Decision Tree Challenge

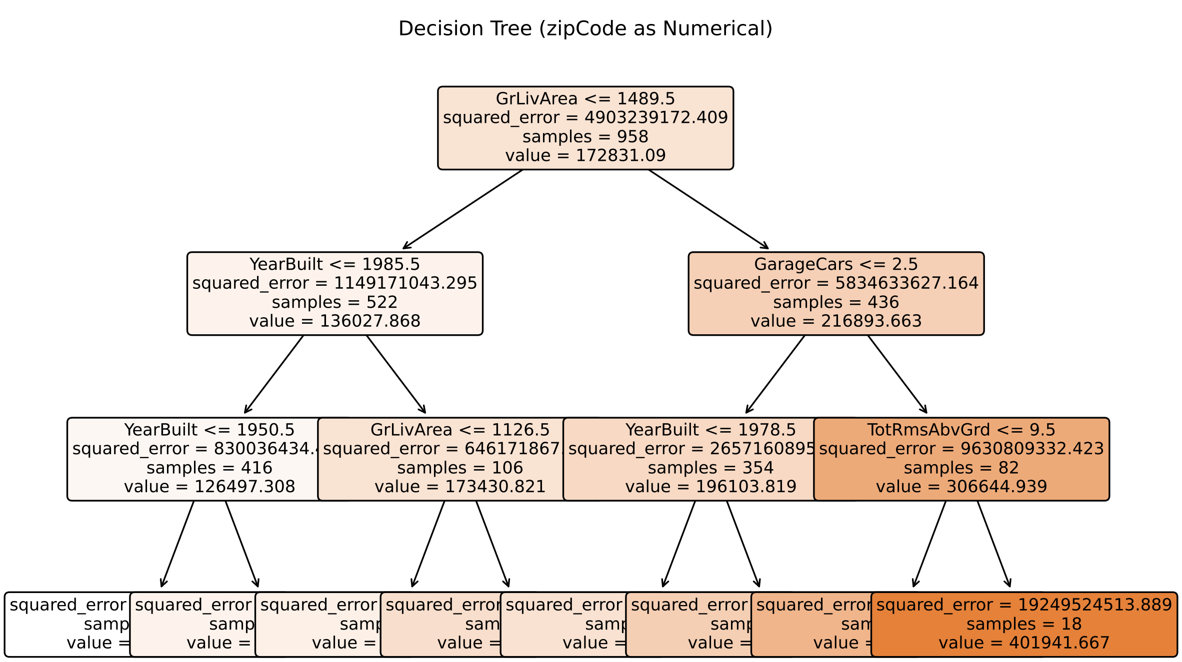
Feature Importance and Categorical Variable Encoding

Decision Tree Challenge - Feature Importance and Variable Encoding

```
Model built with 8 terminal nodes
```

Tree Visualization

Python



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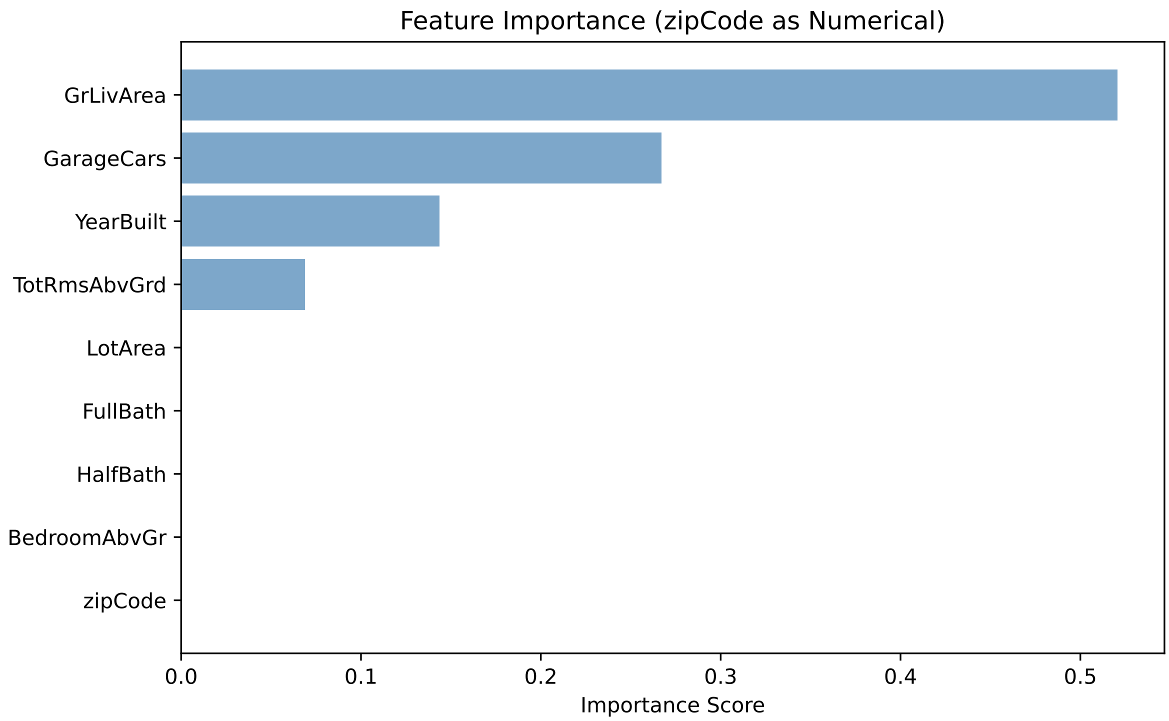
Feature Importance Analysis

