Project - CCPS 844 - Data Mining

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Dataset: [https://archive.ics.uci.edu/ml/datasets/DrivFace (https://archive.ics.uci.edu/ml/datasets/DrivFace)](https://archive.ics.uci.edu/ml/datasets/DrivFace)

The DrivFace database contains images sequences of subjects while driving in real scenarios. It is composed of 606 samples of 640Ã—480 pixels each, acquired over different days from 4 drivers (2 women and 2 men) with several facial features like glasses and beard. The ground truth contains the annotation of the face bounding box and the facial key points (eyes, nose and mouth). A set of labels assigning each image into 3 possible gaze direction classes are given. The first class is the looking-right class and contains the head angles between -45Âº and -30Âº. The second one is the frontal class and contains the head angles between -15Âº and 15Âº. The last one is the looking-left class and contains the head angles between 30Âº and 45Âº.

Column Headers are described as follows: -fileName is the imagen's name into DrivImages.zip - subject = [1:4] -imgNum = int -label = [1/2/3] (head pose class that corresponding to [lr/f/lf], respectively) -ang = [-45, -30/ -15 0 15/ 30 15] (head pose angle) -[xF yF wF hF] = face position - [xRE yRE] = rigth eye position -[xLE yL] = left eye position -[xN yN] = Nose position -[xRM yRM] = rigth corner of mouth -[xLM yLM] = left corner of mouth

In [1]:
```
# Import appropriate libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sea
import copy
from mpl_toolkits.mplot3d import Axes3D
%matplotlib inline
```

Select datasets and visualize

In [2]:
```
# Read in data and display info
dataset = pd.read_csv('drivPoints.txt', index_col = 0)
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 606 entries, 20130529_01_Driv_001_f  to 20130530_04_Driv_090_f
Data columns (total 18 columns):
subject    606 non-null int64
imgNum     606 non-null int64
label      606 non-null int64
ang        606 non-null int64
xF         606 non-null int64
yF         606 non-null int64
wF         606 non-null int64
hF         606 non-null int64
xRE        606 non-null int64
yRE        606 non-null int64
xLE        606 non-null int64
yLE        606 non-null int64
xN         606 non-null int64
yN         606 non-null int64
xRM        606 non-null int64
yRM        606 non-null int64
xLM        606 non-null int64
yLM        606 non-null int64
dtypes: int64(18)
memory usage: 90.0+ KB
```

In [3]:
```
dataset.head()
```

Out[3]:

	subject	imgNum	label	ang	xF	yF	wF	hF	xRE	yRE	xLE	yLE
fileName												
20130529_01_Driv_001_f	1	1	2	0	292	209	100	112	323	232	367	231
20130529_01_Driv_002_f	1	2	2	0	286	200	109	128	324	235	366	235
20130529_01_Driv_003_f	1	3	2	0	290	204	105	121	325	240	367	239
20130529_01_Driv_004_f	1	4	2	0	287	202	112	118	325	230	369	230
20130529_01_Driv_005_f	1	5	2	0	290	193	104	119	325	224	366	225

In [4]:
```
# Lets group the individual persons (4 ppl total) against their facial chara
X_subject_1 = dataset[dataset['subject'] == 1]
X_subject_2 = dataset[dataset['subject'] == 2]
X_subject_3 = dataset[dataset['subject'] == 3]
X_subject_4 = dataset[dataset['subject'] == 4]
```

In [5]:

```
X_subject_1.head()
```

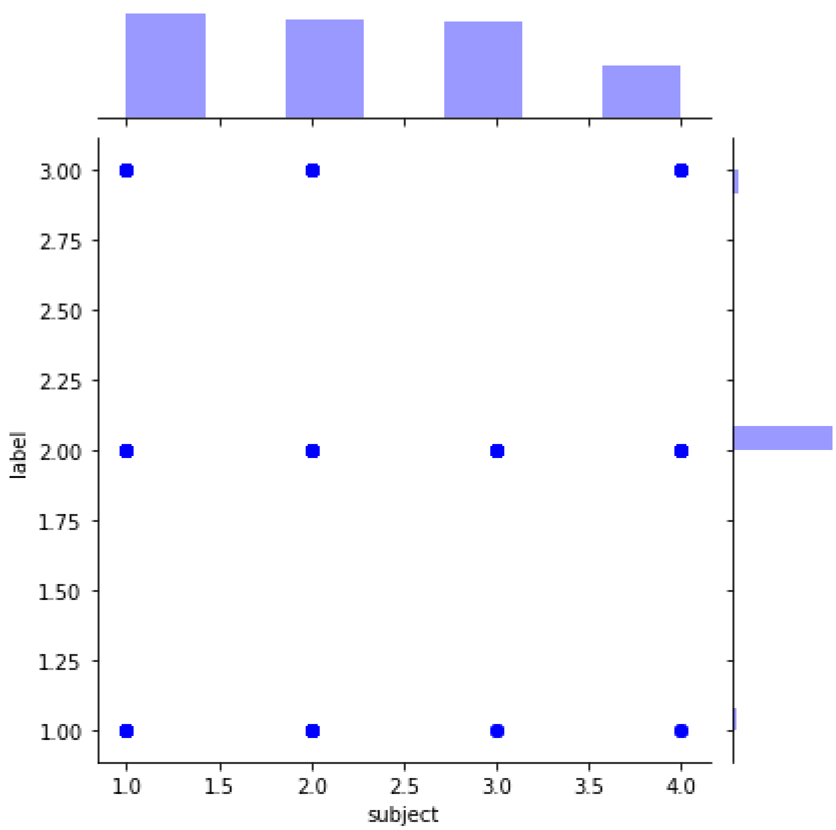
Out[5]:

fileName	subject	imgNum	label	ang	xF	yF	wF	hF	xRE	yRE	xLE	yLE
20130529_01_Driv_001_f	1	1	2	0	292	209	100	112	323	232	367	231
20130529_01_Driv_002_f	1	2	2	0	286	200	109	128	324	235	366	235
20130529_01_Driv_003_f	1	3	2	0	290	204	105	121	325	240	367	239
20130529_01_Driv_004_f	1	4	2	0	287	202	112	118	325	230	369	230
20130529_01_Driv_005_f	1	5	2	0	290	193	104	119	325	224	366	225

In [6]:

```
# A jointplot will allow us to see the distributions of the x,y axis.  Lets

sea.jointplot(x = "subject", y = "label", data = dataset, color = "blue")
```

Out[6]: <seaborn.axisgrid.JointGrid at 0x22795976cc0>



In [7]:

```
# From this we can see the number of readings of each subject is approx equa
# with the exception of the number of subject 4 readings (along top axis) be
# lower than the others.  We can also see that the majority of the time the
# subjects are looking forward (label = 2), and only minimally do they look
# left (label = 1) or to the right (label = 3).
```

In [8]:
```python
# Lets count the number of each label to verify.
print(dataset[dataset['label'] == 1].count())
print(dataset[dataset['label'] == 2].count())
print(dataset[dataset['label'] == 3].count())
```

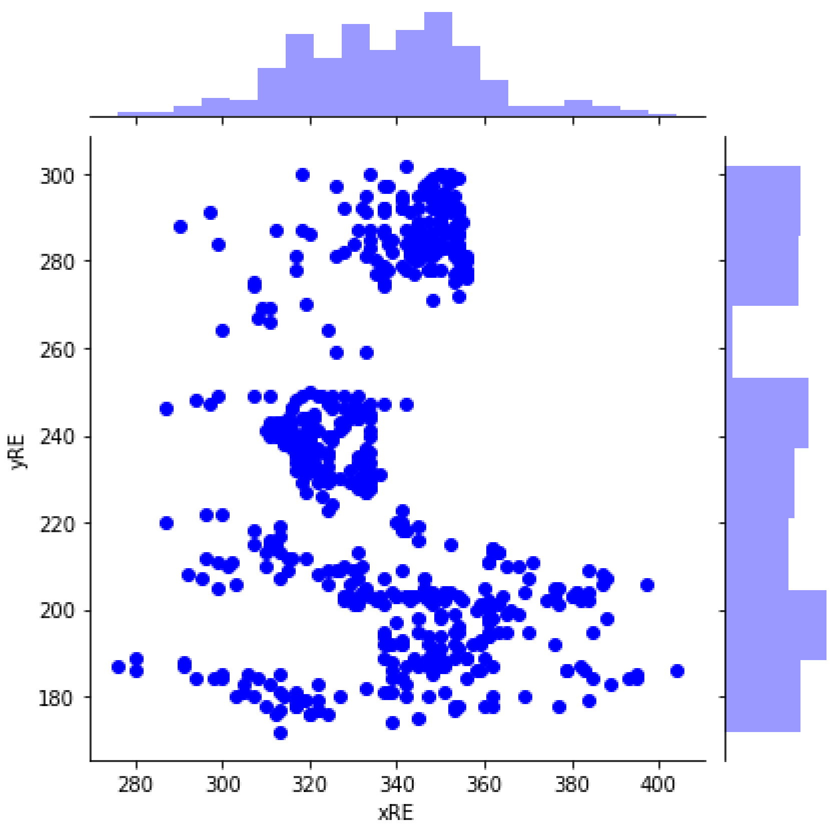
```
subject    27
imgNum     27
label      27
ang        27
xF         27
yF         27
wF         27
hF         27
xRE        27
yRE        27
xLE        27
yLE        27
xN         27
yN         27
xRM        27
yRM        27
xLM        27
yLM        27
dtype: int64
subject    546
imgNum     546
label      546
ang        546
xF         546
yF         546
wF         546
hF         546
xRE        546
yRE        546
xLE        546
yLE        546
xN         546
yN         546
xRM        546
yRM        546
xLM        546
yLM        546
dtype: int64
subject    33
imgNum     33
label      33
ang        33
xF         33
yF         33
wF         33
hF         33
xRE        33
yRE        33
xLE        33
yLE        33
xN         33
```

```
yN          33
xRM         33
yRM         33
xLM         33
yLM         33
dtype: int64
```

In [9]:
```
# Looking forward = 546, looking left = 27, looking right = 33
```

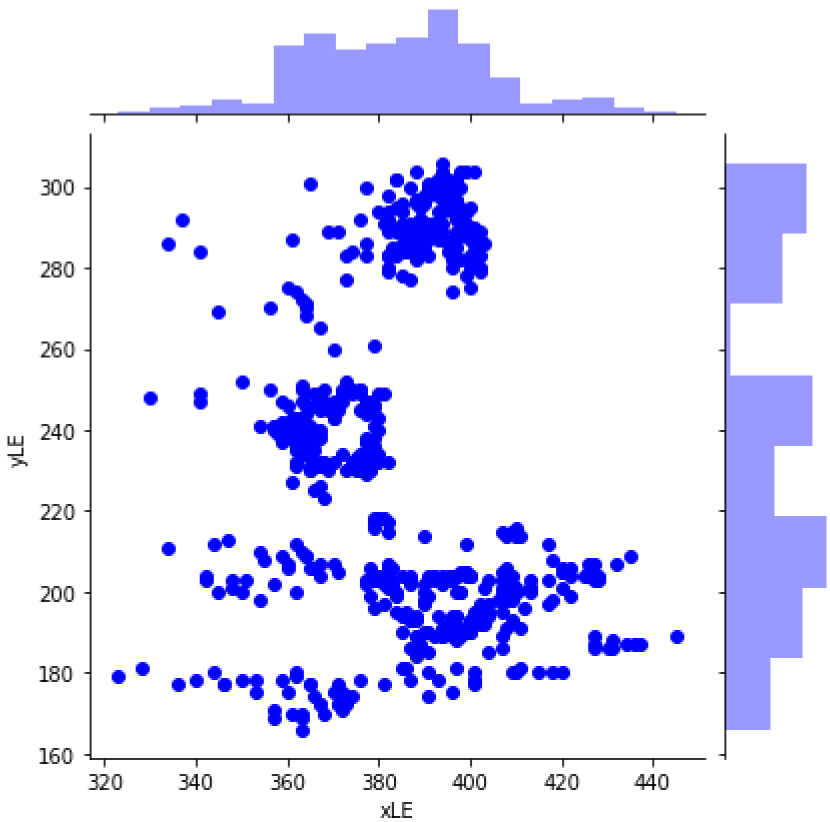
In [10]:
```
# Let's try plotting the eye movements of all subjects.

# First plot is the x, y coordinates of the right eye movements
sea.jointplot(x = "xRE", y = "yRE", data = dataset, color = "blue")
```

Out[10]: <seaborn.axisgrid.JointGrid at 0x22795d6ea58>



In [11]:
```
# This plot is the x, y coordinates of the left eye
sea.jointplot(x = "xLE", y = "yLE", data = dataset, color = "blue")
```

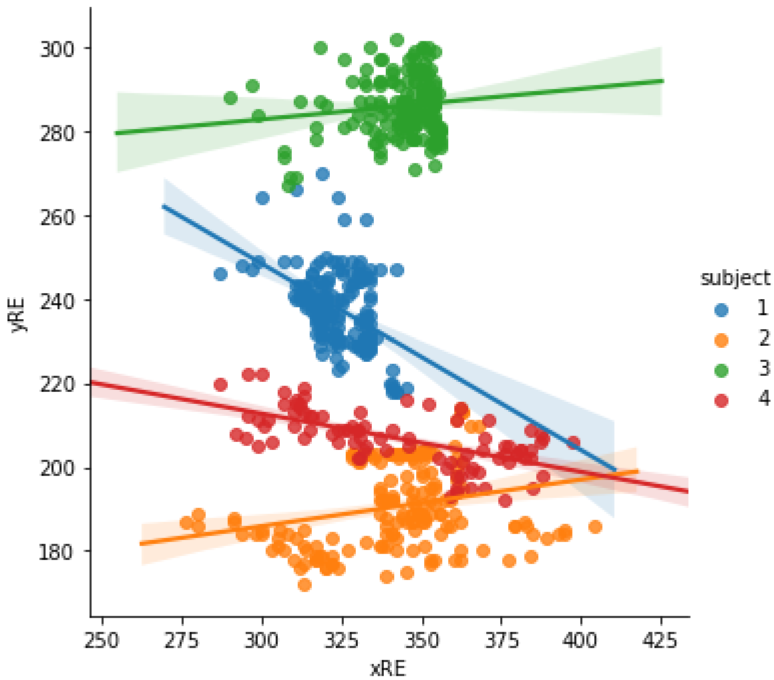
Out[11]: <seaborn.axisgrid.JointGrid at 0x22795e98940>



In [12]:

```
# Data between the right and left eye movements are quite similair, as it sh
# move in tandem.

# Try viewing the eye movements of each subject via hue set to identify each
sea.lmplot(x = 'xRE', y = 'yRE', hue = 'subject', data = dataset, fit_reg =
```

