Data Science

Decision Tree Learning

OBJECTIVE

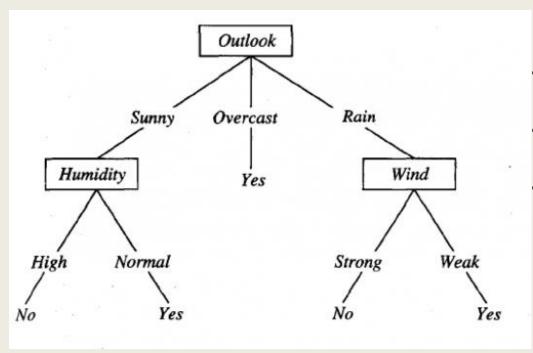
- WHAT IS A DECISION TREE? HOW DO WE USE IT?
- HOW TO BUILD A DECISION TREE
- ADVANTAGES & DISADVANTAGES
- TUNING PARAMETERS
- BUILDING A DECISION TREE IN PYTHON

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- Supervised learning algorithm
 - Regression: Numerical
 - Classification: Categorical
- Builds a tree by repeatedly splitting the dataset
- Easy to interpret
- Variable importance and selection
- Sets the foundation for state of the art ensemble techniques

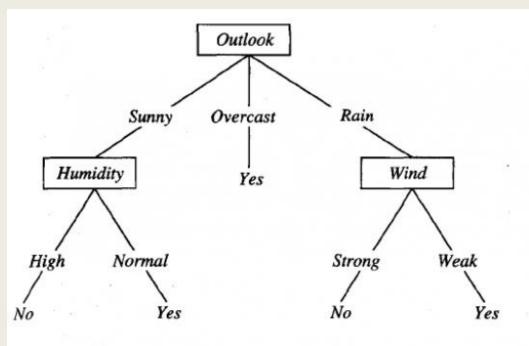
Will there be a tennis match today?



- For new observations follow tree to leaf nodes
- Leaf nodes show the prediction
- Important variables are higher in the tree

Quinlan 1986

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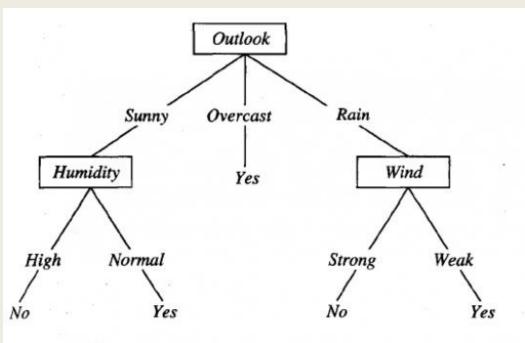


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Q1: The outlook is overcast. Will there be a tennis match?

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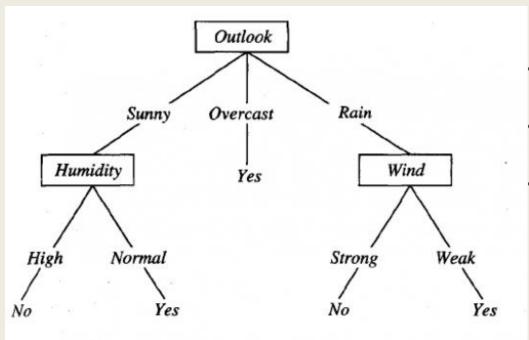
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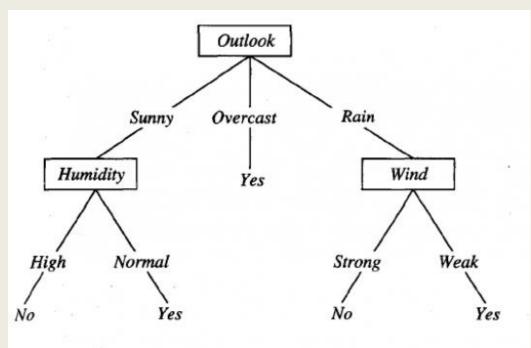
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Q1: The outlook is overcast. Will there be a tennis match?

A1: Yes

Q2: Sunny outlook with normal humidity. Tennis Match?

Will there be a tennis match today?



