Decision Tree Generator

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Quick Start

All programs are tested on macOS 10.14 & Ubuntu 18.04

Requirements

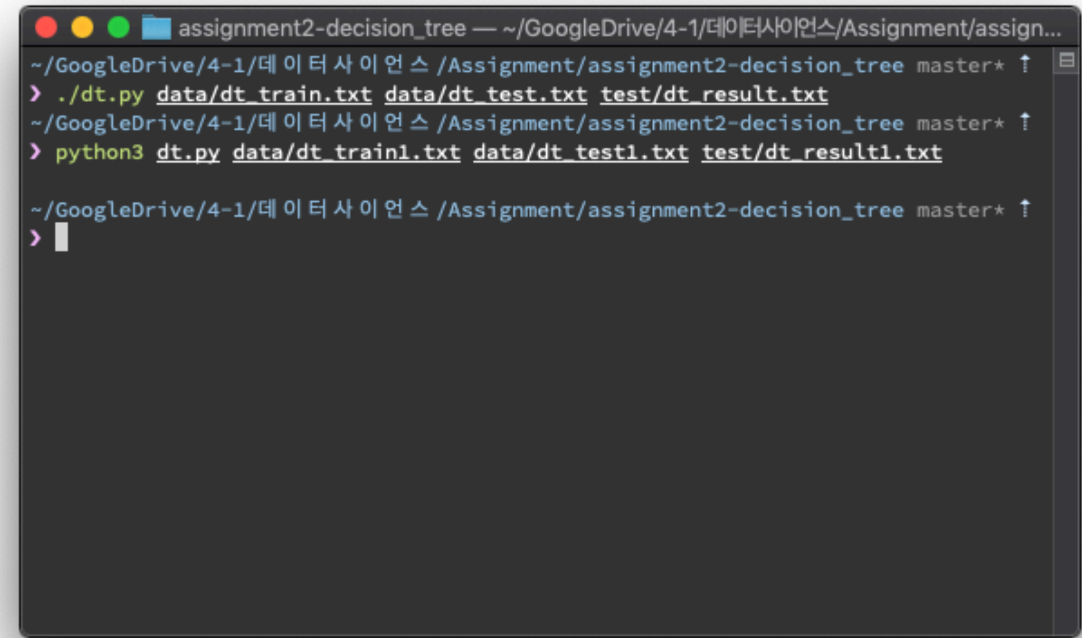
- Python3

How to Run

dt.py

```
./dt.py [train file] [test file] [result file]
python3 dt.py [train file] [test file] [result file]
```

In order to execuate program using first command, you must have execution permission for `dt.py`.
If it gives permission error, either give it a execution permission or use second line command.



evaluate.py

evaluate.py file will generate decision tree by importing functions from **dt.py** and evaluate it's accuracy.

It also gives a user an option to check which tuple prediction went wrong.
If additional tests are required, append train, test, output, answer file lists within **evaluate.py**

```python
if __name__ == "__main__":
    trainFiles  = ["data/dt_train.txt",  "data/dt_train1.txt"  ]
    testFiles   = ["data/dt_test.txt",   "data/dt_test1.txt"   ]
    outputFiles = ["test/dt_result.txt", "test/dt_result1.txt" ]
    answerFiles = ["test/dt_answer.txt", "test/dt_answer1.txt" ]
```

```
assignment2-decision_tree — ~/GoogleDrive/4-1/데이터사이언스/Assignment/assign...
~/GoogleDrive/4-1/데 이 터 사 이 언 스 /Assignment/assignment2-decision_tree master* ⇡
❯ ./evaluate.py
Generating decision tree for dt_train.txt took 0.000504 seconds
5/5
Classification for dt_test.txt took 0.000374 seconds

Generating decision tree for dt_train1.txt took 0.016573 seconds
322/346
Classification for dt_test1.txt took 0.00155 seconds
```

Below is the example output of diffrence tracking.

```
assignment2-decision_tree — ~/GoogleDrive/4-1/데이터사이언스/Assignment/assignment2-decision_tree — -zsh ▸ -zsh — 128×31
Internal Node
attr: safety
classLabel: unacc
count: 1382

Internal Node
attr: persons
classLabel: unacc
count: 458

Internal Node
attr: buying
classLabel: acc
count: 151

Internal Node
attr: maint
classLabel: acc
count: 37

Internal Node
attr: lug_boot
classLabel: acc
count: 9

Leaf Node
classLabel: acc
count: 2

       buying       maint       doors       persons       lug_boot       safety       prediction       answer
   0:  med          vhigh       2           4             med            med          acc              unacc
```

