Easy Tree-sy
An Overview of Decision Trees

Underwriting Collaboration Seminar

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Introductions and Agenda

LEARNING OBJECTIVES

1. Explain the fundamentals of decision trees
2. Evaluate and decide when to apply decision trees to a underwriting business problem
3. Design a decision tree predictive modeling analysis

AGENDA

- Decision Tree Basics via an Example
- Underwriting Specific Applications of Decision Trees
- Predictive Modeling Concepts

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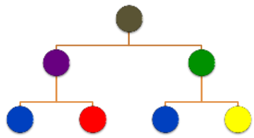
Two Objectives:



Purity

➔ **Measure of variation**

Parsimony

➔ **Desire for simple**

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An Example

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Estimate(predict) the height of an adult, given the following information:

- Age
- Weight
- Gender
- Marital Status
- Zip Code
- Hair Color
- Shoe Size

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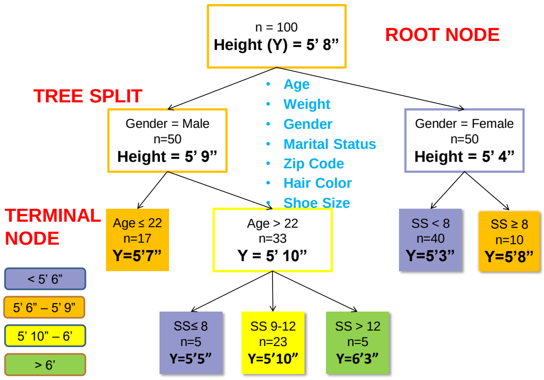

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Terminology

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Target Response,
Predicted Outcome,
Dependent Variable

Y: Height

Explanatory/Independent Variables, Predictors, Features

X_i: Age, Gender, Marital Status
Zip Code, Hair Color, Shoe Size

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If the Target Variable is:

Categorical

➔ **Classification Tree**

Continuous

➔ **Regression Tree**

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UW Example

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First Determine:

What is the business issue?

Renewal Guidelines
Non-Sufficient Funds Prevalence
ACV vs Replacement Cost
Inspection Ordering
Allocation of Resources

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Business issue?

Renewal Guidelines

Predicted Outcome (Target)?

Commercial Auto Loss Ratio

Currently 80% overall LR

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Explanatory/Independent Variables, Predictors

Vehicle Type
Principal Garaging
Business Type
Annual Mileage
Driving Record
Claim History

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Individual Variable Analysis

Overall Loss Ratio = 80%

Vehicle Type (VT)

PPA = 71%; Heavy = 86%; Light = 82%

Principal Garaging (PG)

Urban = 80%; Rural = 81%; Suburb = 80%

Business Type (BT)

10 Classifications LR ranges 78% - 89%

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Individual Variable Analysis

Overall Loss Ratio = 80%

Annual Mileage (AM)

Short = 81%; Average = 80%; Long = 80%

Driving Record (DR)

Clean = 78%; Minor = 78%; Major = 84%

Claim History (CH)

None = 81%; 1-2 = 77%; 3+ = 83%

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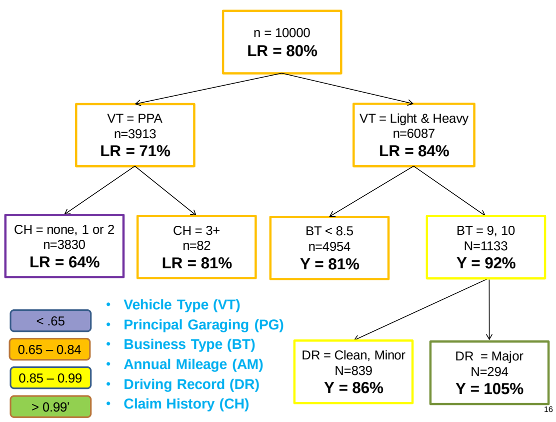

