Research Topic (C)

Title: Using Probability to Build Decision Trees for Classification

Introduction to Decision Trees

Life is all about making decisions. We keep on making decisions in both voluntary and involuntary state. This phenomenon has influenced a wide area of machine learning, covering both classification and regression. But in this research I'll talk in detail about Decision Trees and Classification and explain examples with real datasets. In decision analysis, a decision tree can be utilized to outwardly and expressly speak to choices and decisions . As the name goes, it utilizes a tree-like model of decisions.

What 's a Decision Tree ? (Ref. 1)

A decision tree is a graph or outline that individuals use to decide a game-plan or show a statistical probability. It forms the outline of the namesake woody plant, usually upright but sometimes lying on its side. Each branch or part of the decision tree speaks to a possible decision, result, outcome or response .The farthest branches on the tree represent the end results.

Individuals use decision trees to clarify and find an answer to a complex problem. Decision trees are frequently employed in determining a course of action in finance, investing, or business.

By displaying a sequence of steps, decision trees give people an effective and easy way to visualize and understand the potential options of a decision and its range of possible outcomes. The decision tree also helps people identify every potential option and weigh each course of action against the risks and rewards each option can yield.

An organization may use decision trees as a kind of decision support system. The structured model allows the reader of the chart to see how and why one choice may lead to the next, with the use of the branches indicating mutually exclusive options. The structure allows users to take a problem with multiple possible solutions and to display those solutions in a simple, easy-to-understand format that also shows the relationship between different events or decisions.

If a person uses a decision tree to make a decision, they look at each final outcome and assess the benefits and drawbacks. The tree itself can span as long or as short as needed in order to come to a proper conclusion.

Mathematical formulation of Decision Trees. (Ref. 2)

Information gain IG(A) is the measure of the difference in entropy from before to after the set S is split on an attribute A. In other words, how much uncertainty in S was reduced after splitting set S on attribute A.

$IG(A,S) = H(S) - \sum_{t \in T} p(t)H(t)$

Where,
- H(S) – Entropy of set S
- T – The subsets made from parting set S by attribute A.
- P(t) – The proportion of the number of elements in t to the number of elements in set S
- H(t) – Entropy of subset t.

In ID3, information gain can be calculated (instead of entropy) for each remaining attribute. The attribute with the largest information gain is used to split the set S o()n this iteration.

Example: Contingency Table

Credit Rating	Liability		
	Normal	High	Total
Excellent	3	1	4
Good	4	2	6
Poor	0	4	4
Total	7	7	14

Our target here is Liability variable its values are “Normal” and “High” and we only have only one feature called “Credit Rating” and its values are “Excellent” , “Poor” and “Good” the total observations is 14 ,’High class” and “Normal Class” all take 7 ,So it's an even split by itself. If we look at the top raw we can see 4 observations that have value "Excellent" for the credit rating feature . 3belong to "Normal Liability Class" and one belongs to "High Liability Class" I can similarly figure out such values for other values of Credit Rating from the contingency table. to calculate the entropy of our target variable I will use the contingency table above and then calculate the entropy of our target value using additional information about feature and credit rating **,** this will help me to determine how much additional information does "Credit Rating" provide for my "Liability" target variable

E(Liability) = $-(\frac{7}{14})\log_2(\frac{7}{14}) - (\frac{7}{14})\log_2(\frac{7}{14}) = -\frac{1}{2}\log_2(\frac{1}{2}) - \frac{1}{2}\log_2(\frac{1}{2})$ = 1

The entropy of our target variable is 1, at maximum disorder due to the even split between class label "Normal" and "High". The next step is to determine the entropy of the variable "Liability" with additional information about "Credit Score" ,For this we will determine the entropy for "Liability" for each value of Credit Score and add them using weighted average of the proportion of observations that end up in each value.

Each Value :

E(Liability | CR =Excellent) = - $\frac{3}{4}\log_2(\frac{3}{4}) - \frac{1}{4}\log_2(\frac{1}{4}) \approx 0.811$

E(Liability | CR =Poor) = $0\log_2(0) - \frac{4}{4}\log_2(\frac{4}{4}) \approx 0$

Weighted Average :

E(Liability | CR) = $\frac{4}{14} \times 0.811 + \frac{6}{14} \times 0.918 + \frac{4}{14} \times 0 = 0.625$

Through the Credit Rating feature we got the entropy for our target variable ,now we can determine the Information Gain on "Liability" from credit rating to see how informative this feature is .

Information Gain :

IG (Liability ,CR) = E(Liability) – E(Liability | CR) = 1 - .625 = 0.375

Credit Rating helped us to minimize the uncertainty around our target variable that's exactly how and why decision trees use entropy and information gain to decide which feature to split their nodes on to get closer to predicting the target variable with each split and also to decide when to stop splitting the tree .

Entropy H(S) is a measure of the amount of uncertainty in the (data) set S (i.e. entropy characterizes the (data) set S).

H(S) = $\sum_{c \in C} - p(c) \log_2 p(c)$

Where,

- S – is the current (data) set for which entropy is being calculated (changes every iteration of the ID3 algorithm)
- c – Set of classes in S c = { yes, no}
- p(c) – The proportion of the number of elements in class c to the number of elements in set S.

