IS-ZC444: ARTIFICIAL INTELLIGENCE

Lecture-15: K-NN + Decision Tree + Random Forest

Dr. Kamlesh Tiwari
Assistant Professor
Department of Computer Science and Information Systems,
BITS Pilani, Pilani, Jhunjhunu-333031, Rajasthan, INDIA

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Classification

Finding the right label

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Finding the right label

What feature (attributes) would you choose?

Color, texture, weight, density, hardness .....

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You are most likely as your friends (Bias)

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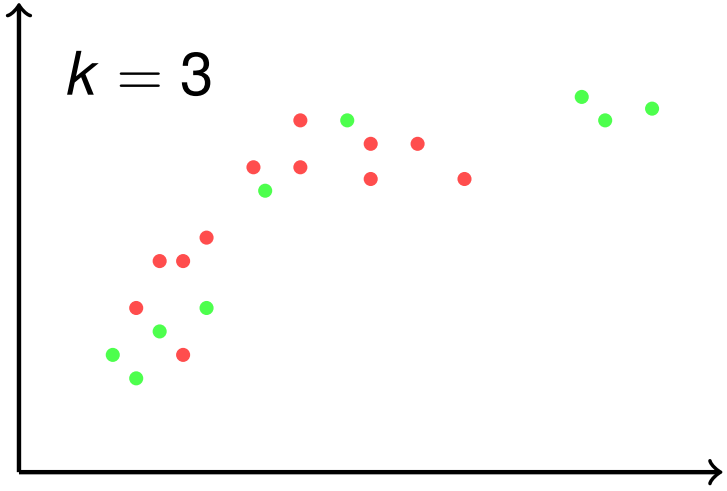

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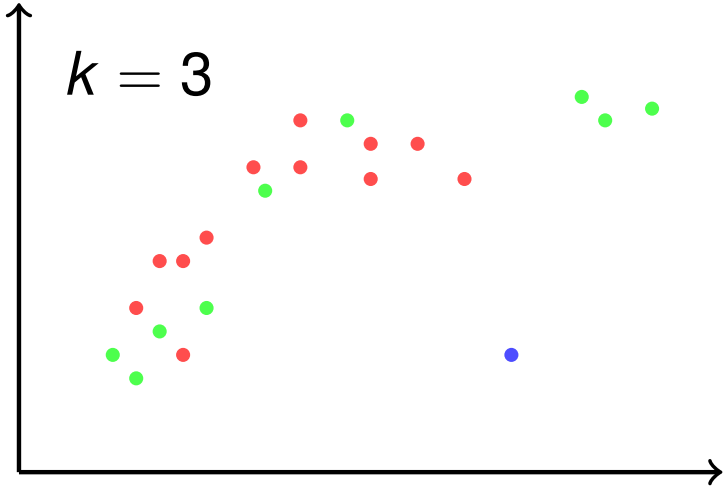

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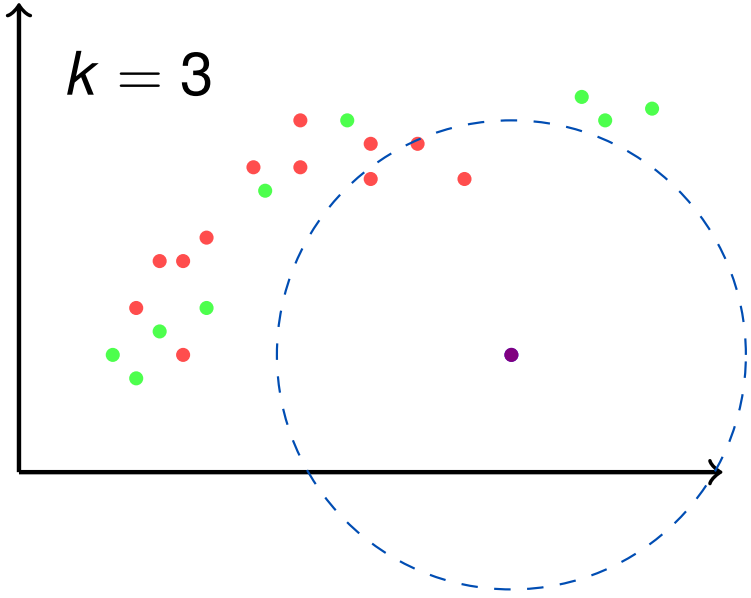

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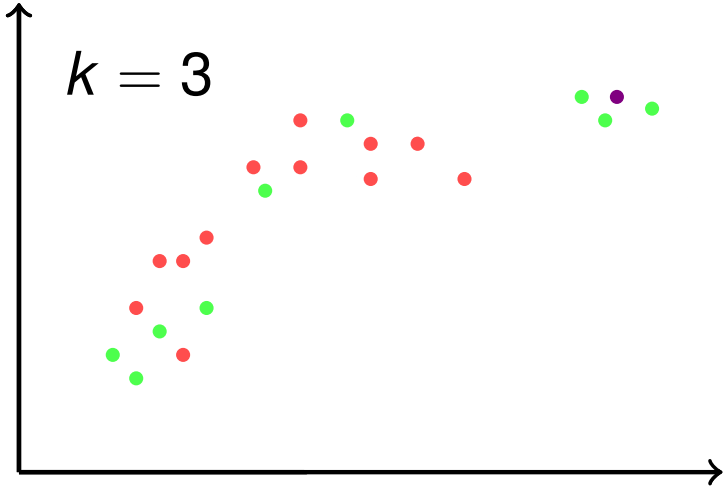

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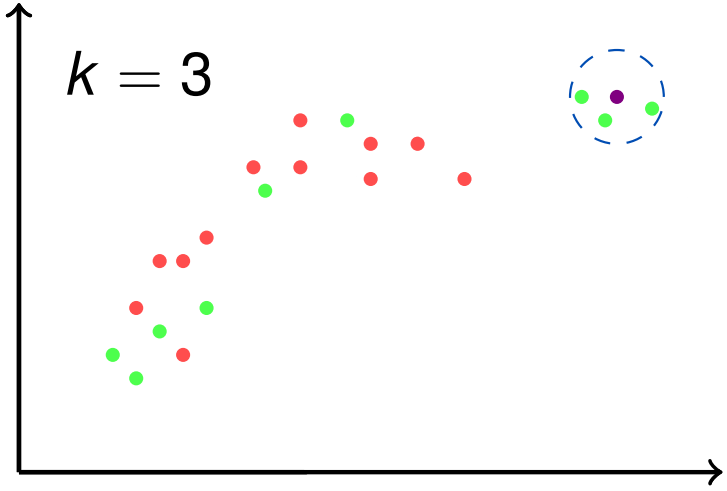

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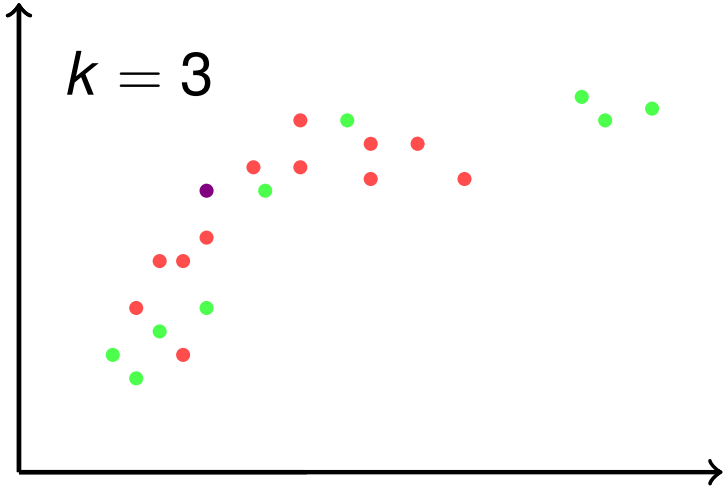

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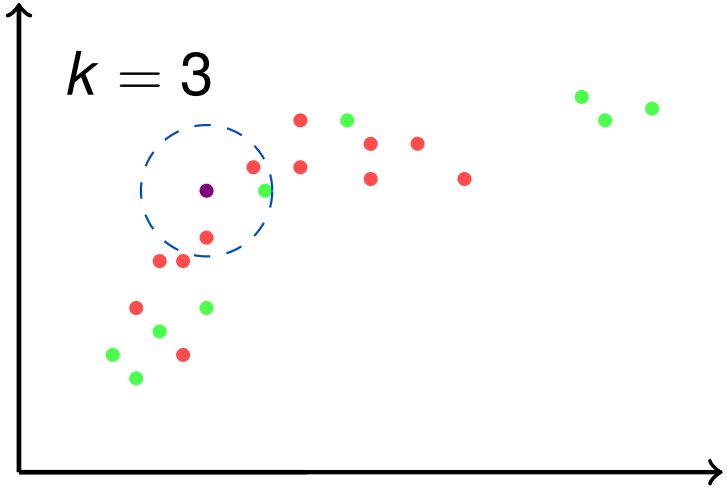

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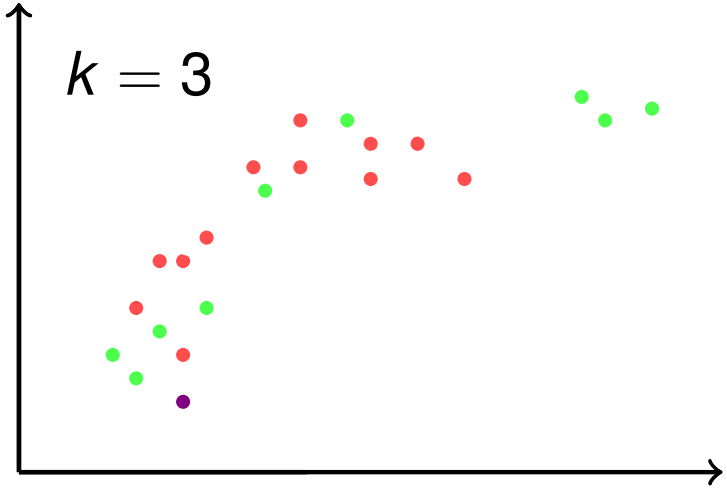

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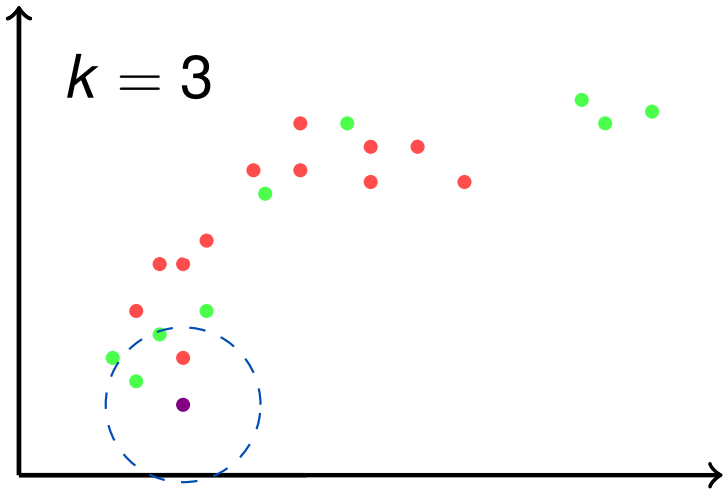