Out[12]: <seaborn.axisgrid.FacetGrid at 0x22795ff7eb8>

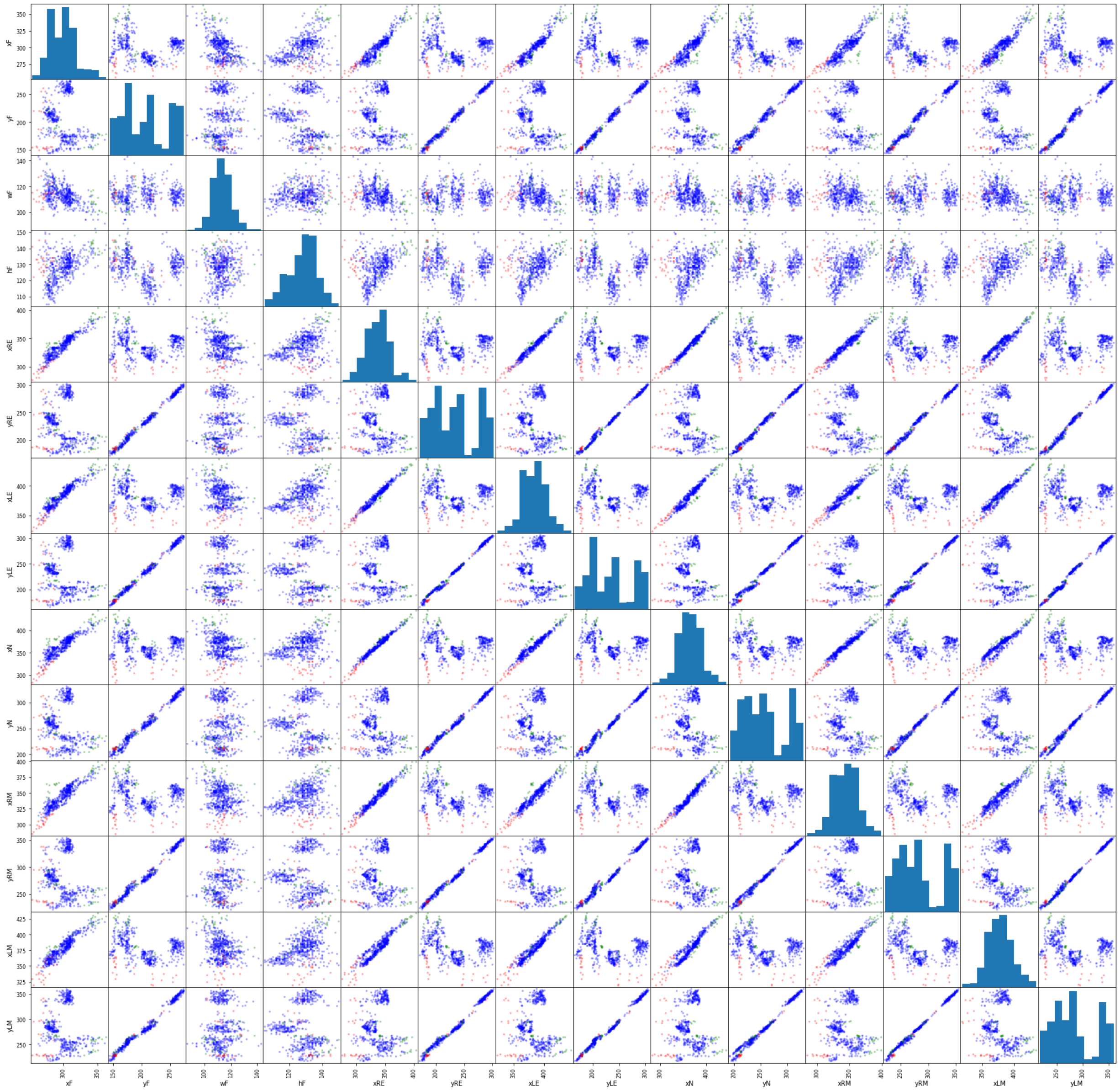


In [13]:

```
# We can see that each subject has a unique distribution of eye movements.
# to identify a specific subject based on their eye movements.
# We can assume that subjects 3's eyes are on average fixed on a point in th
# Subject 1's eyes are fixed lower, but mainly forward as well.  Subject 4 l
# a tendancy to scan with their eyes to the left and right. Subject 2 looks
# and looks up slightly farther down the road.
```

In [14]:

```
# Scatter matrix plot showing all plots between attributes

feature_cols = list(dataset.columns[4:])
color_map = {1:'red', 2:'blue', 3:'green'}
color_mapper = dataset['label'].map(lambda x: color_map.get(x))
scatter_matrix = pd.plotting.scatter_matrix(dataset[feature_cols], c = color
plt.show()

# In the scatter matrix below, we can quickly identify patterns between attr
# and decide which attributes to investigate.
```

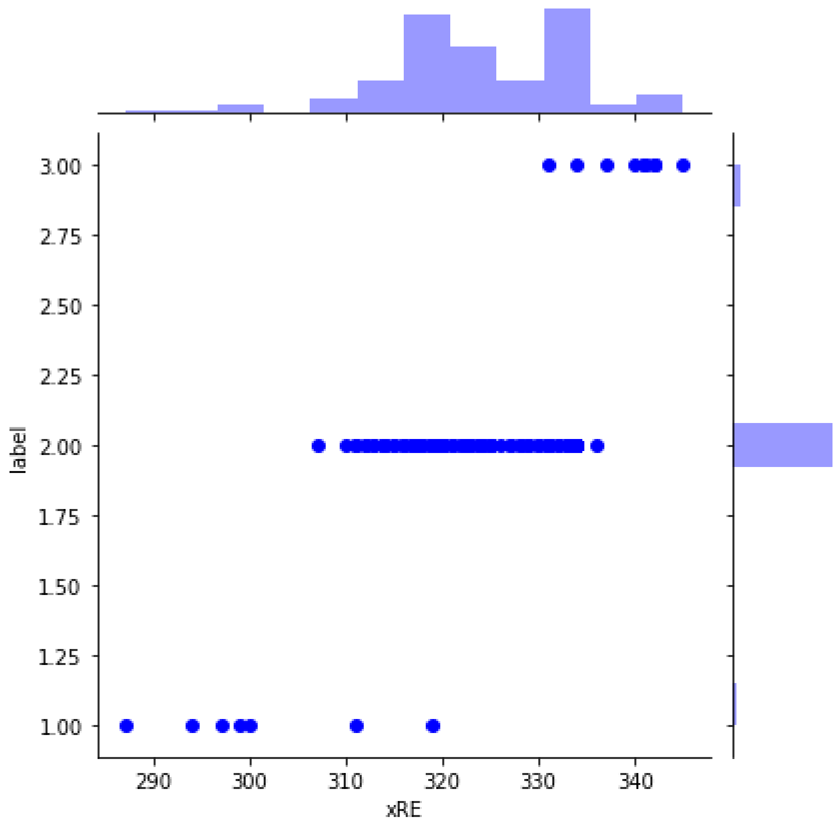


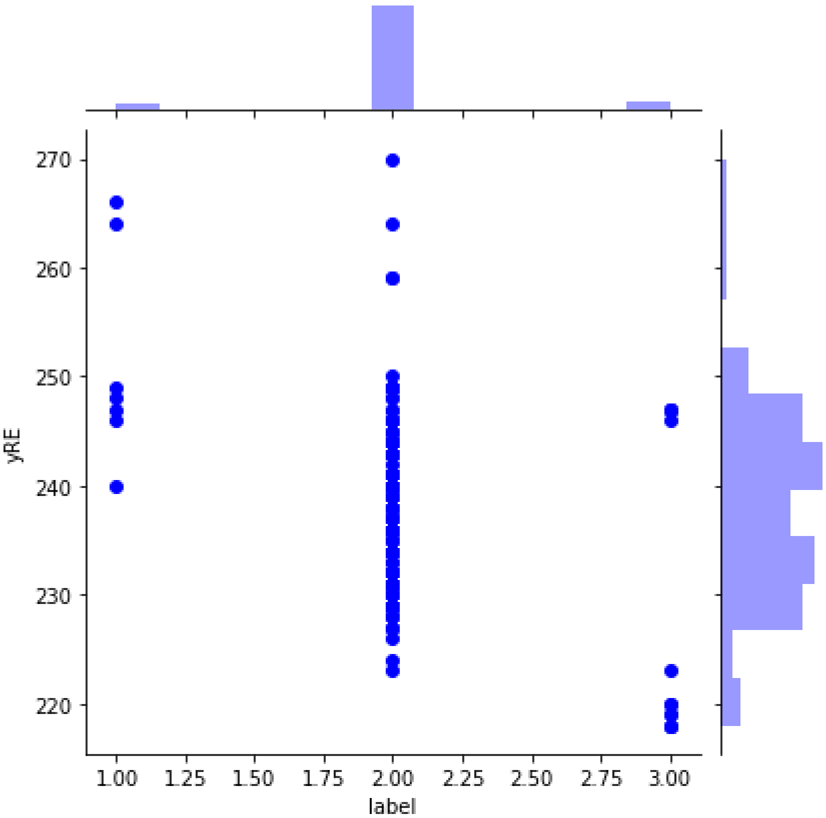
In [15]:

```
# As the class is the 'label' value, tracking a users gaze between frontal,
# able to plot the x,y values for the left and right eyes against the label
# will do this for each subject.

# Plot of right eye x-coordinate vs label.  Again as left eye mimicks the ri
# the right eye movements is a good representation for both.

# Subject 1:
sea.jointplot(x = "xRE", y = "label", data = X_subject_1, color = "blue")
sea.jointplot(x = "label", y = "yRE", data = X_subject_1, color = "blue")
```

Out[15]:

```
<seaborn.axisgrid.JointGrid at 0x2279d04da20>
```

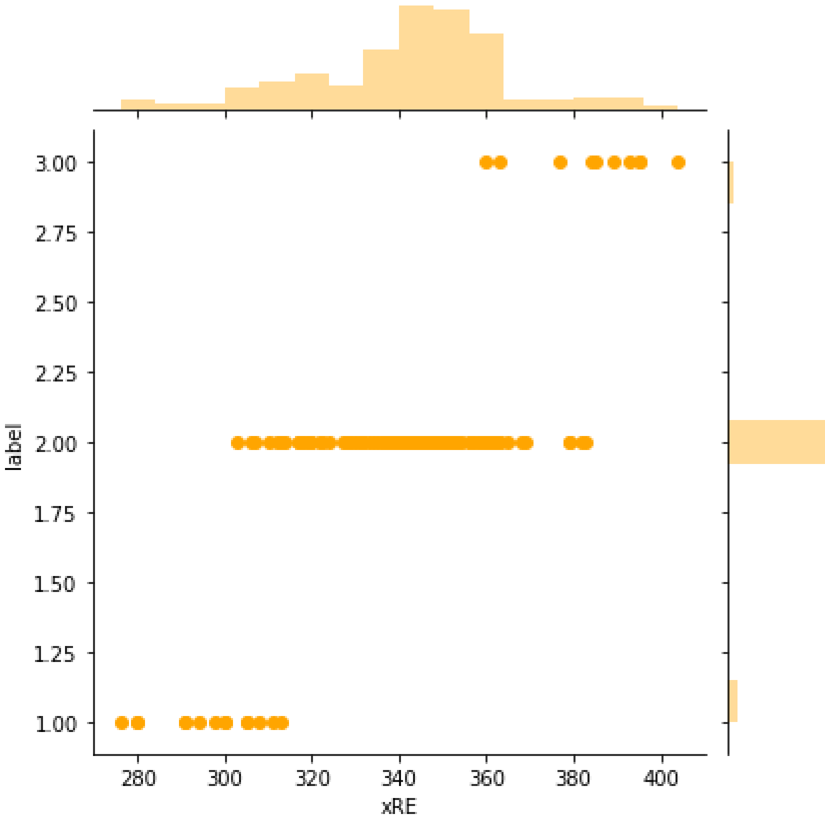


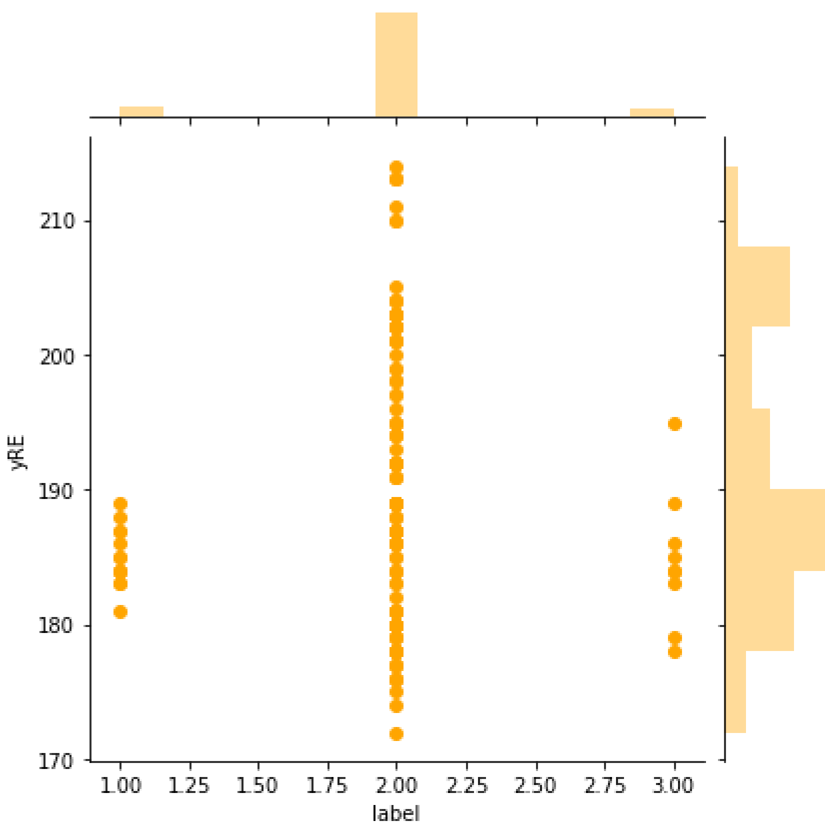


270
260
250
240
230
220
yRE
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00
label

In [16]:
```
# Subject 2:
sea.jointplot(x = "xRE", y = "label", data = X_subject_2, color = "orange")
sea.jointplot(x = "label", y = "yRE", data = X_subject_2, color = "orange")
```