When H(S) = 0, the set S is classified (i.e. all elements in S are of the same class).

Example:

If we have two classes positive and negative class. Therefore 'I' here may be (+) or (-) So if we had 100 data points in total in our dataset , 30 belonging to the positive class and 70 belonging to the negative class then "P+" will be 3/10 and "P-" would be 7/10 .

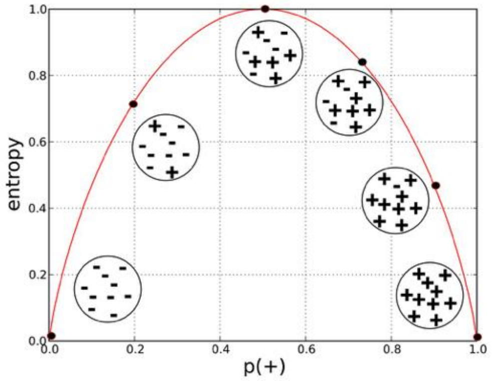
To calculate the entropy of this example using the form above

$$-\frac{3}{10} \times \log_2(\frac{3}{10}) - \frac{7}{10} \times \log_2\left(\frac{7}{10}\right) \sim 0.88$$

The entropy here is around .88 ,this is known to be a high entropy ,high instability level (low purity level) Entropy results is between 0 and 1 (depending on the number of classes in your dataset) it may exceed 1 but it mean a very high

level of instability .

The graph below will understand us more about entropy



The x-axis represents the proportion of data points belonging to the positive class in each bubble and the y-axis represents their entropies ,you can see the inverted 'U' shape of the graph . Entropy is lowest at the edges (when a bubble contains only negative or positive instances) when the bubble is pure the entropy is 0 , entropy is high in middle when the bubble split between positive and negative instances .

Entropy is a measure of disorder or uncertainty and the goal of machine learning models and Data Scientists in general is to reduce uncertainty.

In ID3, entropy is determined for each remaining attribute. The quality with the littlest entropy is utilized to part the set S on this emphasis.
The higher the entropy, the higher the possibility to improve the classification here.

What are the terms in the Decision Trees mean and the intuitions behind them? (Ref. 2)

Important Terminology related to Decision Trees

- **Root Node:** It represents the entire population or sample and this further gets divided into two or more homogeneous sets.
- **Splitting:** It is a process of dividing a node into two or more sub-nodes.
- **Decision Node:** At the point when a sub-hub splits into further sub-nodes, then it is known as the decision node.
- **Leaf / Terminal Node:** Nodes do not part is called Leaf or Terminal node.
- **Pruning:** When we remove sub-nodes of a decision node, this procedure is called pruning. You can say the contrary procedure of parting.
- **Branch / Sub-Tree:** A subsection of the whole tree is called branch or sub-tree.
- **Parent and Child Node:** A node, which is partitioned into sub-nodes is known as a parent node of sub-nodes though sub-nodes are the child of a parent node.

Explain the ID3 method to construct the decision tress how it is related to probability?

ID3 represents Iterative Dichotomiser 3

It is an arrangement calculation that follows an avaricious methodology by choosing a best trait that yields most extreme Information Gain(IG) or least Entropy(H).

What are the steps in ID3 algorithm?

1. Calculate entropy for dataset.
2. For each attribute/feature
   - Calculate entropy for all its categorical values.
   - Calculate information gain for the feature.
3. Find the feature with maximum information gain.
4. Repeat it until we get the desired tree.

The Relation between ID3 and Probability

By Using Probability, we can calculate the entropy and Information Gain that are considered as the mathematical formulas of ID3.

Example shows Use of ID3 algorithm on a data

We'll discuss it mathematically in the next part.

Working a numerical example of how Decision Trees are built.

Ex. ; Make a decision tree that predicts whether tennis will be played on the day?

S. No.	Outlook	Temperature	Humidity	Windy	PlayTennis
1	Sunny	Hot	High	Weak	No
2	Sunny	Hot	High	Strong	No
3	Overcast	Hot	High	Weak	Yes
4	Rainy	Mild	High	Weak	Yes
5	Rainy	Cool	Normal	Weak	Yes
6	Rainy	Cool	Normal	Strong	No
7	Overcast	Cool	Normal	Strong	Yes
8	Sunny	Mild	High	Weak	No
9	Sunny	Cool	Normal	Weak	Yes
10	Rainy	Mild	Normal	Weak	Yes
11	Sunny	Mild	Normal	Strong	Yes
12	Overcast	Mild	High	Strong	Yes
13	Overcast	Hot	Normal	Weak	Yes
14	Rainy	Mild	High	Strong	No

<u>Solution in detail</u>

Step 1 : We'll create a Root Node

- How to choose the root node?

The attribute that best classifies the training data, use this attribute at the root of the tree.

- How to choose the best attribute?

