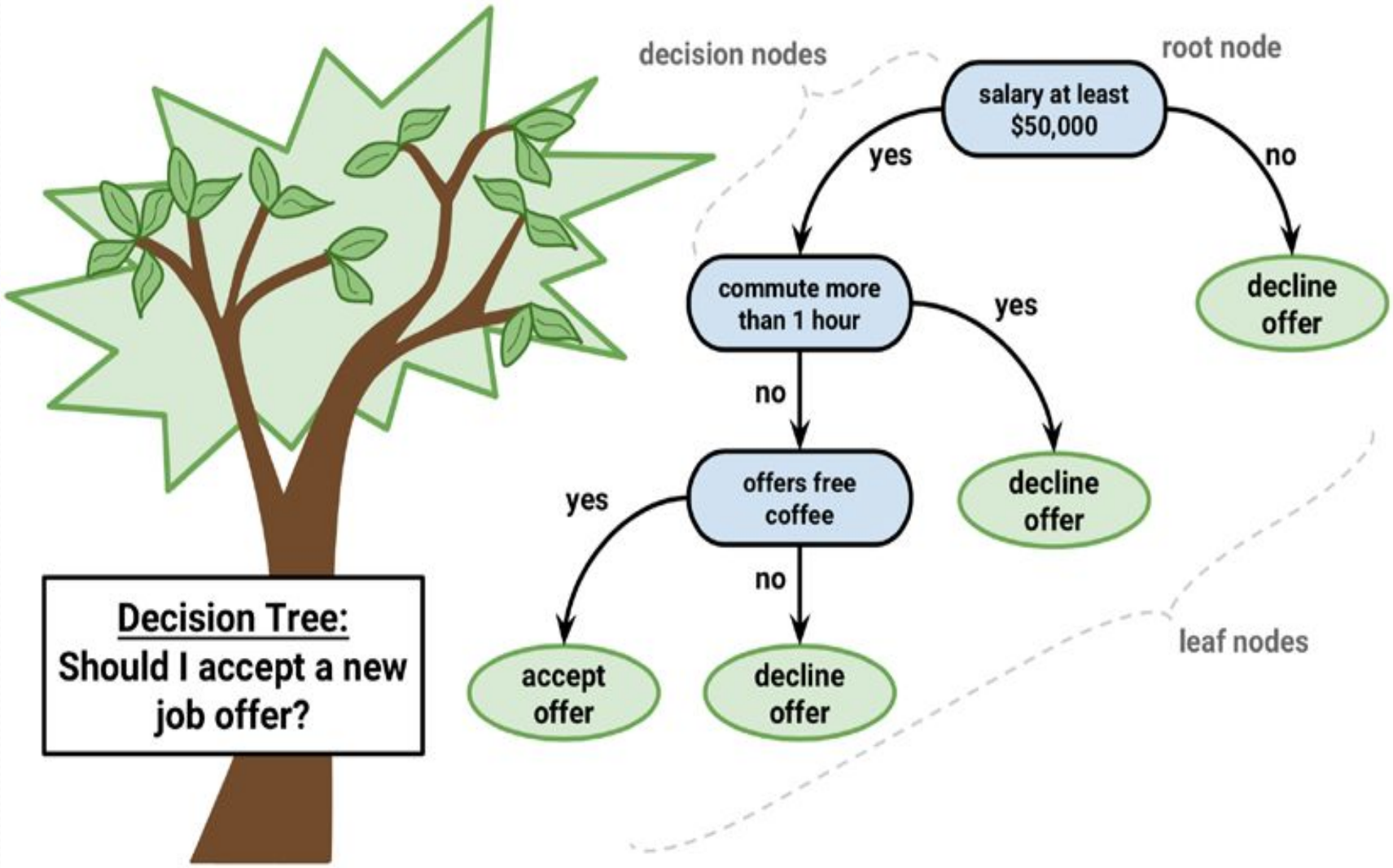
Divide and Conquer – Classification Using Decision Trees and Rules

Decision trees

- Decision tree learners are powerful classifiers, which utilize a **tree structure** to model the relationships among the features and the potential outcomes.
- Its name due to the fact that it mirrors how a literal tree begins at a wide trunk, which if followed upward, splits into narrower and narrower branches.
- In much the same way, a decision tree classifier uses a structure of branching decisions, which channel examples into a final predicted class value.