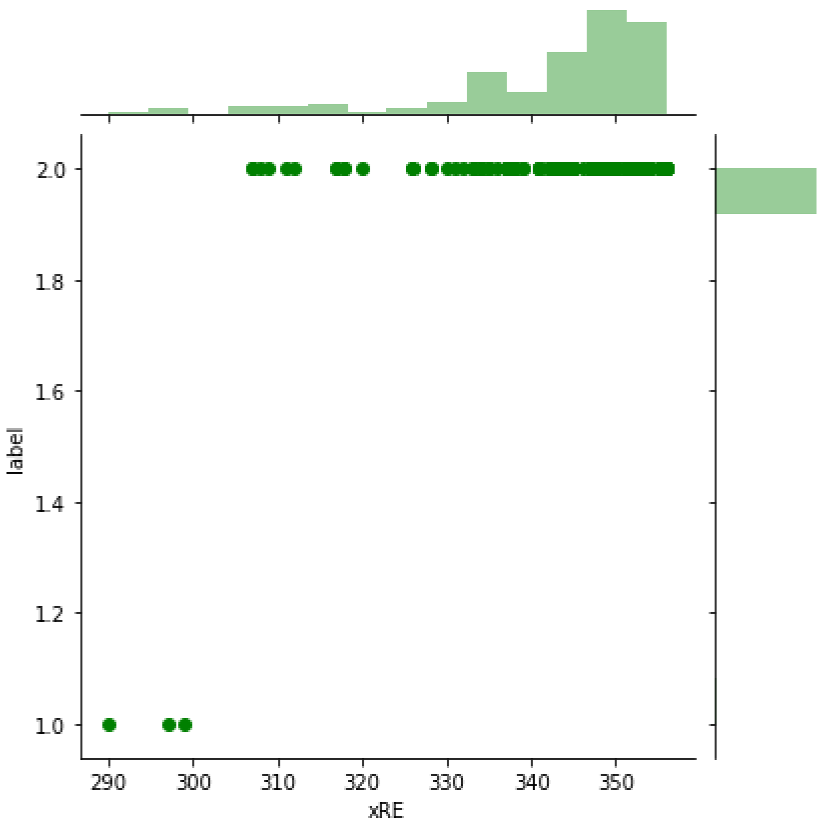
Out[16]: <seaborn.axisgrid.JointGrid at 0x2279d264828>

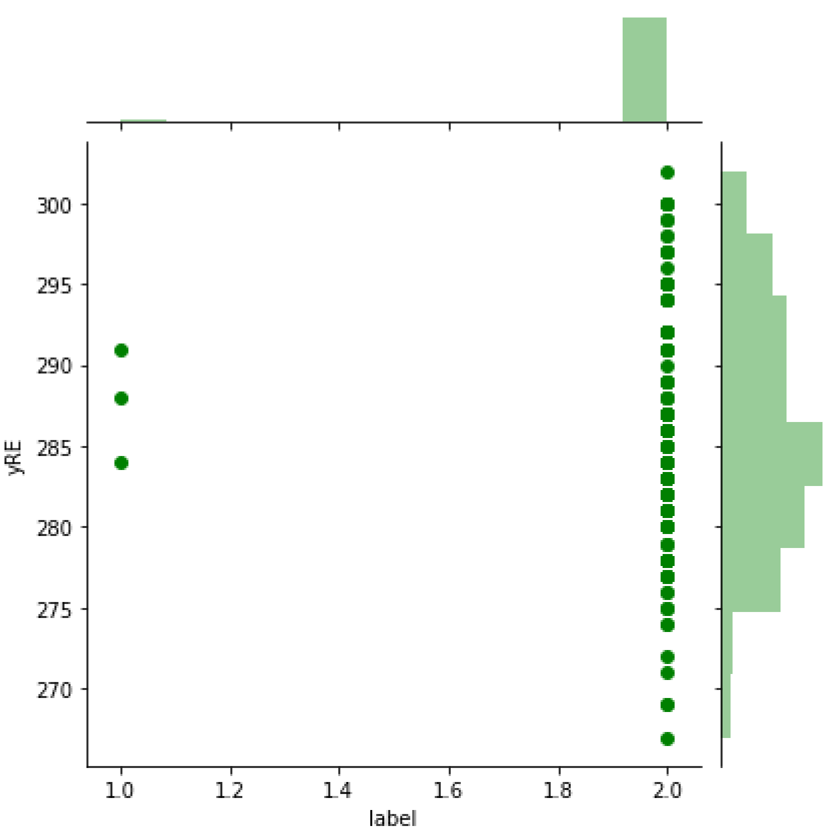




In [17]:
```
# Subject 3:
sea.jointplot(x = "xRE", y = "label", data = X_subject_3, color = "green")
sea.jointplot(x = "label", y = "yRE", data = X_subject_3, color = "green")
```

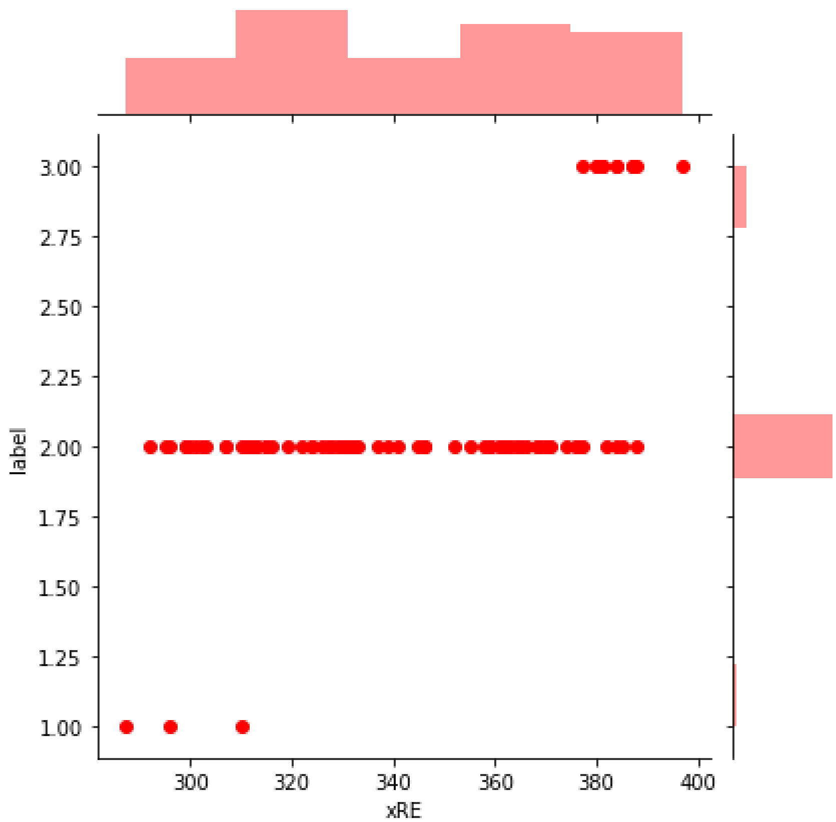
Out[17]: <seaborn.axisgrid.JointGrid at 0x2279c0019b0>

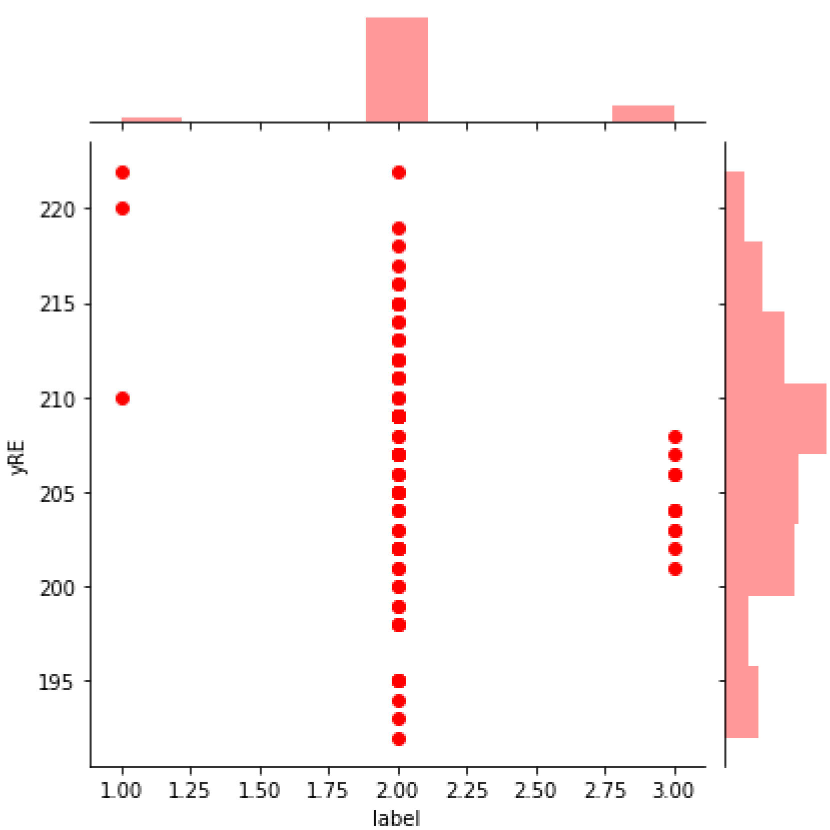




In [18]:
```
# Subject 4:
sea.jointplot(x = "xRE", y = "label", data = X_subject_4, color = "red")
sea.jointplot(x = "label", y = "yRE", data = X_subject_4, color = "red")
```

Out[18]: <seaborn.axisgrid.JointGrid at 0x2279c3b9a58>



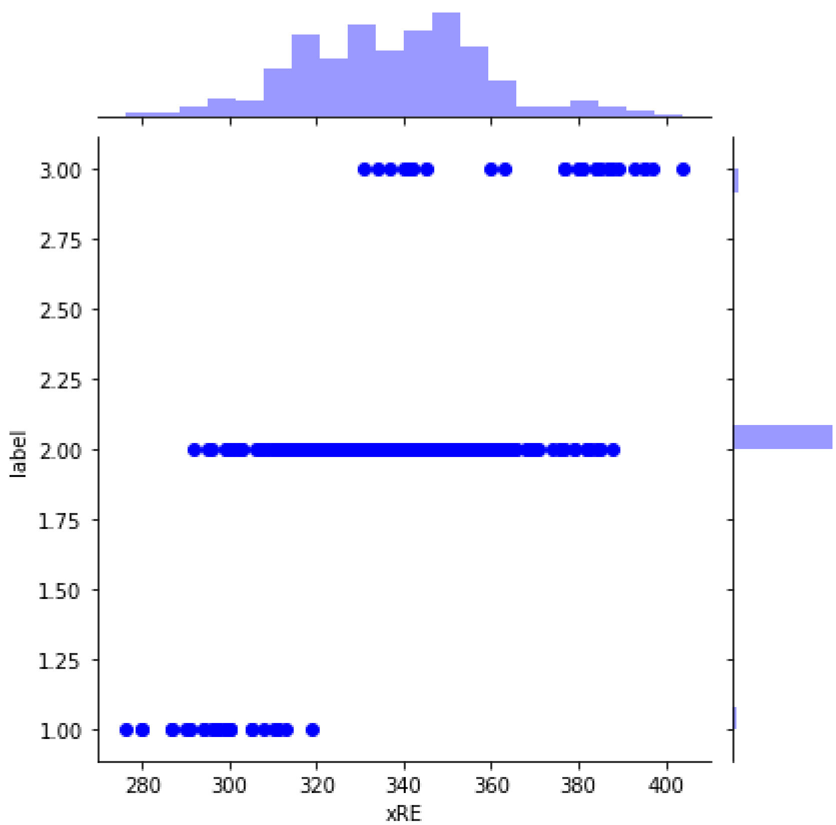


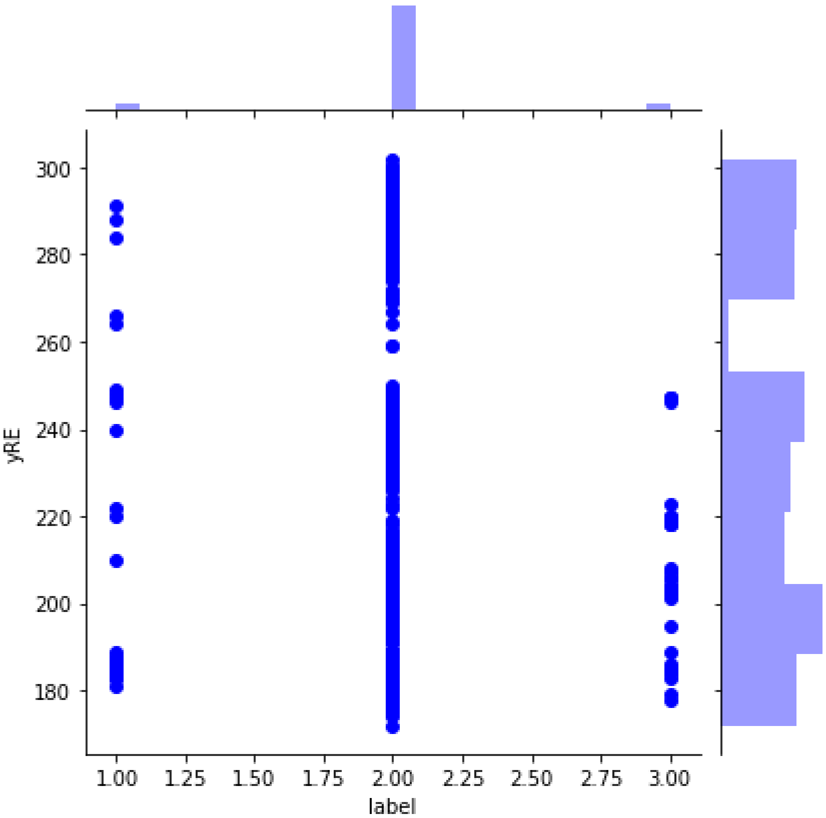
In [19]:

```python
# Can quickly see that subject 3 never looked to the right, as indicated by
# As well subject 3 hardly looked anywhere but forward.

# Lets view them all in a single jointplot to see the avg distribution

# All subjects:
sea.jointplot(x = "xRE", y = "label", data = dataset, color = "blue")
sea.jointplot(x = "label", y = "yRE", data = dataset, color = "blue")
```

