Decision Tree Classifier Analysis

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1 Pseudo-code for a simple Decision Tree

```
func buildDecisionTree(X, y):
    # either reach max depth, min samples split, or pure class
    if stopping_condition() == true:
        return create_leaf_node(class = most_common_class(y))
    best_impurity = infinity
    best_feature = null
    best_threshold = null
    for each feature in X:
        if feature is categorical:
            impurity = sum (weighted (gini)-impurity of each category)
            if impurity < best_impurity:
                best_impurity = impurity
                best_feature = feature
                best_threshold = null   # no threshold for categorical feature
        else:  # feature is numerical
            for each threshold in midpoint of adjacent values in sorted(feature):
                X_left, y_left = subset where feature < threshold
                X_right, y_right = subset where feature >= threshold
                impurity = sum(weighted (gini)-impurity of left and right subsets)
                if impurity < best_impurity:
                    best_impurity = impurity
                    best_feature = feature
                    best_threshold = threshold
    node = DecisionNode(feature = best_feature, threshold = best_threshold)
    if best_feature is categorical:
        for each category in unique values of best_feature:
            X_subset =  X[best_feature] == category
            y_subset = y[best_feature] == category
            node.children[category] = buildDecisionTree(X_subset, y_subset)
    else:  # best_feature is numerical
        X_left = X[best_feature] < best_threshold
        X_right = X[best_feature] >= best_threshold
        y_left = y[best_feature] < best_threshold
        y_right = y[best_feature] >= best_threshold
        node.children["left"] = buildDecisionTree(X_left, y_left)
        node.children["right"] = buildDecisionTree(X_right, y_right)
```

2 Decision Tree Algorithm Testing

```
[ ]: import pandas as pd
     from main import handle_missing_values
     from decision_tree import DecisionTree
     train_data = pd.read_csv("data/train.csv")
     test_data = pd.read_csv("data/test.csv")
     train_data = handle_missing_values(train_data)
     test_data = handle_missing_values(test_data)
```

2.0.1 DT model with `max_depth=10`, `min_sample_split=20`, and `criterion='gini'` index

```
[9]: dt = DecisionTree(max_depth=10,
                       min_samples_split=20,
                       criterion='gini')
     dt.fit(train_data.drop('income', axis=1), train_data['income'])
     print("Train Accuracy:",
           dt.evaluate(train_data.drop('income', axis=1), train_data['income']))
     print("Test Accuracy:",
           dt.evaluate(test_data.drop('income', axis=1), test_data['income']))
     # Take about 1m10s to run
```

```
Train Accuracy: 0.8343109855348423
Test Accuracy: 0.8304772434125668
```

2.0.2 DT model with `max_depth=10`, `min_sample_split=20`, and `criterion='entropy'` index

```
[10]: dt = DecisionTree(max_depth=10,
                        min_samples_split=20,
                        criterion='entropy')
      dt.fit(train_data.drop('income', axis=1), train_data['income'])
      print("Train Accuracy:",
            dt.evaluate(train_data.drop('income', axis=1), train_data['income']))
      print("Test Accuracy:",
            dt.evaluate(test_data.drop('income', axis=1), test_data['income']))
      # Take about 1m30s to run
```

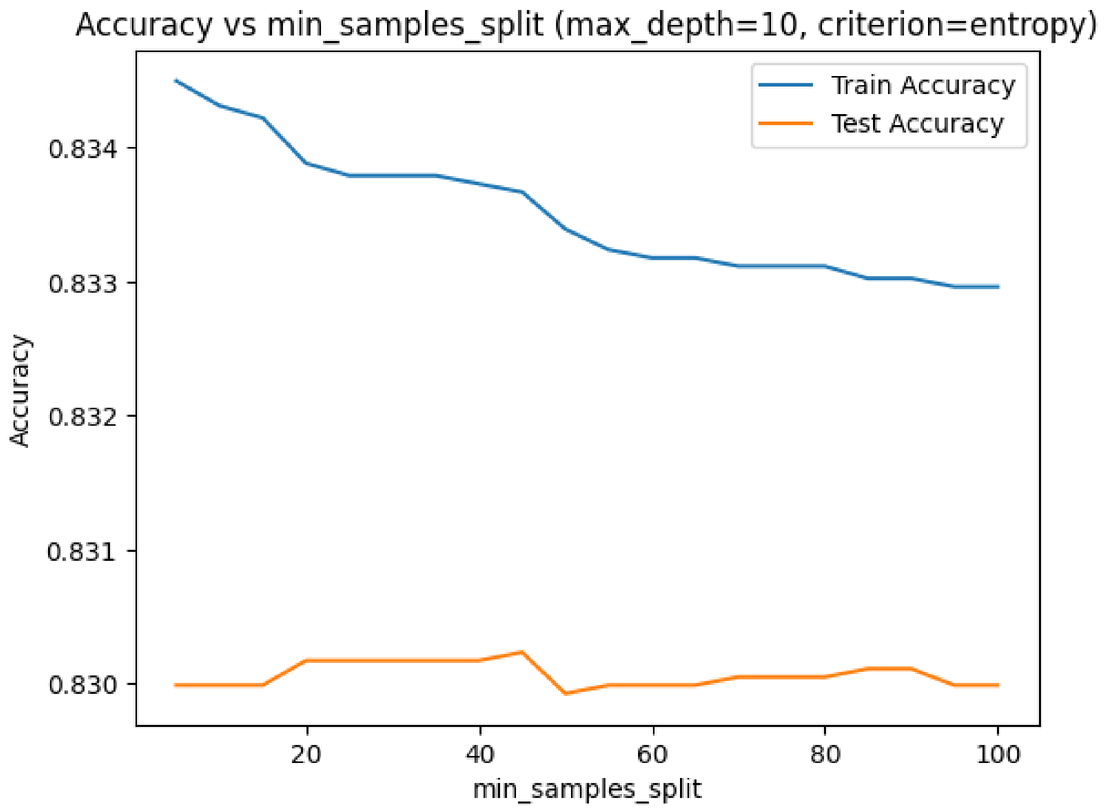
```
Train Accuracy: 0.833881023310095
Test Accuracy: 0.8301701369694736
```