Decision trees



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Divide and conquer

- Decision trees are built using a heuristic called **recursive partitioning**.
- This approach is also commonly known as **divide and conquer** because it splits the data into subsets, which are then split repeatedly into even smaller subsets, and so on and so forth until the process stops when the algorithm determines the data within the subsets are sufficiently homogenous, or another stopping criterion has been met.

Divide and conquer

- Working down each branch, the algorithm continues to divide and conquer the data, choosing the best candidate feature each time to create another decision node, until a stopping criterion is reached.

Divide and conquer might stop at a node in a case that:

- All (or nearly all) of the examples at the node have the same class
- There are no remaining features to distinguish among the examples
- The tree has grown to a predefined size limit

The C5.0 decision tree algorithm

- This algorithm was developed by computer scientist J. Ross Quinlan as an improved version of his prior algorithm, **C4.5**, which itself is an improvement over his **Iterative Dichotomiser 3** (**ID3**)algorithm.
- The C5.0 algorithm has become the industry standard to produce decision trees, because it does well for most types of problems directly out of the box.

The C5.0 decision tree algorithm

Strengths	Weaknesses
• An all-purpose classifier that does well on most problems • Highly automatic learning process, which can handle numeric or nominal features, as well as missing data • Excludes unimportant features • Can be used on both small and large datasets • Results in a model that can be interpreted without a mathematical background (for relatively small trees) • More efficient than other complex models.	• Decision tree models are often biased toward splits on features having a large number of levels • It is easy to overfit or underfit the model • Can have trouble modeling some relationships due to reliance on axis-parallel splits • Small changes in the training data can result in large changes to decision logic • Large trees can be difficult to interpret and the decisions they make may seem counterintuitive

Choosing the best split

- The first challenge that a decision tree will face is to identify which feature to split upon.
- In the previous example, we looked for a way to split the data such that the resulting partitions contained examples primarily of a single class.
- The degree to which a subset of examples contains only a single class is known as **purity**, and any subset composed of only a single class is called **pure**.

Choosing the best split

- There are various measurements of purity that can be used to identify the best decision tree splitting candidate.
- C5.0 uses **entropy**, a concept borrowed from information theory that quantifies the randomness, or disorder, within a set of class values.
- Sets with high entropy are very diverse and provide little information about other items that may also belong in the set, as there is no apparent commonality.

Choosing the best split

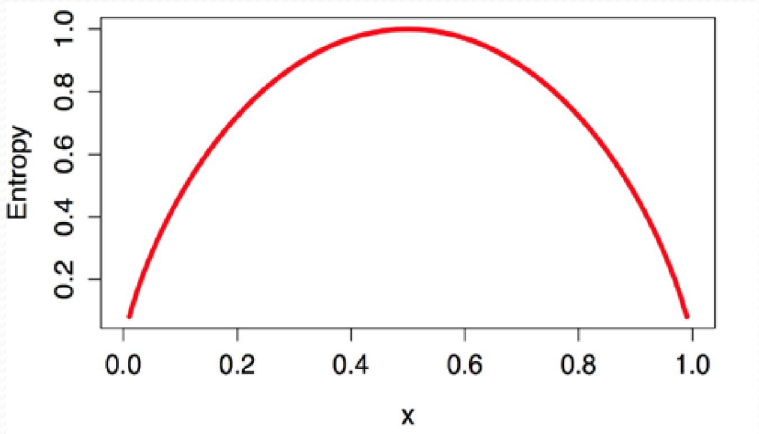
- The decision tree hopes to find splits that reduce entropy, ultimately increasing homogeneity within the groups. Typically, entropy is measured in **bits**.
- If there are only two possible classes, entropy values can range from 0 to 1.
- For *n* classes, entropy ranges from 0 to *log2(n)*. In each case, the minimum value indicates that the sample is completely homogenous, whilet he maximum value indicates that the data are as diverse as possible, and no group has even a small plurality.

Choosing the best split

- In the mathematical notion, entropy is specified as follows:
- Entropy (S) $= \sum_{i=1}^{c} -p_i \log_2(p_i)$
- In this formula, for a given segment of data *(S)*, the term *c* refers to the number of class levels and *pi* refers to the proportion of values falling into class level *i*. For example, suppose we have a partition of data with two classes: red (60 percent) andwhite (40 percent).

Choosing the best split

- he peak in entropy at $x = 0.50$, a 50-50 split results in maximum entropy. As one class increasingly dominates the other, the entropy reduces to zero.