Out[19]:

```
<seaborn.axisgrid.JointGrid at 0x2279c001ac8>
```





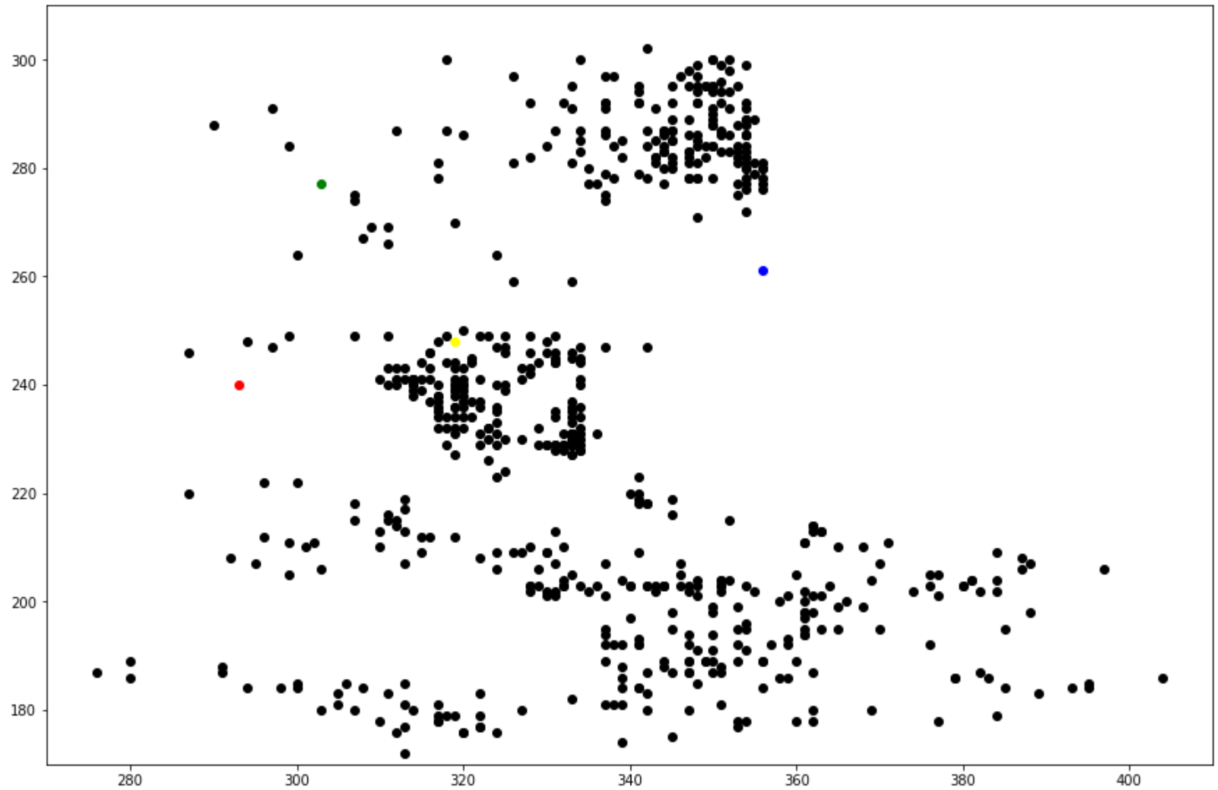
In [20]:
```
# There is a sensible pattern, however the overlap of the eye movements over
# label refers to the direction of the drivers face: 1 = left, 2 = front
# 3 = right.  However we plotted the eye direction, so a driver could have
# been looking to the right, with their eyes shifted to the left, and
# vice versa.
```

K - MEANS CLUSTERING & HIERARCHICAL

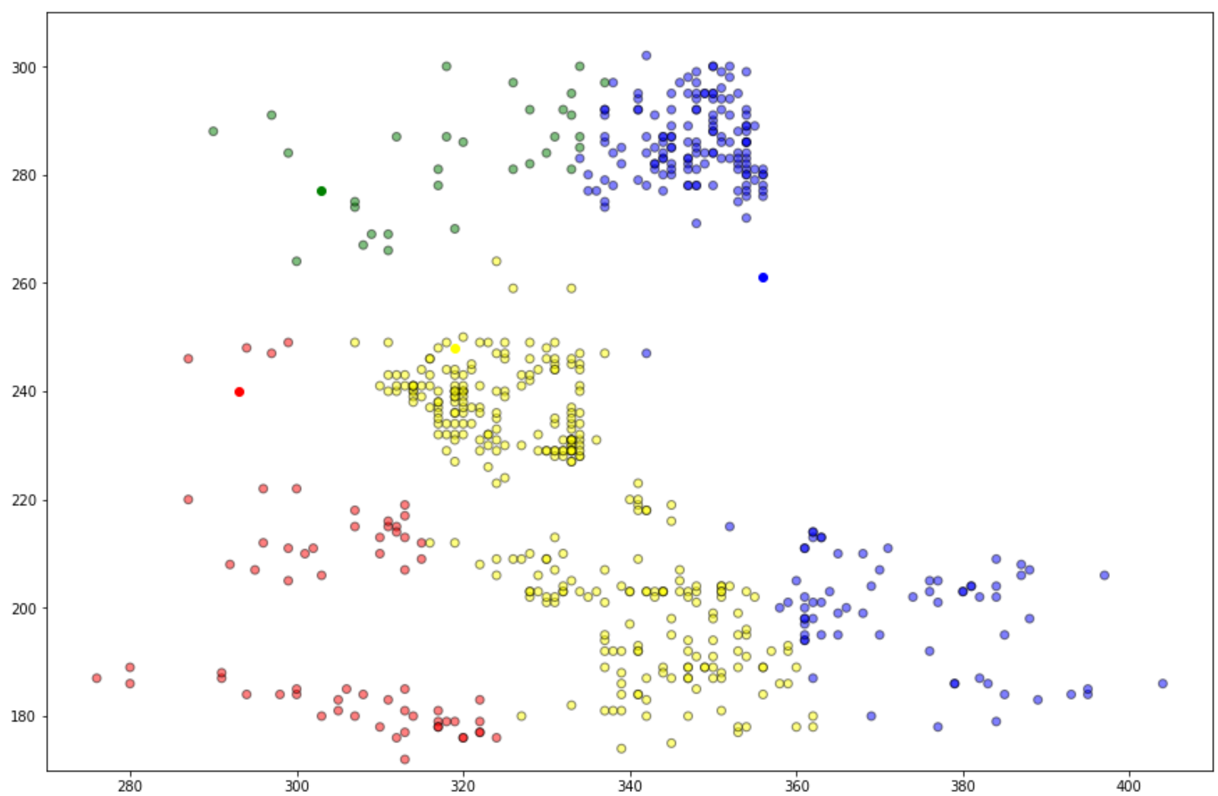
In [21]:

```
# Let's see how clustering performs for a couple attributes.  Let's see if w
# based on the eye movements.

# Initialize

# try k = 4 (subjects)
# find max & min of xRE and yRE
df = dataset.copy()

print(df.xRE.max())
print(df.xRE.min())
print(df.yRE.max())
print(df.yRE.min())
np.random.seed(200)
k = 4
centroids = {
    i+1: [np.random.randint(277, 403), np.random.randint(172, 301)]
    for i in range(k)
}
print(centroids)
plt.figure(figsize = (15,10))
plt.scatter(x = df.xRE, y = df.yRE, color = 'black')
color_map = {1: 'green', 2: 'red', 3: 'yellow', 4: 'blue'}
for i in centroids.keys():
    plt.scatter(*centroids[i], color = color_map[i])
plt.xlim(270, 410)
plt.ylim(170, 310)
plt.show()
```

```
404
276
302
172
{1: [303, 277], 2: [293, 240], 3: [319, 248], 4: [356, 261]}
```

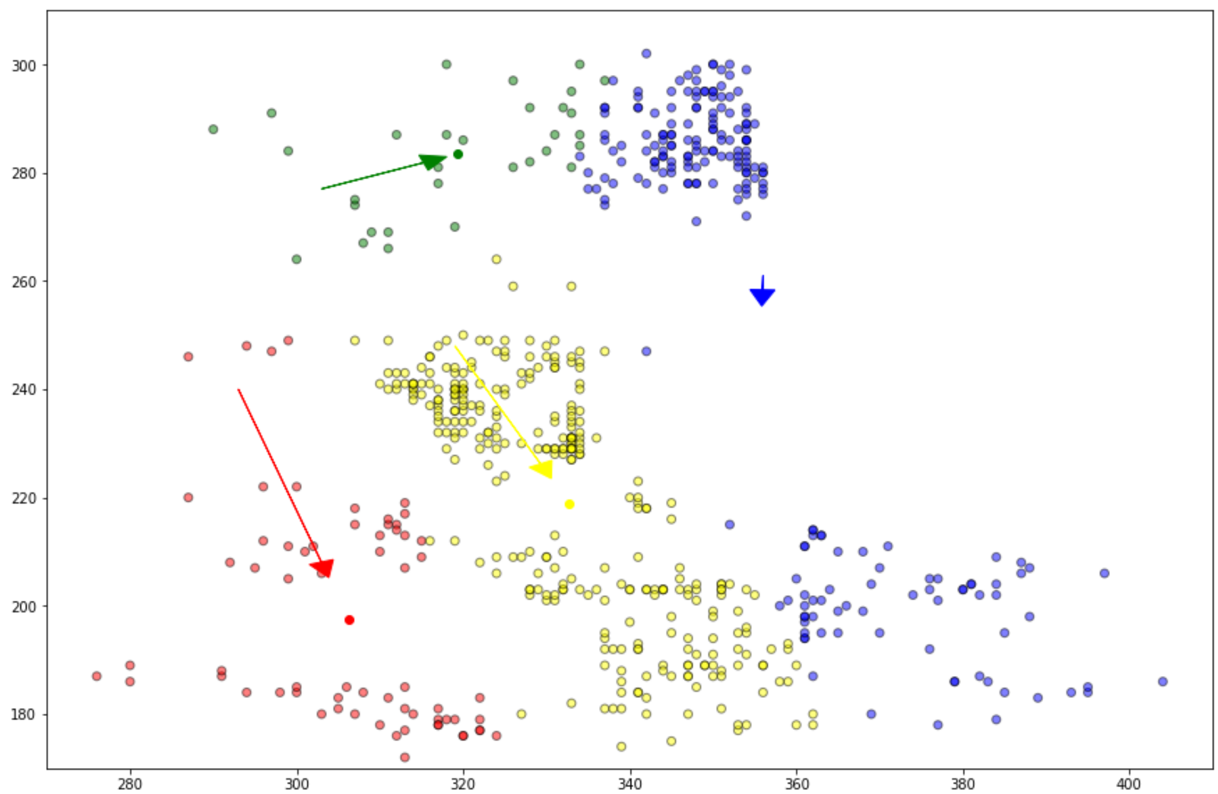

300
280
260
240
220
200
180
280
300
320
340
360
380
400

In [22]:
```
# Assignment

def assignment(df, centroids):
    for i in centroids.keys():
        df['distance_from_{}'.format(i)] = (
            np.sqrt(
                (df['xRE'] - centroids[i][0]) ** 2
                + (df['yRE'] - centroids[i][1]) ** 2
            )
        )
    centroid_distance_cols = ['distance_from_{}'.format(i) for i in centroid
    df['closest'] = df.loc[:, centroid_distance_cols].idxmin(axis = 1)
    df['closest'] = df['closest'].map(lambda x: int(x.lstrip('distance_from_
    df['color'] = df['closest'].map(lambda x: color_map[x])
    return df

df = assignment(df, centroids)
plt.figure(figsize = (15, 10))
plt.scatter(x = df.xRE, y = df.yRE, color = df.color, alpha = 0.5, edgecolor
for i in centroids.keys():
    plt.scatter(*centroids[i], color = color_map[i])
    #ax.arrow(old_x, old_y, dx, dy, head_width = 2, head_length = 3, fc = co
plt.xlim(270, 410)
plt.ylim(170, 310)
plt.show()
```



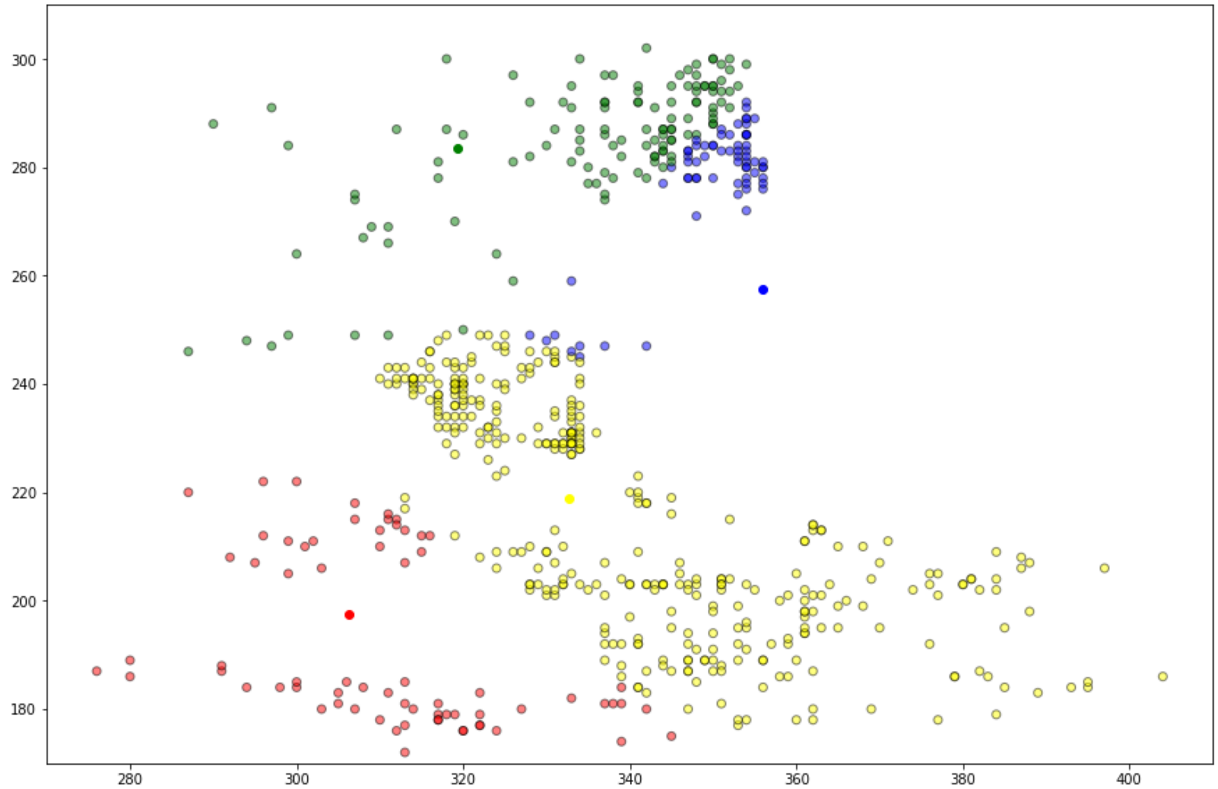
In [23]:

```
# Update

old_centroids = copy.deepcopy(centroids)

def update(k):
    for i in centroids.keys():
        centroids[i][0] = np.mean(df[df['closest'] == i]['xRE'])
        centroids[i][1] = np.mean(df[df['closest'] == i]['yRE'])
    return k

centroids = update(centroids)

plt.figure(figsize = (15, 10))
ax = plt.axes()
plt.scatter(x = df.xRE, y = df.yRE, color = df.color, alpha = 0.5, edgecolor
for i in centroids.keys():
    plt.scatter(*centroids[i], color = color_map[i])
plt.xlim(270, 410)
plt.ylim(170, 310)
for i in old_centroids.keys():
    old_x = old_centroids[i][0]
    old_y = old_centroids[i][1]
    dx = (centroids[i][0] - old_centroids[i][0]) * 0.75
    dy = (centroids[i][1] - old_centroids[i][1]) * 0.75
    ax.arrow(old_x, old_y, dx, dy, head_width = 3, head_length = 3, fc = col
plt.show()
```



