Decision Tree: Regression

Decision Tree: Regression

- Decision Trees can be used to do regression as well.
- When the target variable is continuous, one can use a decision tree regressor.
- The prediction is the mean value of the target variable.
- Let’s take an example:

Decision Tree: Regression

Country	Rim	Tires	Type	Price
Japan	R14	195/60	Small	11.95
Japan	R15	205/60	Medium	24.76
Germany	R15	205/60	Medium	26.9
Germany	R14	175/70	Compact	18.9
Germany	R14	195/65	Compact	24.65
Germany	R15	225/60	Medium	33.2
USA	R14	185/75	Medium	13.15
USA	R14	205/75	Large	20.225
USA	R14	205/75	Large	16.145
USA	R15	205/70	Medium	23.04

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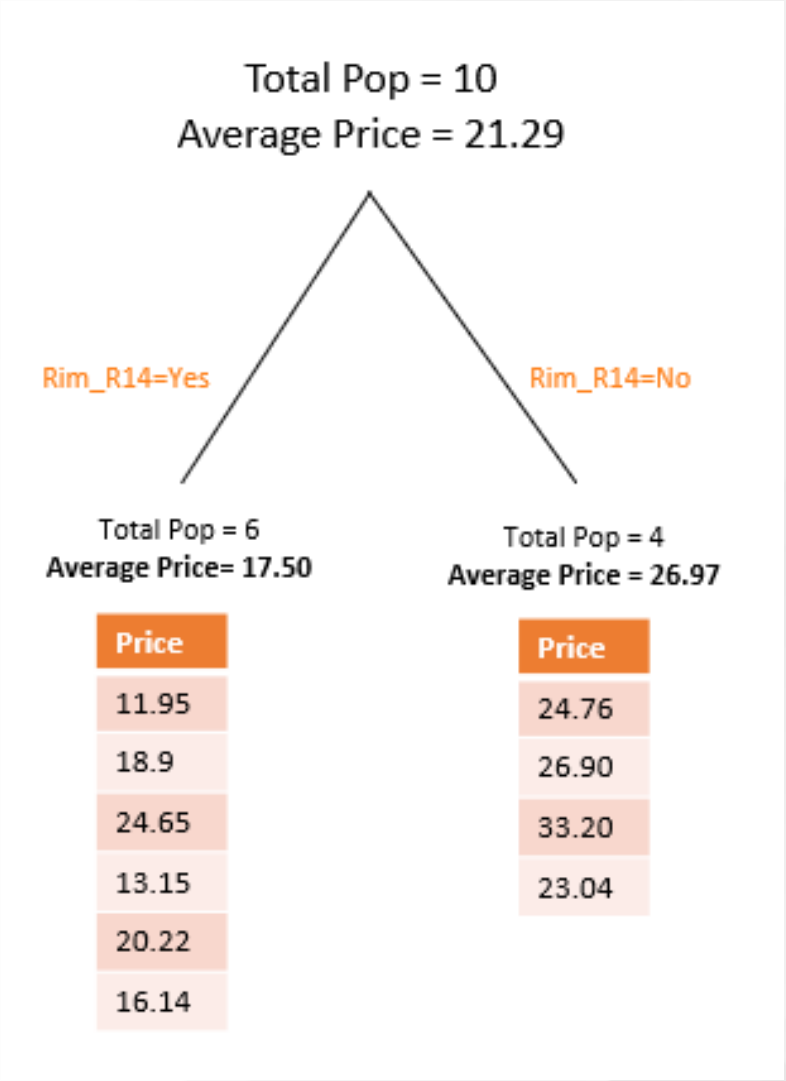
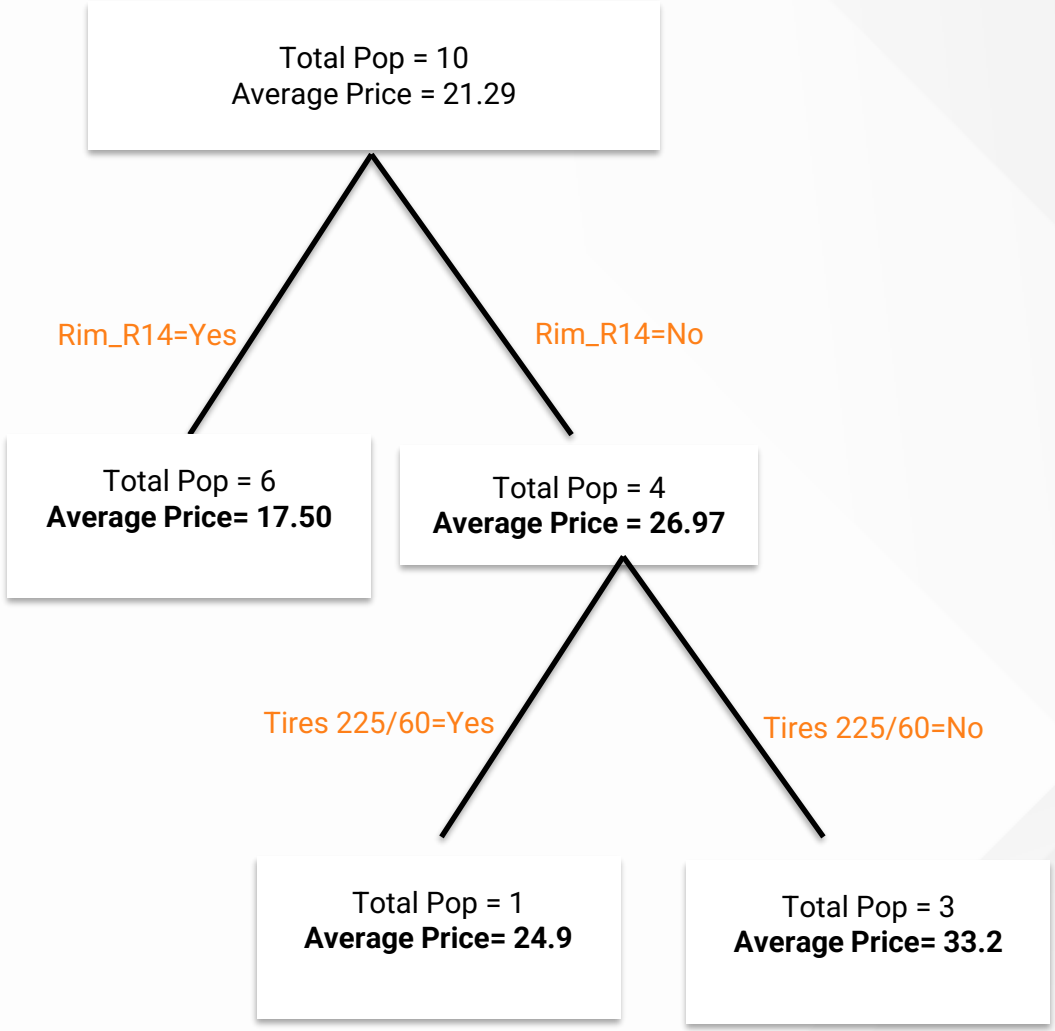