Choosing the best split

- To use entropy to determine the optimal feature to split upon, the algorithm calculates the change in homogeneity that would result from a split on each possible feature, which is a measure known as **information gain**.
- The information gain for a feature *F* is calculated as the difference between the entropy in the segment before the split *(S1)* and the partitions resulting from the split *(S2)*:

  InfoGain (*F*) = Entropy(S1)- Entropy(S2)

Choosing the best split

- One complication is that after a split, the data is divided into more than one partition. Therefore, the function to calculate *Entropy(S2)* needs to consider the total entropy across all of the partitions.
- It does this by weighing each partition's entropy by the proportion of records falling into the partition. This can be stated in a formula as:

$$\text{Entropy (S)} = \sum_{i=1}^{n} -w_i \, \text{Entropy}(P_i)$$

Choosing the best split

- In simple terms, the total entropy resulting from a split is the sum of the entropy of each of the *n* partitions weighted by the proportion of examples falling in the partition (*wi*).
- The higher the information gain, the better a feature is at creating homogeneous groups after a split on this feature.
- If the information gain is zero, there is no reduction in entropy for splitting on this feature.

Choosing the best split

- On the other hand, the maximum information gain is equal to the entropy prior to the split.
- This would simply that the entropy after the split is zero, which means that the split results in completely homogeneous groups.

- Information gain is not the only splitting criterion that can be used to build decision trees.
- Other commonly used criteria are **Gini index**, **Chi-Squared statistic**, and **gain ratio**

Pruning the decision tree

- A decision tree can continue to grow indefinitely, choosing splitting features and dividing the data into smaller and smaller partitions until each example is perfectly classified or the algorithm runs out of features to split on.
- However, if the tree grows overly large, many of the decisions it makes will be overly specific and the model will be overfitted to the training data.
- The process of **pruning** a decision tree involves reducing its size such that it generalizes better to unseen data.

Pruning the decision tree

- One solution to this problem is to stop the tree from growing once it reaches a certain number of decisions or when the decision nodes contain only a small number of examples.
- This is called **early stopping** or **pre-pruning** the decision tree.

Pruning the decision tree

- An alternative, called **post-pruning**, involves growing a tree that is intentionally too large and pruning leaf nodes to reduce the size of the tree to a more appropriate level.
- This is often a more effective approach than pre-pruning, because it is quite difficult to determine the optimal depth of a decision tree without growing it first.
- Pruning the tree later on allows the algorithm to be certain that all the important data structures were discovered.

Pruning the decision tree

- One of the benefits of the C5.0 algorithm is that it is opinionated about pruning— it takes care of many decisions automatically using fairly reasonable defaults.
- Its overall strategy is to post-prune the tree.
- It first grows a large tree that overfits the training data. Later, the nodes and branches that have little effect on the classification errors are removed.

Pruning the decision tree

- In some cases, entire branches are moved further up the tree or replaced by simpler decisions.
- These processes of grafting branches are known as **subtree raising** and **subtree replacement**, respectively.
- Balancing overfitting and underfitting a decision tree is a bit of an art, but if model accuracy is vital, it may be worth investing some time with various pruning options to see if it improves the performance on test data. As you will soon see, one of the strengths of the C5.0 algorithm is that it is very easy to adjust the training options.

Boosting the accuracy of decision trees

- This is a process in which many decision trees are built and the trees vote on the best class for each example.
- By combining a number of weak performing learners, you can create a team that is much stronger than any of the learners alone.
- Each of the models has a unique set of strengths and weaknesses and they may be better or worse in solving certain problems.
- Using a combination of several learners with complementary strengths and weaknesses can therefore dramatically improve the accuracy of a classifier.

Understanding classification rules

- Classification rules represent knowledge in the form of logical if-else statements that assign a class to unlabeled examples.
- They are specified in terms of an **antecedent** and a **consequent**; these form a hypothesis stating that "if this happens, then that happens."
- A simple rule might state, "if the hard drive is making a clicking sound, then it is about to fail."
- The antecedent comprises certain combinations of feature values, while the consequent specifies the class value to assign when the rule's conditions are met.