- Both criteria produce very similar results on both training and testing data.
- One reason that could explain why the results are so similar because the size of the dataset which is sufficiently large enough
- If training time matters, Gini usually slightly faster to compute than Entropy (because of log in Entropy)
- The very similar results also mean the data features and tree configuration (except criterion) dominate the model performance; criterion choice has minimal impact for this specific case.

2.0.3 Accuracy against min_sample_split graph

```
[14]: accuracy_dict = {}
for min_sample_split in range(5, 101, 5):
    dt = DecisionTree(max_depth=10,
                      min_samples_split=min_sample_split,
                      criterion='entropy')
    dt.fit(train_data.drop('income', axis=1), train_data['income'])
    train_accuracy = dt.evaluate(train_data.drop('income', axis=1),␣
 ↪train_data['income'])
    test_accuracy = dt.evaluate(test_data.drop('income', axis=1),␣
 ↪test_data['income'])
    accuracy_dict[min_sample_split] = [train_accuracy, test_accuracy]

import matplotlib.pyplot as plt
plt.plot(list(accuracy_dict.keys()), [v[0] for v in accuracy_dict.values()],
         label='Train Accuracy')
plt.plot(list(accuracy_dict.keys()), [v[1] for v in accuracy_dict.values()],
         label='Test Accuracy')
plt.xlabel('min_samples_split')
plt.ylabel('Accuracy')
plt.title('Accuracy vs min_samples_split (max_depth=10, criterion=entropy)')
plt.legend()
plt.show()
```



- As `min_sample_split` increases, training accuracy slightly decrease. This is because larger minnimum spits prevent the tree from making more specific splits, reudcing overfitting to training data
- Test accuracy stays roughtly constant, with minor increase from 17 to 45 `min_sample_split`
- Overfitting is relatively significant with `min_sample_split` being less than 10
- Increase `min_sample_split` is a technique help control overfitting by requiring internal node to have more data before splitting

2.0.4 Why training data accuracy is not 100%?

- There are many factors that can potentially contribut to why the accuracy of training data is not 100%
- Real-world data is messy. This could include overlap classes (same feature but different class), hardware/software/human makes error while collecting the data
- The pattern of the data is more complex than the model, thus the model cannot perfectly seperate the patterns
- Sometimes all the available features still cannot explain all the variation in the target class.

Is there a way to get 100% accuracy on training dataset?

- We ca get 100% accuracy by overfitting the training data

What parameters should you change to get a tree with perfect training accuracy?

- Set `max_depth` to a very large value and `min_sample_split` to 1. This give the tree to grow as deep and complex as possible so it keeps splitting until each leaf node contains single class.

How would that affect the accuracy of the test data?