Decision Tree: Regression



Decision Tree: Regression, Purity Metrics

- How does a regression tree split?
- We want regression estimates to be accurate.
- Regression estimate at a given node is an average of the target variable.
- So, accuracy could be RSS or MSE.

Decision Tree: Regression, Purity Metrics

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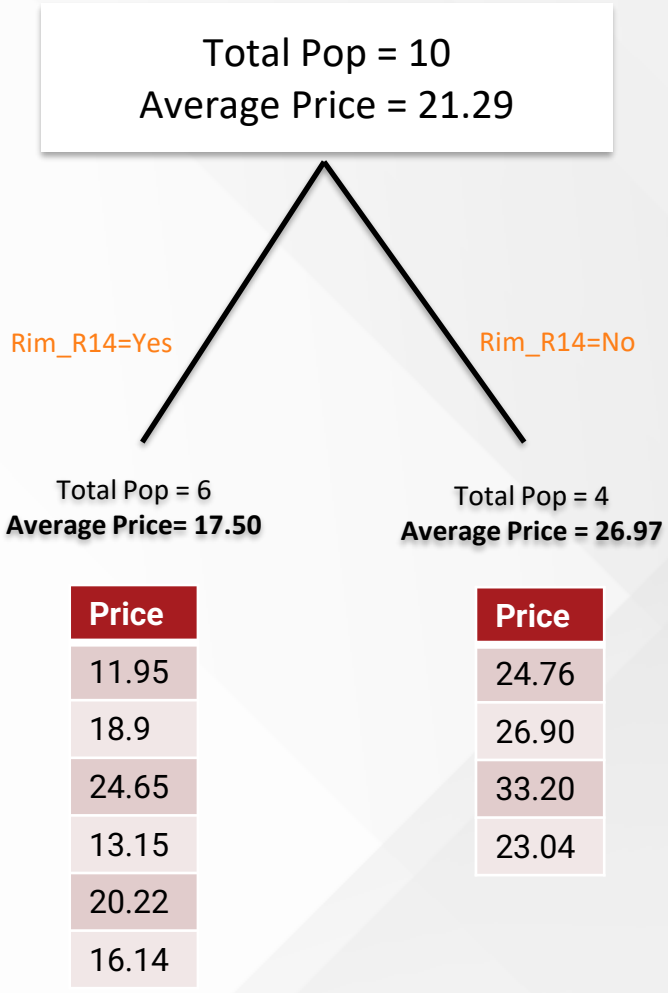

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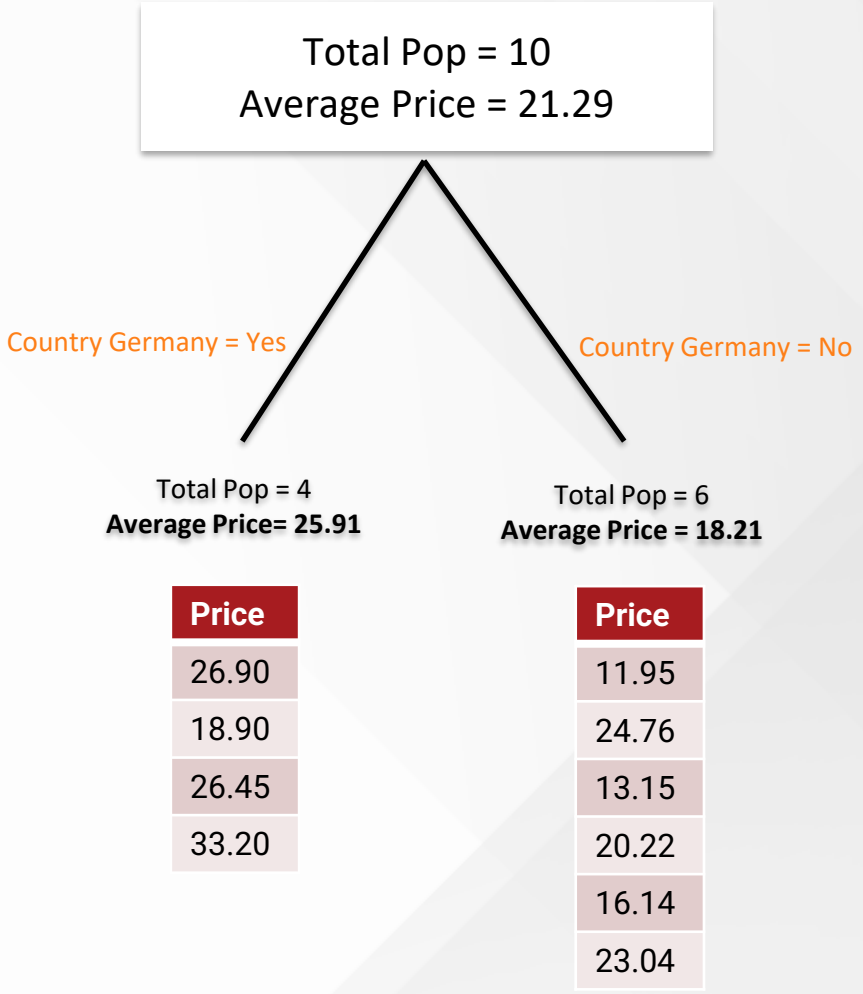
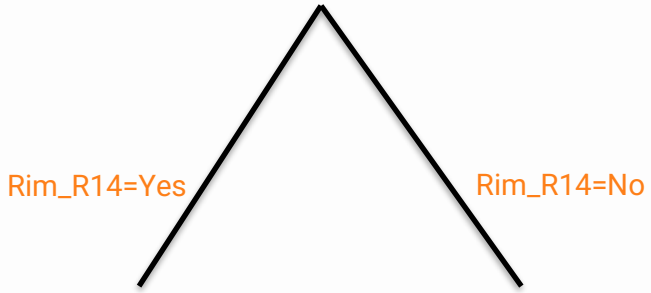


