A2: Algorithm Implementation | 31005 | Advanced Data

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Link to Github: https://github.com/DamienSmith/UTS_ML2019_ID13039957/blob/master/A2_PracticalProject_1

Video url: https://youtu.be/mEefphtMhcc

Introduction - a project overview

The Decision Tree (CART) Algorithm

A decision tree is a decision support tool that models possible outcomes based on a number of conditions (Sing
algorithm is applied that splits into additional nodes recursively resulting in a workflow that predicts an outcome
algorithms include Iterative Dichotomiser (ID3) and Classification and Regression Trees (CART) which use differ
identifies the best way to split a dataset (Singh & Gupta 2014).

For this project, the CART algorithm was implemented from scratch using Python 3. The representation of the C
have zero, one or two child nodes (Brownlee 2016). All input variables and all possible split points are evaluated
impurity function. The Gini impurity provides a purity score representing the miss-classification rate within a dat
of depth. Splitting continues until a stopping condition is reached such as nodes contain a minimum number of
reached. Once created, a tree can be navigated by following the rules at each branch until a final prediction is rea

CART has the following advantages and disadvantages (Timofeev 2004) & (Singh & Gupta 2014):

Advantages:

- CART can handle both numerical and categorical variables.
- CART algorithm will identify the most significant variables.
- CART can handle outliers.

Disadvantages:

- CART may have unstable decision tree. Minor modification such as changes in splitting variables and valu
- CART can only split by one variable.

Define Input/Output

This algorithm was designed to handle any dataset that includes features and target columns with numeric valu
value (i.e. not a multivariable entry). For this reason, we have imported the sklearn dataset library to provide the
requirements. Note, that the dataset is turned into a Panda dataframe. Pandas is a Python library providing integ
data manipulations and analysis on data sets (McKinney 2011). The provided code will convert the sklearn data
tree based on the maxdepth inputted by the users. After running the algorithm, the decision tree and the predict
command line.

```
##Exploration

**Practical Significance**

Decision trees are practically significant as they are intuitively understood by laypeople
stakeholders. This makes it a useful tool for explanation purposes. They also form a founda
of understanding machine learning.

The implementation of the CART decision tree algorithm is a practically significant project
represents the value of decision tree learning. These include:
```

1.   Demonstrating the generalization of unobserved instances (when described in terms of t
that are correlated with a target class).
2. Demonstrating that the computation efficiency is proportional to the number of observed
instances (the size of the dataset).
3.   Demonstrating that a decision tree model as an intuitive classification process that i
relatively easy to understand (e.g. doctors use it when diagnosing patients).

Challenges

The following challenges were encountered when designing our decision tree, and implementin
solution:

* Dataset Selection

A challenge faced was having an appropriate dataset to use for training the CART decision t
was solved by using sklearn database datasets that meet the requirements for implementing t
algorithm. As is expected, this project cannot handle multivariable data as this is a known
of CART.

* Finding the best split

Originally the net sum of the gini impurity at each split point was calculated by summing t
impurity of both the left and right side of each possible split. We found that although it
well for some splits, it would start to favour 'edge' cases; i.e. choosing a split close t
point since that would give the best 'net' impurity. This was solved by implementing a weig
gini impurity. This was calculated based on the proportion of data points remaining in each
point/leaf. This weighted calculation gave less importance to edge cases and improved the c
splitting.

* Training Storage

Another challenge faced was how to 'store' the structure of the decision tree. It was easy
how to do each split and draw the tree manually, however, putting that information into Pyt
difficult.

The first approach was a 'test' row would be stored, and then tested simultaneously as the
created. This would have been disastrous for performance, however, since every entry would
tree created.

We solved this by storing the tree model into a Python dictionary, storing every possible n
For example at depth 1, we created a dictionary containing 2 sets of nodes with all possibl
For depth 2, we created 4, and for depth 3 we'd create 8. This proved effective as we are a
a 'complete' and symmetrical tree, however it is also exponentially taxing, computationall
depth increases.

* Predicting & Pruning

Knowing when the decision tree should 'commit' to a prediction was a challenge. It was deci
the algorithm should make a 'decision' if there was only one target value remaining for a p
leaf. For example, with the Iris data set, splitting at Petal Length <= 1.9, resulted in on
'Setosa' Irises left. Further improving this, a decision was set to be made when the max de
parameter was met. Note that if more than one target value remained on a leaf node the targ
with the highest mode, and if the mode was equal, the first entry would be selected as the

This might still lead to challenges if depth is increased too much, causing overfitting to
prominent since it may split when only one target data point remains.
Pruning also provided a challenge as there is no way to check when to stop pruning. The alg
required manual observation to determine the best depth to 'prune' the tree. This project h
'max depth' method that requires 'trial and error' in order to check each depth for meaning
predictions..

