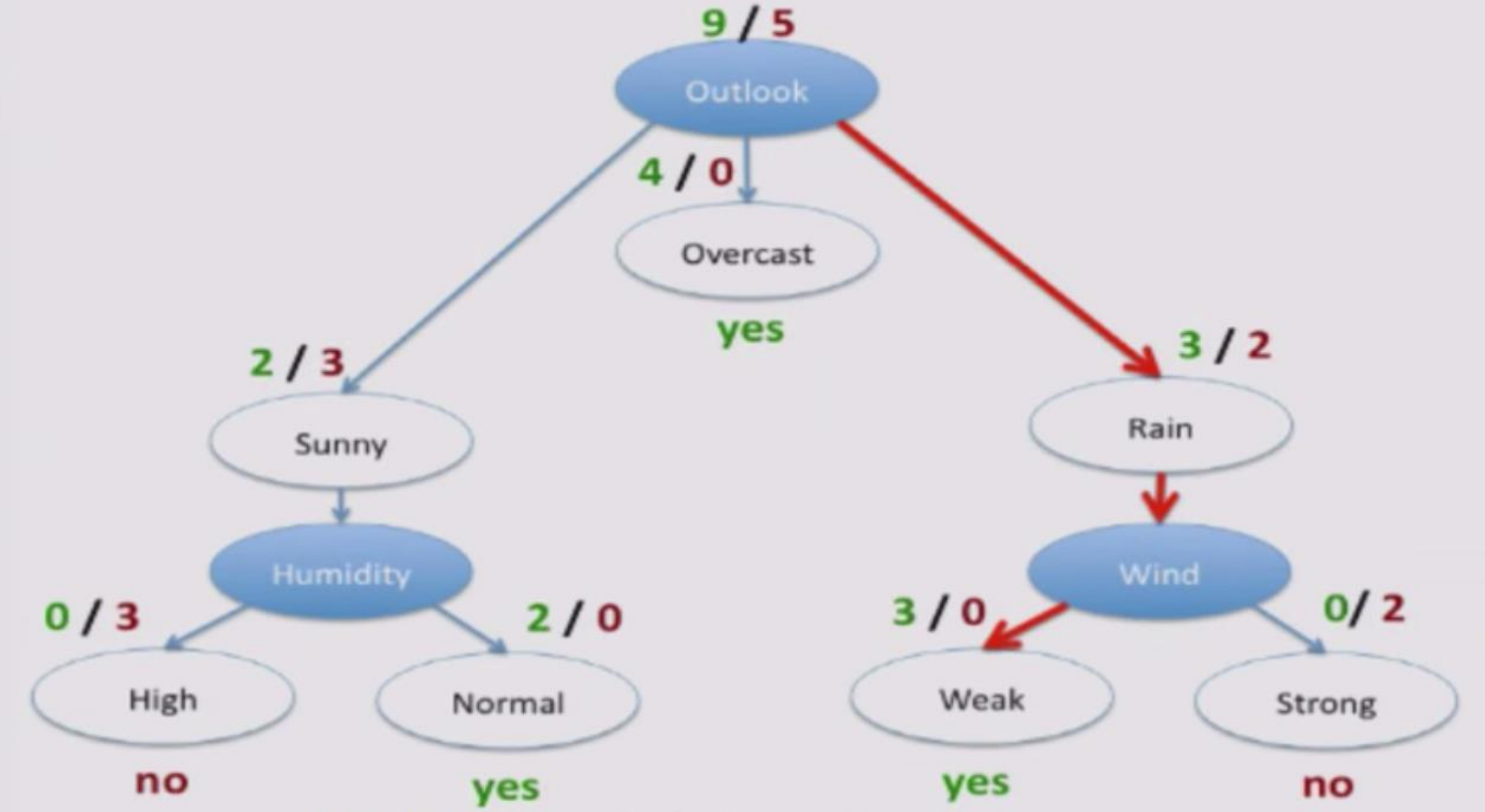
New data:

Day	Outlook	Humid	Wind
D15	Rain	High	Weak



New data:

Day	Outlook	Humid	Wind	
D15	Rain	High	Weak	→ Yes



New data:

Day	Outlook	Humid	Wind	
D15	Rain	High	Weak	→ Yes

ID3 Algorithm

- ID3 - Ross Quinlan, 1986
- Suppose feature A is the **best attribute** to split on.
    - Split entire training set on attribute A
    - For each subset/ child node:
        - If subset is pure: stop
        - Else: split subset

Which attribute to split on?