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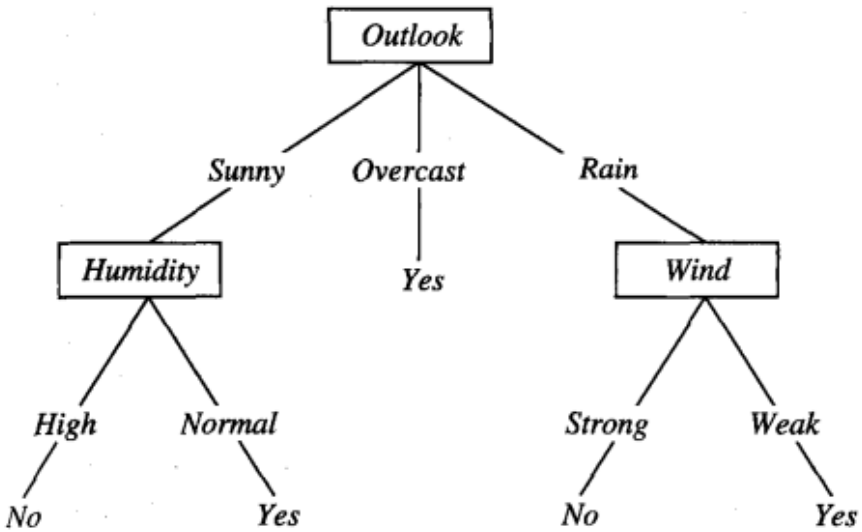

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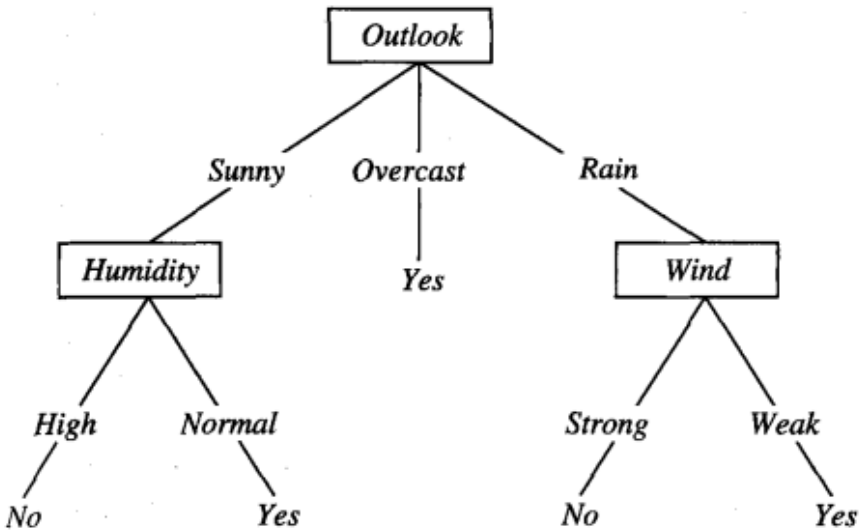

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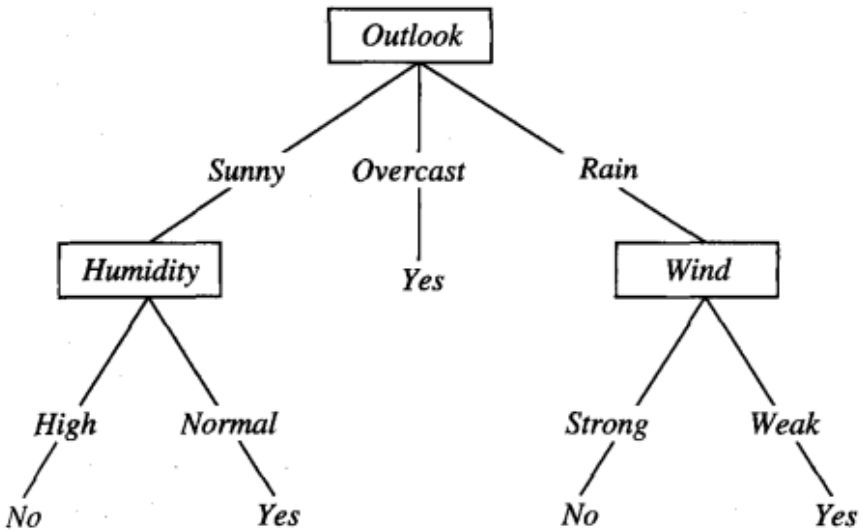

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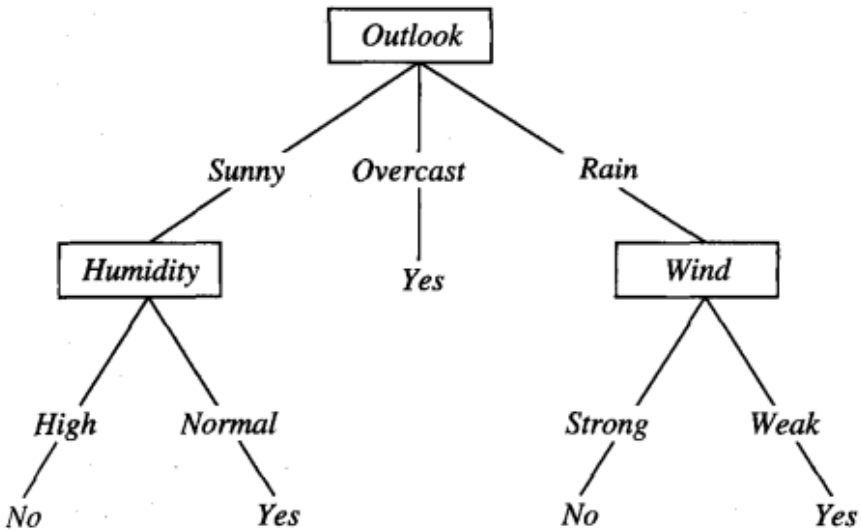

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$$(Outlook = Sunny \wedge Humidity = Normal)$$
$$\vee \quad (Outlook = Overcast) \vee (Outlook = Rain \wedge Wind = Weak)$$

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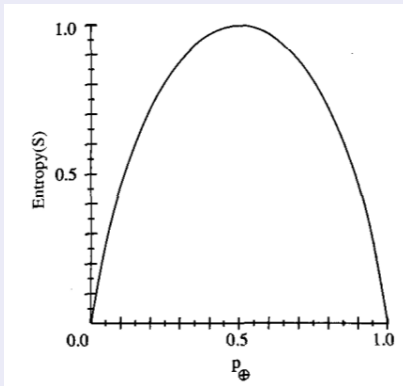

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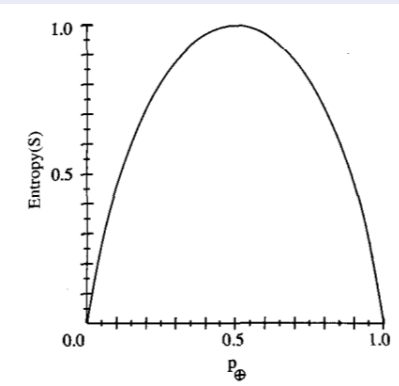

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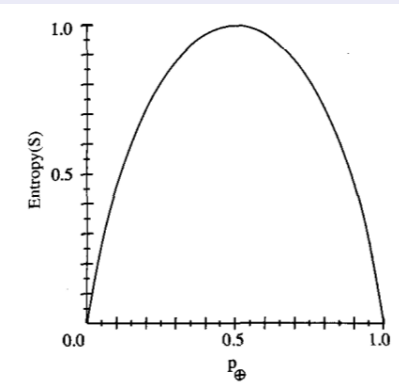

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$Entropy([9+, 5-])$

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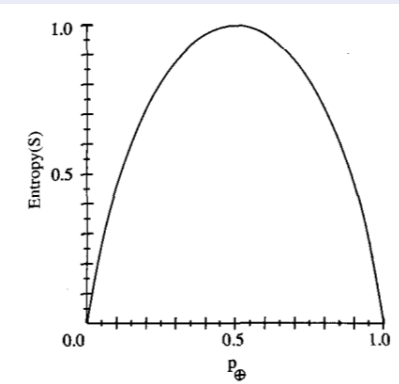

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$$Entropy([9+, 5-])$$

$$= -(9/14)\log_2(9/14) - (5/14)\log_2(5/14)$$

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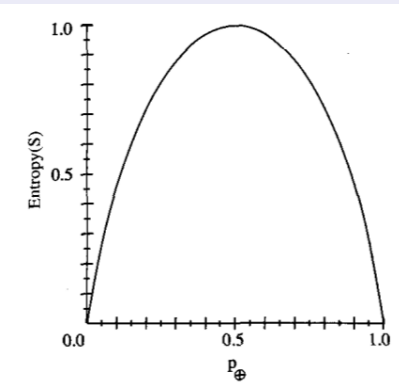

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$$\begin{aligned} Entropy([9+, 5-]) \\ &= -(9/14)\log_2(9/14) \\ &\quad -(5/14)\log_2(5/14) \\ &= 0.94 \end{aligned}$$

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[1] Outlook, Temperature, Humidity, Wind

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For example

$$S_{Sunny} = \{D1, D2, D8, D9, D11\}$$
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$$S_{Cool} = \{D5, D6, D7, D9\}$$
$$S_{Hot} = \{D1, D2, D3, D13\}$$
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And so on....