Design Data Structures

In general, a learning problem considers a set of n samples of data and then tries to predi
properties of unknown data. When planning the algorithm implementation we started with the
defined how to calculate the best split points (Hastie et al 2008, at p 308).

It was decided to use the gini impurity to determine impurity since we had a classificatio
opposed to a regression) problem, and gini impurity was the more appropriate measure of im
was differentiable, sensitive to change and was intuitively understood (Hastie et al 2008,

We also decided to do binary splits rather than multiway splits as we didn’t want to split
too quickly, especially since datasets like the Iris set did not have a huge amount of dat

When determining the decision node, we decided that unique value as a deciding factor mixe
maximum depth would be appropriate, especially upon a visual inspection of the Iris data s
options such as a minimum impurity level or working out smoothness or linear combination s
unnecessarily complex for our given data.

* data acquisition

The Scikit-learn library provides datasets, for example the iris and wine datasets for cla
and the boston house prices dataset for regression (Louppe 2016). Each dataset is a Python
like object that holds all the data and some metadata about the data. This data is stored
member, which is a n_samples and n_features array.

In the case of supervised problem, one or more response variables are stored in the target
This is the number corresponding classification that we are trying to learn.
For each dataset, the.data member gives access to the features that can be used to classif

* quality control

Quality control refers to the state of completeness, conformity, consistency, timeliness,
integrity, and accuracy that makes data appropriate for a specific use (Strong, Lee. & Wan
the purpose of simplification, the sklearn database library has been used as a way to mana
quality of each dataset. Each dataset is provided in identical format, which has allowed
the project to be on the algorithm implementation and streamline a common standard of data

* modelling techniques

The decision tree was modeled into a series of python dictionaries, which represented node
Each dictionary holds relevant information of the depth, decision, feature, value and righ
for each node. Each level of depth was used as a reference and further rules applied if ‘d
none. The right left value is used to determine if the value is greater than or less than.

An example of a python dictionary decision tree model on the iris dataset after running
subsequent_split(df, 1, 3)

```
      {1: {'decision': 0,

           'feature': 'petal length (cm)',
           'side': 'left',
           'value': 1.9},

       2: {'decision': None,
           'feature': 'petal length (cm)',
           'side': 'right',
           'value': 1.9}}

      {1: {0},

        2: {0},

       3: {'decision': 1,

           'feature': 'petal width (cm)',
           'side': 'left',
           'value': 1.7},

       4: {'decision': 1,
           'feature': 'petal width (cm)',
           'side': 'right',
           'value': 1.7}}
```

{}

CART is characterized by it construction of binary trees where each internal node has exact
outgoing edges (Breiman et al. 1984). The splits for our implementation are selected by fir
lowest weighted net impurity score on features as the splitting criteria. The prediction ir
is based on the weighted mode for a node.

* Split Calculations:

* Gini Impurity:

${\displaystyle 1 - \sum _{i \neq j}(P_{i}P_{j})^2}$

* Weighted net impurity:

sum of the impurity of the left and right leaves weighted by the proportion of data points
respective side.

* Evaluation Method:

If predicted value is equal to the target value than it is correct.
The details of its implementation is covered in the methodology section of this report.

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Plan Data Models and Tests

The project is designed to work in Google Colaboratory (Colab). Colab is a cloud service ba
Jupyter Notebooks for disseminating machine learning education and research (Carneiro et a
comments in the code guide the user through the code logic.

As a user of the code, you are invited to input different sklearn databases through the dro
provided. A user can also enter the maximum depth of a tree by inputting it into the
subsequent_split() function. After building a model, a user can input test data that has au
been split off the input dataset. Running the testDataAccuracy() function will test the per
the model and provide an overall accuracy score.

Possible alternatives

A number of possible alternatives presented themselves while researching decision tree impl
these include:

* **Impurity functions:** Use additional impurity functions such as cost function/entropy t
is the most appropriate impurity function for a given data set.

* **Tree Pruning.** An important technique for reducing overfitting of the training dataset
prune the trees. The algorithm currently determines a maximum tree depth manually, however
methods such as grid searching, a better method to determine the optimal tree depth could b

* **Terminal nodes.** Alternative methods for splitting the data could be made such as mini
impurity levels, having a minimum observation requirement for a terminal node or maximum nu
possible nodes.

* **Algorithm Tuning:** experimenting with different parameter to achieve better performanc
weighing a minimum classes (if the dataset was not balanced)

* **Categorical Dataset.** The example was designed for input data with numerical or ordina
attributes. Whilst a data set should optimally be cleaned to only contain numerical data, t
algorithm could be expanded to be more flexible with messy data such as dealing with catego
data or missing data.