- Want to measure the **"purity"** of the split
- More certain about Yes/No after the split
  - **Pure set →** (4 Yes / 0 No) 100% certain
  - **Impure Set →** (3 Yes / 3 No) 50 % certain
- **Entropy** – a way to measure certainty
  - Higher entropy → more uncertain

Entropy

$$Entropy(S) = -p_{yes}\log_2 p_{yes} \; - p_{no}\log_2 p_{no}$$

S – subset of training examples

p_{yes} – proportion of positive (yes) examples

p_{no} – proportion of negative (no) examples

Entropy, more generally

$$Entropy(S) = -\sum_{c \in Classes} p_c \log_2 p_c$$

S – subset of examples

p_c – proportion of examples in S belonging to class c

Entropy example

e.g. (3 yes / 3 no)

Entropy example

e.g. (3 yes / 3 no)

$$\text{Entropy} = -\frac{3}{6}\log_2\frac{3}{6} - \frac{3}{6}\log_2\frac{3}{6} = 1$$

Entropy example

e.g. (3 yes / 3 no)

$$\text{Entropy} = -\frac{3}{6}\log_2\frac{3}{6} - \frac{3}{6}\log_2\frac{3}{6} = 1$$

e.g. (4 yes / 0 no)

Entropy example

e.g. (3 yes / 3 no)

$$\text{Entropy} = -\frac{3}{6}\log_2\frac{3}{6} - \frac{3}{6}\log_2\frac{3}{6} = 1$$

e.g. (4 yes / 0 no)

$$\text{Entropy} = -\frac{4}{4}\log_2\frac{4}{4} - \frac{0}{4}\log_2\frac{0}{4} = 0$$

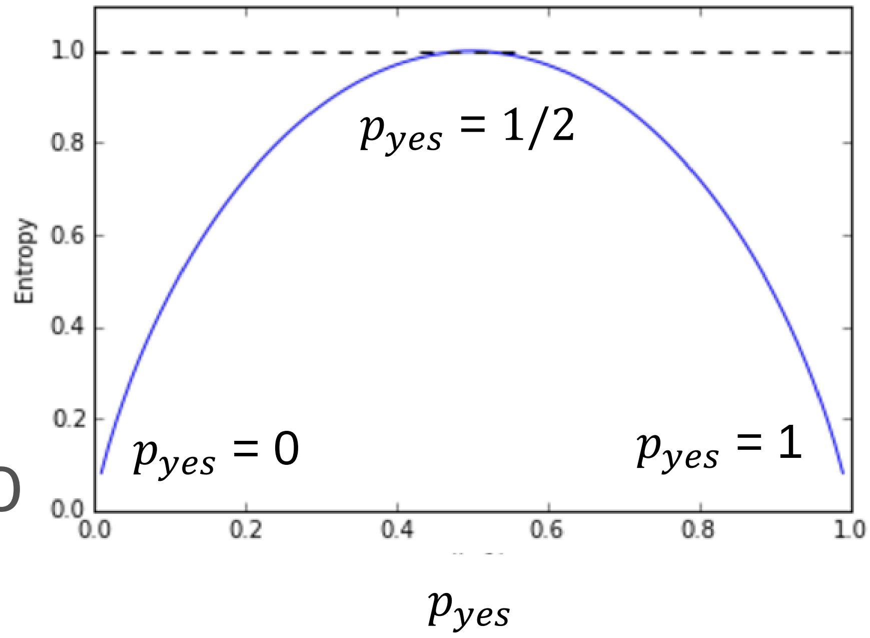
Entropy example

e.g. (3 yes / 3 no)

$$\text{Entropy} = -\frac{3}{6}\log_2\frac{3}{6} - \frac{3}{6}\log_2\frac{3}{6} = 1$$