Python



Critical Analysis: The Encoding Problem

> ⚠ The Problem Revealed
>
> **What to note:** Our decision tree treated `zipCode` as a numerical variable. This leads to zip code being unimportant. Not surprisingly, because there is no reason to believe allowing splits like "zipCode $<$ 50012.5" should be beneficial for house price prediction. This false coding of a variable creates several problems:
>
> 1. **Potentially Meaningless Splits:** A zip code of 50013 is not "greater than" 50012 in any meaningful way for house prices
> 2. **False Importance:** The algorithm assigns importance to zipCode based on numerical splits rather than categorical distinctions OR the importance of zip code

is completely missed as numerical ordering has no inherent relationship to house prices.

3. **Misleading Interpretations:** We might conclude zipCode is not important when our intuition tells us it should be important (listen to your intuition).

The Real Issue: Zip codes are categorical variables representing discrete geographic areas. The numerical values have no inherent order or magnitude relationship to house prices. These must be modelled as categorical variables.

Proper Categorical Encoding: The Solution

Now let's repeat the analysis with zipCode properly encoded as categorical variables to see the difference.

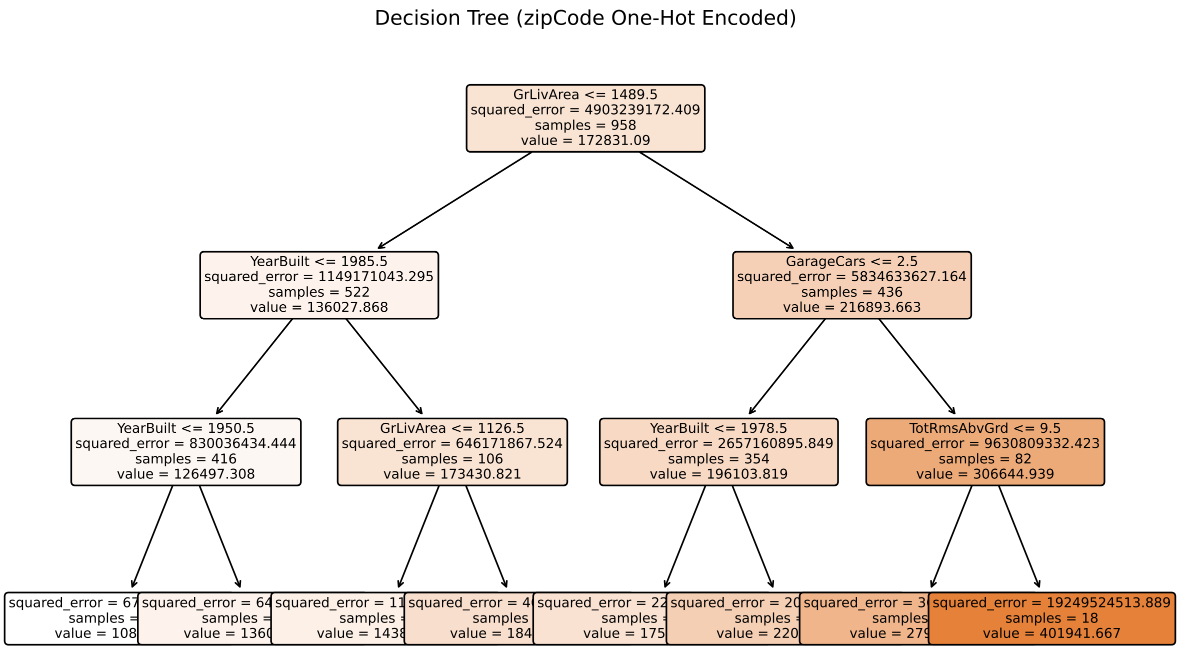
Python Approach: One-hot encode zipCode (create dummy variables for each zip code)