* **Different datasets.** The algorithm fits relatively well with the Iris dataset, however
alternatives could be done to include more datasets

Methodology

The general method we undertook when creating the devision tree algorithm was as follows:

1. Input dataset (sklearn database):

   1.1 Ensure that the dataset was cleaned and contains non-categorical data; and

   1.2 Split into training/testing dataset.

2. For every feature in the training dataset:

   2.1 Select each value for each feature in the dataset;

   2.2 Calculate gini index for the left (less than and equal to) and right (greater than) side of each of these v

   2.3 Calculate the 'weight' of number of targets for each side of split;

   2.4 Pick the best weighted net gini score (lowest score);

   2.5 Split dataset and start the next 'depth' layer; and

   2.6 storing the node/split decision in a dictionary.

3. Loop this feature selection and splitting until:

   3.1 Max depth reached; or

   3.2 Only unique target values remain in split dataset; otherwise

   3.3 Continue splitting.

4. When predicting, for every row in testing dataset

```
4.1 Test features against decision tree dictionary for each relevant depth
4.2 Print row and predicted value
4.3 Print overall prediction accuracy
```

Additional explanation can be found in the comments

Gini Impurity calculation:

- for each class:
  - Calculate probability of class in the given branch.
  - Square the class probability.
- Sum the squared class probabilities
  - Subtract the sum from 1.
  - Weight each branch based on the baseline probability.
  - Sum the weighted gini index for each split.

A perfectly classified, Gini Index would be zero. An evenly distributed would be 1 – (1/# Classes). You want a va