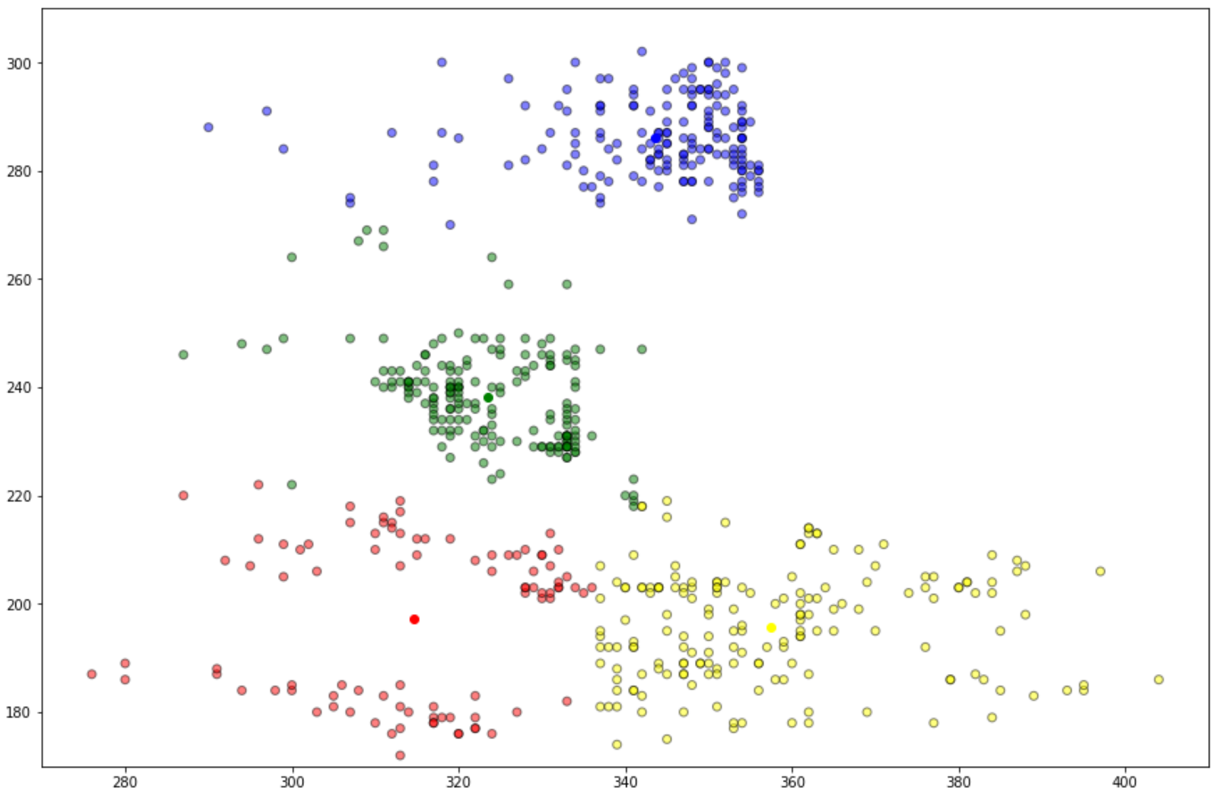
In [24]:

```
df = assignment(df, centroids)
fig = plt.figure(figsize = (15, 10))
plt.scatter(x = df.xRE, y = df.yRE, color = df['color'], alpha = 0.5, edgeco
for i in centroids.keys():
    plt.scatter(*centroids[i], color = color_map[i])
plt.xlim(270, 410)
plt.ylim(170, 310)
plt.show()
```



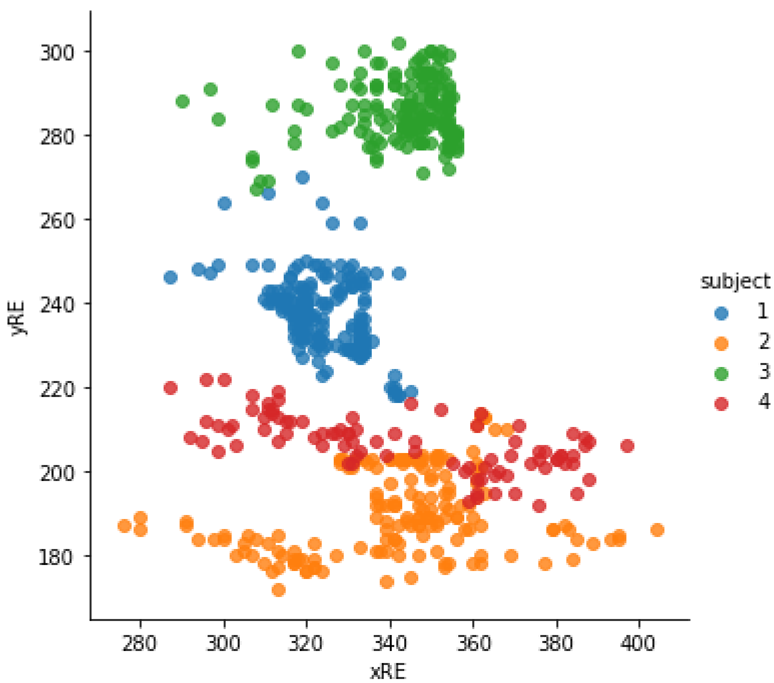
In [25]:

```python
# Loop to continue updates until centroid shift is under a certain value
while True:
    closest_centroids = df['closest'].copy(deep = True)
    centroids = update(centroids)
    df = assignment(df, centroids)
    if closest_centroids.equals(df['closest']):
        break

fig = plt.figure(figsize = (15, 10))
plt.scatter(x = df.xRE, y = df.yRE, color = df['color'], alpha = 0.5, edgeco
for i in centroids.keys():
    plt.scatter(*centroids[i], color = color_map[i])
plt.xlim(270, 410)
plt.ylim(170, 310)
plt.show()
```



In [26]:
```
# Original plot.
sea.lmplot(x = 'xRE', y = 'yRE', hue = 'subject', data = dataset, fit_reg =
```

Out[26]: <seaborn.axisgrid.FacetGrid at 0x2279d0a41d0>

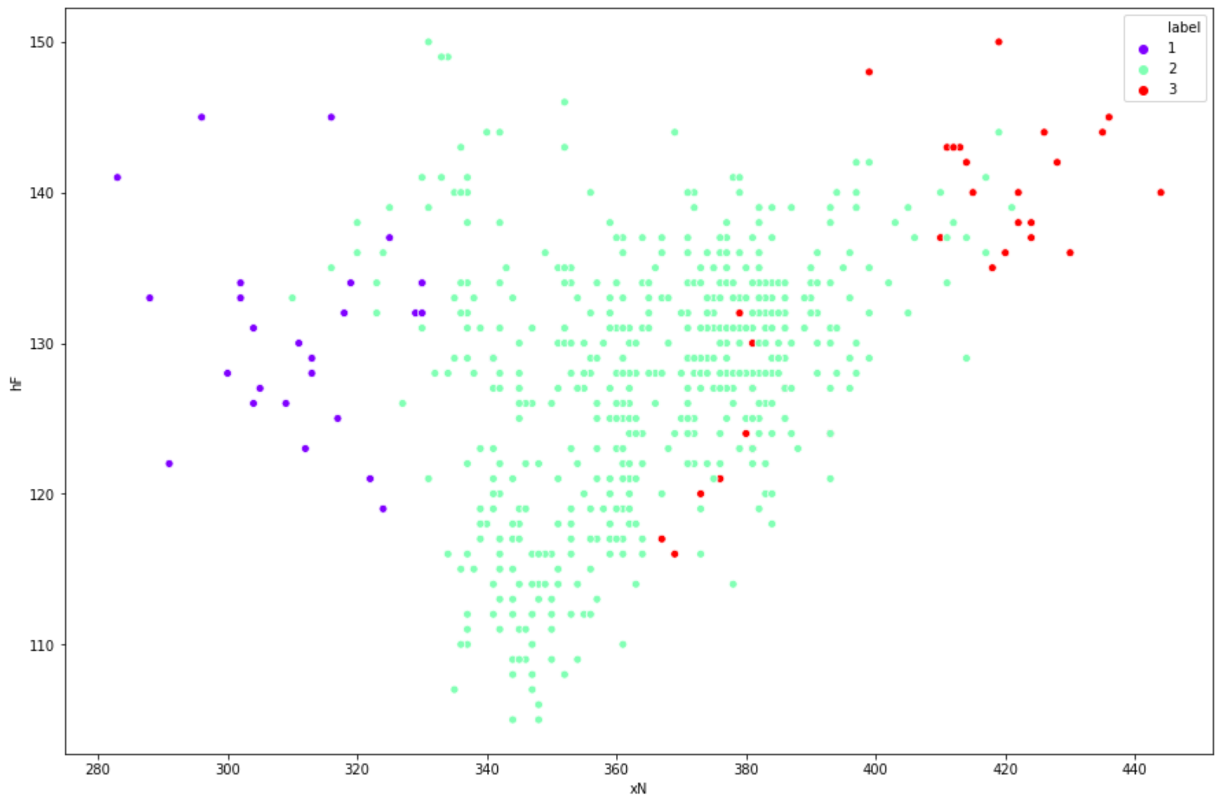


In [27]:
```
# Not bad, except subject 3 and 4's eye movements were seperated by clusteri
```

In [28]:

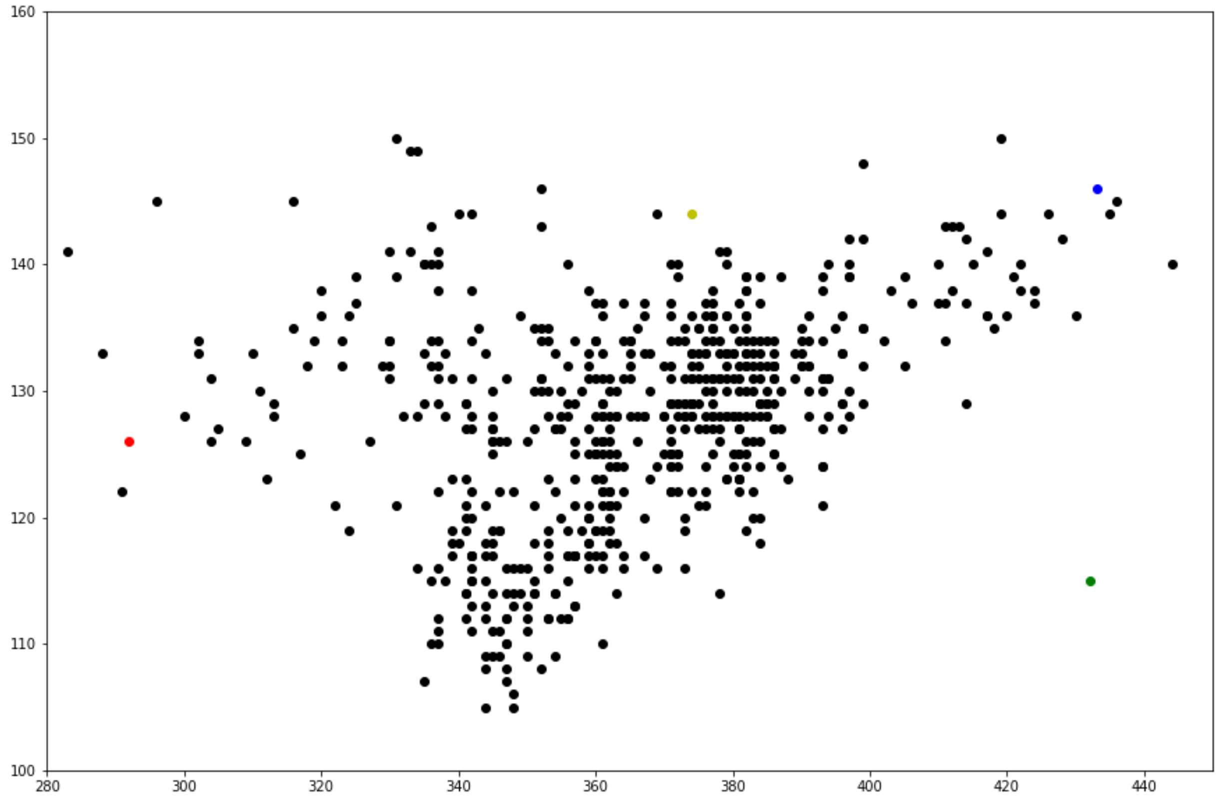
```python
# Lets try to estimate the label value of a driver using some other attribut

# Plot nose and a single measure of face position.
plt.figure(figsize = (15,10))
sea.scatterplot(x = 'xN',
                y = 'hF',
                hue = 'label',
                data = dataset,
                legend = 'full',
                palette = 'rainbow')
```

Out[28]: <matplotlib.axes._subplots.AxesSubplot at 0x2279ed995f8>



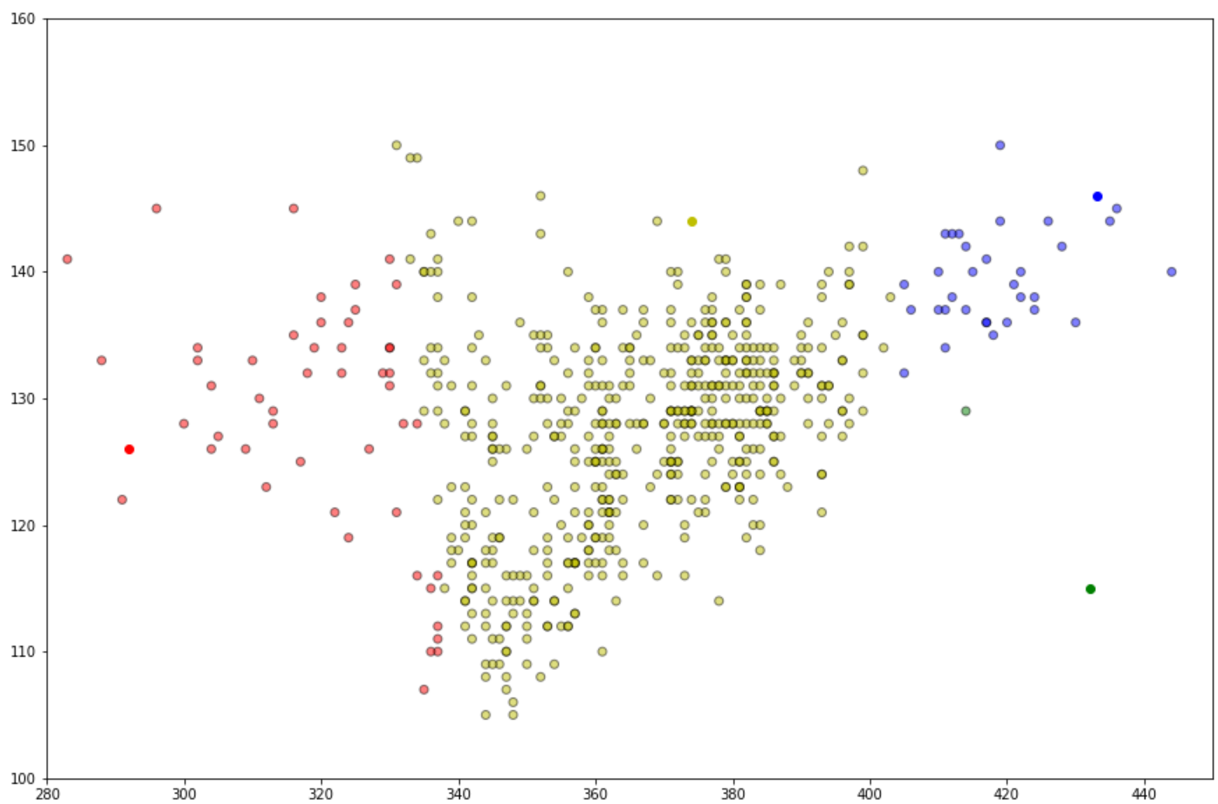
In [29]:
```
# Clustering with xN and hF could work.  Let's try clustering algorithm with
# The cluster alogithm below was originally completed with k = 3, however
# the result did not accurately represent the plot above. With k = 4,
# and combining the two central labels, the result is closer to the original
# plot above.  Perhaps the data would have been better represented with
# the frontal view split to front slight left, and front slight right.

# Initialize

# find max & min of xRE and yRE

df = dataset.copy()
print(df.xN.max())
print(df.xN.min())
print(df.hF.max())
print(df.hF.min())
np.random.seed(300)
k = 4
centroids = {
    i+1: [np.random.randint(283, 444), np.random.randint(105, 150)]
    for i in range(k)
}
print(centroids)
plt.figure(figsize = (15,10))
plt.scatter(x = df.xN, y = df.hF, color = 'black')
color_map = {1: 'g', 2: 'r', 3: 'y', 4: 'b'}
for i in centroids.keys():
    plt.scatter(*centroids[i], color = color_map[i])
plt.xlim(280, 450)
plt.ylim(100, 160)
plt.show()
```

```
444
283
150
105
{1: [432, 115], 2: [292, 126], 3: [374, 144], 4: [433, 146]}
```