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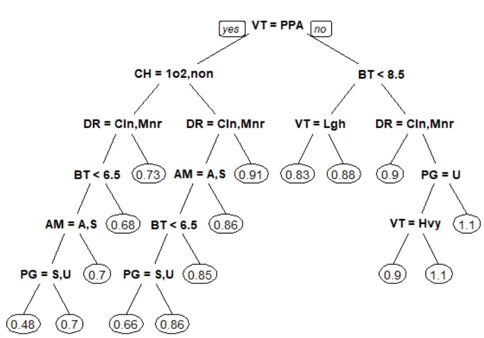

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Theory

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The Process

- **Splitting Procedure**
  The domain space of explanatory variables $X_1,\ldots X_n$ is split into two subsets where observed values in X_j belong to one of the subsets
  i.e. ***< s*** **or** ***>= s*** *OR* ***s₁=male s₂=female***

- **Improvement Value**
  The dimensions ***j*** and ***s*** above are chosen to minimize the error in the prediction among all such binary (two-leveled) trees. Process is iterated.

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Measures for Splitting Criteria

Significance — Measures Independence
- Numeric purity
- p-values of Chi-square variance reduction

Entropy — Measures Disorder
- Categorical
- Measures pureness of the level

Gain Ratio — Measures Gain in Intrinsic Information
- Information Gain = Entropy (parent) – Weighted sum of Entropy (children)
- Penalizes large values/splits

Gini — Measures Misclassification
- Max = 1 – (1 / # of classes)
- Minimum = 0 (all records belong to one class)

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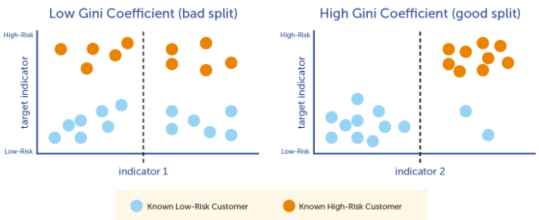
Gini Coefficient



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Stopping Criterion

- No stopping criterion
- Minimum leaf (node) size
- Maximum number of levels or splits
- Let data determine the stopping criterion (see Appendix)

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Advantages

- Non-parametric
- Simple to understand / Easy to interpret
- Automatic variable and interaction selection
- Handles missing values and outliers

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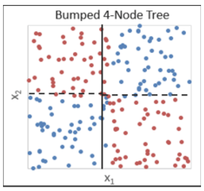
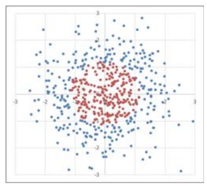
Limitations

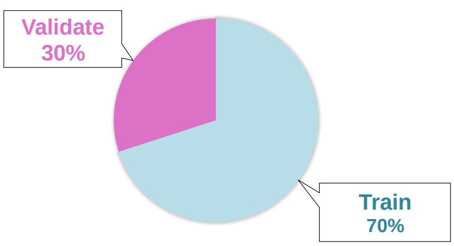
- Over-fit and Instability
- Some relationships difficult to find



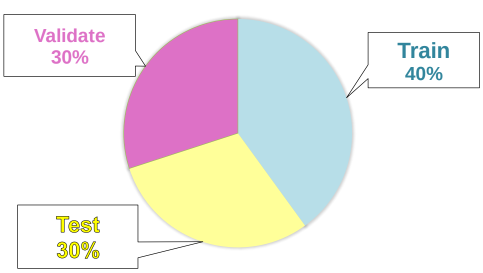


Validating Results - Avoiding Over Fit

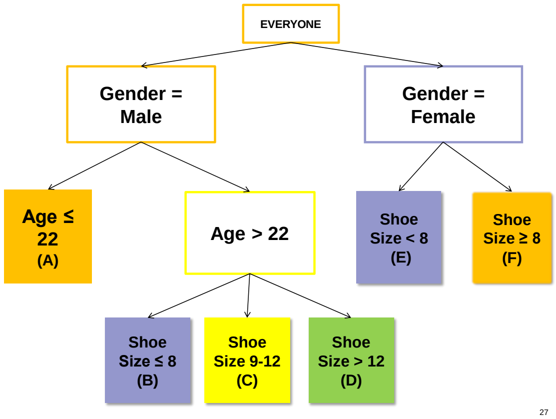
The validation dataset ensures a way to accurately measure your model's performance.