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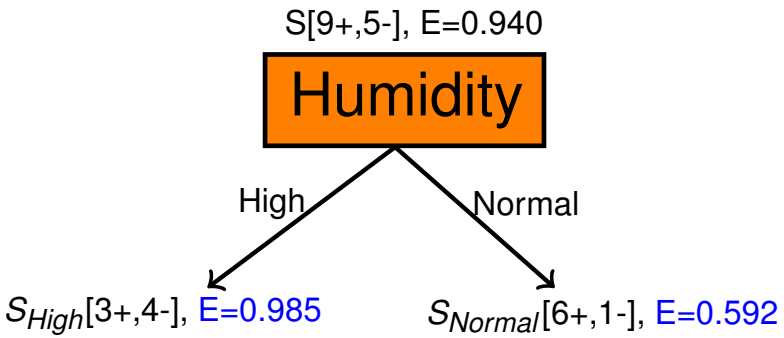

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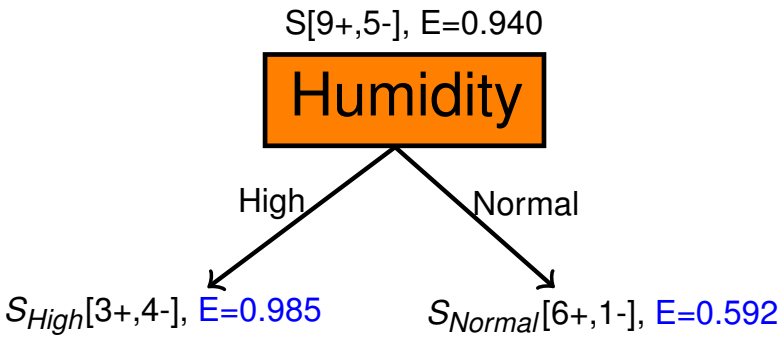

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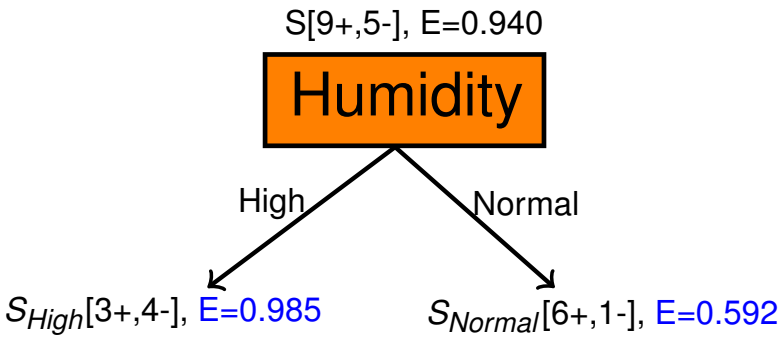

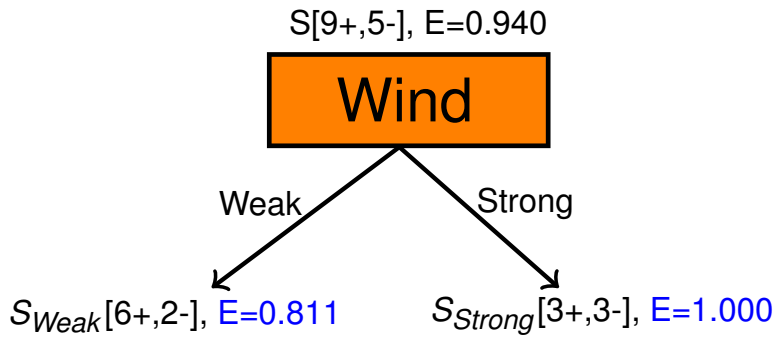

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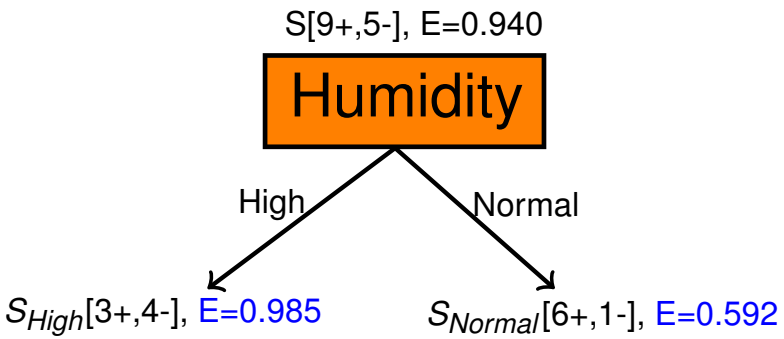

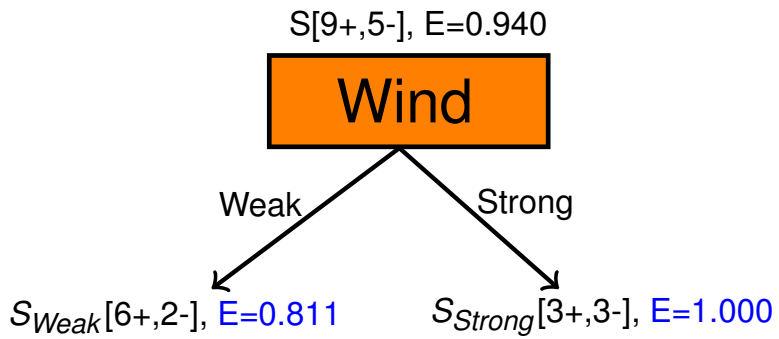

Gain(S,Humidity)$= 0.940 - (7/14)0.985 - (7/14)0.592 = 0.151$

Gain(S,Wind) $= 0.940 - (8/14)0.811 - (6/14)1.000 = 0.048$

Information Gain and Decision Tree

$$
\begin{aligned}
Gain(S, Humidity) &= 0.151 \\
Gain(S, Wind) &= 0.048 \\
Gain(S, Outlook) &= 0.246 \\
Gain(S, Temperature) &= 0.029
\end{aligned}
$$

Information Gain and Decision Tree

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$[D_1, D_2, D_3, D_4, D_5, D_6, D_7, D_8, D_9, D_{10}, D_{11}, D_{12}, D_{13}, D_{14}]$

{9+,5-}

Outlook

Information Gain and Decision Tree

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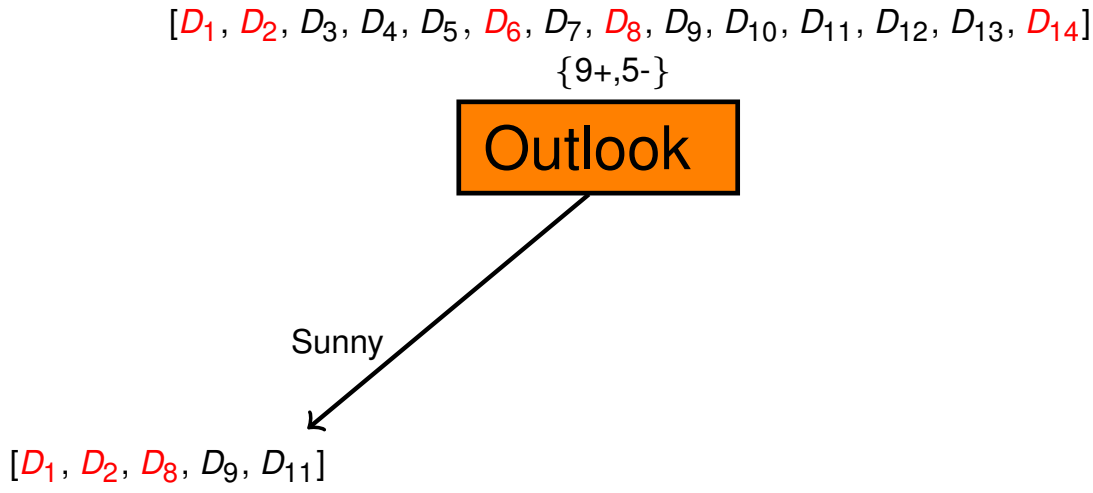

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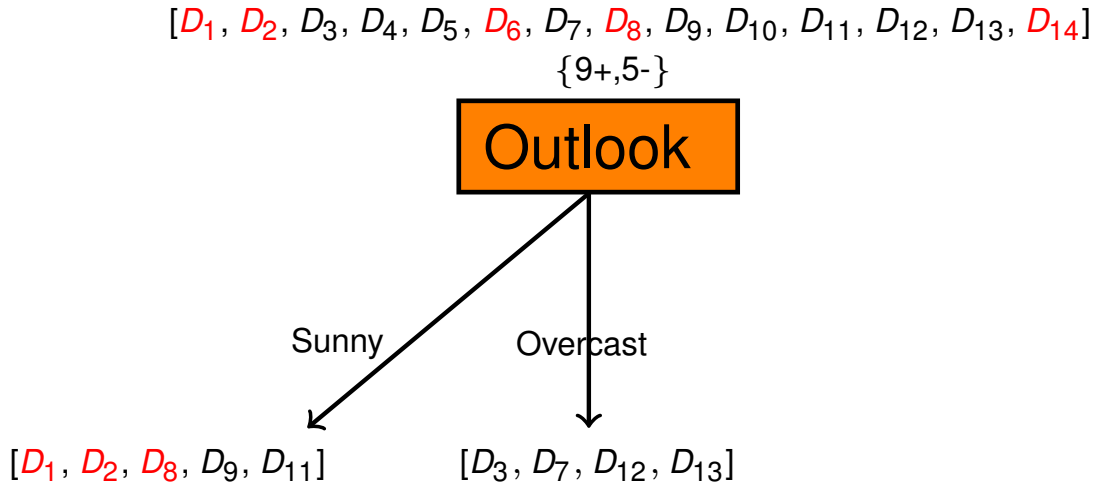

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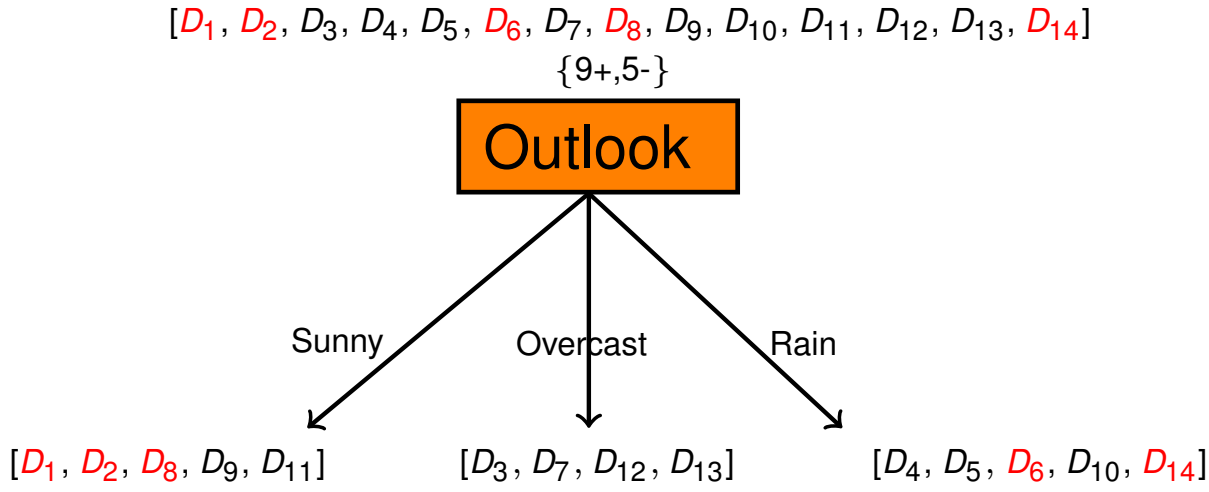