Decision Tree Model

```
##
##    A2: Algorithm Implementation | 31005 | Advanced Data Analytics
##
##    Authors: Rae Ho (13026998) & Damien Smith (13039957)
##    Goals: - Implement Decision Tree Algorithm
##           - Build & Train a model
##           - Explore/Compare different parameters
##    Code: Python 3
##    Github: https://github.com/DamienSmith/UTS_ML2019_ID13039957/blob/master/A2_PracticalProjec
##
##


#Import Libraries
#numpy to work with arrays
#panda for dataframe
#sklearn to import iris dataset

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from sklearn import datasets
from sklearn.model_selection import train_test_split


#Get data
#using iris data. Get it from sklearn dataset
dataset = datasets.load_iris() #@param ["datasets.load_iris()", "datasets.load_boston()", "datase

# We want to turn the dataset into a panda dataframe
df = pd.DataFrame(dataset['data'])
X_train, X_test, y_train, y_test = train_test_split(df, df['target'], test_size=0.3, random_state

# We also want to add the names of each feature to the dataframe
df.columns = [name[:] for name in dataset['feature_names']]

#We want to add the target to the dataframe too
df['target'] = dataset['target']

#this is to create a random sample of 30 entries
testdf = df.sample(n=30, random_state=1).reset_index(drop=True)


# We create target variable (into binary) in order to get a 'count' of all items in the dataframe
df['dummy'] = 1
```

```
#function to return the count of rows in the dataframe that match a condition

def count_target(dframe, right, feature, value):
  #this is to find the impurity to the left of and to the right of a slice on a cartesian plane
  if right:
    cond = dframe[feature]>value
  else:
    cond = dframe[feature]<=value

  #this works by counting the total number of target items, 'mean' helps find probability of corr
  #count = len(dframe[cond])
  count = sum(cond)
  return count


#We want to create a method to determine what the impurity is for any 'slice' of a feature.
#We have decided to use the gini impurity which shows how likely it is that a randomly selected f

##this takes the parameters:
    #dframe which allows you to put in the dataframe you want to find the impurity for
    #right which takes True or False to look at right or left impurity of a split point
    #feature which is the feature (column) that you want to use/look at
    #value which is the value that is to be split at
    #target variable to be determined (which for the iris df we are using is 'target')


#find gini impurity of a slice
def gini_impurity_leaf(dframe, right, feature, value, target_variable):
```

```python
#this is to find the impurity to the left of and to the right of a slice on a cartesian plane
  if right:
    cond = dframe[feature]>value
  else:
    cond = dframe[feature]<=value

  #this works by counting the total number of target items, 'mean' helps find probability of corr
  count_of_target = dframe[cond].groupby(target_variable)['dummy'].count()
  #print("count of target is: ")
  #print(count_of_target)
  #this uses the impurity formula of impurity = 1 - sum of (probability of being correct [count/l
  gini_impurity = 1 - (np.divide(count_of_target, len(dframe[cond])) ** 2).sum()

  return gini_impurity


#this finds the net gini impurity by adding the left and right slice
# we want to find the 'slice' with the lowest net gini impurity

def net_gini_impurity(dframe, feature, value, target_variable):

#  net_gini = gini_impurity_leaf(dframe, True, feature, value, target_variable) + gini_impurity_l
# we had to use a weighted gini index

  right_weight = count_target(dframe, True, feature, value) / len(dframe)
  left_weight = 1 - right_weight
 #print("right weight is:{}".format(right_weight))
  net_gini = (right_weight * gini_impurity_leaf(dframe, True, feature, value, target_variable)) +

  return net_gini
```

```python
# This finds best split

def find_best_split(dataframe):
# Find the best split by going over every value in each feature and choosing the split with the l
    lowest_impurity = 2  # keep track of the worst impurity
    best_split = ['there is no split', 0]  # keep train of the feature / value that produced it


    for f in range(len(dataframe.columns) -2):  # loop through each feature --> the -2 is because
        feat = dataframe.columns[f]             # store the name of the feature as 'feat'
        for val in dataframe[feat].unique():  # loop through each unique value for that feature
          #Calculate the net impurity of each value in feature
          #print(feat,val)
          net_imp = net_gini_impurity(dataframe, feat, val, 'target')
          #print(feat,val,net_imp)
          split = [feat, val]
          # store best gain and best feature
          if net_imp < lowest_impurity:
            lowest_impurity = net_imp
            best_split = split
            #print("the current best split is:")
            #print(lowest_impurity,best_split)

    return lowest_impurity, best_split


#this splits a dataframe to right and left sides

def splitter(dframe):
  impurity, featsplit = find_best_split(dframe)
  feature = featsplit[0]
  value = featsplit[1]

  #and store the values of those sides into a new data_frame
  right_split = dframe[dframe[feature]>value]
  left_split =dframe[dframe[feature]<=value]

  #print("I have been split for the feature ", feature, "at value", value)

  return right_split, left_split, feature, value
```

```
#This returns what the target is
# This returns a predicted value for the terminal node
# The returned value is the end value with the most common end result

#def final_guess(feature, value, dframe, boolean=False):
def final_guess(dframe):

  dataset = dframe
  targets = dataset.target
  outcome = None

  outcome = targets.value_counts().idxmax()  #this is the first most common value in that set - s

  return outcome

  #alternatively you could do 'outcomes = targets.mode()' but then you wont get a single int if t



#this creates an depth of arrays which we use to store values for later predict
#the aim is to create a list of dictionaries to store the trained data

def createDepthArray(maxdepth):
  for i in range(1,maxdepth):
    depth = i
    name = 'depth{}'.format(depth)          #get the name of the dict array

    #populate the array with futher arrays
    if name not in globals():
      globals()['depth%s' % depth] = {}       #create an array called depth#

    if len(globals()['depth%s' % depth]) < 1:
      for n in range(1, 2**depth + 1):
        globals()['depth%s' % depth][n] = {}
      #elif name in globals():
      #  print("already exists")


#this helps insert values into the previous 'depth array' parts
def insertNodeValue(depth, number, feature, value, side, guess):
  #number = getNumberPos(depth)
  globals()['depth%s' % depth][number] = {'feature': feature, 'value': value, 'side': side, 'deci


#to fill subsequent depths's numbers that already has a final decision

def depthFiller(depth, outcome, number, maxdepth):
  new_depth = depth+1
  #number = getNumberPos(depth)
  if new_depth < maxdepth:

    #print("i am at position {} and am filling lower depth".format(number))
    number_left = (number*2 - 1)
    number_right = (number * 2)
    globals()['depth%s' % new_depth][number_right] = {outcome}
    globals()['depth%s' % new_depth][number_left] = {outcome}
    #and then repopulate the sub-depths until max-depth
    depthFiller(new_depth, outcome, number_right, maxdepth)
    depthFiller(new_depth, outcome, number_left, maxdepth)


#this returns the next empty number for that depth
def getNumberPos(depth):
  for i in range(1, 2**depth+1):
    if len(globals()['depth%s' % depth][i]) == 0:
      return i
      break
    else:
      continue


#this is the main code that creates the tree by iteratively splitting
```

```
#data at the best point

def subsequent_split(dataframe, depth, maxdepth):
  global maxDepth
  maxDepth = maxdepth
  createDepthArray(maxdepth)
  depthspace = "  "*depth
  right_split, left_split, feature, value = splitter(dataframe)
  #create a bunch of dict to max depth


  # store:  [number: {feature = '', value ='', side = 'left', decision = 0,1,3,null}]

  if depth < maxdepth:
    #print("I am doing left side")

    if left_split.empty:
      print("I am working at depth", depth)
      print("left side is empty")

    #this currently looks for a unique value, and if only 1
    #consider doing a mininum impurity
    elif len(left_split['target'].unique()) < 2:
      print("{} I am working at depth {}".format(depthspace, depth))
      #print("i am now uniquely left")
      guess = final_guess(left_split)
      print("{} for {} <= {}, we predict {}".format(depthspace, feature, value, guess))
      number = getNumberPos(depth)
      depthFiller(depth, guess, number, maxdepth)
      insertNodeValue(depth, number, feature, value, 'left', guess)

    #if we have reached max depth, then it will predict anyway
    elif depth == maxdepth - 1:
      guess = final_guess(left_split)
      print("{} for {} <= {}, we predict {}".format(depthspace, feature, value, guess))
      number = getNumberPos(depth)
      depthFiller(depth, guess, number, maxdepth)
      insertNodeValue(depth, number, feature, value, 'left', guess)

    #else if it hasnt reached max depth, then it will keep splitting
    else:
      #print(len(left_split['target'].unique()))
      print("{} I am working at depth {}".format(depthspace, depth))
      print("{} i am now branching for {} <= {}".format(depthspace, feature, value))
      number = getNumberPos(depth)
      insertNodeValue(depth, number, feature, value, 'left', None)
      subsequent_split(left_split,depth+1,maxdepth)

    #print("I am doing right side")
    if right_split.empty:
      #print("depth is", depth)
      print("right side is empty")

    #checks if theres a unique target left
    elif len(right_split['target'].unique()) < 2:
      print("{} I am working at depth {}".format(depthspace, depth))
      #print("i am now uniquely right")
      guess = final_guess(right_split)
      print("{} for {} > {}, we predict {}".format(depthspace, feature, value, guess))
      number = getNumberPos(depth)
      depthFiller(depth, guess, number, maxdepth)
      insertNodeValue(depth, number, feature, value, 'right', guess)

    #checks if max depth is reached and if so predict
    elif depth == maxdepth - 1:
      guess = final_guess(left_split)
      print("{} for {} > {}, we predict {}".format(depthspace, feature, value, guess))
      number = getNumberPos(depth)
      depthFiller(depth, guess, number, maxdepth)
      insertNodeValue(depth, number, feature, value, 'right', guess)

    #else keep splitting
    else:
      #print("depth is", depth)
      print("{} I am now branching for {} > {}".format(depthspace, feature, value))
      number = getNumberPos(depth)
      insertNodeValue(depth, number, feature, value, 'right', None)
      subsequent_split(right_split,depth+1,maxdepth)



#def to clear the dictionary. Needed if we want to re-train/subsequent_split
def clearTrainedData():
  for n in range(1, maxDepth):
    globals()['depth%s' % n].clear()


#this is for subsequent predictions after the first depth
def subsequentPredict(test_df_row, number, depth):
  index = number
  depth = depth + 1
  if depth < maxDepth:
    for x in test_df_row.columns:                  #for each df header
      if globals()['depth%s' % depth][index]['feature'] == x:            #to see if feature is sam
        dictVal = globals()['depth%s' % depth][index]['value']                 # value of depth1
        for n in range(len(test_df_row[x])):      #loop each index row in testdf
          rowVal = test_df_row.loc[n, x ]   #store the value for that row

          if globals()['depth%s' % depth][index]['side'] == 'right':      # if depth entry is lef
            if rowVal > dictVal:
              if globals()['depth%s' % depth][index]['decision'] is not None:
                print("the prediction is {}".format(globals()['depth%s' % depth][index]['decision
              else:
                #print("need to continue")
                subsequentPredict(test_df_row, index*2 - 1, depth)
                subsequentPredict(test_df_row, index*2, depth)

          if globals()['depth%s' % depth][index]['side'] == 'left':      # if depth entry is left
            if rowVal <= dictVal:
              if globals()['depth%s' % depth][index]['decision'] is not None:
                print("the prediction is {}".format(globals()['depth%s' % depth][index]['decision
              else:
                #print("need to continue")
                subsequentPredict(test_df_row, index*2 - 1, depth)
                subsequentPredict(test_df_row, index*2, depth)
  #else:
  #  print("reached max depth already")


def firstPredict(test_df_row):
  for x in test_df_row.columns:                  #for each df header
    for i in range(1,len(depth1)+1):             #loop through each dict key
      if depth1[i]['feature'] == x:              #to see if feature is same
        #print("feature to look over is{}".format(x))
        dictVal = depth1[i]['value']                   # value of depth1
        #print("dictval is {}".format(dictVal))
        #print(type(dictVal))

        for n in range(len(test_df_row[x])):      #loop each index row in testdf
          rowVal = test_df_row.loc[n, x ]   #store the value for that row
          #print("rowVal is {}".format(rowVal))
          #print(type(rowVal))
          #print(depth1[i]['side'])

          if depth1[i]['side'] == 'right':      # if depth1 entry is left or right
            if rowVal > dictVal:
              #print("Row Val is greater than DictVal")
              if depth1[i]['decision'] is not None:
                print("the prediction is {}".format(depth1[i]['decision']))
              elif depth1[i]['decision'] is None:
                #print("need to continue")
                subsequentPredict(test_df_row, i*2 - 1, 1)
                subsequentPredict(test_df_row, i*2, 1)
            #else:
            #  print("rowVal does not match this node")

          if depth1[i]['side'] == 'left':      # if depth1 entry is left or right
          if rowVal <= dictVal:
            #print("Row Val is less than DictVal")
            if depth1[i]['decision'] is not None:
              print("the prediction is {}".format(depth1[i]['decision']))
            elif depth1[i]['decision'] is None:
              #print("need to continue")
              subsequentPredict(test_df_row, i*2 - 1, 1)
              subsequentPredict(test_df_row, i*2, 1)


#this is to test each row of the inputed dataframe
def testData(dataframe):
  testdata = dataframe

  for i in range(len(testdf)):
    testrow = testdata[:1]
    print("for the row:")
    print(testrow.to_string(index=False))
    firstPredict(testrow)
    testdata = testdata.drop([0,0]).reset_index(drop=True)
    print("\n")


#this tests each row but can work out accuracy when the target value is known
def testDataAccuracy(dataframe):
  from io import StringIO  # Python3
  import sys

  testdata = dataframe
  count = 0
  correct = 0
  for i in range(len(testdf)):
    testrow = testdata[:1]
    print("for the row:")
    print(testrow.to_string(index=False))
    test = testrow['target'].values[0]
    print("the correct value was {}".format(test))
    firstPredict(testrow)

    old_stdout = sys.stdout
    result = StringIO()
    sys.stdout = result
    firstPredict(testrow)
    sys.stdout = old_stdout

    result_string = result.getvalue()
    a, b, c, last = result_string.split()
    #guess = int(last)
    #print("last is {}".format(last))
    count = count + 1
    if str(test) == str(last):
      correct = correct + 1
      print ("I predicted correctly")
    else:
      print("I was wrong")
    testdata = testdata.drop([0,0]).reset_index(drop=True)
    print("\n")
  print("Total rows was {} and I predicted {} correctly".format(count, correct))
  print("My accuracy is {}%".format(correct/count * 100))


####################################################
#######this is where we finally call things ########
####################################################


#You will need to clear the training data if you want to 'train' different data
try:
  clearTrainedData()
except:
  print("nothing to clear")
```

```python
#this is to build the tree
#the first parameter is the training dataframe
#the second parameter is the depth to start at, which is always 1
#the third parameter is the max depth you want to trim the decision tree to
subsequent_split(df, 1, 5)    #put 1 more than the max depth you want



# when you have the target variable in the testing data you can check
# the accuracy of the data
testDataAccuracy(testdf)



# when you dont have the target variable in the testing data you can check
# the prediction
testData(testdf)



# you can print the dictionaries for each depth of the tree (as you desire)
import pprint
pprint.pprint(depth1)
pprint.pprint(depth2)
pprint.pprint(depth3)
pprint.pprint(depth4)
pprint.pprint(depth5)
```

