Project Scope

This was a follow along project from Code Academy using a Kaggle Dataset. The article recommended to follow along in Jupyter, so now it's posted to GitHub =)

Data is from Kaggle (https://www.kaggle.com/datasets/mohansacharya/graduate-admissions)

Data Points

- GRE Scores (out of 340)
- TOEFL Scores (out of 120)
- University Rating (out of 5)
- Statement of Purpose and Letter of Recommendation Strength (out of 5)
- Undergraduate GPA (out of 10)
- Research Experience (either 0 or 1)
- Chance of Admit (ranging from 0 to 1)

In [9]:

```
#Imports
import pandas as pd

#Load Dataframe
df = pd.read_csv('Admission_Predict.csv')

#update the column headers to be more reasonable
#print(df.head())
df.columns = df.columns.str.strip().str.replace(' ', '_').str.lower()
#print(df.head())
```

In [30]:

```
#Set up X and y for the tree model
X = df.loc[:,'gre_score':'research']
y = df['chance_of_admit']>=.8
```

In [14]:

```
#Import train test split and Decission Tree Classifier
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier

#Split the data
x_train, x_test, y_train, y_test = train_test_split(X,y, random_state=0, test_size=0.2)

#Make the Decision Tree Model, check the score with the test data
dt = DecisionTreeClassifier(max_depth = 2, ccp_alpha=.01, criterion='gini')
dt.fit(x_train, y_train)
y_pred = dt.predict(x_test)
print('This Tree has a score is {}'.format(dt.score(x_test, y_test)))
```

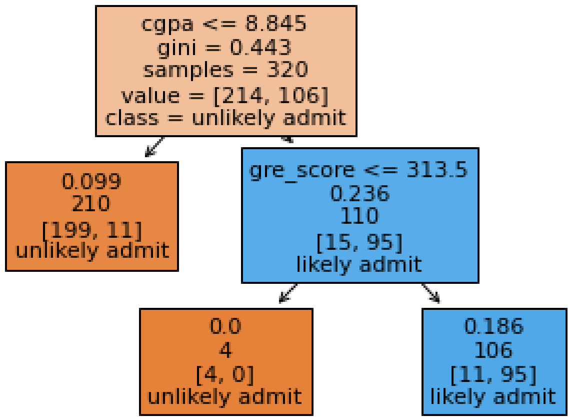
```
This Tree has a score is 0.925
```

In [19]:

```
#Plotting of the Tree, via treeplot
```

```python
#Import MatPlotLib
import matplotlib.pyplot as plt
from sklearn import tree

tree.plot_tree(dt, feature_names = x_train.columns, max_depth=3,\
               class_names=['unlikely admit', 'likely admit'],\
              label='root', filled=True)
plt.show()
plt.clf()
```

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```

In [20]:

```python
#Plotting of the Tree, via text output
print(tree.export_text(dt, feature_names = X.columns.tolist()))
```

```
|--- cgpa <= 8.85
|   |--- class: False
|--- cgpa >  8.85
|   |--- gre_score <= 313.50
|   |   |--- class: False
|   |--- gre_score >  313.50
|   |   |--- class: True
```

In [21]:

```python
#Verifying the Gini gain of the first decision on the tree
def gini(data):
    """Calculate the Gini Impurity Score
    """
    data = pd.Series(data)
    return 1 - sum(data.value_counts(normalize=True)**2)

gi = gini(y_train)
print(f'Gini impurity at root: {round(gi,3)}')
```

```
Gini impurity at root: 0.443
```

In [23]:

```python
#Verifying the gini split table for the first decision

def info_gain(left, right, current_impurity):
    """Information Gain associated with creating a node/split data.
    Input: left, right are data in left branch, right banch, respectively
    current_impurity is the data impurity before splitting into left, right branches
```

```
    """
    # weight for gini score of the left branch
    w = float(len(left)) / (len(left) + len(right))
    return current_impurity - w * gini(left) - (1 - w) * gini(right)

info_gain_list = []
for i in x_train.cgpa.unique():
    left = y_train[x_train.cgpa<=i]
    right = y_train[x_train.cgpa>i]
    info_gain_list.append([i, info_gain(left, right, gi)])

ig_table = pd.DataFrame(info_gain_list, columns=['split_value',\
                        'info_gain']).sort_values('info_gain', ascending=False)
ig_table.head(10)
```