160
150
140
130
120
110
100
280
300
320
340
360
380
400
420
440

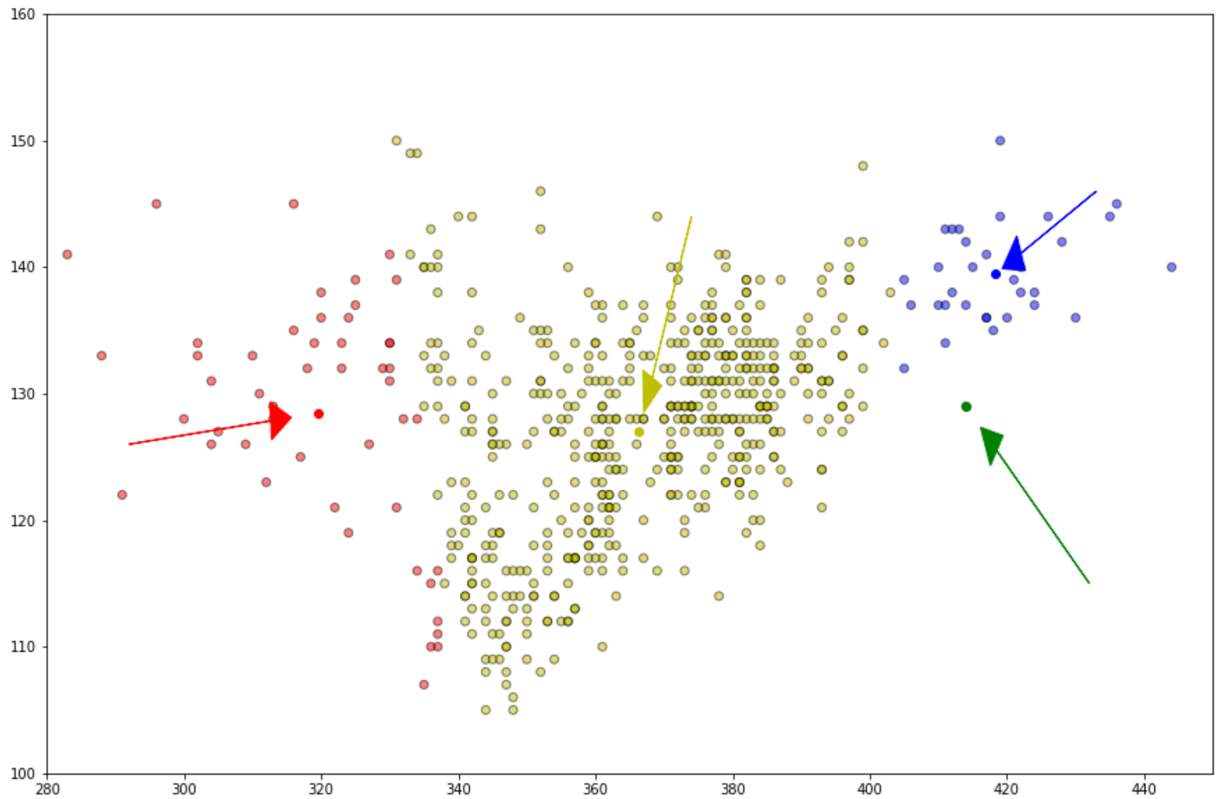
In [30]:

```
# Assignment

def assignment(df, centroids):
    for i in centroids.keys():
        df['distance_from_{}'.format(i)] = (
            np.sqrt(
                (df['xN'] - centroids[i][0]) ** 2
                + (df['hF'] - centroids[i][1]) ** 2
            )
        )
    centroid_distance_cols = ['distance_from_{}'.format(i) for i in centroid
    df['closest'] = df.loc[:, centroid_distance_cols].idxmin(axis = 1)
    df['closest'] = df['closest'].map(lambda x: int(x.lstrip('distance_from_
    df['color'] = df['closest'].map(lambda x: color_map[x])
    return df

df = assignment(df, centroids)
plt.figure(figsize = (15, 10))
plt.scatter(x = df.xN, y = df.hF, color = df.color, alpha = 0.5, edgecolor =
for i in centroids.keys():
    plt.scatter(*centroids[i], color = color_map[i])
    #ax.arrow(old_x, old_y, dx, dy, head_width = 2, head_length = 3, fc = co
plt.xlim(280, 450)
plt.ylim(100, 160)
plt.show()
```



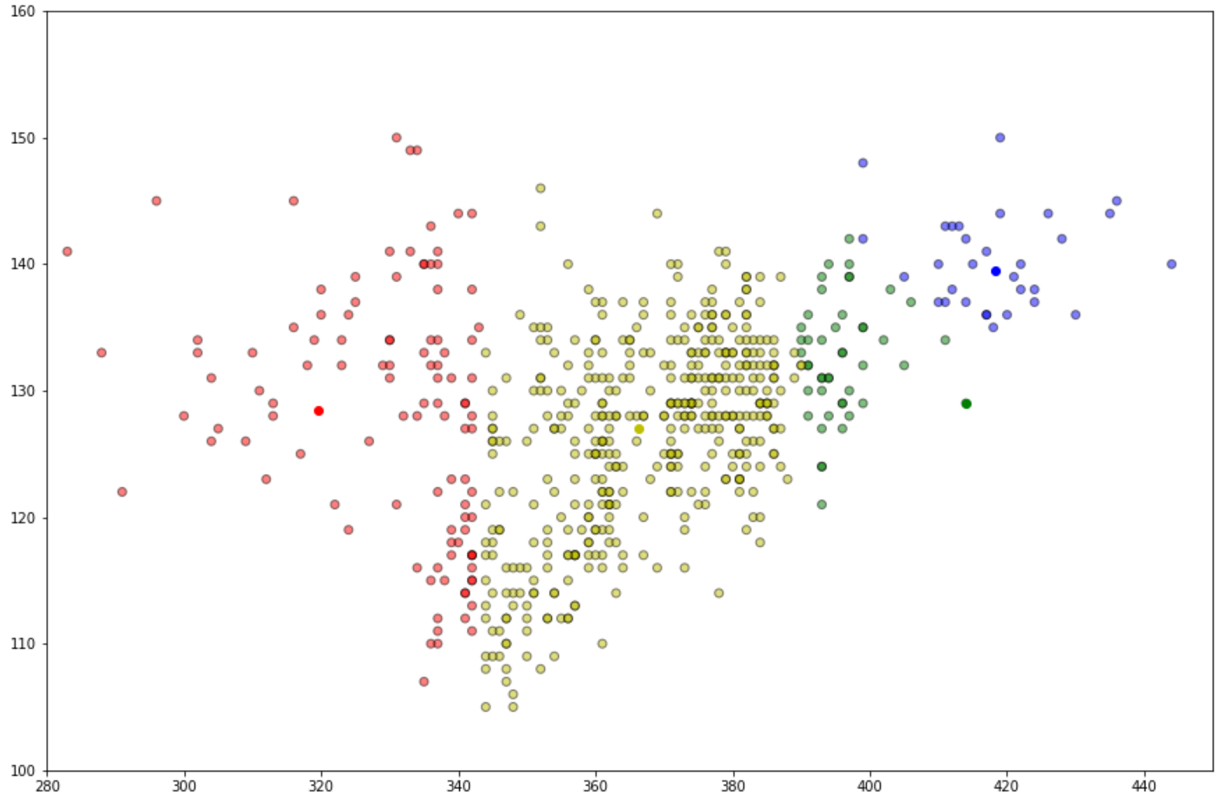
In [31]:

```python
# Update

old_centroids = copy.deepcopy(centroids)

def update(k):
    for i in centroids.keys():
        centroids[i][0] = np.mean(df[df['closest'] == i]['xN'])
        centroids[i][1] = np.mean(df[df['closest'] == i]['hF'])
    return k

centroids = update(centroids)

plt.figure(figsize = (15, 10))
ax = plt.axes()
plt.scatter(x = df.xN, y = df.hF, color = df.color, alpha = 0.5, edgecolor =
for i in centroids.keys():
    plt.scatter(*centroids[i], color = color_map[i])
plt.xlim(280, 450)
plt.ylim(100, 160)
for i in old_centroids.keys():
    old_x = old_centroids[i][0]
    old_y = old_centroids[i][1]
    dx = (centroids[i][0] - old_centroids[i][0]) * 0.75
    dy = (centroids[i][1] - old_centroids[i][1]) * 0.75
    ax.arrow(old_x, old_y, dx, dy, head_width = 3, head_length = 3, fc = col
plt.show()
```



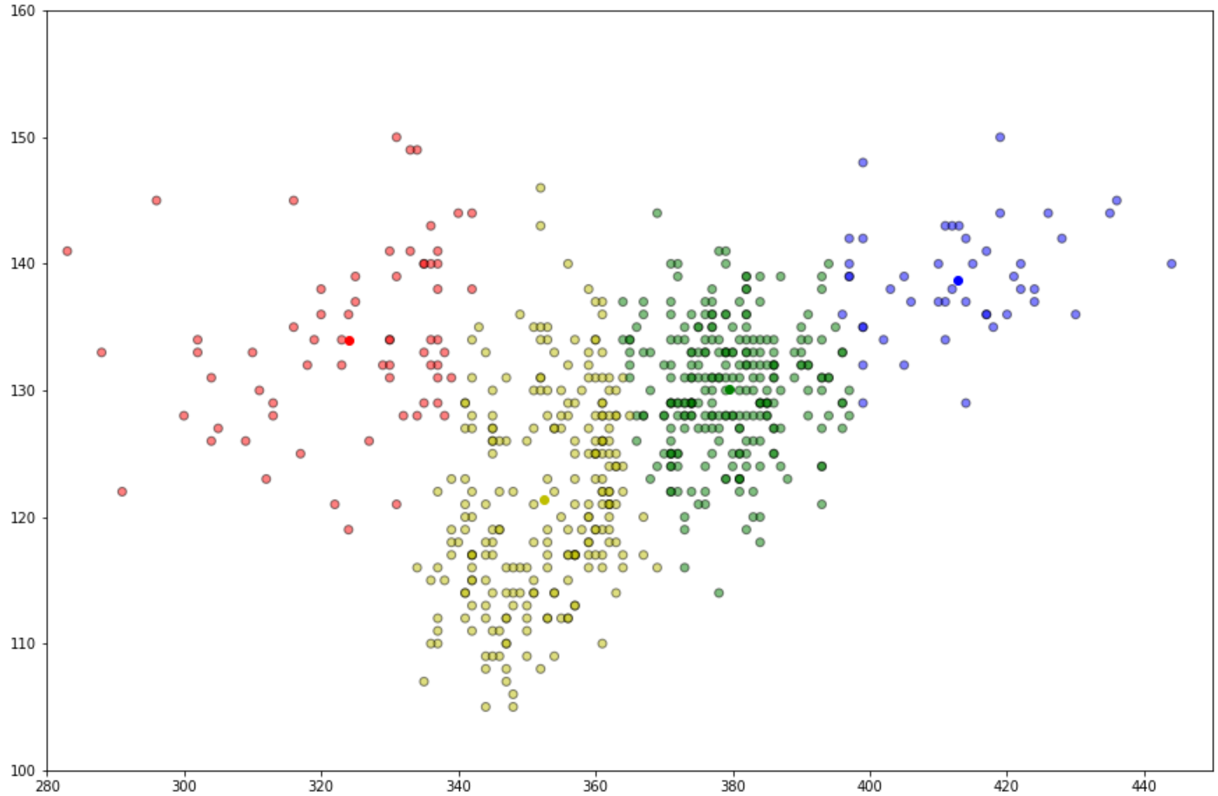
In [32]:

```
df = assignment(df, centroids)
fig = plt.figure(figsize = (15, 10))
plt.scatter(x = df.xN, y = df.hF, color = df['color'], alpha = 0.5, edgecolo
for i in centroids.keys():
    plt.scatter(*centroids[i], color = color_map[i])
plt.xlim(280, 450)
plt.ylim(100, 160)
plt.show()
```



In [33]:

```
# At this point we are somewhat close to the original xN, hF, label plot abo
# Let's keep going.

# Loop to continue updates until centroid shift is under a certain value
while True:
    closest_centroids = df['closest'].copy(deep = True)
    centroids = update(centroids)
    df = assignment(df, centroids)
    if closest_centroids.equals(df['closest']):
        break

fig = plt.figure(figsize = (15, 10))
plt.scatter(x = df.xN, y = df.hF, color = df['color'], alpha = 0.5, edgecolo
for i in centroids.keys():
    plt.scatter(*centroids[i], color = color_map[i])
plt.xlim(280, 450)
plt.ylim(100, 160)
plt.show()
```