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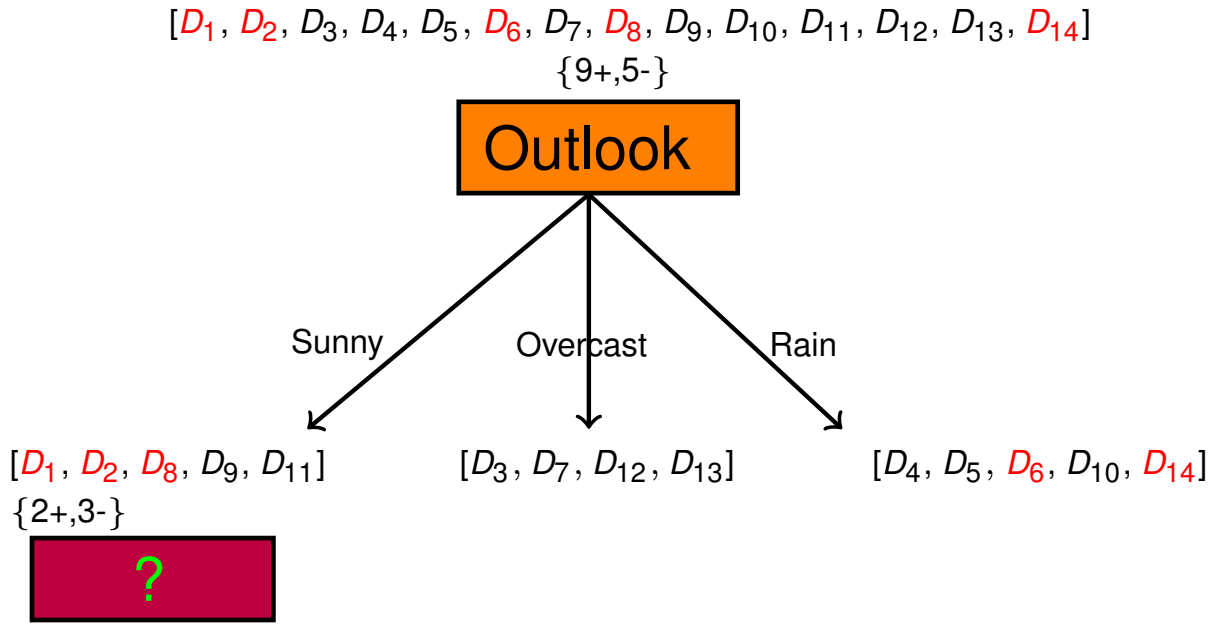

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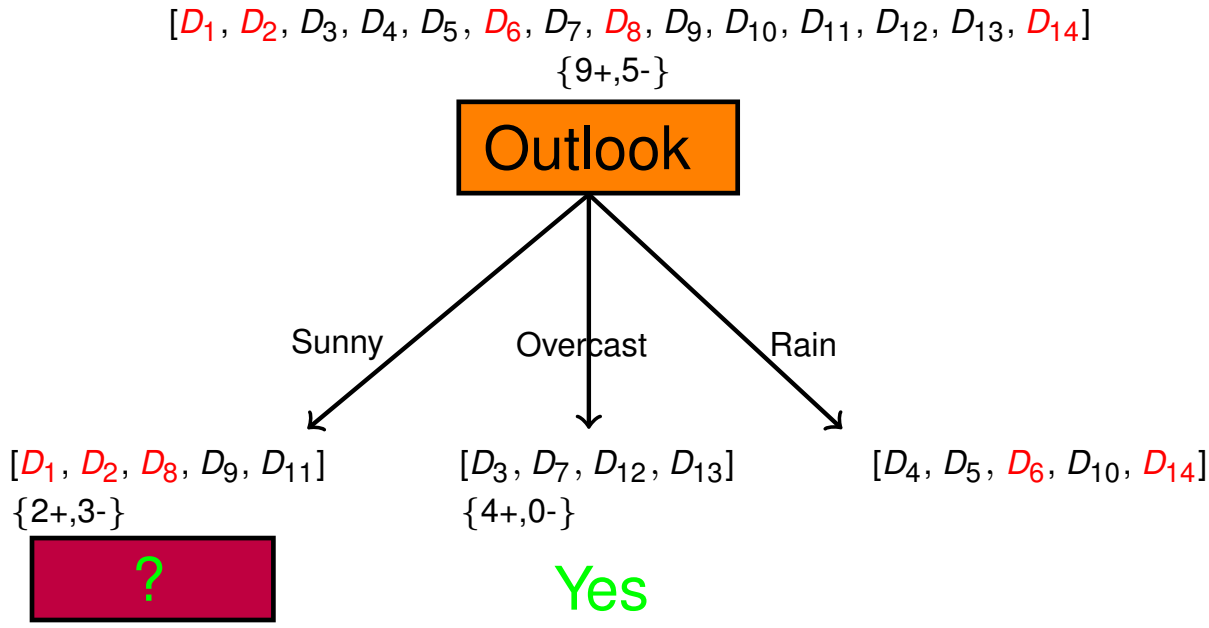

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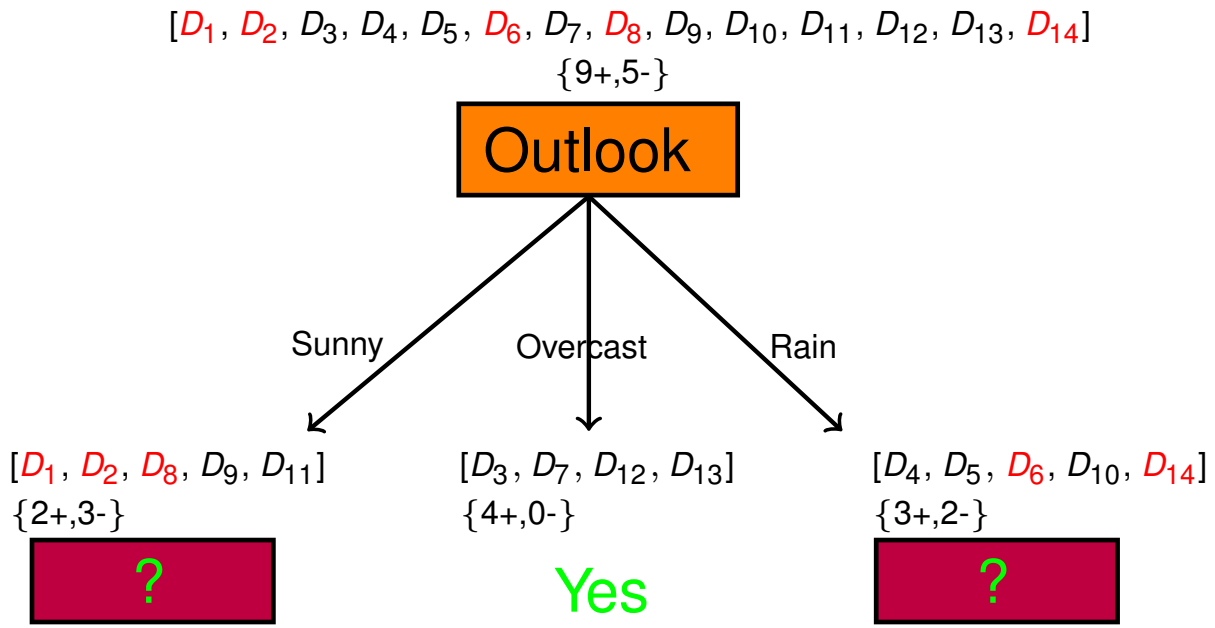
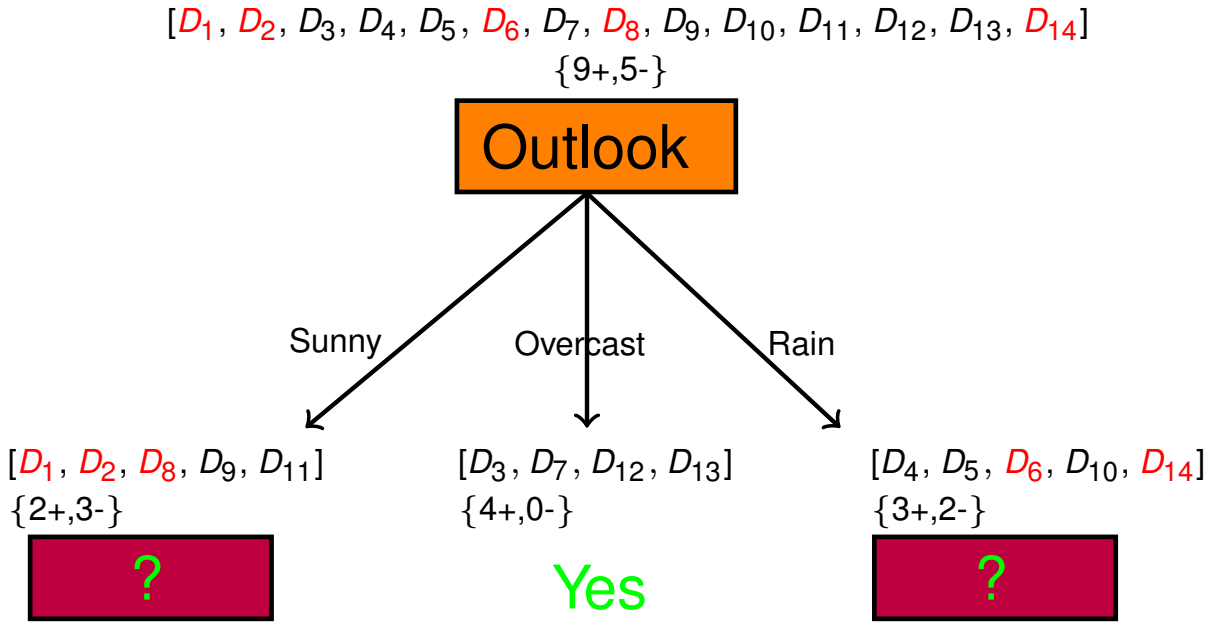