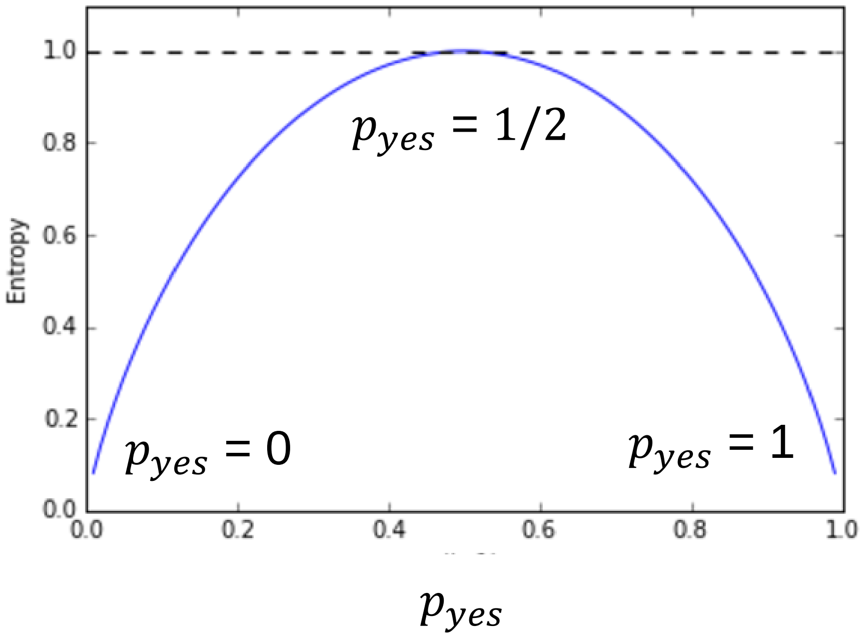
e.g. (4 yes / 0 no)

$$\text{Entropy} = -\frac{4}{4}\log_2\frac{4}{4} - \frac{0}{4}\log_2\frac{0}{4} = 0$$



Entropy example

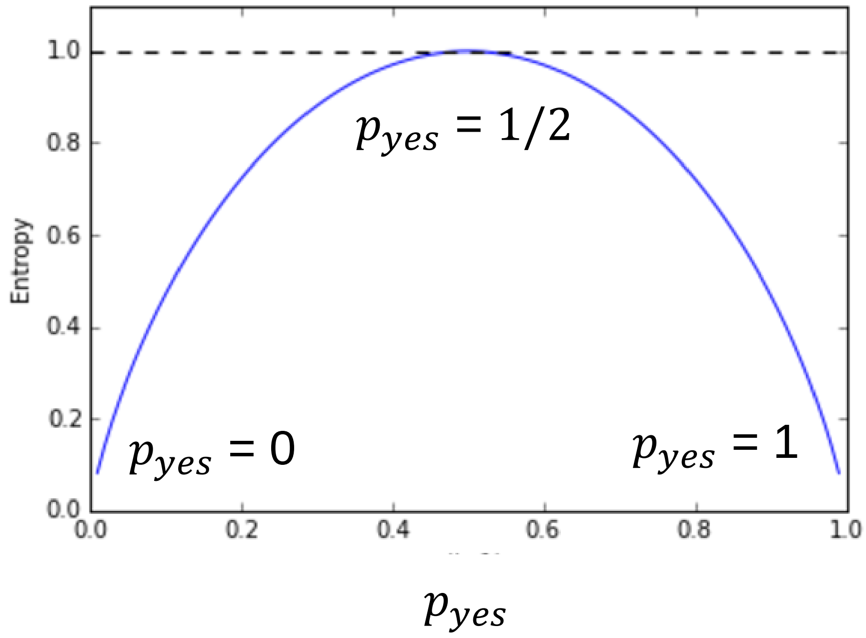
exercise: (9 yes / 5 no)



Entropy example

exercise: (9 yes / 5 no)