Implementation

Node class

```python
class Node:
    def __init__(self, parent, attr, classLabel, cnt, isLeaf=False):
        self.parent = parent
        self.attr = attr
        self.children = dict()
        self.classLabel = classLabel
        self.cnt = cnt
        self.isLeaf = isLeaf

    def __repr__(self):
        if self.isLeaf:
            return "Leaf Node"
        else:
            return "Internal Node"

    def __str__(self):
        ret = repr(self) + "\n"
        if not self.isLeaf:
            ret += "attr: " + self.attr + "\n"
        ret += "classLabel: " + self.classLabel + "\n"
        ret += "count: " + str(self.cnt) + "\n"
        return ret
```

decision tree is generated with above `class Node`.
`attr` : Selected attribution for splitting. If current node is leaf, it will be empty string.
`children` : Dictionary of node's children. `Key` is attribute value.
`classLabel` : Result of prediction if classification ends at current node.
`cnt` : Number of tuples in data partition.

generateTree(*parent*, *attributes*, *dataPartitions*, *attrValues*)

This function is recursively called to construct decision tree.
Recursion ends at 3 conditions.

1. tuples are all of the same class.
2. attributes list is empty (MAJORITY VOTING)
3. data partition is empty.

Algorithm

let D = data partition; set of training tuples

1. If tuples in D are all of the same class OR attribute list is empty

return *leaf node* with majority vote as *class label*

2. Use `attributeSelection()` method to find splitting attribute.
3. Split tuples in D based on split attribute value.
   Either call `generateTree()` recursively or create leaf node(split ends up with 0 tuple)

Current version of `generateTree` uses improved version of gain ratio. Accuracy of each implementation will be shown at Test Results. `reducedErrorPruning()` is implemented but not activated since pruning only makes accuracy worse.