So from here, ID3 algorithm begins

- Calculate **Entropy** (The amount of uncertainty in dataset):

$$\text{Entropy} = \frac{-p}{p+n} \log_2 \left(\frac{p}{p+n}\right) - \frac{n}{p+n} \log_2 \left(\frac{n}{p+n}\right)$$

- Calculate **Average Information :**

$$\text{I (Attribute)} = \sum \frac{pi+ni}{p+n} \text{ Entropy (A)}$$

- Calculate **Information Gain:** (Difference in Entropy before and after splitting dataset on attribute A)

Gain = Entropy (S) – I (Attribute)

1.compute the entropy for data-set Entropy(s)
2.for every attribute/feature:

- calculate entropy for all other values Entropy(a)
- take average information entropy for the current attribute
- calculate gain for the current attribute

3. pick the highest gain attribute.
4. Repeat until we get the tree we desired.

P = 9 , N = 5 , Total = 14

- Calculate **Entropy (S)**

$$\text{Entropy} = \frac{-p}{p+n} \log_2 \left(\frac{p}{p+n}\right) - \frac{n}{p+n} \log_2 \left(\frac{n}{p+n}\right)$$

$$\text{Entropy(S)} = \frac{-9}{9+5} \log_2 \left(\frac{9}{9+5}\right) - \frac{5}{9+5} \log_2 \left(\frac{5}{9+5}\right)$$

$$\text{Entropy(S)} = \frac{-9}{14} \log_2 \left(\frac{9}{14}\right) - \frac{5}{14} \log_2 \left(\frac{5}{14}\right) = \mathbf{0.940}$$

For Each Attribute: (let say **Outlook**)

- Calculate Entropy for each values, i.e. for 'Sunny', 'Rainy', 'Overcast'

Outlook	**Play Tennis**
Sunny	No
Sunny	No
Sunny	No
Sunny	Yes
Sunny	Yes

Outlook	**Play Tennis**
Rainy	Yes
Rainy	Yes
Rainy	No
Rainy	Yes
Rainy	Yes

Outlook	**Play Tennis**
Overcast	Yes
Overcast	Yes
Overcast	Yes
Overcast	Yes

- Calculate **Entropy (Outlook = 'Value'):**

  E (Outlook = sunny) = $\frac{-2}{5}\ \log_2 \left(\frac{2}{5}\right) - \frac{3}{5}\ \log_2 \left(\frac{3}{5}\right)$ = **0.971**

  E (Outlook = overcast)= $-1\ \log_2\ (1) -\ 0\ \log_2 (0)\ =\ \mathbf{0}$

  E (Outlook = rainy) = $\frac{-3}{5}\ \log_2 \left(\frac{3}{5}\right) - \frac{2}{5}\ \log_2 \left(\frac{5}{5}\right)$ = **0.971**

- Calculate **Average Information Entropy**:

  I (Outlook) = $\frac{p\ sunny + n\ sunny}{p+n}$ Entropy (Outlook = Sunny) +
  $\frac{p\ rainy + n\ rainy}{p+n}$ Entropy (Outlook = Rainy) +
  $\frac{p\ \text{overcast} + n\ \text{overcast}}{p+n}$ Entropy (Outlook = Overcast)

  I (Outlook) = $\frac{3+2}{9+5}$ * 0.971 + $\frac{2+3}{9+\ 5}$ * 0.971 + $\frac{4+0}{9+\ 5}$ * 0 = 0.693

- Calculate **Gain**: attribute is Outlook

  Gain = Entropy (S) – I (Attribute)

  Entropy (S) = 0.940

  Gain (Outlook) = 0.940 – 0.693 = 0.247

Outlook	**P**	**n**	**Entropy**
Sunny	2	3	0.971
Rainy	3	2	0.971
Overcast	4	0	0

For Each Attribute: (let say **Temperature**)

- Calculate Entropy for each Temp, i.e. for 'Hot', 'Mild, 'Cool'

Temperature	Play Tennis
Hot	No
Hot	No
Hot	Yes
Hot	Yes

Temperature	Play Tennis
Mild	Yes
Mild	No
Mild	Yes
Mild	Yes
Mild	Yes
Mild	No

Temperature	Play Tennis
Cool	Yes
Cool	No
Cool	Yes
Cool	Yes

Temperature	p	n	Entropy
Hot	2	2	1
Mild	4	2	0.918
Cool	3	1	0.811

- Calculate **Average Information Entropy**:

  I (Temperature) = $\frac{p\ hot + n\ hot}{p+n}$ Entropy (Temperature = Hot) +
  $\frac{p\ mild + n\ mild}{p+n}$ Entropy (Temperature = Mild) +
  $\frac{p\ cool + n\ cool}{p+n}$ Entropy (Temperature = Cool)

  I (Temperature) = $\frac{2+2}{9+5} * 1 + \frac{4+2}{9+5} * 0.918 + \frac{3+1}{9+5}$ * 0.811 => 0.911

- Calculate **Gain**: attribute is Temperature
  Gain = Entropy (S) – I (Attribute)
  Entropy (S) = 0.940
  Gain (Temperature) = 0.940 – 0.911 = 0.029

For Each Attribute: (let say **Humidity**)

- Calculate Entropy for each Temp, i.e. for 'High', 'Normal'

Humidity	**Play Tennis**
Normal	Yes
Normal	No
Normal	Yes
Normal	Yes
Normal	Yes
Normal	Yes
Normal	Yes

Humidity	**Play Tennis**
High	No
High	No
High	Yes
High	Yes
High	No
High	Yes
High	No