Answer: 0.940

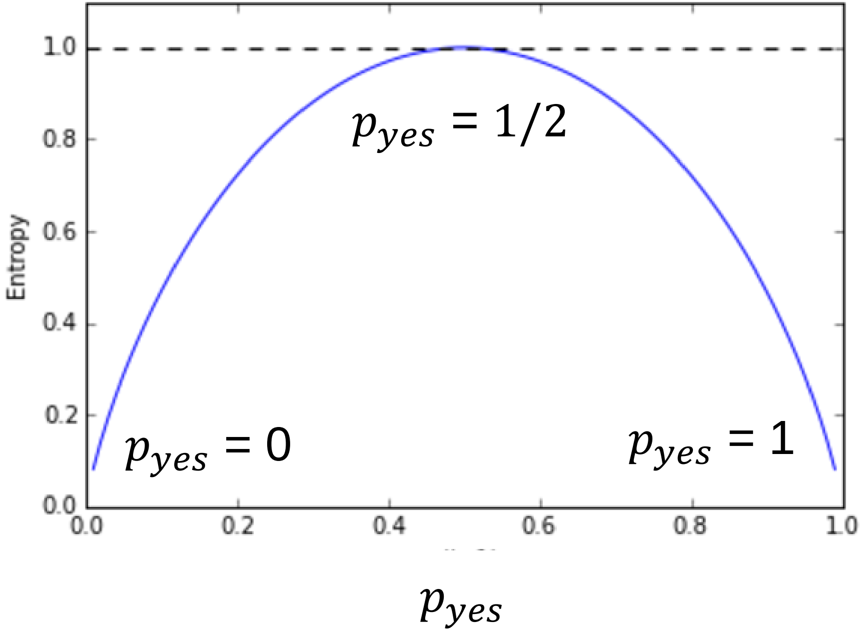


Entropy example

exercise: (9 yes / 5 no)

Answer: 0.940

exercise: (3 yes / 4 no)



Entropy

- Entropy tells us how pure **one subset** is.
- But we want a measure of the **effectiveness of an attribute** in classifying the training data.
- We actually want to aggregate info on different subsets.
- Simply averaging the entropies don’t work. (Why not?)

Information Gain

- Want many items in pure sets
- **Information Gain** – expected reduction in entropy after a split on an attribute

$$Gain(S, A) = Entropy(S) - \sum_{v \in Values(A)} \frac{|S_v|}{|S|} Entropy(S_v)$$

A – Attribute

$Values(A)$ – possible values of A

S – subset of training examples

S_v – subset of S for which attribute A have value v

Information Gain

e.g. Find $Gain(S, Wind)$.

Training examples: **9 yes / 5 no**

Day	Outlook	Humidity	Wind	Play
D1	Sunny	High	Weak	No
D2	Sunny	High	Strong	No
D3	Overcast	High	Weak	Yes
D4	Rain	High	Weak	Yes
D5	Rain	Normal	Weak	Yes
D6	Rain	Normal	Strong	No
D7	Overcast	Normal	Strong	Yes
D8	Sunny	High	Weak	No
D9	Sunny	Normal	Weak	Yes
D10	Rain	Normal	Weak	Yes
D11	Sunny	Normal	Strong	Yes
D12	Overcast	High	Strong	Yes
D13	Overcast	Normal	Weak	Yes
D14	Rain	High	Strong	No

Information Gain

e.g. Find $Gain(S, Wind)$.

Answer: 0.048

ex. Find $Gain(S, Humidity)$

Training examples: 9 yes / 5 no

Day	Outlook	Humidity	Wind	Play
D1	Sunny	High	Weak	No
D2	Sunny	High	Strong	No
D3	Overcast	High	Weak	Yes
D4	Rain	High	Weak	Yes
D5	Rain	Normal	Weak	Yes
D6	Rain	Normal	Strong	No
D7	Overcast	Normal	Strong	Yes
D8	Sunny	High	Weak	No
D9	Sunny	Normal	Weak	Yes
D10	Rain	Normal	Weak	Yes
D11	Sunny	Normal	Strong	Yes
D12	Overcast	High	Strong	Yes
D13	Overcast	Normal	Weak	Yes
D14	Rain	High	Strong	No

Information Gain

e.g. Find $Gain(S, Wind)$.

Answer: 0.048

ex. Find $Gain(S, Humidity)$

Answer: 0.151

ex. Find $Gain(S, Outlook)$.