Test Results

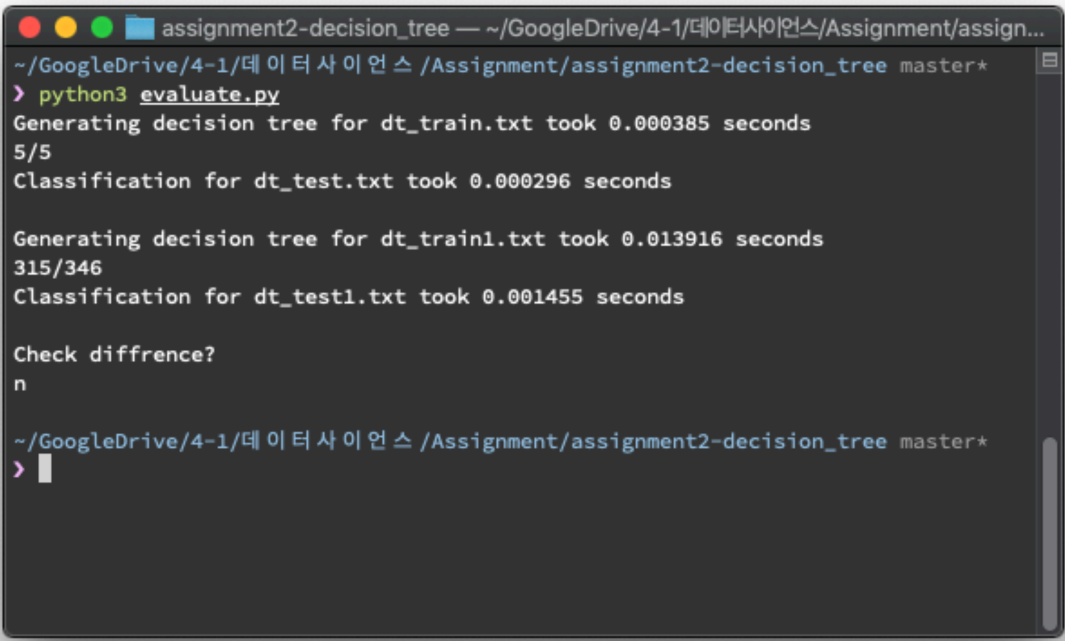
Information Gain

It's the first implementation I used. choose attribute with highest information gain.

```
def calcEntropy(classified):
  ret = 0.0
  for val in classified:
    p = val / sum(classified)
    ret -= p * log(p, 2)
  return ret


def calcGains(rows):
  infoGains = []
  DBsize = len(rows)
  totalEntropy = calcEntropy(Counter([row[-1] for row in rows]).values())
  for col in range(len(rows[0]) - 1):
    entropy = 0.0
    # {attrValue : {className : cnt}}
    classCounter = defaultdict(lambda: defaultdict(lambda: 0))
    for row in rows:
      classCounter[row[col]][row[-1]] += 1
    for classified in classCounter.values():
      entropy += sum(classified.values()) / DBsize *
calcEntropy(classified.values())
    infoGains.append(totalEntropy - entropy)
  return infoGains


def attributeSelection(rows):
  infoGains = calcGains(rows)
  return infoGains.index(max(infoGains))
```



Gain Ratio

Information gain is biased toward attributes having a large number of values.
Gain ratio applies a kind of normalization to *information gain* using a "split information" to overcome bias.

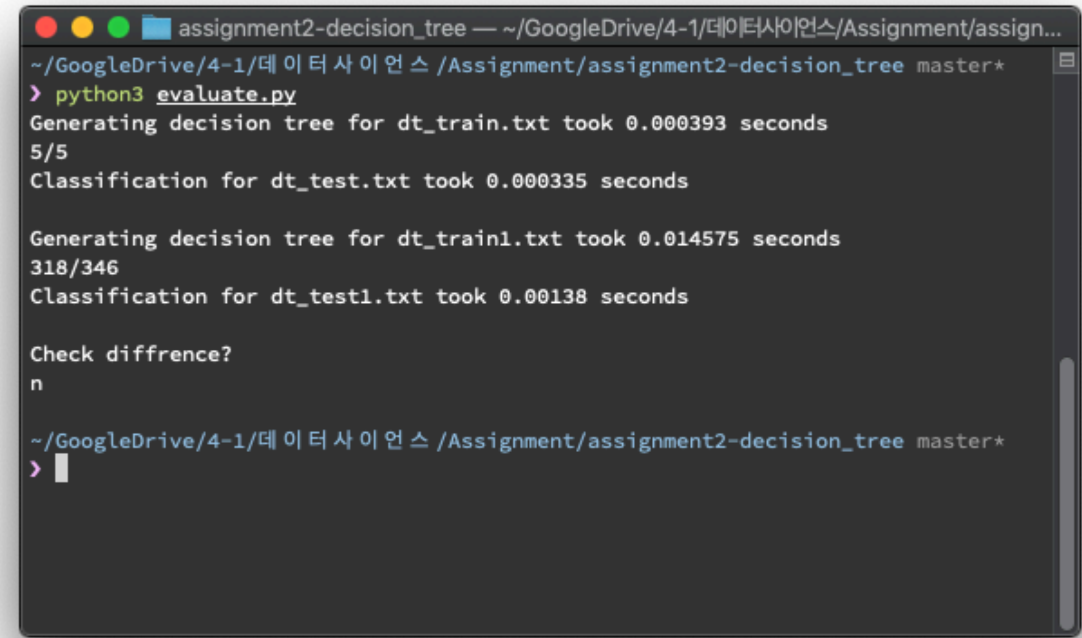
```
def calcEntropy(classified):
    info = 0.0
    for val in classified:
        p = val / sum(classified)
        info -= p * log(p, 2)
    return info


def calcSplitInfo(classCounter, totalD):
    splitInfo = 0.0
    for classified in classCounter.values():
        partition = sum(classified.values()) / totalD
        splitInfo -= partition * log(partition, 2)
    return splitInfo


# Calculate gain ratio to be precise.
def calcGains(rows):
    infoGains = []
    totalD = len(rows)
    totalEntropy = calcEntropy(Counter([row[-1] for row in rows]).values())
    for col in range(len(rows[0]) - 1):
```

```
        entropy = 0.0
        # {attrValue : {className : cnt}}
        classCounter = defaultdict(lambda: defaultdict(lambda: 0))
        for row in rows:
            classCounter[row[col]][row[-1]] += 1
        for classified in classCounter.values():
            entropy += sum(classified.values()) / totalD *
calcEntropy(classified.values())
        infoGains.append((totalEntropy - entropy) /
calcSplitInfo(classCounter, totalD))
    return infoGains


# Calculate all gain ratio of attributes at the moment.
# Return index of most highest value.
def attributeSelection(rows):
    infoGains = calcGains(rows)
    return infoGains.index(max(infoGains))
```