Categorical Encoding Analysis

Python

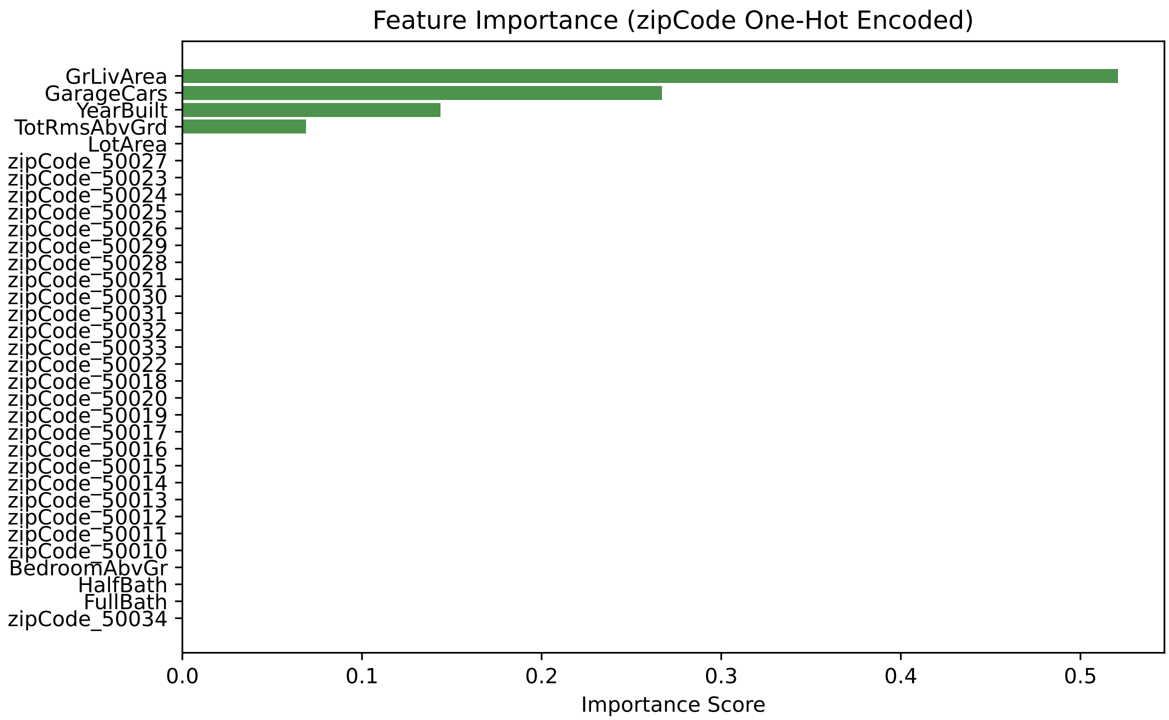
Tree Visualization: Categorical zipCode

Python



Feature Importance: Categorical zipCode

Python



Discussion Questions for Challenge

Your Task: Add thoughtful narrative answers to these two questions in the Discussion Questions section of your rendered HTML site.

1. **Numerical vs Categorical Encoding:** There are two modelsin Python written above. For each language, the models differ by how zip code is modelled, either as a numerical variable or as a categorical variable. Given what you know about zip codes and real estate prices, how should zip code be modelled, numerically or categorically? Is zipcode and ordinal or non-ordinal variable?

Zip code should be modelled as a categorical variable. Although it is written in a numerical format, you should not treat it as something that you can subtract from, find the mean of, etc. Each Zip Code ultimately represents a location and should be treated as a categorical variable. A zip code would fall under the category of being a non-ordinal variable.

2. **R vs Python Implementation Differences:** When modelling zip code as a categorical variable, the output tree and feature importance would differ quite significantly had you used R as opposed to Python. Investigate why this is the case. What does R offer that Python does not? Which language would you say does a better job of modelling zip code as a categorical variable? Can you quote the documentation at https://scikit-learn.org/stable/modules/tree.html suggesting a weakness in the Python implementation? If so, please provide a quote from the documentation.

When you model zip code as a categorical variable, R and Python behave very differently, and it in fact ends up affecting the entire structure of the tree. This is particularly easier for R because it is a programming language that has known factors for categorical models, unlike Python that many a times relies on the programmer creatively categorizing what is a categorical variable. Python's Decision Trees, on the other hand, do not support categorical variables. Instead, the zip codes need to be encoded, after which the tree begins to split on the encoded variable, as opposed to splitting on the categorical variable that is the zip code itself. This is because, as stated by scikit-learn itself, "the scikit-learn implementation does not support categorical variables for now." In this particular situation, R is far more effective because it uses the zip codes in a manner they are meant to be used, unlike Python, which might require a workaround that, in effect, affects how the values are recognized.

3. **Are There Any Suggestions for Implementing Decision Trees in Python With Prioper Categorical Handling?** Please poke around the Internet (AI is not as helpful with new libraries) for suggestions on how to implement decision trees in Python with better (i.e. not one-hot encoding) categorical handling. Please provide a link to the source and a quote from the source. There is not right answer here, but please provide a thoughtful answer, I am curious to see what you find.

If you want to stick with Python yet still have your decision tree treat categorical variables correctly, you typically need to look beyond the basic scikit-learn implementation. Libraries like CatBoost, LightGBM, and H2O contain implementations that can handle categorical variables without one-hot encoding. As an example, CatBoost explicitly claims it can "convert categorical values into numbers using various statistics," which is really just a more intelligent way of incorporating categorical information without forcing artificial numeric orderings or exploding the feature space. This is particularly important for variables like zip code, in which the category itself carries meaning related to geography and market behavior rather than numeric magnitude. So while Python's default decision tree does not handle categorical variables that well, there are clearly some good alternatives within the Python ecosystem. You simply need to choose models that actually know what a categorical variable is meant to represent instead of jamming it into a numerical structure that can distort underlying relationships within the data.