Training examples: 9 yes / 5 no

Day	Outlook	Humidity	Wind	Play
D1	Sunny	High	Weak	No
D2	Sunny	High	Strong	No
D3	Overcast	High	Weak	Yes
D4	Rain	High	Weak	Yes
D5	Rain	Normal	Weak	Yes
D6	Rain	Normal	Strong	No
D7	Overcast	Normal	Strong	Yes
D8	Sunny	High	Weak	No
D9	Sunny	Normal	Weak	Yes
D10	Rain	Normal	Weak	Yes
D11	Sunny	Normal	Strong	Yes
D12	Overcast	High	Strong	Yes
D13	Overcast	Normal	Weak	Yes
D14	Rain	High	Strong	No

Information Gain

e.g. Find $Gain(S, Wind)$.

Answer: 0.048

ex. Find $Gain(S, Humidity)$

Answer: 0.151

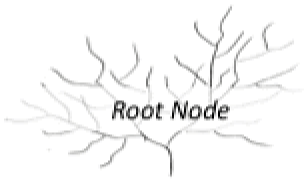
ex. Find $Gain(S, Outlook)$.

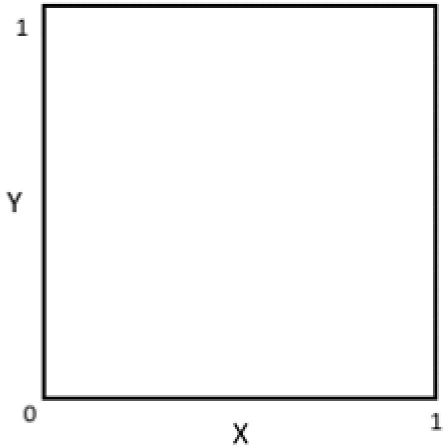
Answer: 0.246

Training examples: 9 yes / 5 no

Day	Outlook	Humidity	Wind	Play
D1	Sunny	High	Weak	No
D2	Sunny	High	Strong	No
D3	Overcast	High	Weak	Yes
D4	Rain	High	Weak	Yes
D5	Rain	Normal	Weak	Yes
D6	Rain	Normal	Strong	No
D7	Overcast	Normal	Strong	Yes
D8	Sunny	High	Weak	No
D9	Sunny	Normal	Weak	Yes
D10	Rain	Normal	Weak	Yes
D11	Sunny	Normal	Strong	Yes
D12	Overcast	High	Strong	Yes
D13	Overcast	Normal	Weak	Yes
D14	Rain	High	Strong	No