Evaluation

Report Execution on Data

Report Execution on Data When executing the code, we store the decision tree into a series of dictionaries that r
equal to value) /right (greater than value) and prediction (None if not a leaf node).

An example output from running the subsequent_split() method with a max depth of 4 on the iris dataset prints t

```
    I am working at depth 1
       for petal length (cm) <= 1.9, we predict 0
     I am now branching for petal length (cm) > 1.9
       I am working at depth 2
       i am now branching for petal width (cm) <= 1.7
         I am working at depth 3
         i am now branching for petal length (cm) <= 4.9
           I am working at depth 4
           for petal width (cm) <= 1.6, we predict 1
           I am working at depth 4
           for petal width (cm) > 1.6, we predict 2
         I am now branching for petal length (cm) > 4.9
           I am working at depth 4
           for petal width (cm) <= 1.5, we predict 2
           for petal width (cm) > 1.5, we predict 2
       I am now branching for petal width (cm) > 1.7
         I am working at depth 3
         i am now branching for petal length (cm) <= 4.8
           I am working at depth 4
           for sepal length (cm) <= 5.9, we predict 1
           I am working at depth 4
           for sepal length (cm) > 5.9, we predict 2
```

```
        I am working at depth 3
        for petal length (cm) > 4.8, we predict 2
```

For each split we see the depth of the decision tree, the rule being created and predicted target value (if exists).