Understanding classification rules

- Rule learners are often used in a manner similar to decision tree learners. Like decision trees, they can be used for applications that generate knowledge for future action, such as:
  - Identifying conditions that lead to a hardware failure in mechanical devices
  - Describing the key characteristics of groups of people for customer segmentation
  - Finding conditions that precede large drops or increases in the prices of shares on the stock market

Understanding classification rules

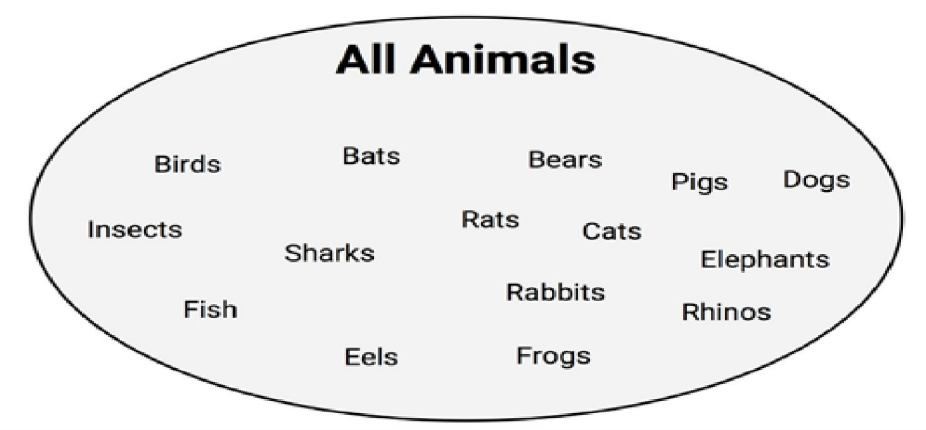
- On the other hand, rule learners offer some distinct advantages over trees for some tasks.
- Unlike a tree, which must be applied from top-to-bottom through a series of decisions, rules are propositions that can be read much like a statement of fact.
- Rule learners are generally applied to problems where the features are primarily or entirely nominal. They do well at identifying rare events, even if the rare event occurs only for a very specific interaction among feature values.

Separate and conquer

- Classification rule learning algorithms utilize a heuristic known as **separate and conquer**.
- The process involves identifying a rule that covers a subset of examples in the training data, and then separating this partition from the remaining data.
- As the rules are added, additional subsets of the data are separated until the entire dataset has been covered and no more examples remain.

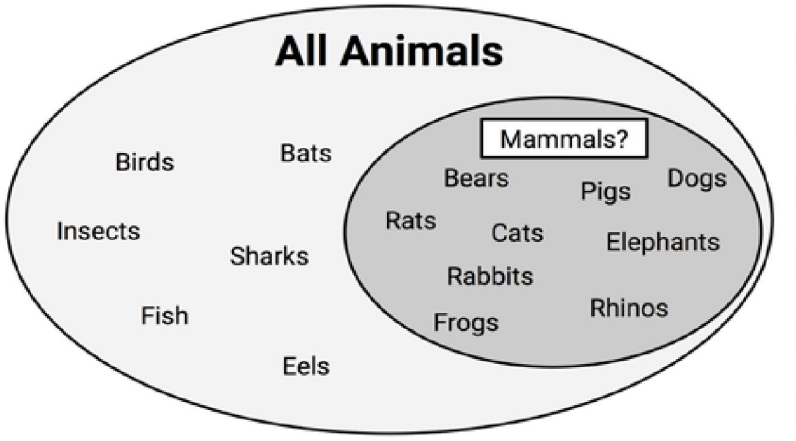
Separate and conquer

- Suppose you were tasked with creating rules to identify whether or not an animal is a mammal.
- You could depict the set of all animals as a large space, as shown in the following diagram:



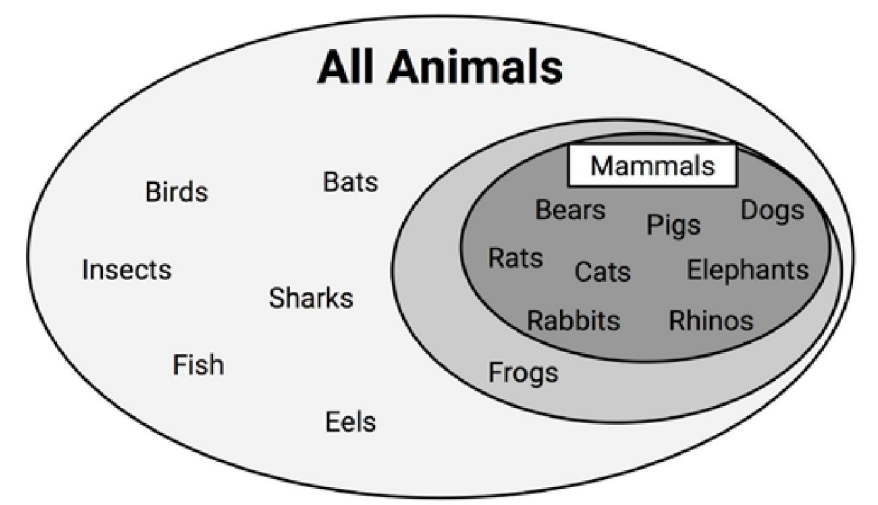
Separate and conquer

- A rule learner begins by using the available features to find homogeneous groups.
- For example, using a feature that indicates whether the species travels via land, sea, or air, the first rule might suggest that any land-based animals are mammals