Humidity	**p**	**n**	**Entropy**
High	3	4	0.985
Normal	6	1	0.591

- Calculate **Average Information Entropy**:

  I (**Humidity**) = $\frac{p\text{ High}+n\text{ High}}{p+n}$ Entropy (Humidity = High) + $\frac{p\text{ Normal}+n\text{ Normal}}{p+n}$ Entropy (Humidity = Normal)

  I (Humidity) = $\frac{3+4}{9+5} * 0.985 + \frac{6+1}{9+5} * 0.591 + \frac{3+1}{9+5}$ * 0.811 => 0.788

- Calculate **Gain**: attribute is Humidity

  Gain = Entropy (S) – I (Attribute)

  Entropy (S) = 0.940

  Gain (Humidity) = 0.940 – 0.788 = 0.152

For Each Attribute: (let say **Windy**)

- Calculate Entropy for each Windy, i.e. for 'Strong', 'Weak'

Windy	**Play Tennis**
Weak	No
Weak	Yes
Weak	Yes
Weak	Yes
Weak	No
Weak	Yes
Weak	Yes
Weak	Yes

Windy	**Play Tennis**
Strong	No
Strong	No
Strong	Yes
Strong	Yes
Strong	Yes
Strong	No

Windy	p	n	**Entropy**
Strong	3	3	1
Weak	6	2	0.811

- Calculate **Average Information Entropy**:

  I (**Windy**) = $\frac{p\text{ Strong}+n\text{ Strong}}{p+n}$ Entropy (Windy = Strong) + $\frac{p\text{ Weak}+n\text{ Weak}}{p+n}$ Entropy (Windy = Weak)

  I (Windy) = $\frac{3+3}{9+5} * 1 + \frac{6+2}{9+5} * 0.811$ => 0.892

- Calculate **Gain**: attribute is Windy

  Gain = Entropy (S) – I (Attribute)

  Entropy (S) = 0.940

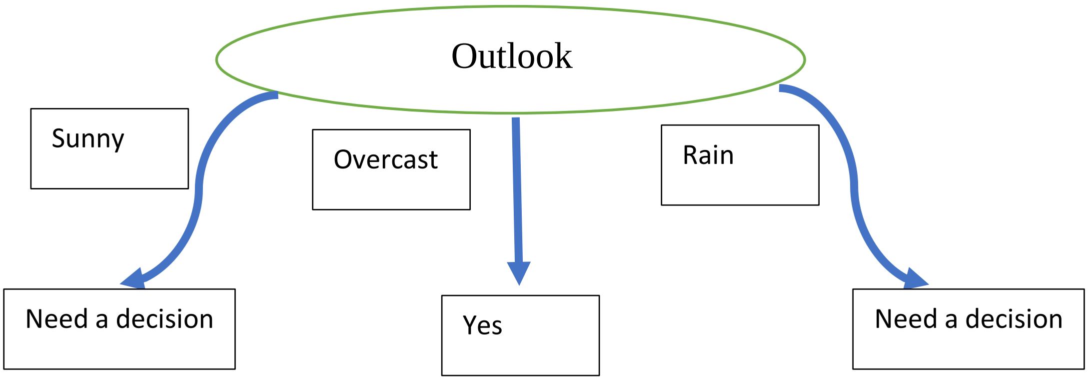
  Gain (Windy) = 0.940 – 0.892 = 0.048

Pick The Highest Gain Attribute.

Attributes	Gain
Outlook	0.247
Temperature	0.029
Humidity	0.152
Windy	0.048

So ➔ **Root Node: OUTLOOK** 🡐

Outlook	Temperature	Humidity	Windy	Play Tennis
Overcast	Hot	High	Weak	Yes
Overcast	Cool	Normal	Strong	Yes
Overcast	Mild	High	Strong	Yes
Overcast	Hot	Normal	Weak	Yes



- **We'll repeat the same thing for Sub-Trees till we get the tree.**

Outlook: Sunny **P = 2 , N = 3, Total = 5**

Outlook	**Temperature**	**Humidity**	**Windy**	**Play Tennis**
Sunny	Hot	High	Weak	No
Sunny	Hot	High	Strong	No
Sunny	Mild	High	Weak	No
Sunny	Cool	Normal	Weak	Yes
Sunny	Mild	Normal	Strong	Yes

Outlook: Rainy **P = 3 , N = 2, Total = 5**

Outlook	**Temperature**	**Humidity**	**Windy**	**Play Tennis**
Rainy	Mild	High	Weak	Yes
Rainy	Cool	Normal	Weak	Yes
Rainy	Cool	Normal	Strong	No
Rainy	Mild	Normal	Weak	Yes
Rainy	Mild	High	Strong	No

- **Entropy:**

Entropy = $\frac{-p}{p+n}\log_2\left(\frac{p}{p+n}\right)-\frac{n}{p+n}\log_2\left(\frac{n}{p+n}\right)$

Entropy (Sunny) = $\frac{-2}{2+3}\log_2\left(\frac{2}{2+3}\right)-\frac{3}{2+3}\log_2\left(\frac{3}{2+3}\right)$ => **0.971**

For Each Attribute: (let say **Humidity**)

- Calculate Entropy for each Humidity, i.e. for 'High', 'Normal'