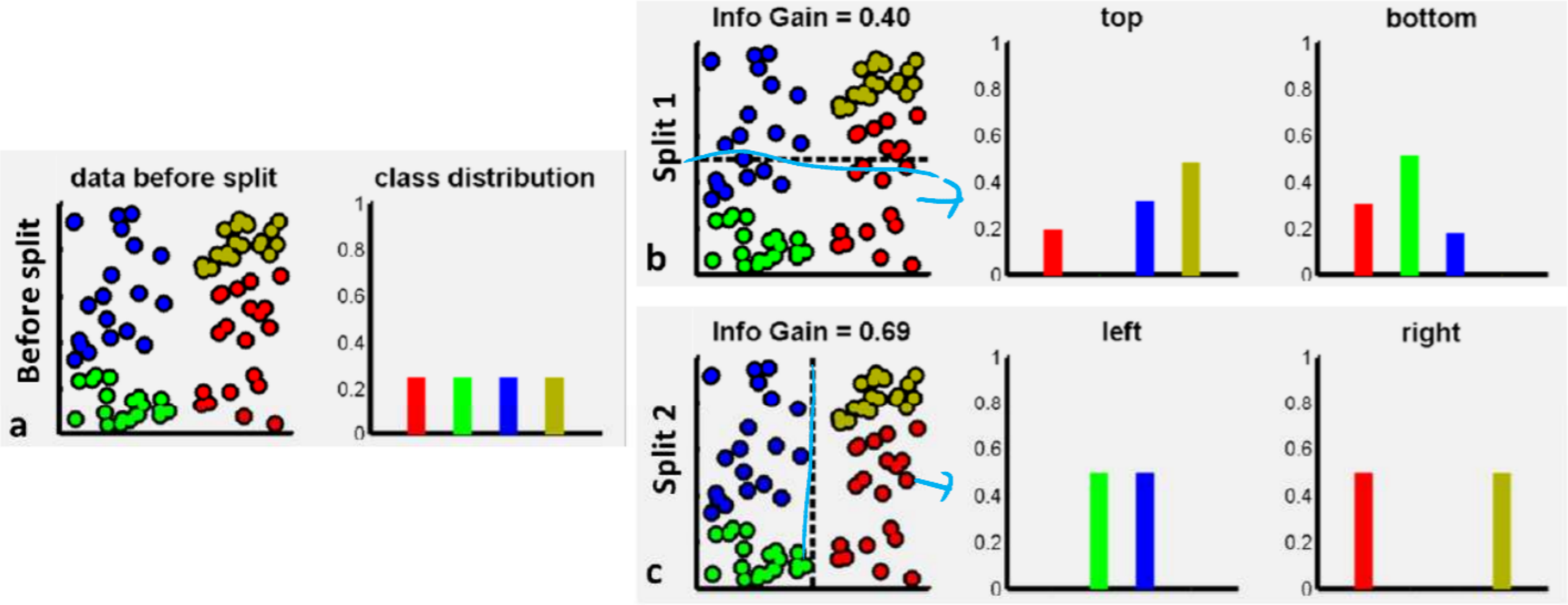
Splitting, visually





For more tutorials: annalyzin.wordpress.com

Information Gain, visually



CART Algorithm (Briemanetal, 1984)

- Uses an alternative impurity metric: *Gini Index*

Gini Index – rate of misclassification

$$Gini(S) = 1 - \sum_{c \in Classes} p_c^2$$

S – subset of training examples

p_c - proportion of examples in S belonging to class c

Higher Gini index → more likely to misclassify

Gini Index example

e.g. (3 yes / 3 no)

Gini Index example

e.g. (3 yes / 3 no)

Gini(S) = $1 - (\frac{3}{6})^2 - (\frac{3}{6})^2 = 0.5$

Gini Index example

e.g. (3 yes / 3 no)

Gini(S) = $1 - (\frac{3}{6})^2 - (\frac{3}{6})^2 = 0.5$

e.g. (4 yes / 0 no)

Gini Index example

e.g. (3 yes / 3 no)

Gini(S) = $1 - (\frac{3}{6})^2 - (\frac{3}{6})^2 = 0.5$

e.g. (4 yes / 0 no)