Recursively apply the same



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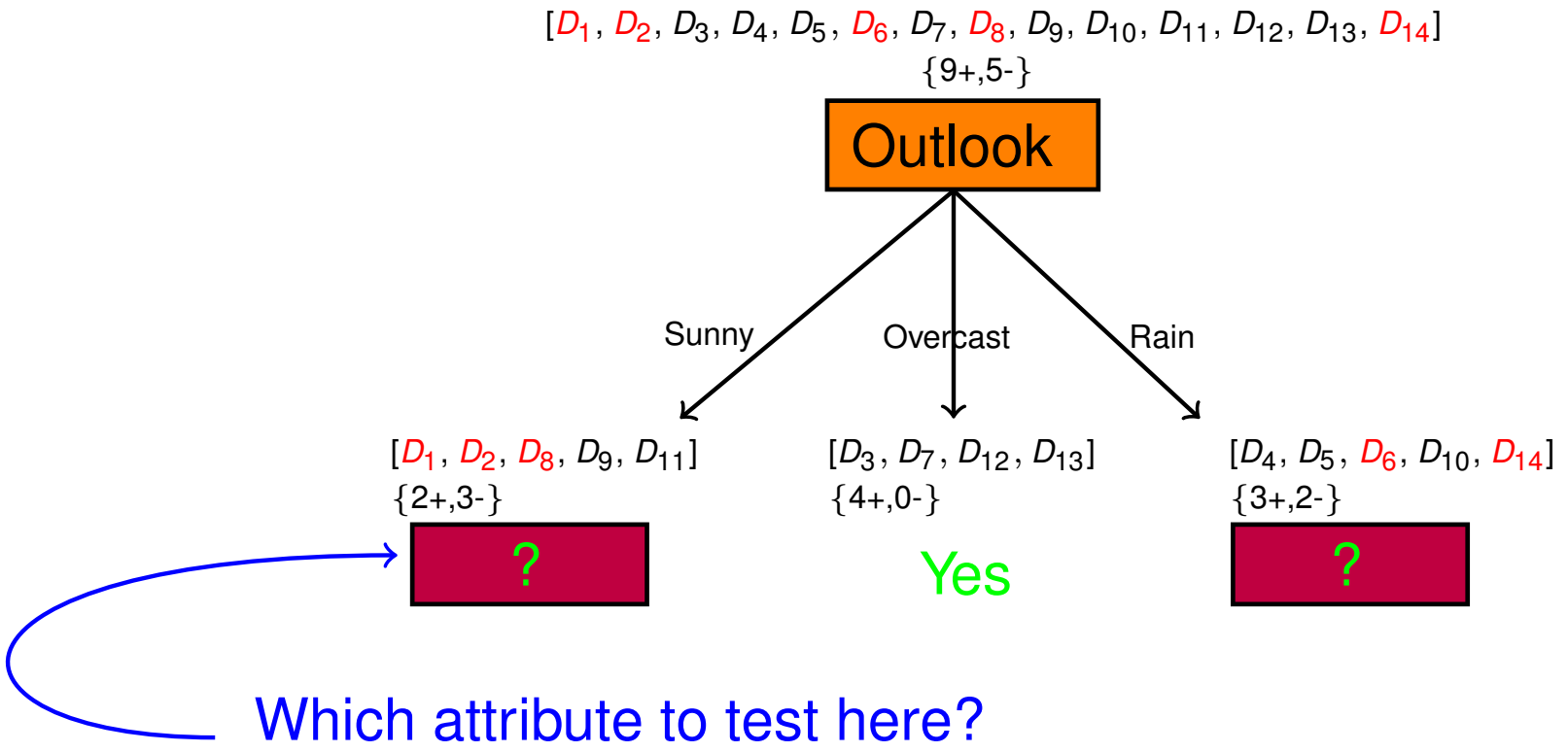

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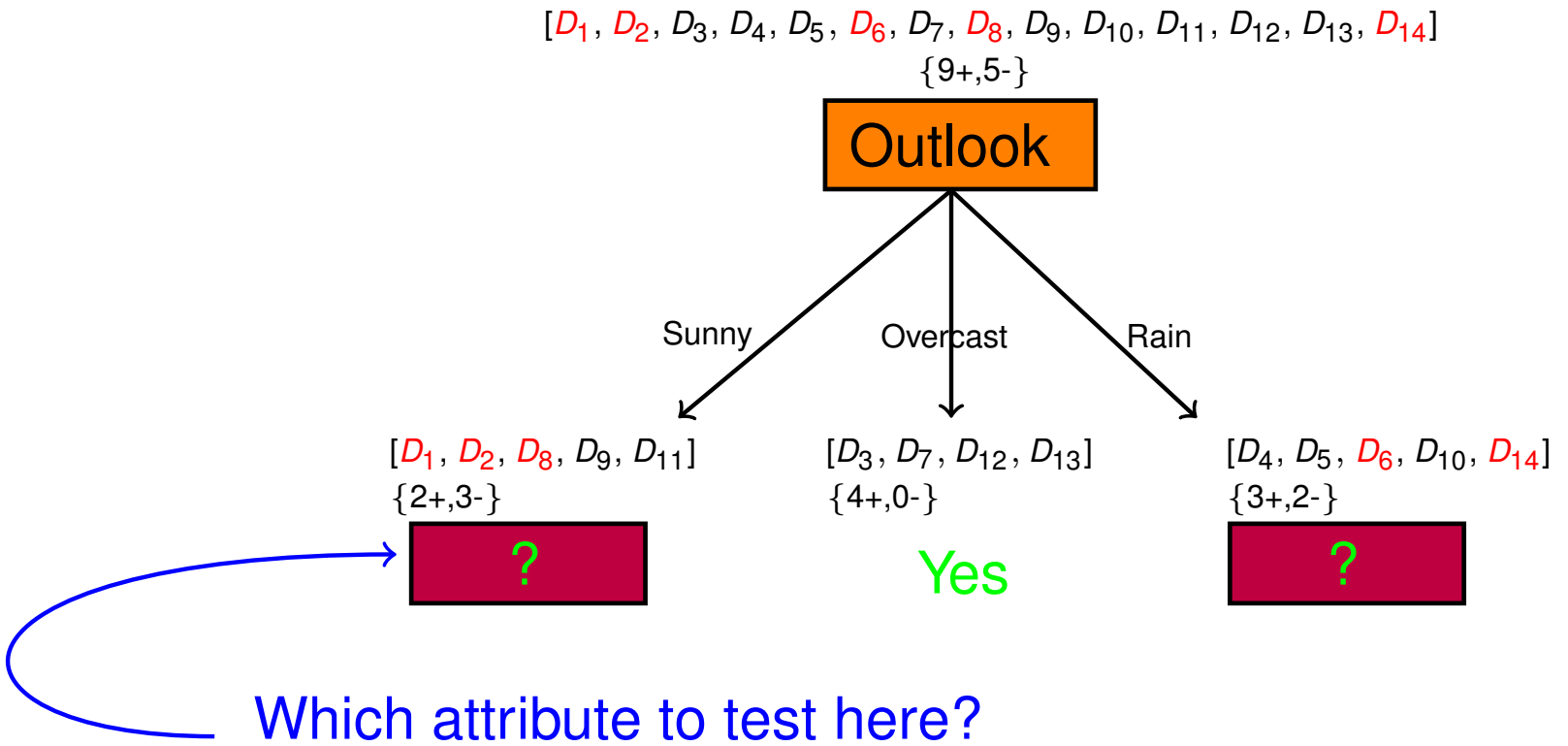
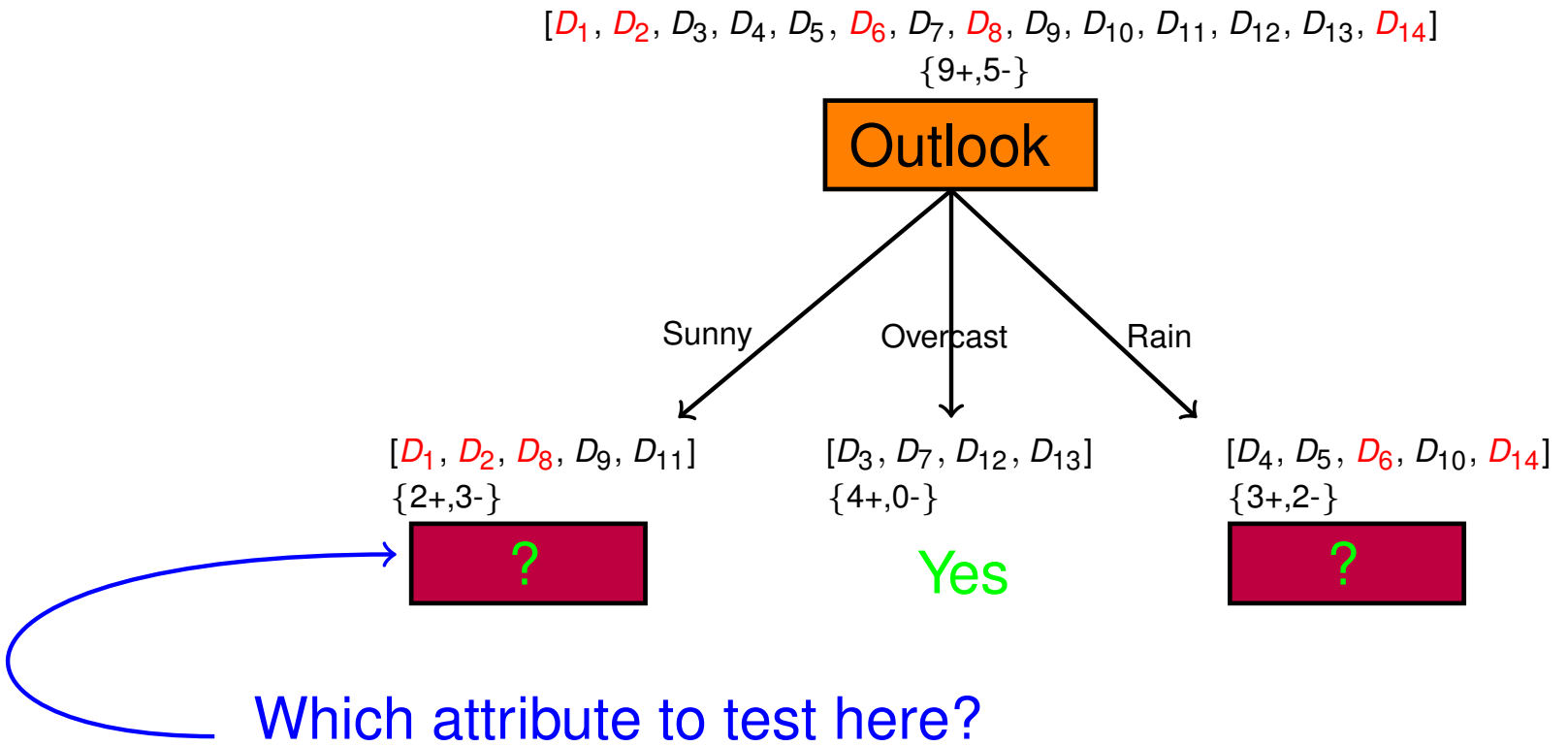