Outlook	Humidity	Play Tennis
Sunny	High	No
Sunny	High	No
Sunny	High	No
Sunny	Normal	Yes
Sunny	Normal	Yes

Humidity	p	n	Entropy
high	0	3	0
normal	2	0	0

- Calculate **Average Information Entropy**: I(Humidity) = 0
- Calculate **Gain:** Gain = 0.971

For Each Attribute: (let say **Windy**)

- Calculate Entropy for each Windy, i.e. for 'Strong', 'Weak'

Outlook	Windy	Play Tennis
Sunny	Strong	No
Sunny	Strong	Yes
Sunny	Weak	No
Sunny	Weak	No
Sunny	Weak	Yes

Windy	p	n	Entropy
Strong	1	1	1
Weak	1	2	0.918

- Calculate **Average Information Entropy**: I(Windy) = 0.951
- Calculate **Gain:** Gain = 0.020

For Each Attribute: (let say **Temperature**)

- Calculate Entropy for each Temp, i.e. for ‘Cool’ ,’Hot’, ‘Mild’

Outlook	**Temperature**	**Play Tennis**
Sunny	Cool	Yes
Sunny	Hot	No
Sunny	Hot	No
Sunny	Mild	No
Sunny	Mild	Yes

Temperature	**p**	**n**	**Entropy**
Cool	1	0	0
Hot	0	2	0
Mild	1	1	

- Calculate **Average Information Entropy**: I(Temp) = 0.4
- Calculate **Gain:** Gain = 0.571

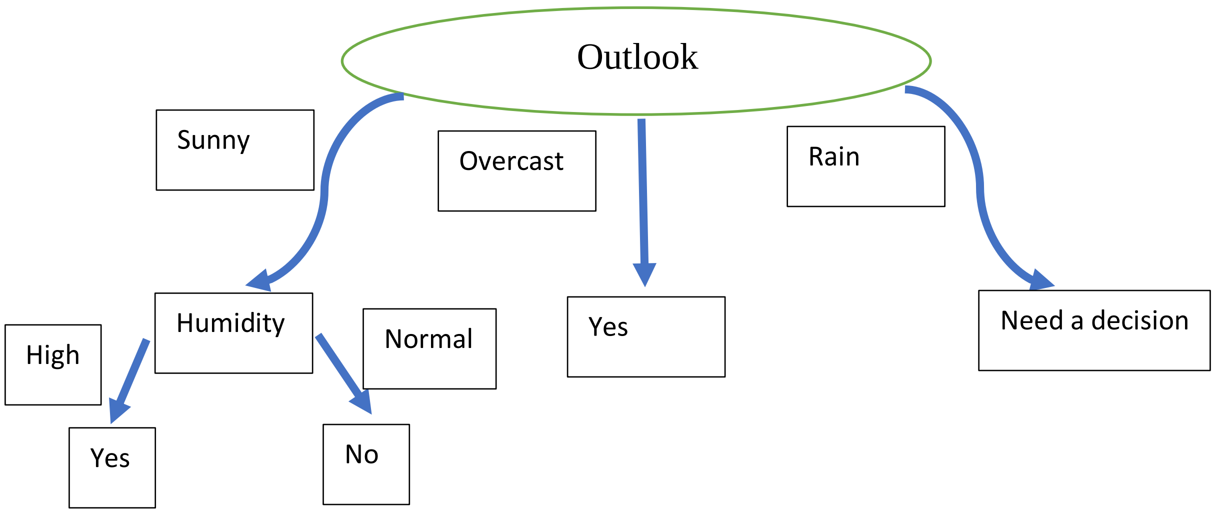
Pick the highest gain attribute.

Attributes	**Gain**
Temperature	0.571
Humidity	0.971
Windy	0.02

So → **Next Node in Sunny: Humidity** ←

Outlook	Temperature	Humidity	Windy	Play Tennis
Rainy	Mild	High	Weak	Yes
Rainy	Cool	Normal	Weak	Yes
Rainy	Cool	Normal	Strong	No
Rainy	Mild	Normal	Weak	Yes
Rainy	Mild	High	Strong	No

Outlook	Humidity	Play Tennis
Sunny	High	No
Sunny	High	No
Sunny	High	No
Sunny	Normal	Yes
Sunny	Normal	Yes



- **Entropy:**

Entropy = $\frac{-p}{p+n}\log_2\left(\frac{p}{p+n}\right) - \frac{n}{p+n}\log_2\left(\frac{n}{p+n}\right)$

Entropy (S Rainy) = $\frac{-3}{3+2}\log_2\left(\frac{3}{3+2}\right) - \frac{2}{3+2}\log_2\left(\frac{2}{2+3}\right)$ => **0.971**

<u>For Each Attribute: (let say **Humidity**)</u>

- Calculate Entropy for each Humidity, i.e. for 'High', 'Normal'

Outlook	Humidity	Play Tennis
Rainy	High	Yes
Rainy	High	No
Rainy	Normal	Yes
Rainy	Normal	No
Rainy	Normal	Yes

Attribute	p	n	Entropy
high	1	1	1
normal	2	1	0.918

- Calculate **Average Information Entropy**: I(Humidity) = 0.951
- Calculate **Gain:** Gain = 0.020