Gini(S) = $1 - (\frac{4}{4})^2 - (\frac{0}{4})^2 = 0$

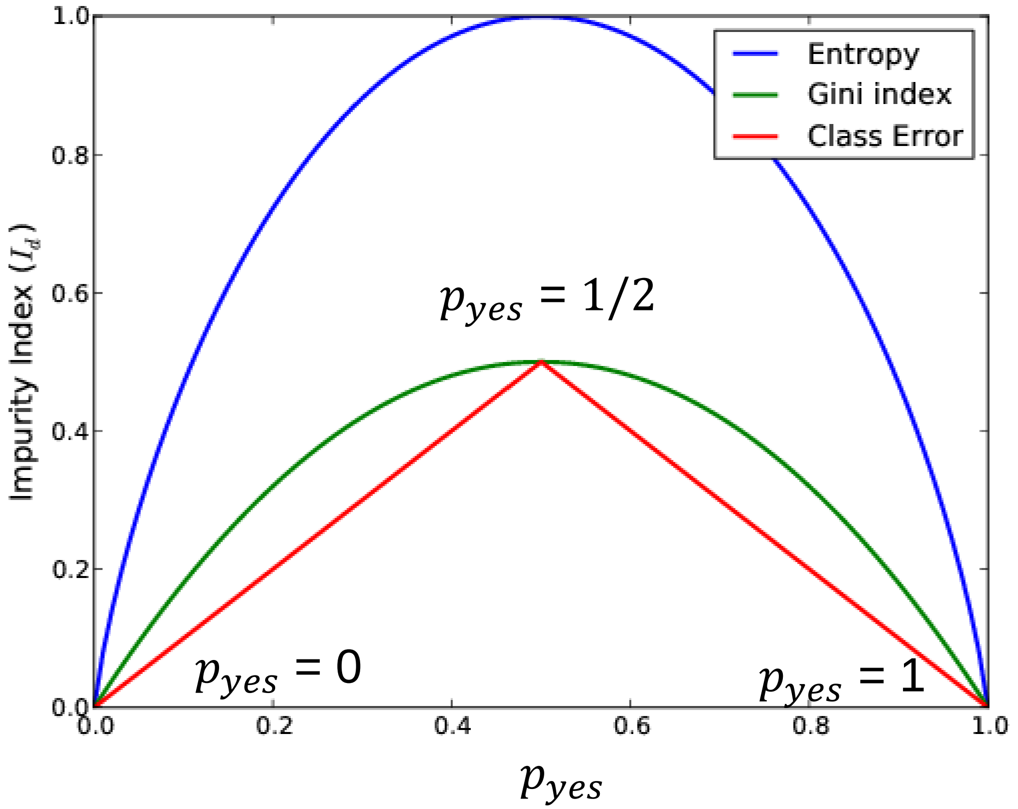
Gini Index example

e.g. (3 yes / 3 no)

Gini(S) = $1 - (\frac{3}{6})^2 - (\frac{3}{6})^2 = 0.5$

e.g. (4 yes / 0 no)

Gini(S) = $1 - (\frac{4}{4})^2 - (\frac{0}{4})^2 = 0$



Gini Index example

Splitting Binary Attributes (using Gini)

Example :

	Parent
C0	6
C1	6
Gini = 0.5	

Gini : $1-(6/12)^2-(6/12)^2$ **= 0.5**

Suppose there are two ways (A and B) to split the data into smaller subset.

A

	N1
C0	4
C1	3

Gini Index: 0.4898

	N2
C0	2
C1	3

Gini Index: 0.480

B

	N1
C0	1
C1	4

Gini Index: 0.320

	N2
C0	5
C1	2

Gini Index: 0.4082

Which one is a better split??

Compute the **weighted average of the Gini index** of both attribute

Information Gain

- **Information Gain** – expected reduction in the *misclassification rate* after a split on an attribute

$$Gain(S, A) = Gini(S) - \sum_{v \in Values(A)} \frac{|S_v|}{|S|} Gini(S_v)$$

A – Attribute

$Values(A)$ – possible values of A

S – subset of training examples

S_v – subset of S for which attribute A have value v

Entropy vs Gini Index

- So which impurity measure should be used:

  Entropy or Gini index?
- Resulting trees are very similar in practice.
- Best advice is that it is good practice when building decision tree models to
  - Try out different impurity metrics
  - Compare results to see which suits the dataset

EXERCISE OPTIONS

1. Solve by hand / calculator (takes a lot of time!)
2. Use python to to write function(s) that compute the entropy, gini index, and information gain.
3. Advanced: Write a program that builds a decision tree!

   - Requires some knowledge on recursion, ADTs

Partner/Group/Individual Exercise

Predicting virus infection in files:

	WRITABLE	UPDATED	SIZE	CLASS
1	yes	no	small	infected
2	yes	yes	large	infected
3	no	yes	med	infected
4	no	no	med	clean
5	yes	no	large	clean
6	no	no	large	clean

Challenge

Classify the type of vegetation that is likely to grow in areas of land based on descriptive feature.

ID	Stream	Slope	Elevation	Vegetation
1	False	Steep	High	Chapparal
2	True	Moderate	Low	Riparian
3	True	Steep	Medium	Riparian
4	False	Steep	Medium	Chapparal
5	False	Flat	High	Conifer
6	True	Steep	Highest	Conifer
7	True	Steep	High	Chapparal

What type of vegetation would likely grow on terrain with a steep slope and medium elevation and is near a stream?

How about on terrain near a stream with high elevation, moderate slope?

Partner/Group/Individual Presentation

Next time

- More on decision trees - pros and cons
- **Random Forests!**

References

Decision Tree Lecture by Victor Lavrenko (Youtube)

T.I.L.

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THANK YOU :)