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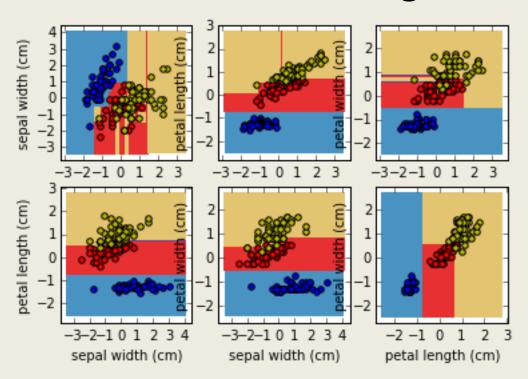
A1: Yes

Q2: Sunny outlook with normal humidity. Tennis Match?

A2: Yes

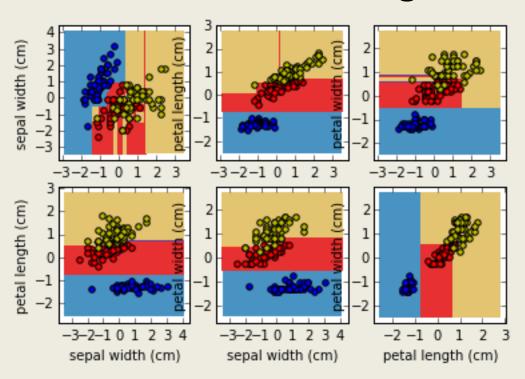
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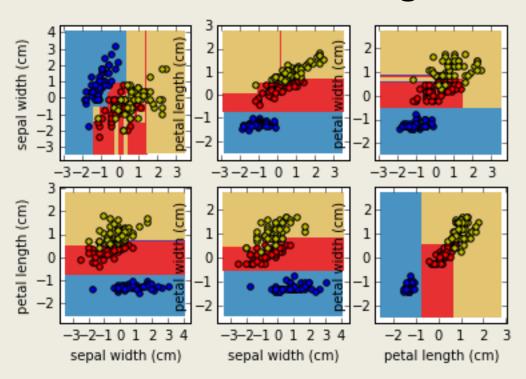
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A: Feature space is partitioned into rectangles. Take a vote or average within rectangle.

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Q: What questions would you ask?

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- How many features should I use?
- How big do I make my tree?
- Are there any constraints on the leaf nodes?

- Various algorithms:
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Questions:

- What feature to use at a node?
- How many features should I use?
- How big do I make my tree?
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Q: Why are these questions important?

- Various algorithms:
 - ID3, C4.5, CART, etc

- What feature to use at a node?
- How many features should I use?
- How big do I make my tree?
- Are there any constraints on the leaf nodes?
 - Q: Why are these questions important?
 - Q: Any ideas on how to solve these problems?

- What feature to use at a node?
 - 3

- How many features should I use?
- How big do I make my tree?
- Are there any constraints on the leaf nodes?

- What feature to use at a node?
 - Information Gain
 - Gini Impurity
 - Etc
- How many features should I use?
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Entropy: Expected information contained in a message

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A: 90/10 = .47 50/50 = 1.0

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X	Υ	Z	С
1	1	1	1
1	1	0	1
0	0	1	0
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Example:

Q: What feature is the best?

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Example:

Q: What feature is the best?

- Entropy(Parent) = 1
- X:?

Entropy = $-\Sigma$ p log(p)

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Example:

Q: What feature is the best?

- Entropy(Parent) = 1
- X: $C1 = -(1/3)\log(1/3) (2/3)\log(2/3) = .9184$, C2 = 0
 - Info Gain = 1 (3/4) * 0.9184 0 = 0.3112
- Y:?

Entropy = $-\Sigma$ p log(p)

Information Gain = Entropy(parent) - average entropy(children)

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- Z:?

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- Z: C1 = 1, C2 = 1
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Example:

Q: What feature is the best?

A: Feature Y is the best feature

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Advantage & Disadvantages

Advantages:

- Can handle continuous and categorical predictors
- Interpretability
- Ensembles are extremely powerful

Disadvantages

- Overfitting
- Predictive power
- High Variance

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