Decision Tree: Regression, Purity Metrics

Total Pop = 10
Average Price = 21.29

$$MSE = \frac{1}{n}\sum(y_i - \mu)^2$$



Total Pop = 6
Average Price= 17.50

Price	Pred
11.95	17.50
18.9	17.50
24.65	17.50
13.15	17.50
20.22	17.50
16.14	17.50

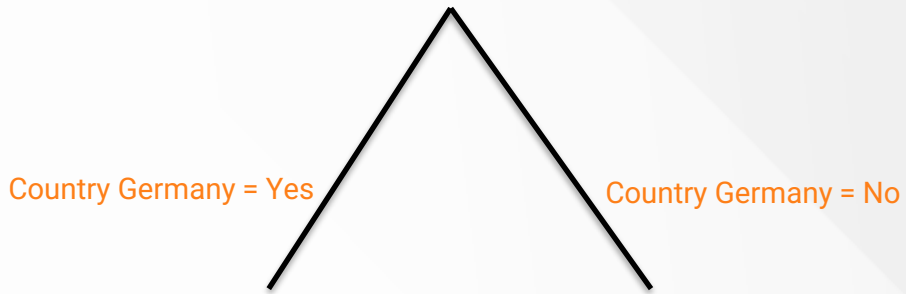
Total Pop = 4
Average Price = 26.97

Price	Pred
24.76	26.97
26.90	26..97
33.20	26.97
23.04	26.97

$$\frac{1}{4}(24.76 - 26.97)^2 + (26.90 - 26.97)^2 + .. + (23.04 - 26.97)^2$$

$$\frac{1}{6}(11.95 - 17.50)^2 + (18.90 - 17.50)^2 + .. + (16.14 - 17.50)^2$$

Total Pop = 10
Average Price = 21.29



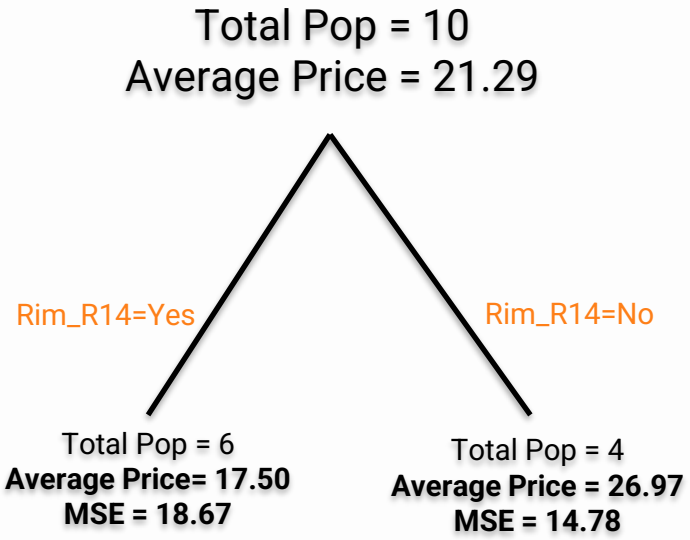
Total Pop = 4
Average Price= 25.91

Price	Pred
26.90	25.91
18.90	25.91
26.45	25.91
33.20	25.91

Total Pop = 6
Average Price = 18.21

Price	Pred
26.90	18.21
18.90	18.21
26.45	18.21
33.20	18.21
16.14	18.21
23.04	18.21