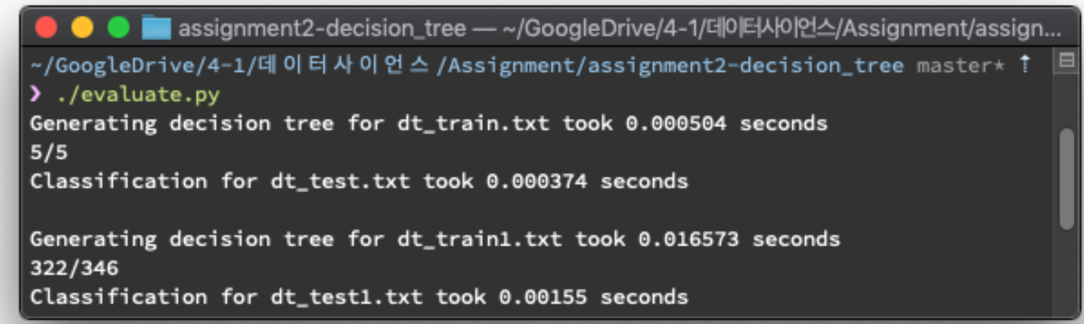


Improved Gain Ratio

Gain ratio favors the creation of an unbalanced tree([Information Gain Versus Gain Ratio: A Study of Split Method Biases]()). So if one attribute's value has large portion in training sets, it is very likely to be chosen as class label during classification. In order to reduce this effect, I've made a modification on `getMajorityVoted()` to **select least popular attribute if their is a tie**.

```
# If there is a tie, return attribute that has least amount.
def getMajorityVoted(classCounter, classHeader, attrValues):
```

```python
    candidates = classCounter.most_common()
    vote = candidates[0][1]
    candidates = [x for x in candidates if x[1] == vote]
    voted = candidates[0][0]
    if len(candidates) == 1:
        return voted
    vote = attrValues[classHeader][voted]
    for candidate in candidates:
        if vote > attrValues[classHeader][candidate[0]]:
            vote = attrValues[classHeader][candidate[0]]
            voted = candidate[0]
    return voted
```



Reduced Error Pruning

Tree pruning method helps resolve *overfitting* issue.

If you intend to use pruning, you must split test tuples in two. One for training, and one for pruning.