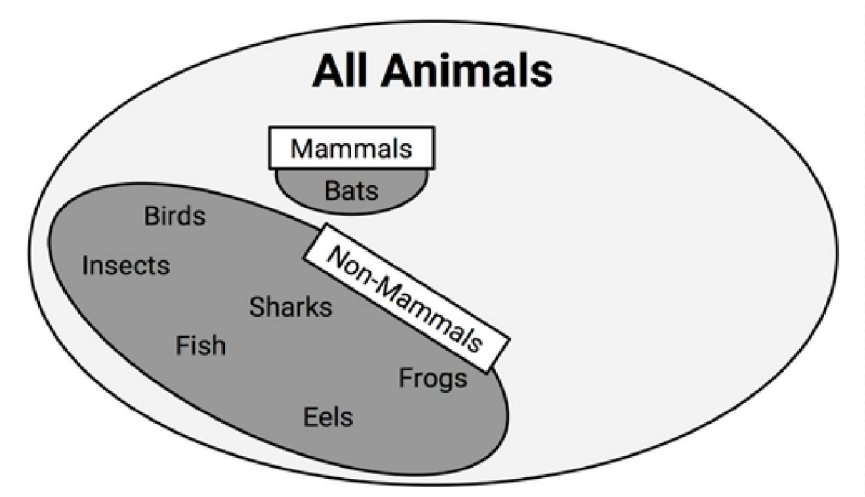
Separate and conquer

- If you're an animal lover, you might have realized that frogs are amphibians, not mammals.
- Therefore, our rule needs to be a bit more specific. Let's drill down further by suggesting that mammals must walk on land and have a tail



Separate and conquer

- An additional rule can be defined to separate out the bats, the only remaining mammal.
- A potential feature distinguishing bats from the other remaining animals would be the presence of fur.



Separate and conquer

- At this point, since all of the training instances have been classified, the rule learning process would stop. We learned a total of three rules:
  - Animals that walk on land and have tails are mammals
  - If the animal does not have fur, it is not a mammal
  - Otherwise, the animal is a mammal

The previous example illustrates how rules gradually consume larger and larger segments of data to eventually classify all instances.

Separate and conquer

- As the rules seem to cover portions of the data, separate and conquer algorithms are also known as **covering algorithms**, and the resulting rules are called covering rules.

The 1R algorithm

- The **1R algorithm** (**One Rule** or **OneR**),
- Selects a single rule. Although this may seem overly simplistic, it tends to perform better than you might expect. As demonstrated in empirical studies, the accuracy of this algorithm can approach that of much more sophisticated algorithms for many real-world tasks.

The 1R algorithm

• Strengths	• Weaknesses
• Generates a single, easy-to understand, human-readable rule of thumb • Often performs surprisingly well • Can serve as a benchmark for more complex algorithms	• Uses only a single feature • Probably overly simplistic

The 1R algorithm

The way this algorithm works is simple.

- For each feature, 1R divides the data into groups based on similar values of the feature.
- Then, for each segment, the algorithm predicts the majority class.
- The error rate for the rule based on each feature is calculated and the rule with the fewest errors is chosen as the one rule.

Animal	Travels By	Has Fur	Mammal
Bats	Air	Yes	Yes
Bears	Land	Yes	Yes
Birds	Air	No	No
Cats	Land	Yes	Yes
Dogs	Land	Yes	Yes
Eels	Sea	No	No
Elephants	Land	No	Yes
Fish	Sea	No	No
Frogs	Land	No	No
Insects	Air	No	No
Pigs	Land	No	Yes
Rabbits	Land	Yes	Yes
Rats	Land	Yes	Yes
Rhinos	Land	No	Yes
Sharks	Sea	No	No