<u>For Each Attribute: (let say **Windy**)</u>

- Calculate Entropy for each Windy, i.e. for 'Strong', 'Weak'

Attribute	p	n	Entropy
Strong	0	2	0
Weak	3	0	0

Outlook	Windy	Play Tennis
Rainy	Strong	No
Rainy	Strong	No
Rainy	Weak	Yes
Rainy	Weak	Yes
Rainy	Weak	Yes

- Calculate **Average Information Entropy**: I(Windy) = 0
- Calculate **Gain:** Gain = 0.971

<u>For Each Attribute: (let say **Temperature**)</u>

- Calculate Entropy for each Temp, i.e. for ‘Cool’ ,’Hot’, ‘Mild’

Outlook	Temperature	Play Tennis
Rainy	Mild	Yes
Rainy	Cool	Yes
Rainy	Cool	No
Rainy	Mild	Yes
Rainy	Mild	No

Attribute	p	n	Entropy
Cool	1	1	1
Mild	2	1	0.918

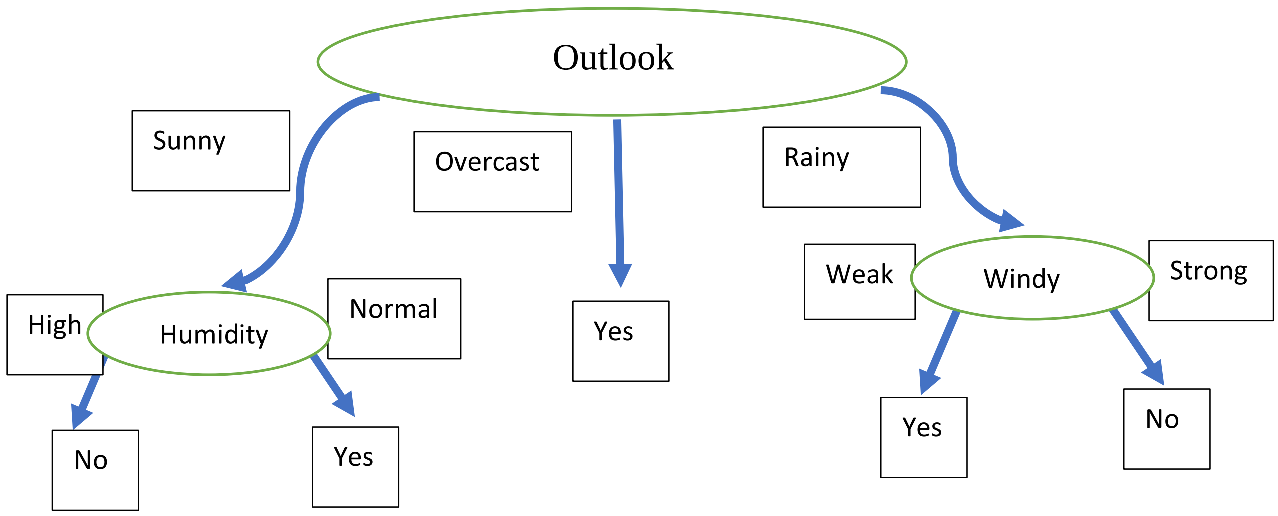
- Calculate **Average Information Entropy**: I(Temp) = 0.951
- Calculate **Gain:** Gain = 0.020

Pick the highest gain attribute.

Attributes	Gain
Temperature	0.02
Humidity	0.02
Windy	0.971

So ➔ **Next Node in Rainy: Windy** 🡐

Final Decision Tree



Working numerical examples of how Decision Trees are used in classification.

In the previous part, I explained how the decision tree is built but here I'll go on explaining how we can use it in classification for machine learning .

When we trace the first row of the previous dataset over the decision tree that we got previously :

S. No.	Outlook	Temperature	Humidity	Windy
1	Sunny	Hot	High	Weak

<u>First Step:</u>

In the most left part of the tree, we will get into branch of “sunny”.

<u>Second Step:</u>

When we come to Humidity node, I’ll get into branch of “high” as mentioned in the row.

<u>Final Step:</u>

We’ll get the answer “**NO**” and It’s the correct result.

So NO one’ll play tennis on that day.

What’re the Applications of Decision Trees in Real Life? (Ref. 3)

1. **Selecting a flight to travel**
   Assume you have to choose a trip for your next movement. How would we go about it? We check first if the flight is accessible on that day or not. In the event that it isn't accessible, we will search for some other date yet on the off chance that it is accessible, at that point we search for might be the span of the flight. On the off chance that we need to have just non-stop flights, at that point we look whether the cost of that flight is in your pre-characterized spending plan or not. On the off chance that it is excessively costly, we take a gander at some different flights else we book it!

2. **Choosing a best friend**
   Well, this example can be very subjective but nevertheless, we will proceed with it. We all have many friends but a best friend is always one or two maybe but not all for sure. In this case, we may go about first whether the other person understands you or not? If another person is not pretty much understanding, we look for someone else. When we find people who have a good understanding level, we look for people who have similar habits or hobbies as we have and the selection criteria go on till we find people whom we can call “close friends”!

3. **Handling late night cravings**
   I guess the following picture will explain it all to you.