S_{sunny}=[D_1, D_2, D_8, D_9, D_{11}]

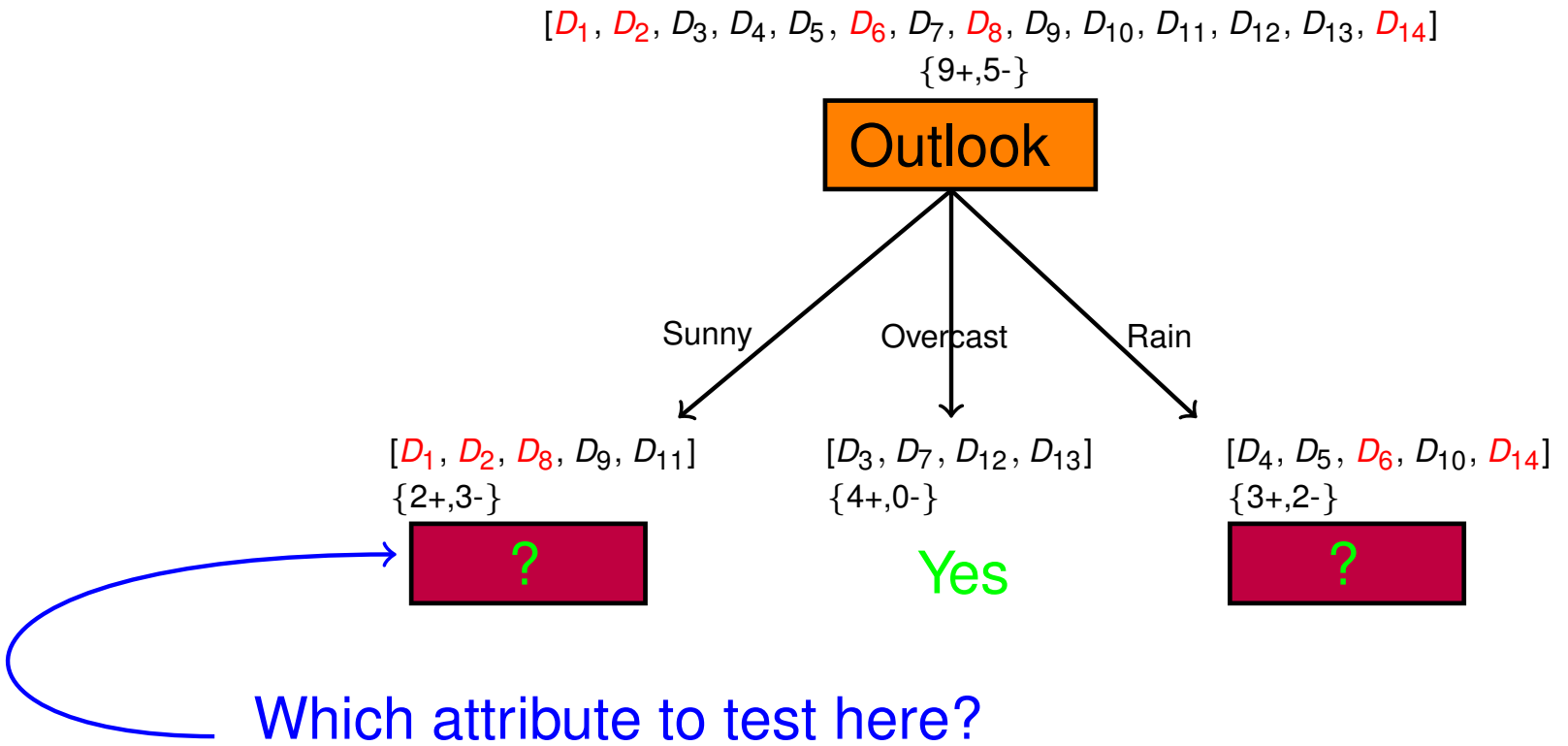
Recursively apply the same



S_{sunny}=[D_1, D_2, D_8, D_9, D_{11}]

Gain(S_{sunny},Humidity) $= 0.970 - (3/5)0.0 - (2/5)0.0 = 0.970$

Recursively apply the same



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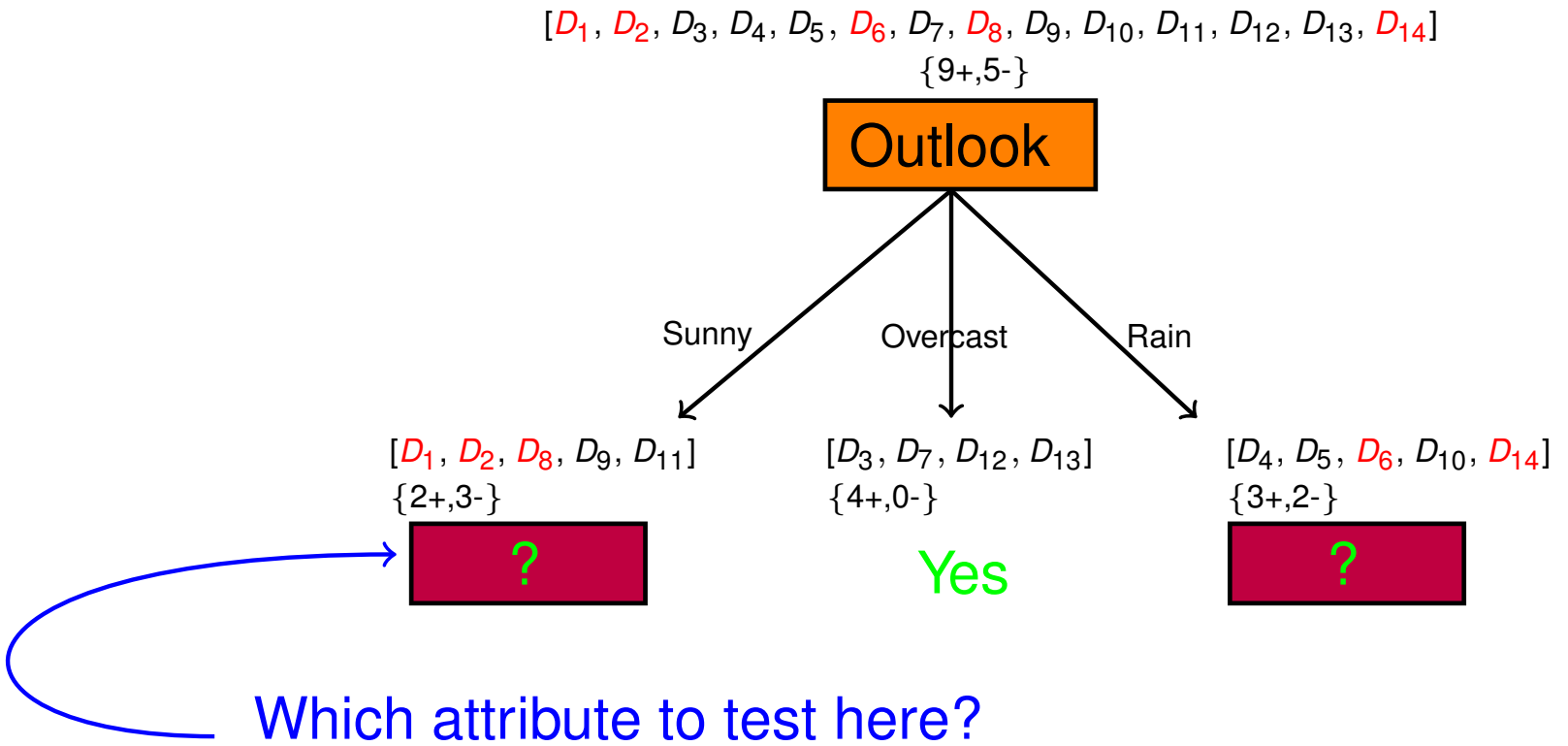
Gain(S_{sunny},Humidity) $= 0.970 - (3/5)0.0 - (2/5)0.0 = 0.970$

Gain(S_{sunny},Temperature)$= 0.970 - (2/5)0.0 - (2/5)1.0 - (1/5)0.0 = 0.57$

Recursively apply the same



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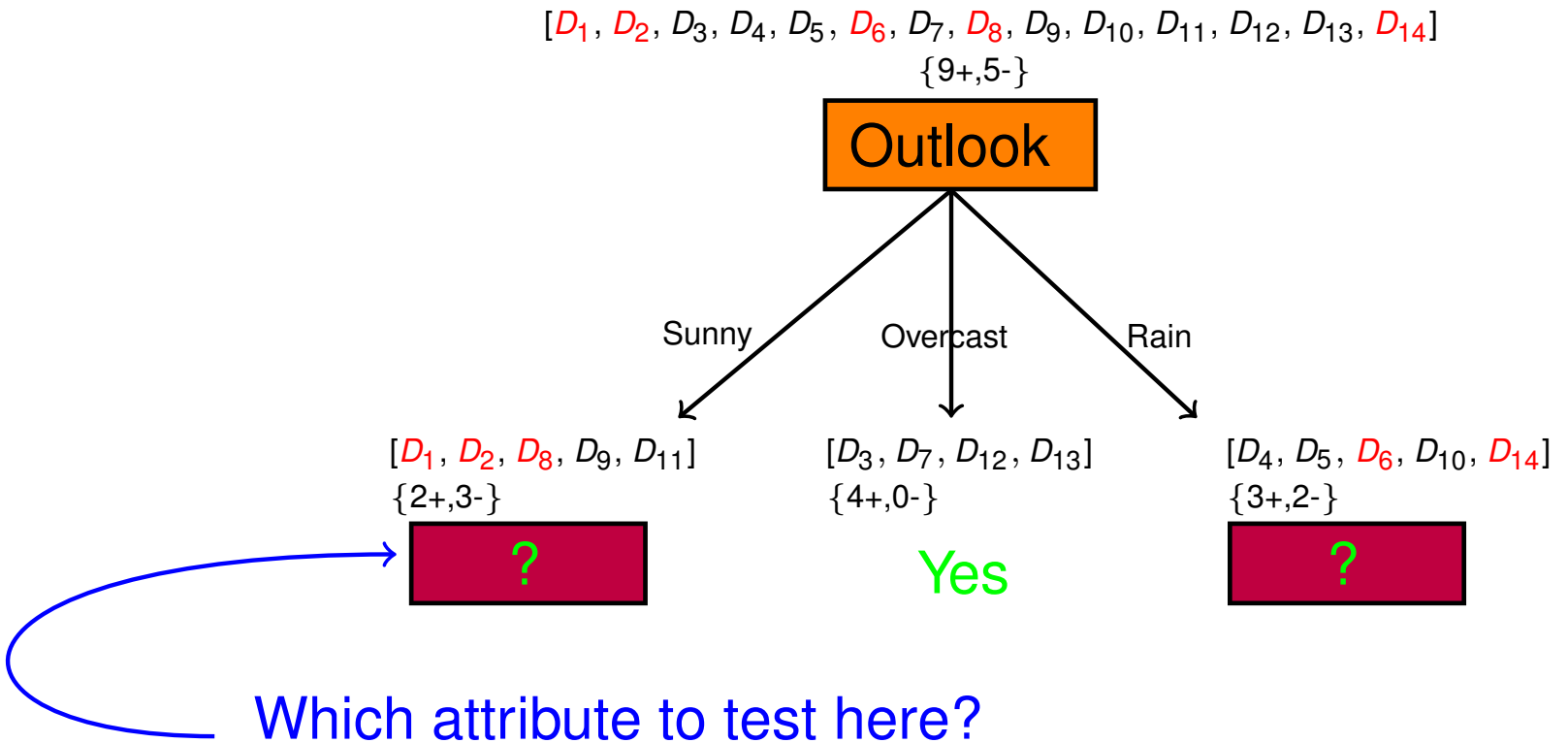
Gain(S_{sunny},Wind)$= 0.970 - (2/5)1.0 - (3/5)1.0 = 0.019$