Full Dataset

Travels By	Predicted	Mammal	
Air	No	Yes	✘
Air	No	No	
Air	No	No	
Land	Yes	Yes	
Land	Yes	Yes	
Land	Yes	Yes	
Land	Yes	Yes	
Land	Yes	No	✘
Land	Yes	Yes	
Land	Yes	Yes	
Land	Yes	Yes	
Land	Yes	Yes	
Sea	No	No	
Sea	No	No	
Sea	No	No	

Rule for "Travels By"

Error Rate = 2 / 15

Has Fur	Predicted	Mammal	
No	No	No	
No	No	No	
No	No	Yes	✘
No	No	No	
No	No	No	
No	No	No	
No	No	Yes	✘
No	No	Yes	✘
No	No	No	
Yes	Yes	Yes	
Yes	Yes	Yes	
Yes	Yes	Yes	
Yes	Yes	Yes	
Yes	Yes	Yes	
Yes	Yes	Yes	

Rule for "Has Fur"

Error Rate = 3 / 15

The 1R algorithm

- For the **Travels By** feature, the dataset was divided into three groups: **Air**, **Land**, and **Sea**.
- Animals in the **Air** and **Sea** groups were predicted to be non-mammal, while animals in the **Land** group were predicted to be mammals.
- This resulted in two errors: bats and frogs.

The 1R algorithm

- The **Has Fur** feature divided animals into two groups.
- Those with fur were predicted to be mammals, while those without fur were not predicted to be mammals.
- Three errors were counted: pigs, elephants, and rhinos.

The 1R algorithm

- As the **Travels By** feature results in fewer errors, the 1R algorithm will return the following "one rule" based on **Travels By**:
  - If the animal travels by air, it is not a mammal
  - If the animal travels by land, it is a mammal
  - If the animal travels by sea, it is not a mammal

- The algorithm stops here, having found the single most important rule.

The RIPPER algorithm

- Early rule learning algorithms had a couple of problems.
  - Being slow, made them ineffective for the increasing number of large datasets.
  - Secondly, they were often prone to being inaccurate onnoisy data.

The RIPPER algorithm

- Rule learners took another step forward in 1995 when William W. Cohen introduced the **Repeated Incremental Pruning to Produce Error Reduction (RIPPER)algorithm**, which improved upon IREP to generate rules that match or exceed the performance of decision trees.

The RIPPER algorithm

Strengths	Weaknesses
• Generates easy-to-understand, human-readable rules	• May result in rules that seem to defy common sense or expert knowledge
• Efficient on large and noisy datasets	• Not ideal for working with numeric data
• Generally produces a simpler model than a comparable decision tree.	• Might not perform as well as more complex models

The RIPPER algorithm

- In general there are three-steps
  1. Grow
  2. Prune
  3. Optimize
- The growing phase uses the separate and conquer technique to greedily add conditions to a rule until it perfectly classifies a subset of data or runs out of attributes for splitting.
- Similar to decision trees, the information gain criterion is used to identify the next splitting attribute. When increasing a rule's specificity no longer reduces entropy, the rule is immediately pruned.

The RIPPER algorithm

- Steps one and two are repeated until it reaches a stopping criterion, at which point the entire set of rules is optimized using a variety of heuristics.
- The RIPPER algorithm can create much more complex rules than can the 1R algorithm, as in can consider more than one feature.
- This means that it can create rules with multiple antecedents such as "if an animal flies and has fur, then it is a mammal."
- This improves the algorithm's ability to model complex data, but just like decision trees, it means that the rules can quickly become more difficult to comprehend.

- Decision trees and rule learners are known as **greedy learners** because they use data on a first-come, first-served basis.
- Both the divide and conquer heuristic used by decision trees and the separate and conquer heuristic used by rule learners attempt to make partitions one at a time, finding the most homogeneous partition first, followed by the next best, and so on, until all examples have been classified.
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- The downside to the greedy approach is that greedy algorithms are not guaranteed to generate the optimal, most accurate, or smallest number of rules for a particular dataset. By taking the low-hanging fruit early, a greedy learner may quickly find a single rule that is accurate for one subset of data; however, in doing so, the learner may miss the opportunity to develop a more nuanced set of rules with better overall accuracy on the entire set of data. However, without using the greedy approach to rule learning, it is likely that for all but the smallest of datasets, rule learning would be computationally infeasible.

Differences

- once divide and conquer splits on a feature, the partitions created by the split may not be re-conquered, only further subdivided.
- In this way, a tree is permanently limited by its history of past decisions. In contrast, once separate and conquer finds a rule, any examples not covered by all of the rule's conditions maybe re-conquered.