Applications in Business

1. **Alternatives**
   Decision trees help organizations to view alternatives to different events that can happen. For example, an organization is planning to build a new product. A lot of resources and money will be invested in it. Decision trees will help the organization to have a look at all other alternatives if they do not want to build the product from scratch. Alternatives may include not building the new product at all or bringing modifications to existing products to incorporate new features in them
2. **Events**
   An event is an occurrence that happens outside your direct control and as a result of your actions. In the example of whether to change the technical stack of the platform, the possible results from the decision to proceed would be the development of a successful product or a product failure.
3. **Outcomes**
   The outcomes are the results of making a decision, weighted with the probabilities of particular events occurring. For the example of product development, you might have to invest $50,000 to develop the new product, expecting it to generate total profits of $100,000. The probability of developing a successful product might be 80 %. As a result, you have an 80 % chance of earning $100,000, a 20 % chance of earning nothing if the product fails, and a 100 % chance of earning no additional profit if you don't develop the product.

Exploratory data analysis for A real dataset:

The Attached Dataset contains a list of Clients' data of A Bank.

Fields include:

- Age – Age of the person
- Job
- Marital – The Marital of the person
- Education
- Balance – The Balance of the person who going to the bank
- Housing
- Loan - If the person took a loan or not
- Contact
- Day – The Day of going to the bank
- Month - The Month of going to the bank

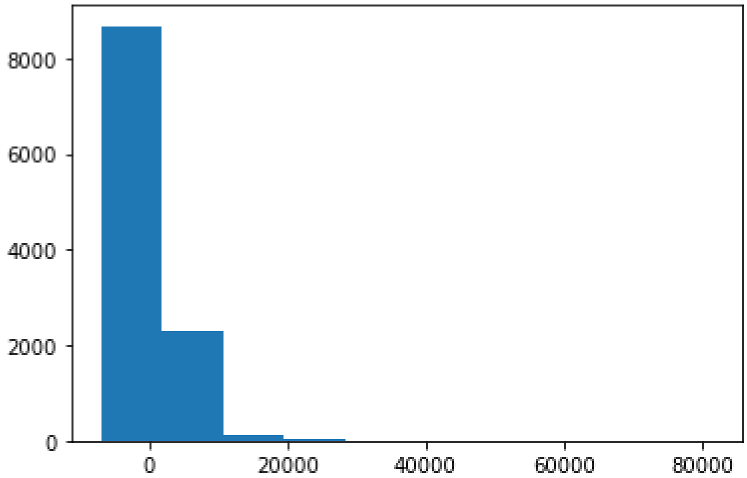
- Duration
- Campaign
- Deposit – If the person will deposit or not

I'll discuss the column of Balance.

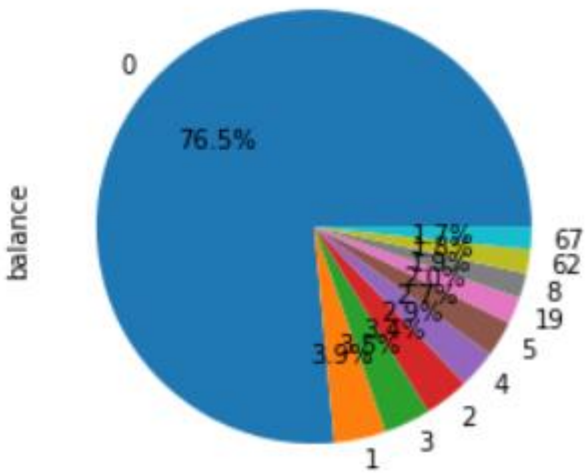
Features:

- **Median**
  550.0
- **Mean**
  1528.5385235620856
- **Mode**
  97
- **Variance**
  10403291.123191012
- **Standard Deviation**
  3225.413325946151
- **Interquartile Range**
  1586.0
- **Min**
  -6847.000000
- **Max**
  81204.000000
- **25%**
  122.000000
- **50%**
  550.000000
- **75%**
  1708.000000