Decision Tree: Regression, Purity Metrics



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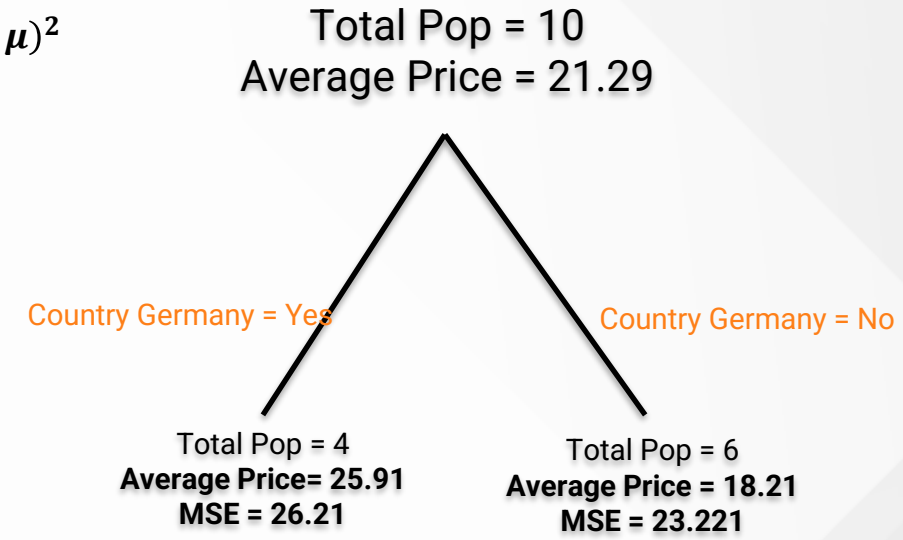
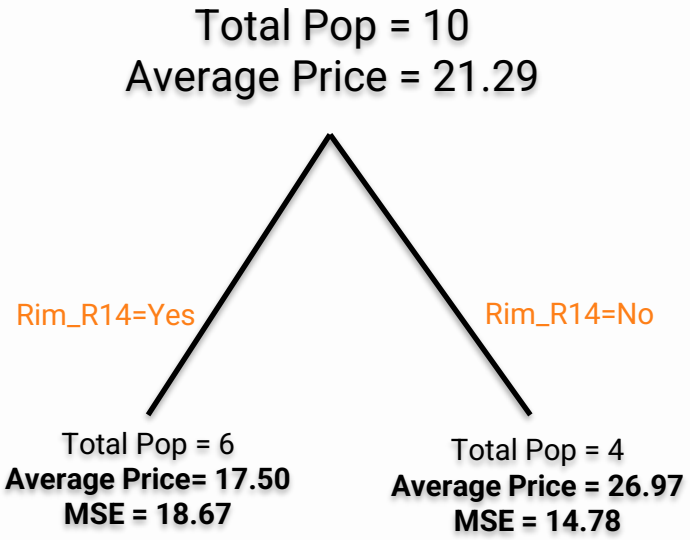