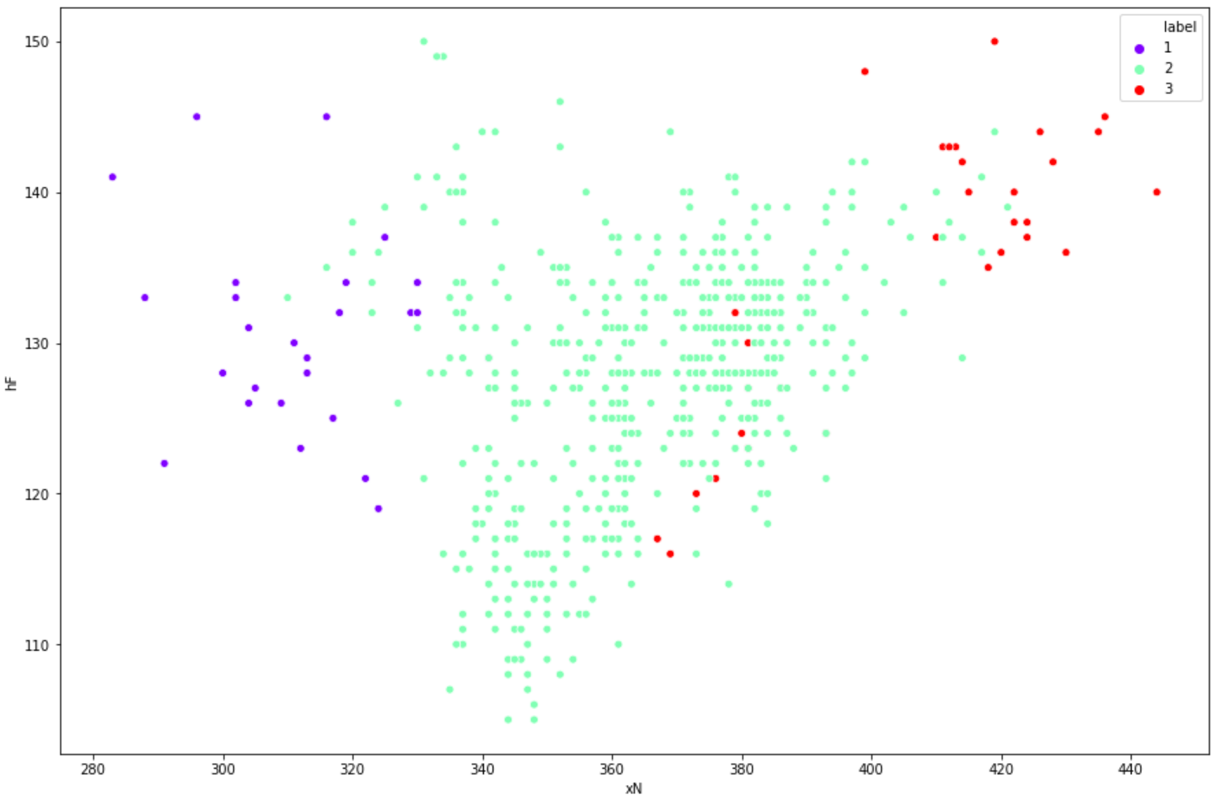
In [34]:

```
# Again, combining yellow and green (central labels) into a single
# label would provide an estimate for class not too far from the original
# plot, seen below. There is some degree of error however, but as the bulk
# of measurements are centrally located and captured within yellow and green
# the degree of error is minimized compared to data that is more equally dis
```

In [35]:

```python
# Original plot
plt.figure(figsize = (15,10))
sea.scatterplot(x = 'xN',
                y = 'hF',
                hue = 'label',
                data = dataset,
                legend = 'full',
                palette = 'rainbow')

```

Out[35]: `<matplotlib.axes._subplots.AxesSubplot at 0x2279ed928d0>`



In [36]:

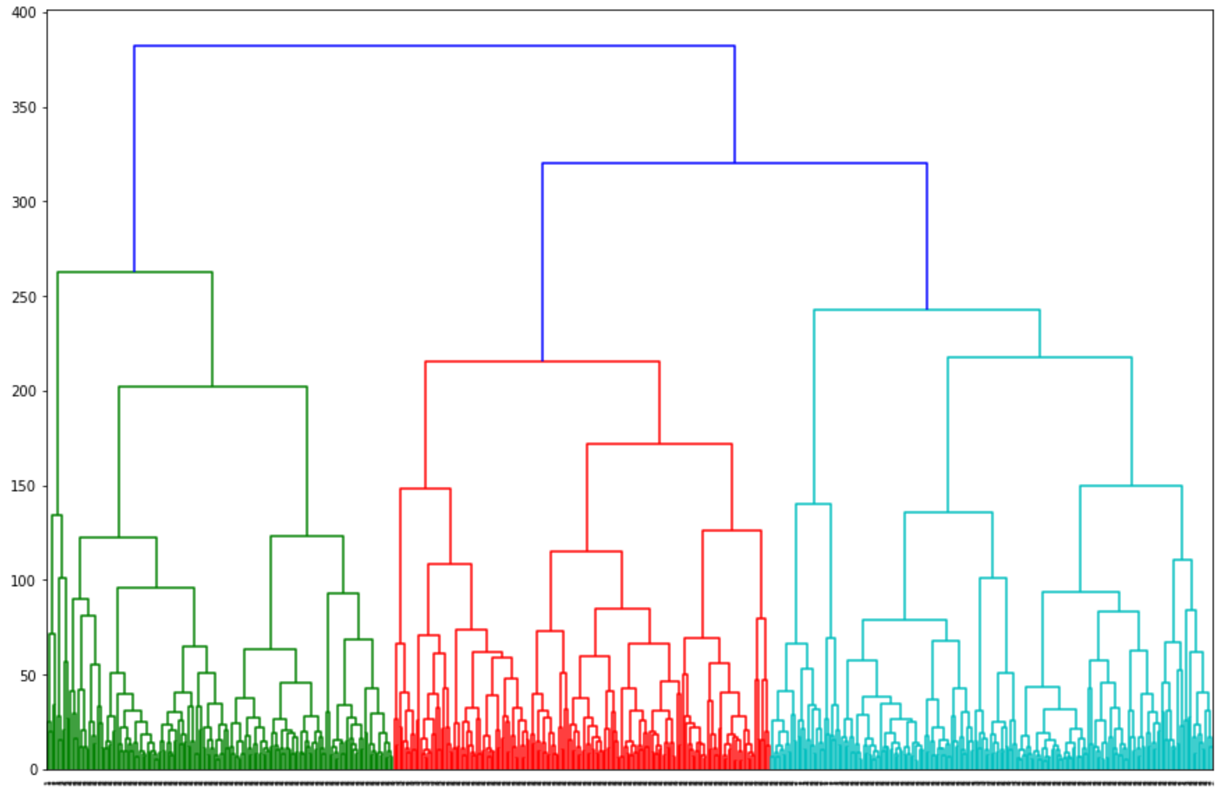
```python
# Apply Heirarchical Clustering

# Let's try various heirachical clustering methods on the attributes

from scipy.cluster.hierarchy import linkage, dendrogram
dataset = pd.read_csv('drivPoints.txt', index_col = 0)
df_hier = dataset.copy()
df_hier_class = list(df_hier.pop('label'))
numbers = dataset.values
numbers
```

Out[36]:

```
array([[  1,   1,   2, ..., 278, 361, 278],
       [  1,   2,   2, ..., 281, 361, 281],
       [  1,   3,   2, ..., 282, 362, 282],
       ...,
       [  4,  88,   1, ..., 272, 337, 270],
       [  4,  89,   2, ..., 261, 351, 251],
       [  4,  90,   2, ..., 255, 362, 247]], dtype=int64)
```

In [37]:

```
mergings = linkage(numbers, method  = 'complete')
plt.figure(figsize = (15,10))
dendrogram(mergings,
           labels = df_hier_class,
           leaf_rotation = 90,
           leaf_font_size = 6,
)
plt.show()
```

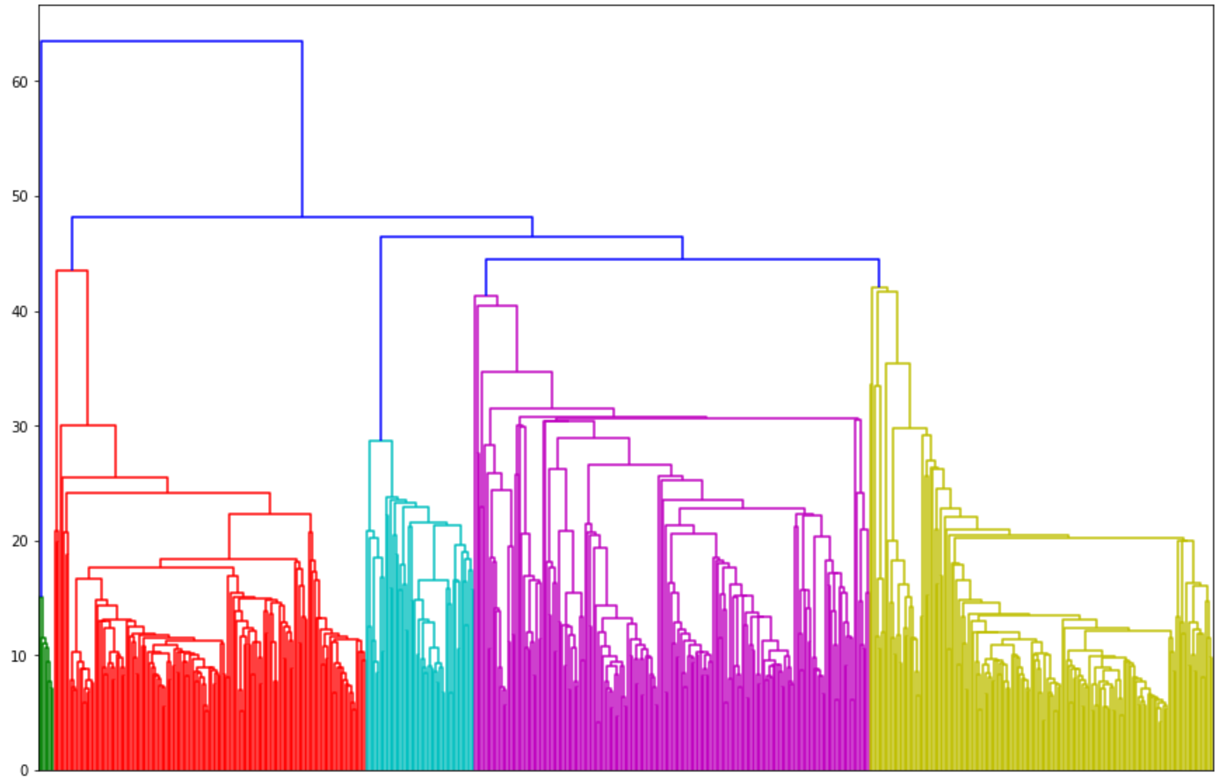


In [38]:

```
# Complete: Quite orderly with 3 clusters.
```

In [39]:

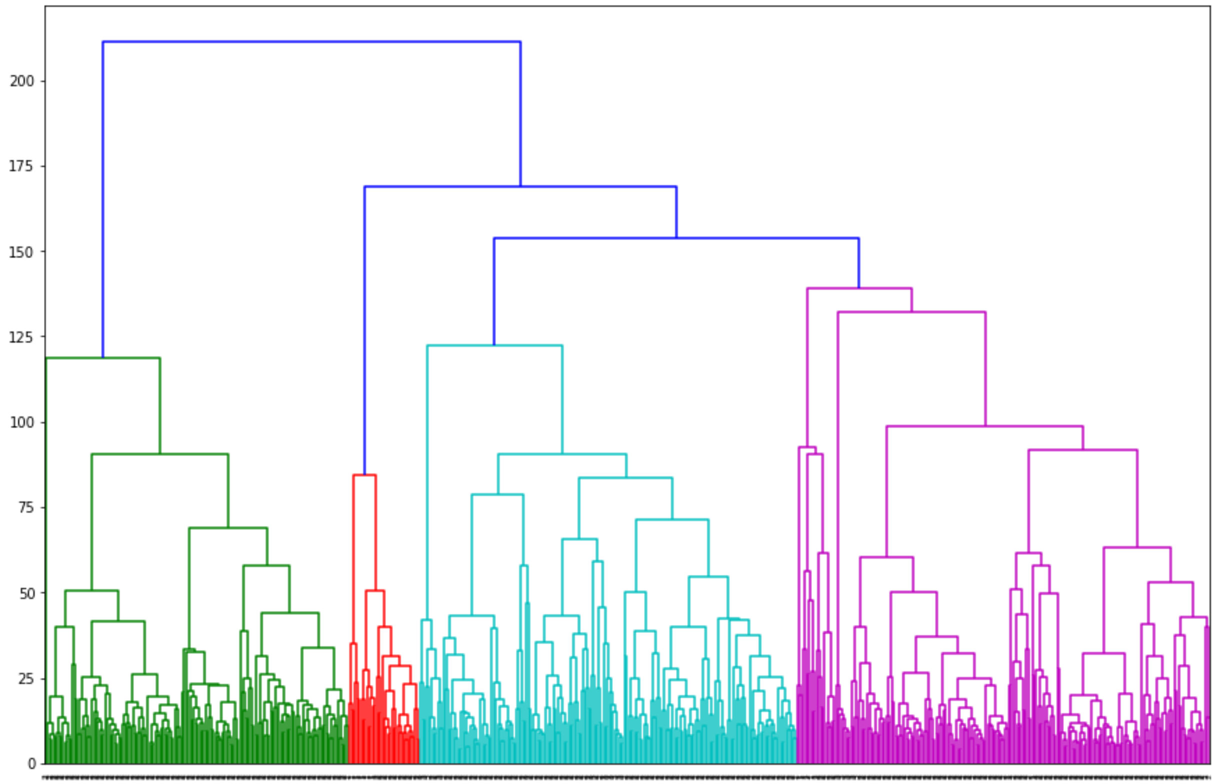
```
mergings = linkage(numbers, method  = 'single')
plt.figure(figsize = (15,10))
dendrogram(mergings,
           labels = df_hier_class,
           leaf_rotation = 90,
           leaf_font_size = 6,
)
plt.show()
```



In [40]:

```
# Single: If you look closely, theres 5 clusters.  Not too orderly or
# distributed
```

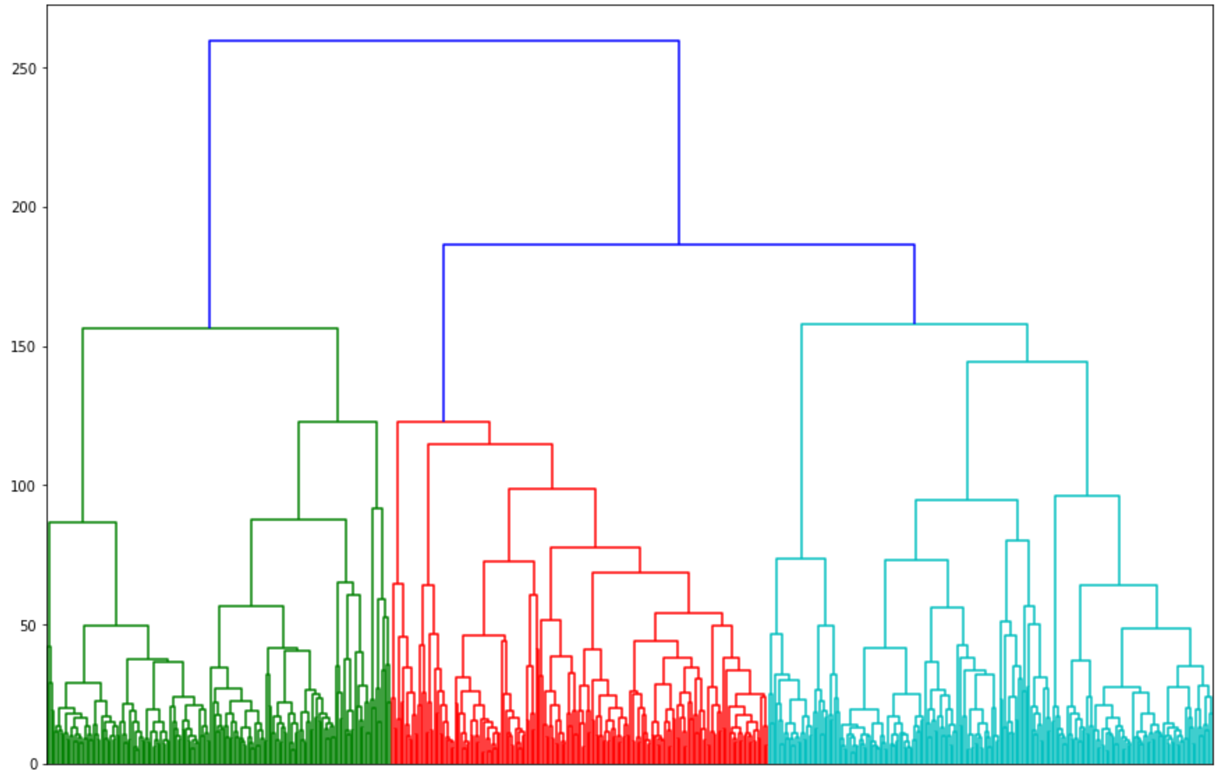
In [41]:
```
mergings = linkage(numbers, method  = 'average')
plt.figure(figsize = (15,10))
dendrogram(mergings,
           labels = df_hier_class,
           leaf_rotation = 90,
           leaf_font_size = 6,
)
plt.show()
```