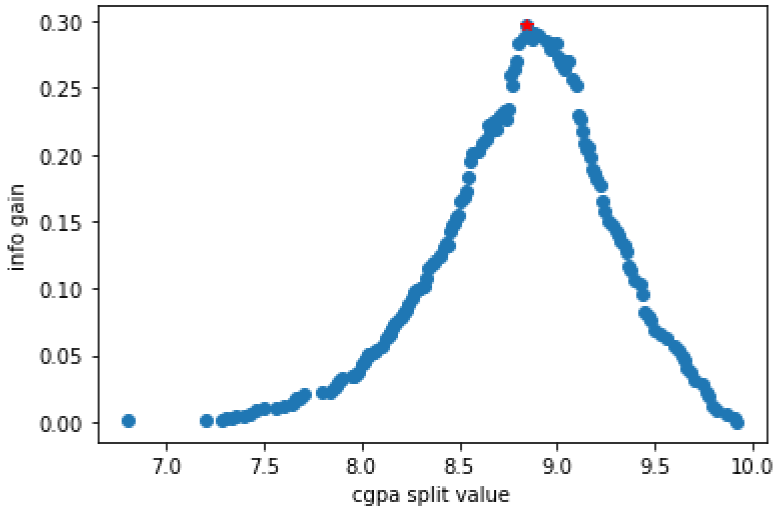
Out[23]:

	split_value	info_gain
10	8.84	0.296932
124	8.85	0.291464
139	8.88	0.290704
18	8.90	0.290054
98	8.83	0.287810
110	8.87	0.286050
152	8.94	0.284714
57	8.96	0.284210
96	8.80	0.283371
21	9.00	0.283364

In [24]:

```
# A quick charting of the info gain split data

plt.plot(ig_table['split_value'], ig_table['info_gain'],'o')
plt.plot(ig_table['split_value'].iloc[0],ig_table['info_gain'].iloc[0],'r*')
plt.xlabel('cgpa split value')
plt.ylabel('info gain')
plt.show()
plt.clf()
```




```
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```

In [31]:

```
# Now some work on regression modeling

# X is already defined (stays the same), change definition of y to actual values instea
X = df.loc[:,'gre_score':'research']
y = df['chance_of_admit']

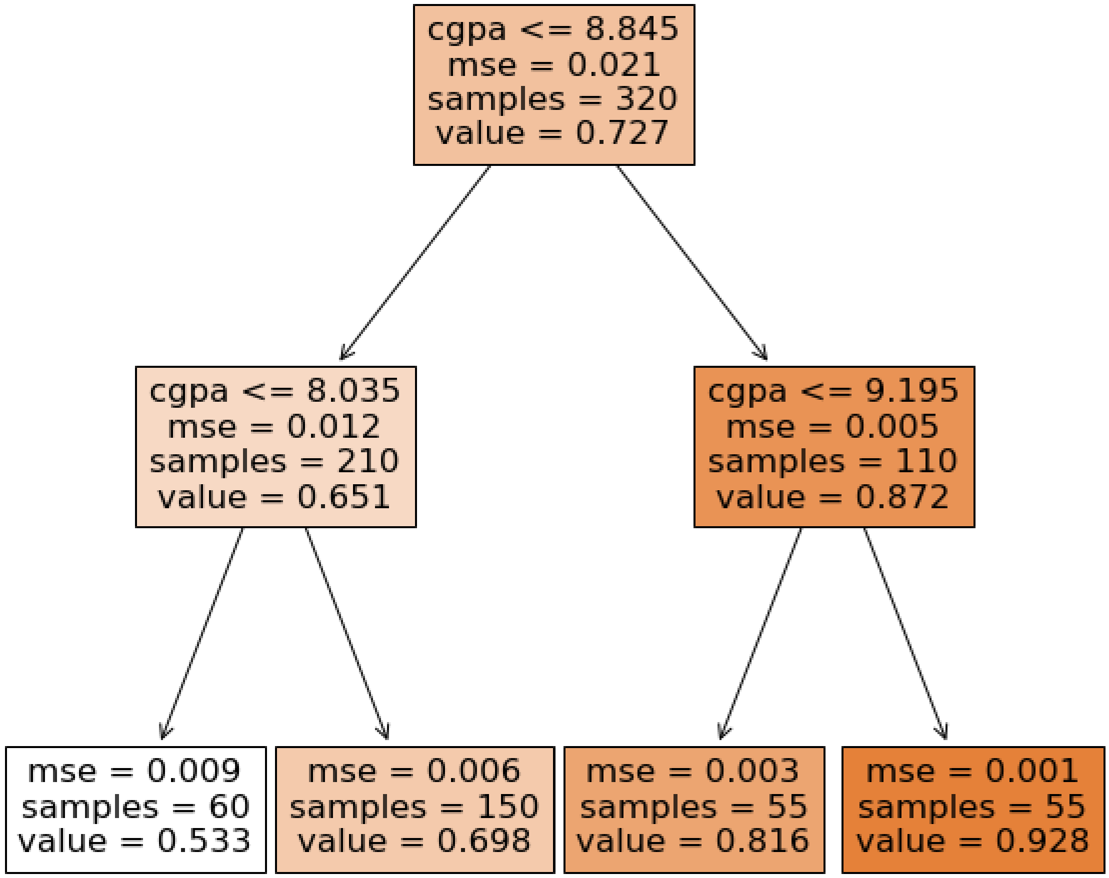
from sklearn.tree import DecisionTreeRegressor