- The tree is essentially memorizing the training data, not learning the underlying patterns of the sample data
- It will likely perform poorly on new, unseen test data because it cannot generalize

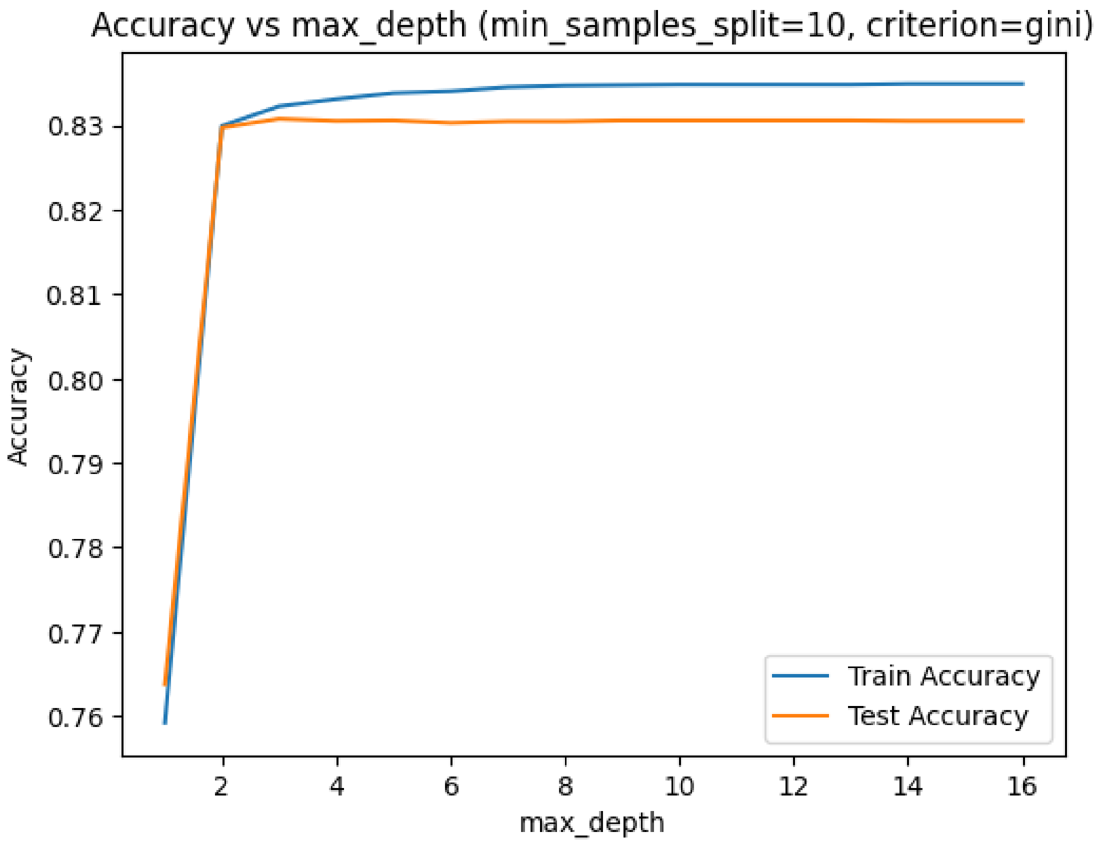
Explain if such a classification model has a high variance or bias

Such decision tree model (unrestricted decision tree) has:

- Low bias: the model fit the training data extremely well, making as few assumptions as possible can capture every subtle details of the training data
- High variance: such model is highly sensitive to small changes in the training data. E.g. If I provide different training samples or alter the data, the model's predictions and decisions can change dramatically.

2.0.5 Accuracy against `min_sample_split` graph

[15]:
```python
accuracy_dict = {}
for depth in range(1, 17):
    dt = DecisionTree(max_depth=depth,
                      min_samples_split=10,
                      criterion='gini')
    dt.fit(train_data.drop('income', axis=1), train_data['income'])
    train_accuracy = dt.evaluate(train_data.drop('income', axis=1),␣
 ↪train_data['income'])
    test_accuracy = dt.evaluate(test_data.drop('income', axis=1),␣
 ↪test_data['income'])
    accuracy_dict[depth] = [train_accuracy, test_accuracy]
import matplotlib.pyplot as plt
plt.plot(list(accuracy_dict.keys()), [v[0] for v in accuracy_dict.values()],
         label='Train Accuracy')
plt.plot(list(accuracy_dict.keys()), [v[1] for v in accuracy_dict.values()],
         label='Test Accuracy')
plt.xlabel('max_depth')
plt.ylabel('Accuracy')
plt.title('Accuracy vs max_depth (min_samples_split=10, criterion=gini)')
plt.legend()
plt.show()
```



- Both training and testing accuracy improve significantly at `max_depth` equals 1 and 2
- With `max_depth > 2`, the accuracy of traing and testing sets diverse, with training accuracy slightly higher than test accuracy

- The gap between train and test accuracy is small, indicating minimal overfitting under these conditions.
  - The reason why the gap between train and test accuracy being relatively small coule be because `min_sample_split` already prevent the tree to go any further despite the higher freedom in `max_depth`
- Increasing tree depth in general allows the model to capture more complex patterns, but after a certain point, additional complexity would give diminishing returns.
- Both lines grow at similar values suggests this tree generalize well for the current dataset and hyperparameters, without significant overfitting (or underfitting)