In order to highlight the splits being made, below is the first split value rule.

```
    I am working at depth 1
     for petal length (cm) <= 1.9, we predict 0
```

We see that if petal length (cm) is below 1.9 it is predicted to be target value 0. When plotting the values on a sca
clustered below petal length (cm) 1.9.

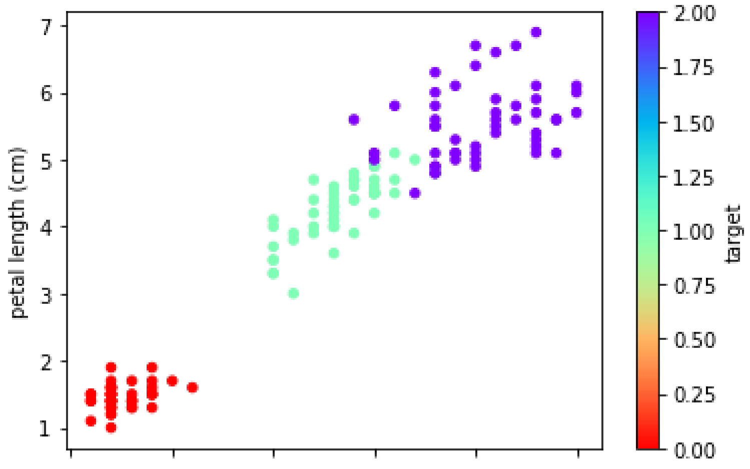
```
#Run this for the scatter plot highlighting the split value

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from sklearn import datasets
from sklearn.model_selection import train_test_split

dataset = datasets.load_iris()

df = pd.DataFrame(dataset['data'])
df.columns = [name[:] for name in dataset['feature_names']]
df['target'] = dataset['target']
df.plot.scatter(x ='petal width (cm)', y='petal length (cm)', c='target', colormap='rainbow_r')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f23f9551cf8>
```



Report Testing

When evaluating the success of the CART decision tree model, we have the ability to compare the actual and pre
example output is as follows:

```
    For a Correctly predicted row
    for the row:
    sepal length(cm)  sepal width(cm)  petal length(cm)  petal width(cm)  target
          6.1               2.8                4.7                1.2           1
    the correct value was 1
    the prediction is 1
    I predicted correctly

    For an Incorrectly predicted row
    for the row:
     sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)  target
          6.3                2.5                5.0               1.9             2
    the correct value was 2
    the prediction is 1
    I was wrong
```

After each row displayed, a final accuracy score is printed

```
    Total rows was 30 and I predicted 24 correctly
    My accuracy is 80.0%
```

We can clearly see that if the target and prediction value match. A simple percentage calculation is used to calcu

(number of correct predictions) / (total instances) * 100

Overall accuracy is an appropriate metric for the Iris dataset since the target variable is balanced across the thre
metrics may be needed.

Efficiency Analysis

When comparing the computation run time between each dataset, we can observe how the size of the dataset is
The following test demonstrates how the number of rows and columns affect the CPU runtime in google Colab.
takes to build a decision tree for each available dataset. It can be seen that the more rows and columns (with eq

```
# run this code to see the %timeit efficiency analysis table
import pandas as pd
import numpy as np

df = pd.DataFrame(columns = ["Dataset (sklearn.database) ", "Rows (Instances)", "Columns (feature
                  data=[["iris", 150, 4, 5, "total: 2.08 s"],
                        ["wine", 178, 13, 5, "total: 25.3 s"],
                        ["diabetes", 442, 10, 5, "total: 31.9 s"],
                        ["boston", 506, 13, 5, "total: 55.3 s"],
                        ["breast_cancer", 569, 30, 5, "total: 4min 58s"]])

df
```

	Dataset (sklearn.database)	Rows (Instances)	Columns (features)	MaxDepth	CPU ru
0	iris	150	4	5	
1	wine	178	13	5	
2	diabetes	442	10	5	
3	boston	506	13	5	
4	breast_cancer	569	30	5	

It is quite intuitive to understand that more data would equal more computation time. It is worth noting, however
significantly more than the number of rows. This is due to the need to consider each feature across each row for
more computation.

Conclusion

- Discuss Reflections

The implementation of the CART decision tree algorithm has demonstrated how to generalize classification of ir
target class. In statistics, overfitting is the production of an analysis that corresponds too closely or exactly to a

predict future observations reliably (Tetko et all 1995). The problem of overfitting is identified and proposed to b
1999).