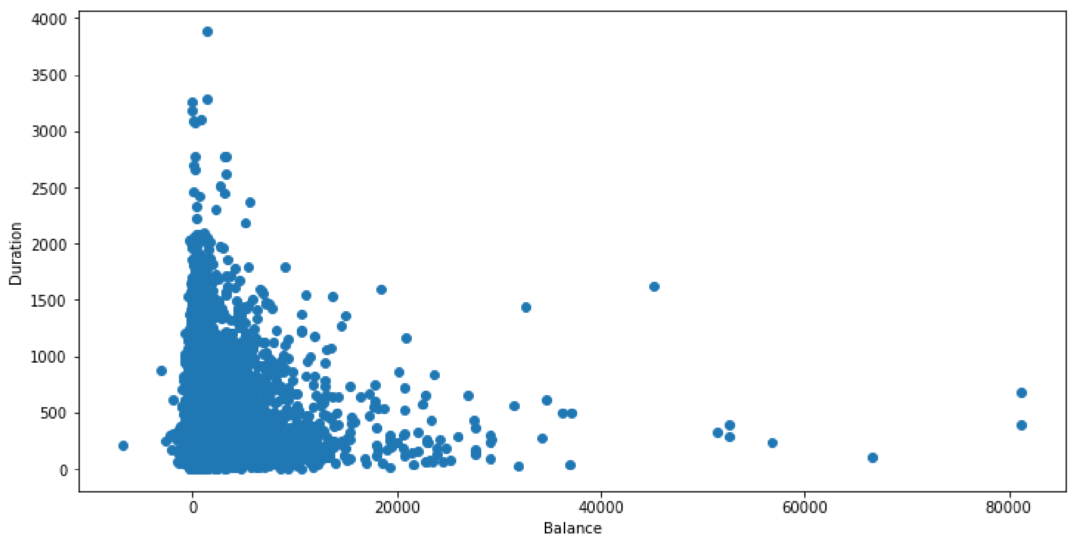
- **Histogram**



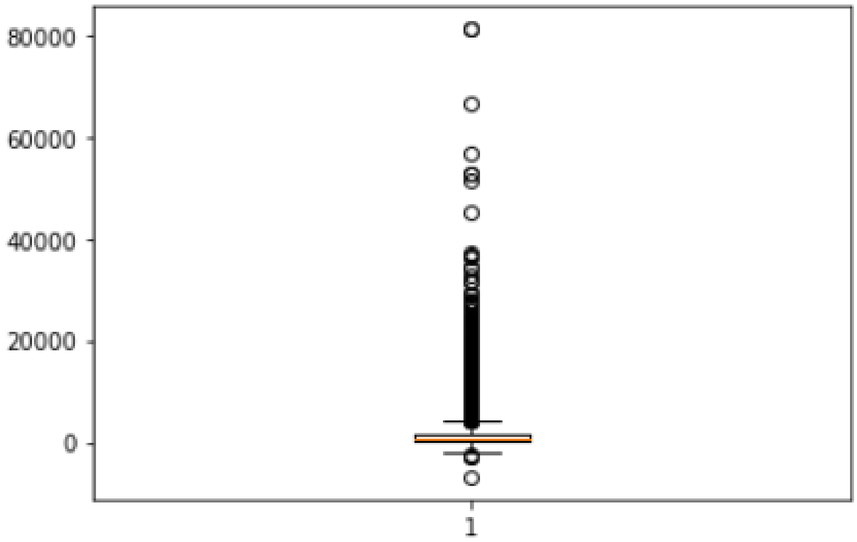
- **Pie Chart**



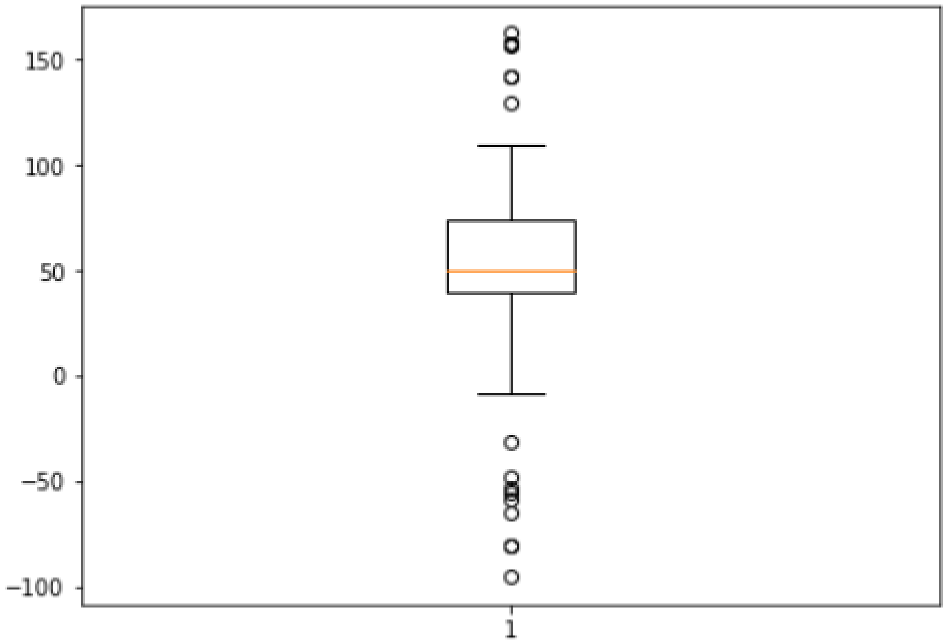
- **Scatter Plot**



- **Box Plot**
  (For all the data**)**



- **Box Plot**
  (For a subset of the data**)**



Conclusion

Decision tree is one of prescient modeling calculations which machine learning relies upon ,Decision tree can be developed utilizing a great deal of calculations, ID3 algorithm is the regularly utilized ,ID3 utilizes a top-down greedy approach to deal with build a decision tree ,ID3 algorithm utilizes Entropy and Information gain algorithms, Entropy gives us questionable information. Thus, we use Information gain to make our information more clear.

References and Books:

[1] **Investopedia** (Website): Link

[2] **Medium** (Website): Link

[3] **Quora** (Website): Link

[4] **Kaggle** (Website): Link

[5] "**Probability and Statistics for Engineers and Scientists**" by Ronald E. Walpole et al.,, 9th Edition, Pearson Education International. (Book): Link