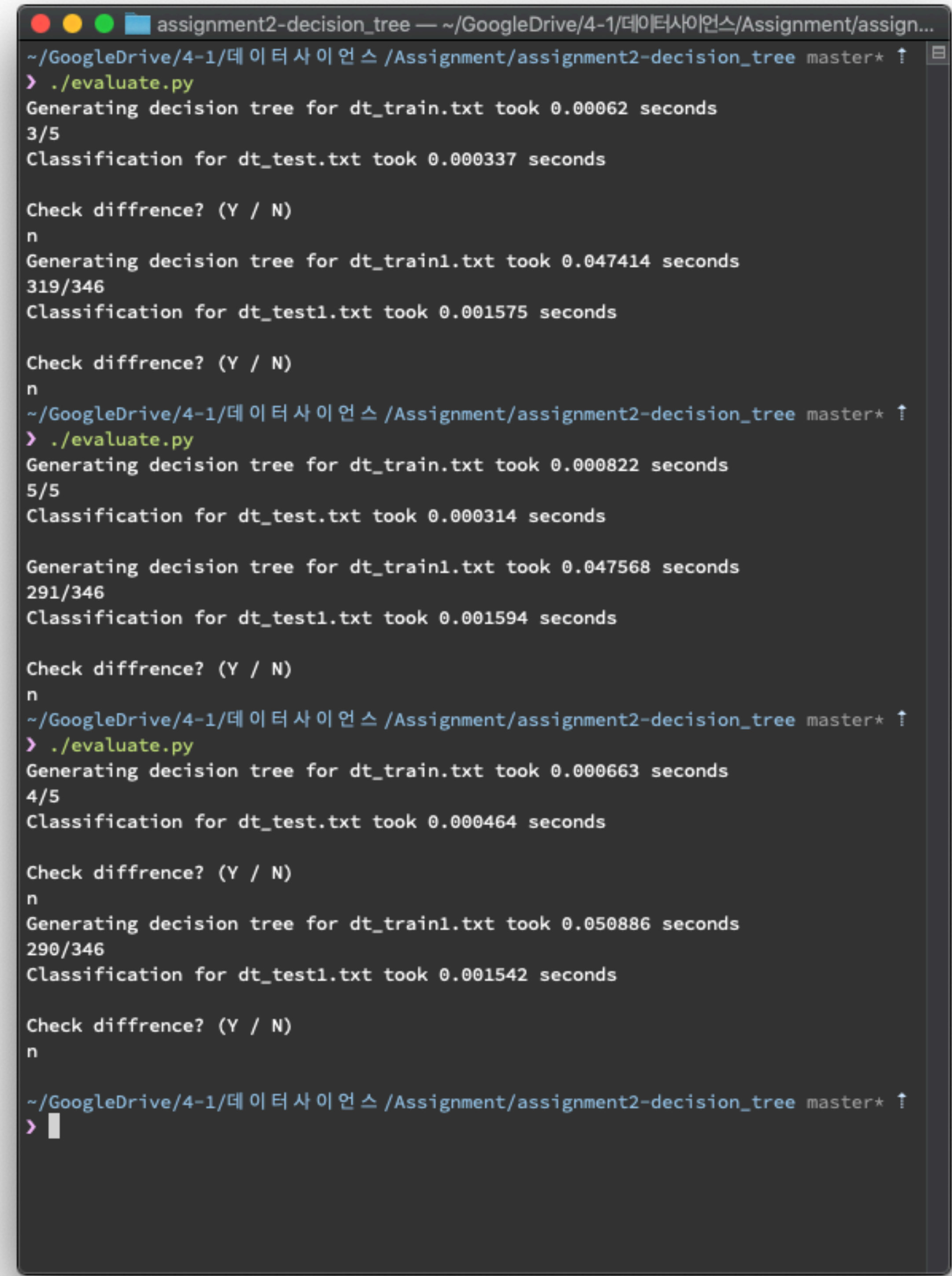
- Using pruning method in evaluate.py
  simply set `usePruning = True` in `runTest()` function.

```python
# Recursive function for the pruning.
def _pruning(tree, node, attributes, samples, prevCnt):
    if node.isLeaf:
        return False
    node.isLeaf = True
    cnt = getPredictionCnt(tree, attributes, samples)
    node.isLeaf = False
    isSubPruned = False
    for child in node.children.values():
        tmp = _pruning(tree, child, attributes, samples, max(prevCnt, cnt))
        if tmp:
            isSubPruned = True
    if not isSubPruned and cnt > prevCnt:
```

```
        node.isLeaf = True
        return True

    return False


# function name tells everything.
# Is not activated because pruning decreases the accuracy at the moment.
def reducedErrorPruning(tree, attrHeader, samples):
    _pruning(tree, tree, attrHeader, samples, getPredictionCnt(tree,
attrHeader, samples))
```



```
assignment2-decision_tree — ~/GoogleDrive/4-1/데이터사이언스/Assignment/assign...
~/GoogleDrive/4-1/데이터사이언스/Assignment/assignment2-decision_tree master*
❯ ./evaluate.py
Generating decision tree for dt_train.txt took 0.00062 seconds
3/5
Classification for dt_test.txt took 0.000337 seconds

Check diffrence? (Y / N)
n
Generating decision tree for dt_train1.txt took 0.047414 seconds
319/346
Classification for dt_test1.txt took 0.001575 seconds

Check diffrence? (Y / N)
n
~/GoogleDrive/4-1/데이터사이언스/Assignment/assignment2-decision_tree master*
❯ ./evaluate.py
Generating decision tree for dt_train.txt took 0.000822 seconds
5/5
Classification for dt_test.txt took 0.000314 seconds

Generating decision tree for dt_train1.txt took 0.047568 seconds
291/346
Classification for dt_test1.txt took 0.001594 seconds

Check diffrence? (Y / N)
n
~/GoogleDrive/4-1/데이터사이언스/Assignment/assignment2-decision_tree master*
❯ ./evaluate.py
Generating decision tree for dt_train.txt took 0.000663 seconds
4/5
Classification for dt_test.txt took 0.000464 seconds

Check diffrence? (Y / N)
n
Generating decision tree for dt_train1.txt took 0.050886 seconds
290/346
Classification for dt_test1.txt took 0.001542 seconds

Check diffrence? (Y / N)
n

~/GoogleDrive/4-1/데이터사이언스/Assignment/assignment2-decision_tree master*
❯
```

Since pruning in **evaluate.py** shuffles training test set before splitting, it generates diffrent result everytime. As you can see from the result, the accuracy gets worse with pruning.
So even after implementation, it is not used in **dt.py** and **evaluate.py** by default.