Decision Tree: Regression, Purity Metrics



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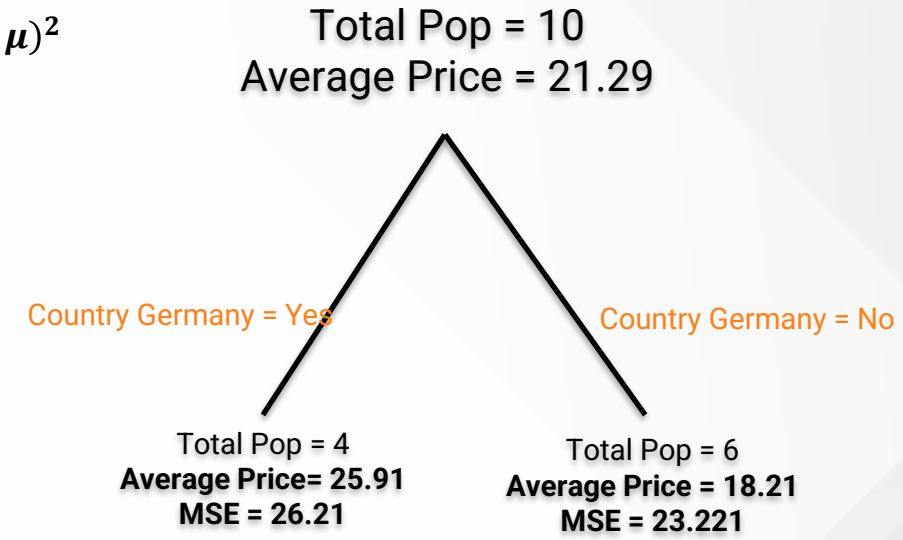
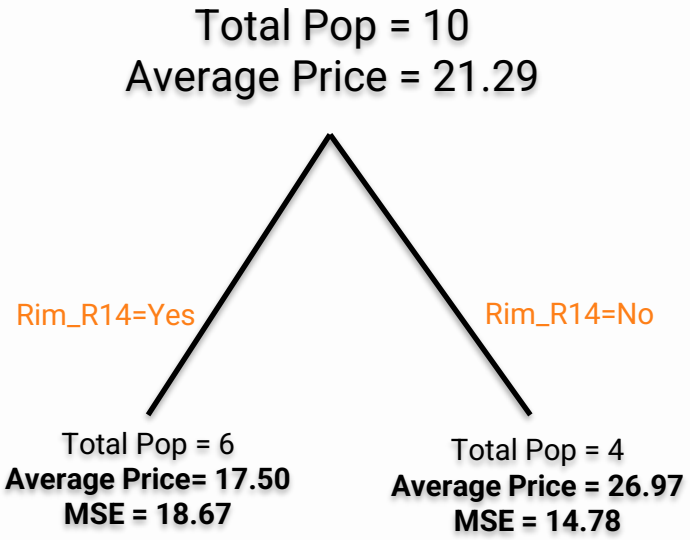


$$\frac{6}{10} * 18.67 + \frac{4}{10} * 14.78 = 17.114$$

$$\frac{4}{10} * 26.21 + \frac{6}{10} * 23.22 = 24.416$$

Decision Tree: Regression, Purity Metrics



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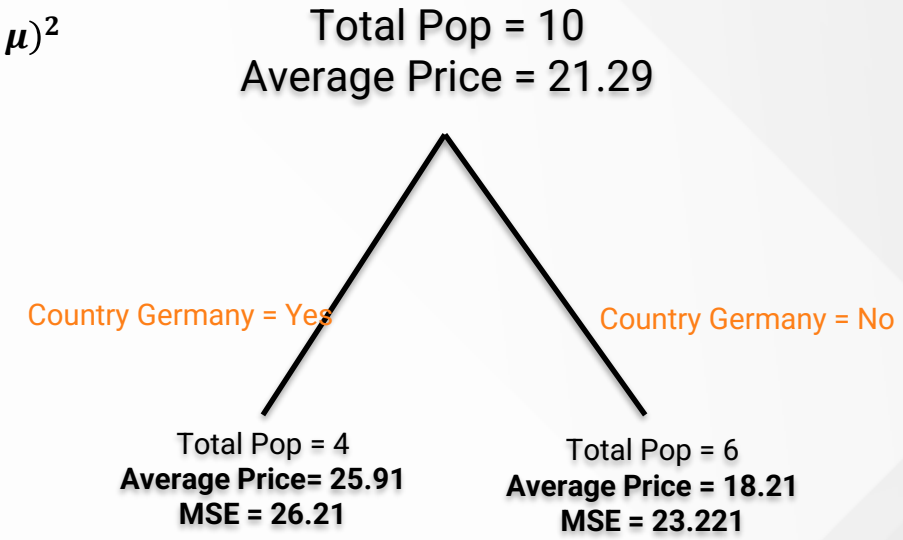

$$\frac{6}{10} * 18.67 + \frac{4}{10} * 14.78 = 17.114$$

$$\frac{4}{10} * 26.21 + \frac{6}{10} * 23.22 = 24.416$$

Decision Tree: Regression, Hyperparameters

- Just like a classification tree, a user has to decide on:
  - Depth of tree
  - Number of observations in terminal nodes, etc.
- One can use a grid search procedure through cross-validation.

Thank You!