Recursively apply the same



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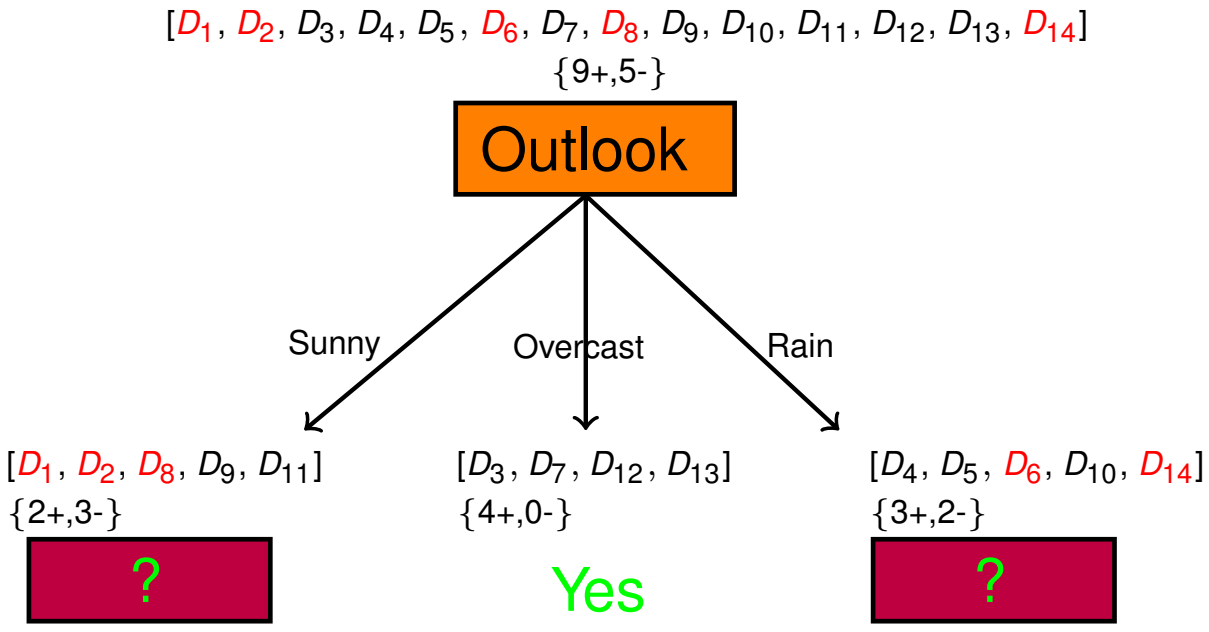
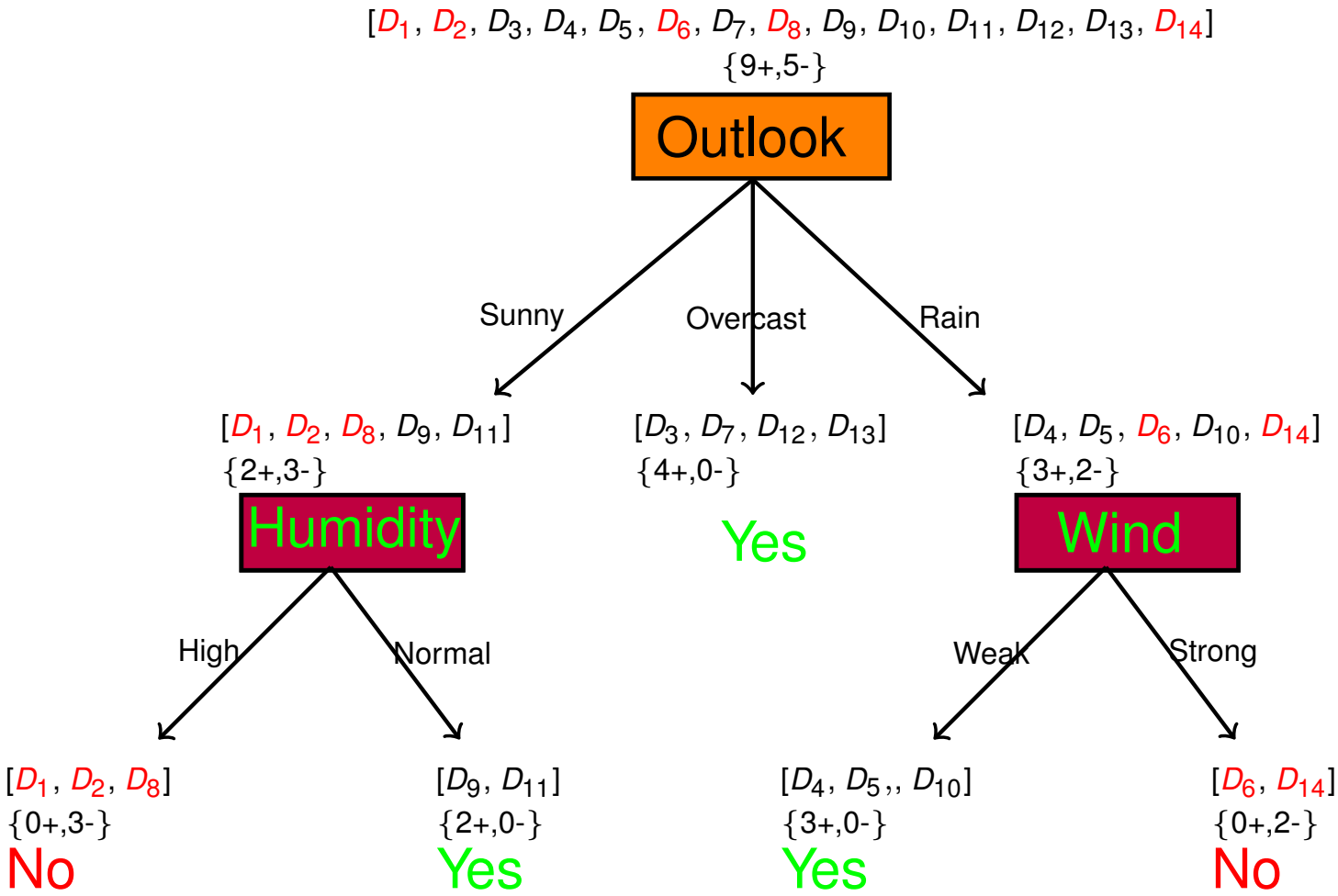


Recursively apply the same



Decision Tree

A method for approximating discrete-valued functions that is robust to noisy data and capable of learning disjunctive expressions

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

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What is classification for

$(Outlook = Rain, Humidity = High, Wind = Weak)$

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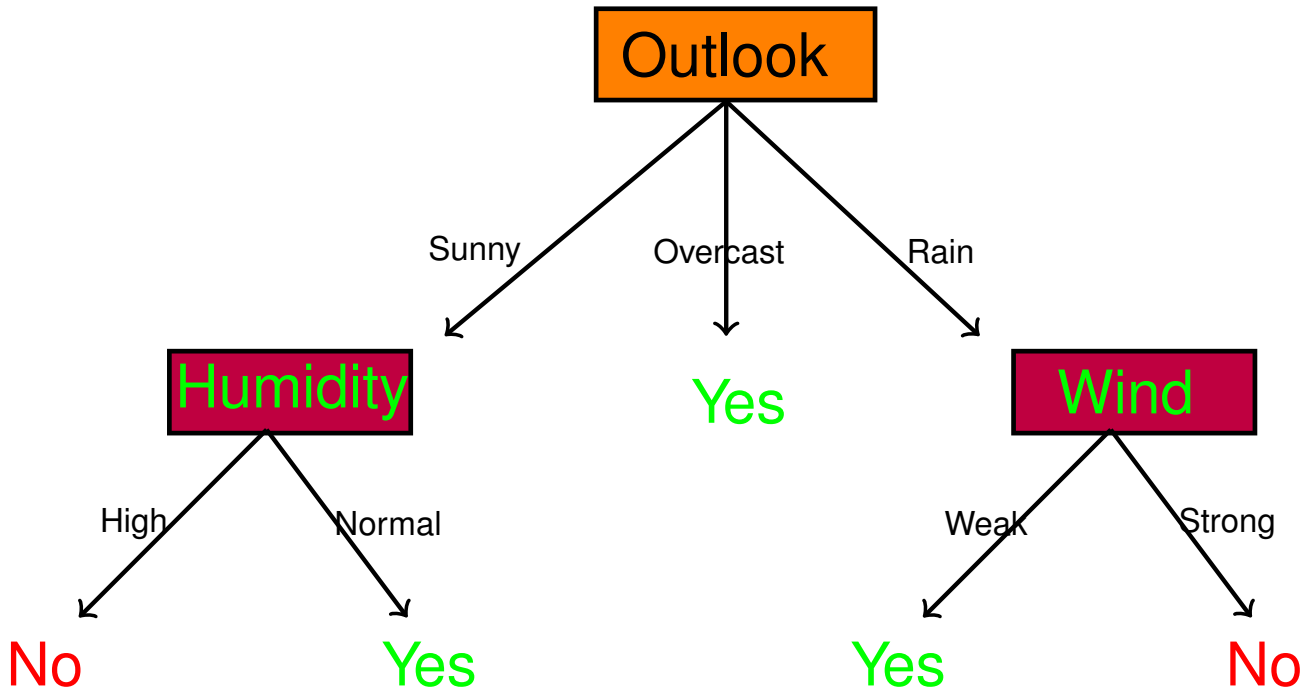
What is classification for

$(Outlook = Rain, Humidity = High, Wind = Weak)$

ALERT: (missing value) what is Temperature?