x_train, x_test, y_train, y_test = train_test_split(X, y, random_state=0, test_size=.2)
dt = DecisionTreeRegressor(max_depth=3, ccp_alpha=.001) #note: ccp_alpha changed to .00
dt.fit(x_train, y_train)
y_pred = dt.predict(x_test)
print('The accuracy score is: {}'.format(dt.score(x_test, y_test)))
```

```
The accuracy score is: 0.5230242793515552
```

In [32]:

```
#Graphing of the tree using regression
plt.figure(figsize = (10, 10))
tree.plot_tree(dt, feature_names = x_train.columns, max_depth = 2, filled=True)
plt.show()
plt.clf()
```

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```

In [35]:

```
#Challenge section of the article, working through the mse gain (vs gini gain)

#Import NumPy
import numpy as np

#Define Functions for mse
def mse(data):
    """Calculate the MSE of a data set
    """
    return np.mean((data - data.mean())**2)

def mse_gain(left, right, current_mse):
    """Information Gain (MSE) associated with creating a node/split data based on MSE.
    Input: left, right are data in left branch, right banch, respectively
    current_impurity is the data impurity before splitting into left, right branches
    """
    # weight for gini score of the left branch
    w = float(len(left)) / (len(left) + len(right))
    return current_mse - w * mse(left) - (1 - w) * mse(right)

#Walk through mse gain process
m = mse(y)
print(f'MSE at root: {round(m,3)}')
```

```
mse_gain_list = []
for i in x_train.cgpa.unique():
    left = y_train[x_train.cgpa<=i]
    right = y_train[x_train.cgpa>i]
    mse_gain_list.append([i, mse_gain(left, right, m)])

mse_table = pd.DataFrame(mse_gain_list,columns=['split_value', 'info_gain']).sort_value
print(mse_table.head(10))

print(f'Split with highest information gain is: {None}')

plt.plot(mse_table['split_value'], mse_table['info_gain'],'o')
plt.plot(mse_table['split_value'].iloc[0], mse_table['info_gain'].iloc[0],'r*')
plt.xlabel('cgpa split value')
plt.ylabel('info gain')
```

```
MSE at root: 0.02
     split_value  info_gain
10          8.84   0.010562
96          8.80   0.010534
98          8.83   0.010520
124         8.85   0.010481
125         8.73   0.010435
110         8.87   0.010429
139         8.88   0.010392
1           8.70   0.010391
17          8.76   0.010355
140         8.74   0.010347
Split with highest information gain is: None
```

Out[35]: Text(0, 0.5, 'info gain')