This project allows a user to experiment with the tree depth and how it affects the accuracy of a prediction.This
management in order to avoid overfitting and maintain generalization.

The computation efficiency has also been demonstrated showing that cpu run time is proportional to the numbe
implementation may not be the most efficient method but it highlights the impact of datasets with different num
explored with the maxdepth parameter and observe its effect. In our learnings we discovered using a class inste
efficiency.

- Propose Possible Improvements

A number of possible improvements have been identified that if implemented would improve the performance a
‘node’ class instead of using dictionaries the performance would increase exponentially due to the fact that we s
subsequent dictionary depth.

Another improvement would be implementing other splitting criteria (e.g. entropy & information gain) so that co
If additional user parameters were included that improved experimentation, such as pruning or setting a gini imp
achieved.

Further methods could also be implemented to work out the optimal depth of the tree than manually determinin

If the algorithm is implemented on different data sets, which are not as balanced as the Iris dataset, further impr
class more heavily. Also, this CART decision tree implementation could be expanded into a random forest algori
of tree builds and picking the best scores for a better chance at building a more accurate model.

Finally, the test data was taken as a subset of the training data. Ideally, these should be independent of each oth
as such the results are over-fitted, but nonetheless currently shows a demonstration of the algorithm working.

Ethical (200)

- Discuss the social/ethical aspect of the project

Ethics refer to the principles of right and wrong that individuals use to make choices that guide their behaviors (
project adopts the utilitarianism model, which aims to do what causes the most good for the most people (Ande
into the algorithm by making decisions based on the best possible split point and aims to guide the user on the
historically observed features.

- Consider how the technique could be misused

The algorithm could be misused if a user considers the output as an absolute truth. If the predicted target value
has the potential to be misguided due to the probabilistic nature of how a prediction is made (Willis 2014). This
less well versed with the algorithm, such as with higher management or stakeholders. Such users will easily con
apply hard and fast rules to something which should have such rules.

The algorithm can also lead to socially unacceptable generalisations and biasedness, such as making decisions
certain features to be prejudicial when making decisions. This can cause further dilemmas such as whether a d
features when classifying data (e.g. is it ethical that race be a feature in determining fraud?).

Ultimately, decisions may be being made without considering unobserved features that would contribute greatly
be race being the determinative of crime rates, but socio-economic backgrounds. With the algorithm, the genera
this.

Video Pitch

Video url: https://youtu.be/mEefphtMhcc

References

Anderson, M. and Anderson, S.L. eds., 2011. Machine ethics. Cambridge University Press.

Breiman, L., Friedman, J., Olshen, R. and Stone, C., 1984. Classification and regression trees. Wadsworth Int. Gro

Brownlee, J., 2016. Master Machine Learning Algorithms: discover how they work and implement them from scr

Carneiro, T., Da Nóbrega, R.V.M., Nepomuceno, T., Bian, G.B., De Albuquerque, V.H.C. and Reboucas

Filho, P.P., 2018. Performance Analysis of Google Colaboratory as a Tool for Accelerating Deep Learning Applica

Friedman, J.H., 1999. Greedy function approximation: a gradient boosting machine. Annals of statistics, pp.118

Hastie, T., Tibshirani, R., Friedman, J. and Franklin, J., 2005. The elements of statistical learning: data mining, infe
Intelligencer, 27(2), pp.83-85.

Louppe, G., 2016. An introduction to Machine Learning with Scikit-Learn.

McKinney, W., 2011. pandas: a foundational Python library for data analysis and statistics. Python for High Perfo

Peng, W., Chen, J. and Zhou, H., 2009. An implementation of ID3-decision tree learning algorithm. From web.arch
21/09/2019

Singh, S. & Gupta, P., 2014. Comparative study ID3, cart and C4. 5 decision tree algorithm: a survey. International
Technology (IJAIST), 27(27), pp.97-103.

Strong, D.M., Lee, Y.W. and Wang, R.Y., 1997. Data quality in context. Communications of the ACM, 40(5), pp.103-

Tetko, I.V., Livingstone, D.J. and Luik, A.I., 1995. Neural network studies. 1. Comparison of overfitting and overtra
computer sciences, 35(5), pp.826-833.

Timofeev, R., 2004. Classification and regression trees (CART) theory and applications. Humboldt University, Ber

Wiley J. & Sons, Inc. 2017, ‘Management Information Systems’, Chapter 6, p2.

Willis, J.E., 2014. Learning analytics and ethics: A framework beyond utilitarianism. Educause Review.