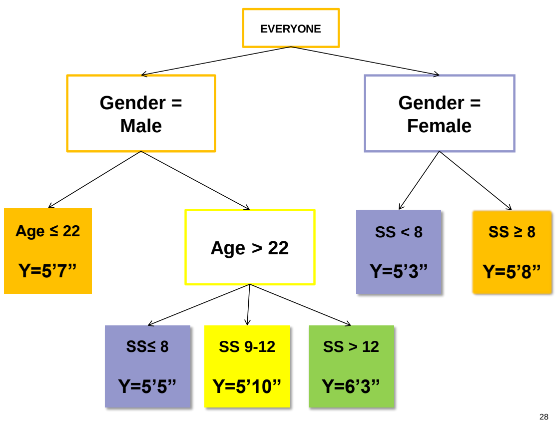


Validating Results - Avoiding Over Fit



Large datasets can be split into 3 unique subsets.





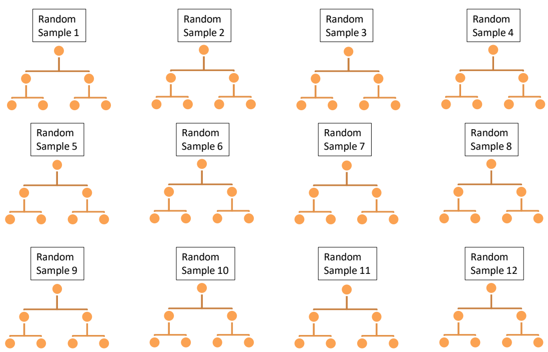
If there is time…

Ensembles

Combine many weak classifiers in order to strengthen the overall result

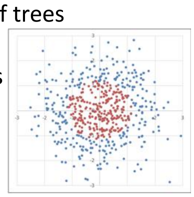
- **Bagging (Bootstrap Aggregating)**
- **Boosting**
- **Stacked Generalization (Blending)**

Random Forests



Boosting

- **Gradient Boosting**
  - Sequential based on residual of prior tree
- **Multiplicative Boosted Trees**
  - Multiplicative residuals
  - Multiplicative combining of trees
- **AdaBoost**
  - Iteratively changes weights of training observations based on errors of previous prediction



Appendix

R

```
Library(rpart)

Library(rpart.plot)

tree <- rpart(LR~VT+PG+BT+AM+DR+CH, data=dataset, weights =
WP)

PRP(tree)
```

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Stopping Criterion – Regression Trees

- To begin, we need to define an error function $E()$ on any leaf of a tree. Think of $E()$ as a measure of how far the predicted are from observed
- Then, for a fixed $\alpha > 0$, find that tree T that minimizes

$$C_\alpha(|T|) = \sum_{k=1}^{|T|} E(L_k) + \alpha|T|$$

- $E(L_k)$ is the error contributed by the kth leaf and α is a parameter that rewards parsimony
- One can see that minimizing the cost complexity criterion $C_\alpha()$ requires a balance between predictive power and parsimony to be struck

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Stopping Criterion – Regression Trees (cont.)

- Define
  1. $|L_k| = \sum_{\substack{i=1 \\ \mathbf{x}_i \in L_k}}^{K} w_i$
  2. $\bar{y}_k = \frac{1}{|L_k|} \sum_{\substack{i=1 \\ \mathbf{x}_i \in L_k}}^{K} w_i y_i$
- A standard choice for $E()$ is

$$E(L_k) \quad = \quad \sum_{\mathbf{x}_i \in L_k} w_i (y_i - \bar{y}_k)^2$$

- There are other standard functions for $E()$, for example
  1. $E(L_k) = \sum_{\mathbf{x}_i \in L_k} w_i |y_i - \bar{y}_k|$
  2. $E(L_k) = \sum_{\mathbf{x}_i \in L_k} w_i |y_i - \bar{y}_k|^p$ for $1 < p < 2$
- User may have choice on what functional form $E()$ may take depending on the software

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Bibliography

- Hastie, T. et al. (2011) *The Elements of Statistical Learning: Data Mining, Inference, and Prediction (2nd Edition)*, Springer, New York.

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