Example



Classification for $(Outlook = Rain, Humidity = High, Wind = Weak)$ is

YES

Iterative-Dichotomiser-3 (ID3) Algorithm By: John Ross Quinlan

Algorithm 1: ID3(Examples,Target_attribute,Attributes)

1 *Examples* are the training data, *Target_attribute* is the attribute whose value is to be predicted by the tree. *Attributes* is a list of other attributes that may be tested by the learned decision tree. Algorithm returns a decision tree that correctly classify the given example.

2 Create a single-node tree *Root*

3 **IF** *Examples* are all +ve **THEN return** *Root* with label +ve

4 **IF** *Examples* are all -ve **THEN return** *Root* with label -ve

5 **IF** *Attributes* $= \phi$ **THEN return** *Root* with most common *Target_attribute*

6 A $\leftarrow$ attribute from *Attributes* that best classifies *Examples*

7 Decision attribute for *Root* $\leftarrow$ A

8 **foreach** *value* v_i *of A* **do**

9 Add a new tree branch below Root, to test A=v_i

10 Examples$_{v_i}$ $\leftarrow$ subset of *Examples* having value v_i for A

11 **IF** Examples$_{v_i} = \phi$ **THEN** below this branch add a leaf with label = most common value of *Target_attribute* in *Examples*

12 **ELSE** below this branch add subtree ID3(Examples$_{v_i}$, *Target_attribute*, *Attributes*-$\{A\}$)

13 **return** *Root*

Issues Decision Tree

Given a collection of training examples, there could be many decision trees consistent with the examples

- ID3 search strategy
  - selects in favor of shorter trees over longer ones, and
  - selects trees that place the attributes with highest information gain closest to the root

Issues Decision Tree

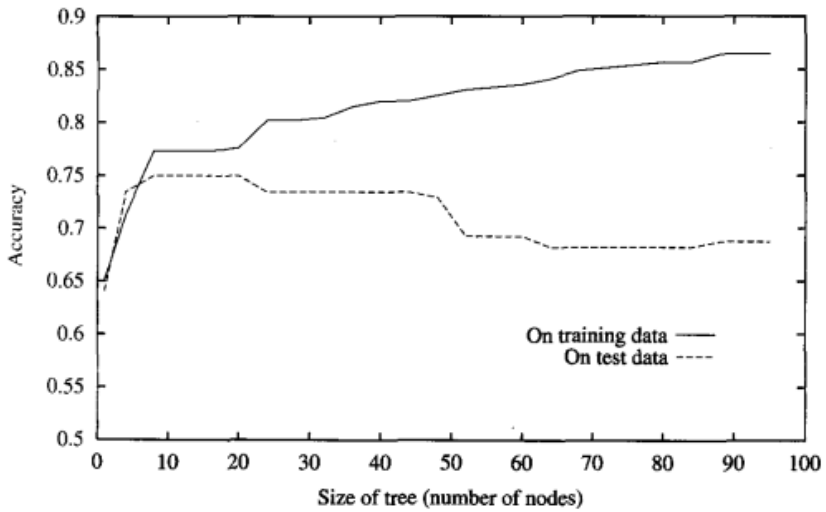
Given a collection of training examples, there could be many decision trees consistent with the examples

- ID3 search strategy
  - selects in favor of shorter trees over longer ones, and
  - selects trees that place the attributes with highest information gain closest to the root
- Issues in decision trees include
  1. how deeply to grow
  2. handling continuous attributes
  3. choosing an appropriate attribute selection measure
  4. missing attribute values
  5. attributes with differing costs, and
  6. improving computational efficiency

Issues in Decision Tree

Overfitting

Given a hypothesis space H, a hypothesis $h \in H$ is said to overfit the training data if there exists some alternative hypothesis $h' \in H$, such that h has smaller error than h' over the training examples, but h' has a smaller error than h over the entire distribution of instances.



- This can occur when training examples contain random errors or noise.

Approaches to avoid overfitting

- Stop growing the tree earlier, before it reaches the point where it perfectly classifies the training data

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Criterion to determine the correct final tree size include:

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- Use all the available data for training, but apply a statistical test (such as chi-square test) to estimate whether expanding (or pruning) a particular node is likely to produce an improvement beyond the training set.
- Use an explicit measure of the complexity for encoding the training examples (such as Minimum Description Length) and the decision tree, halting growth of the tree when this encoding size is minimized.

Random Forest

Combination of learning models (ensemble of classifiers) increases classification accuracy. Averaging compensates noise. Resulting model has low variance

[2] Leo Breiman, “Random Forests”, ML 45, pp 5-32, 2001

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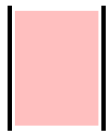

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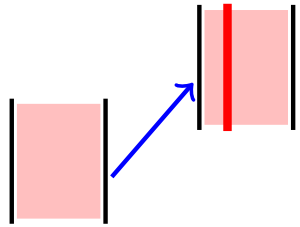

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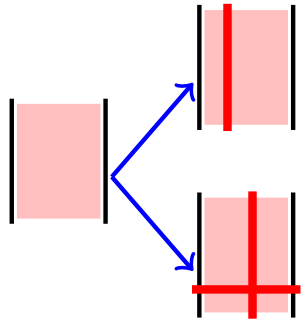

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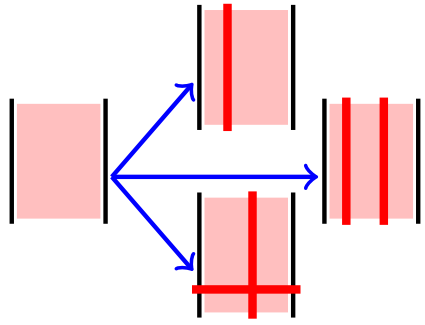

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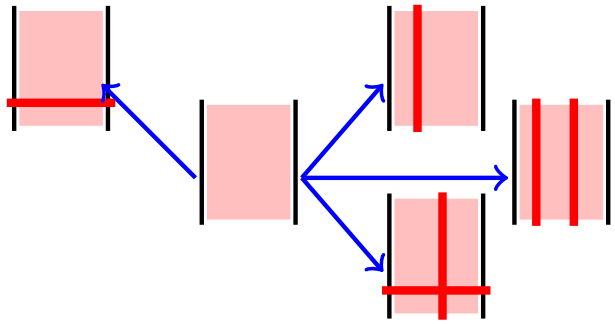

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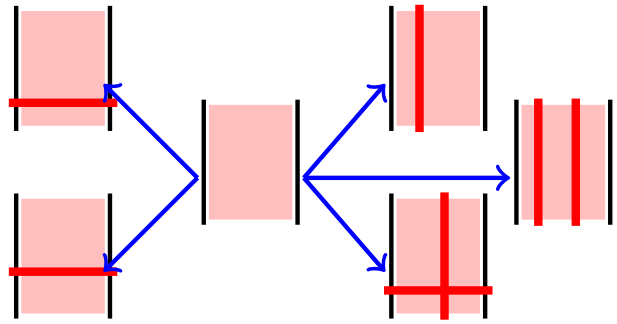

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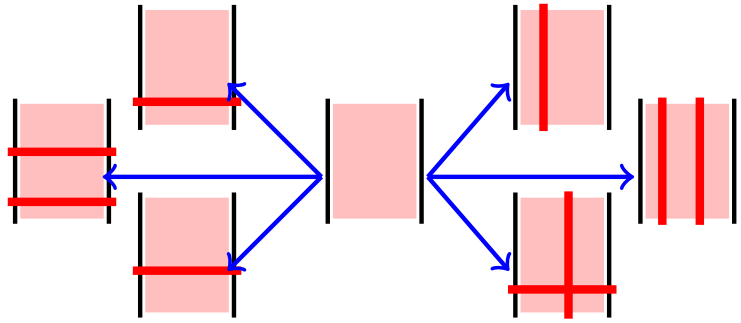

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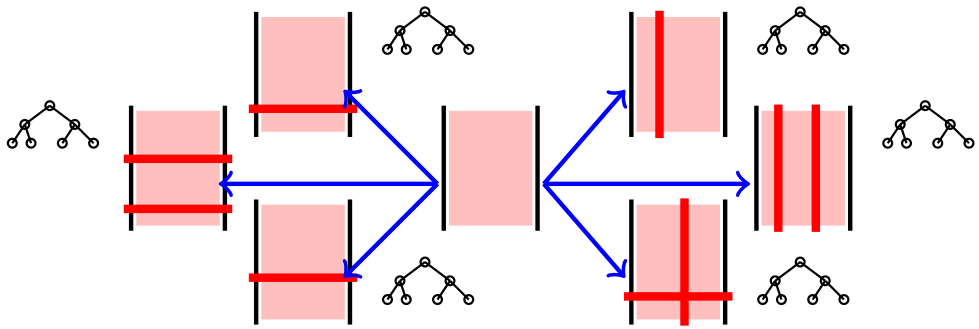

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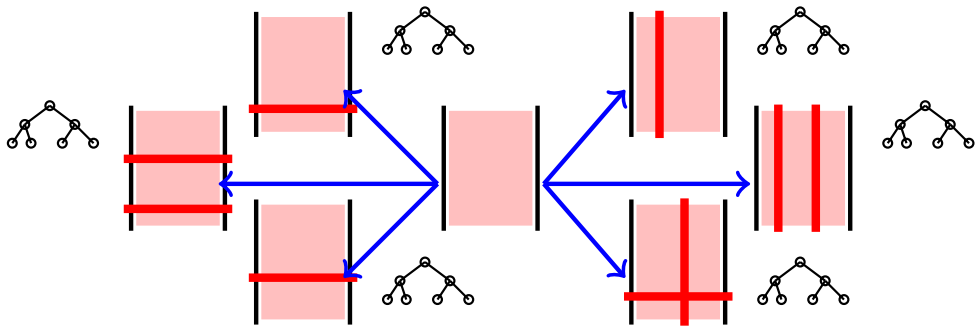
Combination of learning models (ensemble of classifiers) increases classification accuracy. Averaging compensates noise. Resulting model has low variance

Random Forest[2] is a large collection of decorrelated decision trees

- Training data is divided into a number of sub-sets (delete row or columns) that may have overlap (or subset of attributes)



- For every subset, built a decision tree
- To classify new element: **apply voting**

[2] Leo Breiman, "Random Forests", ML 45, pp 5-32, 2001

Thank You!

Thank you very much for your attention!

Queries ?

(Reference[3])

[3] 1) Book - *AIMA*, ch-14, Russell and Norvig. 2) Book - *Bayeian Reasoning and Machine Learning*, ch-04, David Barber.