In [42]:
```
# Average: Somewhat orderly.  4 clusters.
# Complete still the most orderly.
```

In [43]:

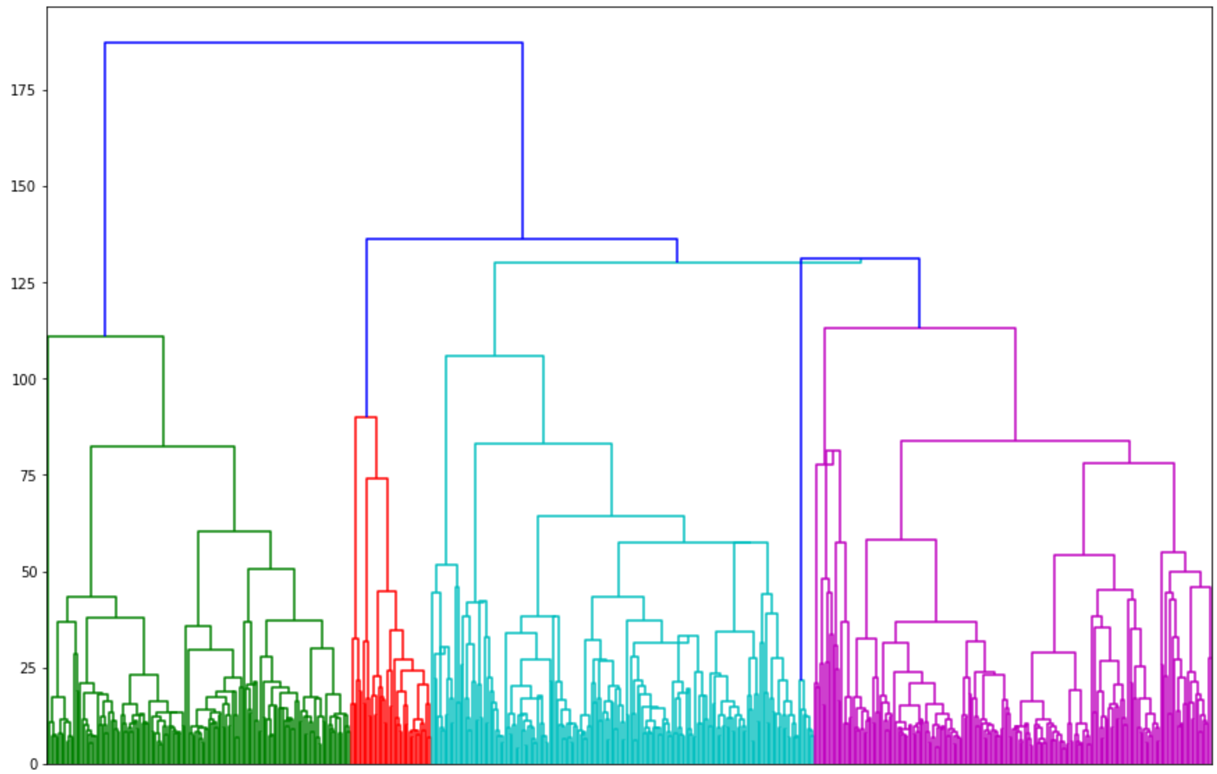
```
mergings = linkage(numbers, method  = 'weighted')
plt.figure(figsize = (15,10))
dendrogram(mergings,
           labels = df_hier_class,
           leaf_rotation = 90,
           leaf_font_size = 6,
)
plt.show()
```



In [44]:

```
# Weighted: Orderly, but as as much as complete. 3 clusters.
# Good distribution.
```

In [45]:
```
mergings = linkage(numbers, method  = 'centroid')
plt.figure(figsize = (15,10))
dendrogram(mergings,
           labels = df_hier_class,
           leaf_rotation = 90,
           leaf_font_size = 6,
)
plt.show()
```



In [46]:
```
# Centroid: Notice clustering returns with 4 clusters, which is what
# we found worked best from the k-means clustering. However, it is not
# as orderly as complete.

# From the dendrograms it appears that complete returns the best result,
# while maintaining clusters at k = 3.
```

Recursive Feature Selection and PCA

In [47]:
```
from sklearn.svm import SVC
from sklearn.model_selection import StratifiedKFold
from sklearn.feature_selection import RFECV
from sklearn.datasets import make_classification
from sklearn.linear_model import LogisticRegression
from sklearn.decomposition import PCA
%matplotlib inline
```

In [48]:
```
dataset.head()
```

Out[48]:

fileName	subject	imgNum	label	ang	xF	yF	wF	hF	xRE	yRE	xLE	yLE
20130529_01_Driv_001_f	1	1	2	0	292	209	100	112	323	232	367	231
20130529_01_Driv_002_f	1	2	2	0	286	200	109	128	324	235	366	235
20130529_01_Driv_003_f	1	3	2	0	290	204	105	121	325	240	367	239
20130529_01_Driv_004_f	1	4	2	0	287	202	112	118	325	230	369	230
20130529_01_Driv_005_f	1	5	2	0	290	193	104	119	325	224	366	225

In [49]:
```python
df = dataset.copy()
y = df['label'].values
label_store = df.pop('label')
subject_store = df.pop('subject')
df.pop('imgNum')
df.pop('ang')
X = df.values
print(df.head())
print("")
print(X)
print("")
print(y)
```

```
                       xF   yF   wF   hF  xRE  yRE  xLE  yLE   xN   yN  \
fileName
20130529_01_Driv_001_f  292  209  100  112  323  232  367  231  353  254
20130529_01_Driv_002_f  286  200  109  128  324  235  366  235  353  258
20130529_01_Driv_003_f  290  204  105  121  325  240  367  239  351  260
20130529_01_Driv_004_f  287  202  112  118  325  230  369  230  353  253
20130529_01_Driv_005_f  290  193  104  119  325  224  366  225  353  244

                       xRM  yRM  xLM  yLM
fileName
20130529_01_Driv_001_f  332  278  361  278
20130529_01_Driv_002_f  333  281  361  281
20130529_01_Driv_003_f  334  282  362  282
20130529_01_Driv_004_f  335  274  362  275
20130529_01_Driv_005_f  333  268  363  268

[[292 209 100 ... 278 361 278]
 [286 200 109 ... 281 361 281]
 [290 204 105 ... 282 362 282]
 ...
 [264 187 127 ... 272 337 270]
 [264 175 143 ... 261 351 251]
 [266 170 141 ... 255 362 247]]

[2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 1 1 1 1 2 2 2 2 2
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 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 3 3 3 3 3 3 3 3 3 3 3 3 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 3 2 2 2 2 2 2 2 2 2 2 2 2 2
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 3 2 2 2 2 3 3 3 3 2 2 2 2 2 2 2 2 2 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 1 2 2 2 3 3 3 3 3 3 3 3 3 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 3 3 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 1 1 2 2]
```

In [50]:
```
model = LogisticRegression(multi_class = 'ovr',solver = 'lbfgs', max_iter =
rfecv = RFECV(estimator = model, step = 1, cv = StratifiedKFold(10), scoring
rfecv.fit(X, y)
```

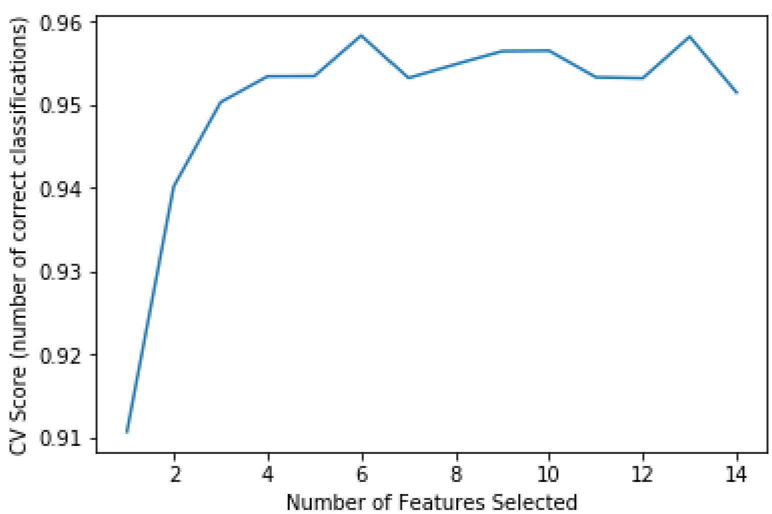
Out[50]:
```
RFECV(cv=StratifiedKFold(n_splits=10, random_state=None, shuffle=False),
   estimator=LogisticRegression(C=1.0, class_weight=None, dual=False, fit_inter
cept=True,
          intercept_scaling=1, max_iter=10000, multi_class='ovr',
          n_jobs=None, penalty='l2', random_state=None, solver='lbfgs',
          tol=0.0001, verbose=0, warm_start=False),
   min_features_to_select=1, n_jobs=None, scoring='accuracy', step=1,
   verbose=0)
```

In [51]:
```
print("Optimal number of features : " + str(rfecv.n_features_))
```

```
Optimal number of features : 6
```

In [52]:
```
plt.xlabel("Number of Features Selected")
plt.ylabel("CV Score (number of correct classifications)")
plt.plot(range(1, len(rfecv.grid_scores_) + 1), rfecv.grid_scores_)
```

Out[52]:
```
[<matplotlib.lines.Line2D at 0x2279f084ba8>]
```



In [53]:
```
rfecv.n_features_
```

Out[53]: 6

In [54]:
```
rfecv.support_
```

Out[54]:
```
array([False,  True, False, False,  True, False,  True, False,  True,
        True, False,  True, False, False])
```

In [55]:
```
rfecv.ranking_
```

Out[55]:
```
array([5, 1, 8, 9, 1, 2, 1, 7, 1, 1, 4, 1, 3, 6])
```

In [56]:
```
# The features selected are yF, xRE, xLE, xN, yN, yRM
```

In [57]:
```
# PCA

from sklearn import decomposition

print("Shape of Original Dataset is : " + str(X.shape))
X_red = df.values
pca = decomposition.PCA(n_components = 3)
pca.fit(X)
X_red = pca.transform(X_red)
```

```
Shape of Original Dataset is : (606, 14)
```

In [58]:
```
X_red
```

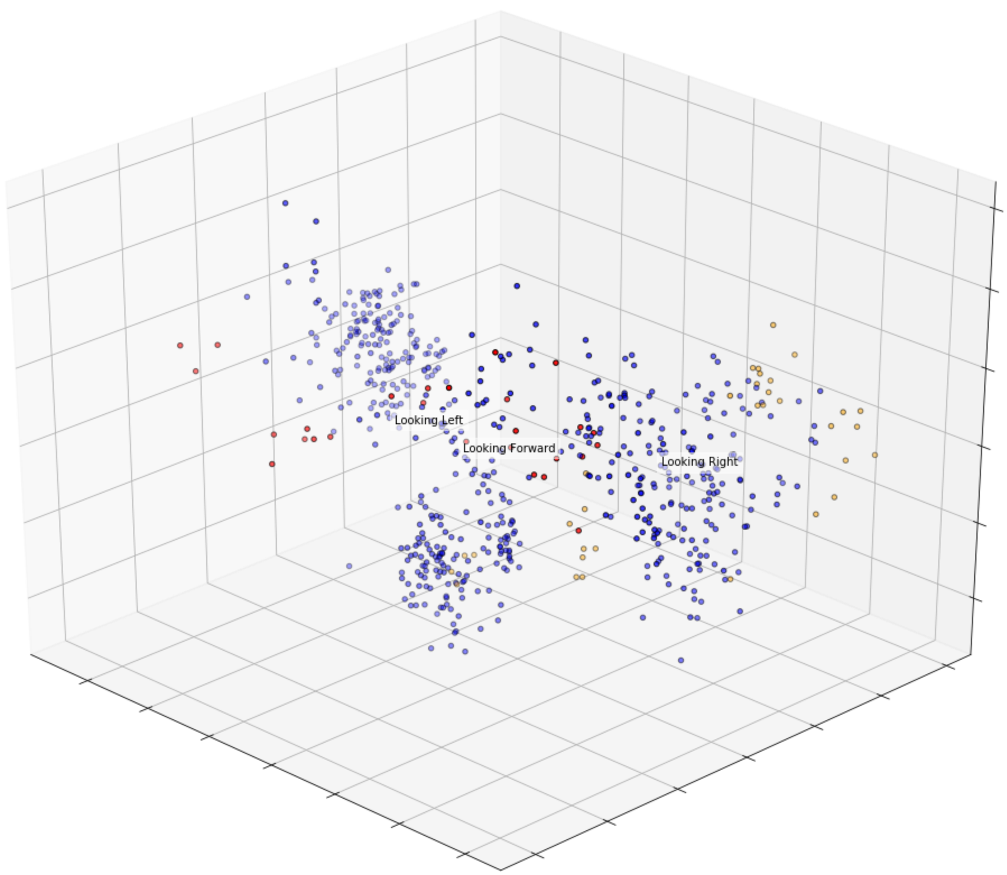
Out[58]:
```
array([[ -5.02483462,  33.29206542, -15.55607068],
       [ -1.69954237,  34.00519782,  -0.44559128],
       [  5.09979862,  32.0693496 ,  -5.98350046],
       ...,
       [-31.95085066, 115.98117104,  17.35342064],
       [-65.46335867,  93.97339745,  18.32652384],
       [-75.89991244,  75.11178559,  17.6630584 ]])
```

In [59]:
```
print("Shape of New Dataset is : " + str(X_red.shape))
```

```
Shape of New Dataset is : (606, 3)
```

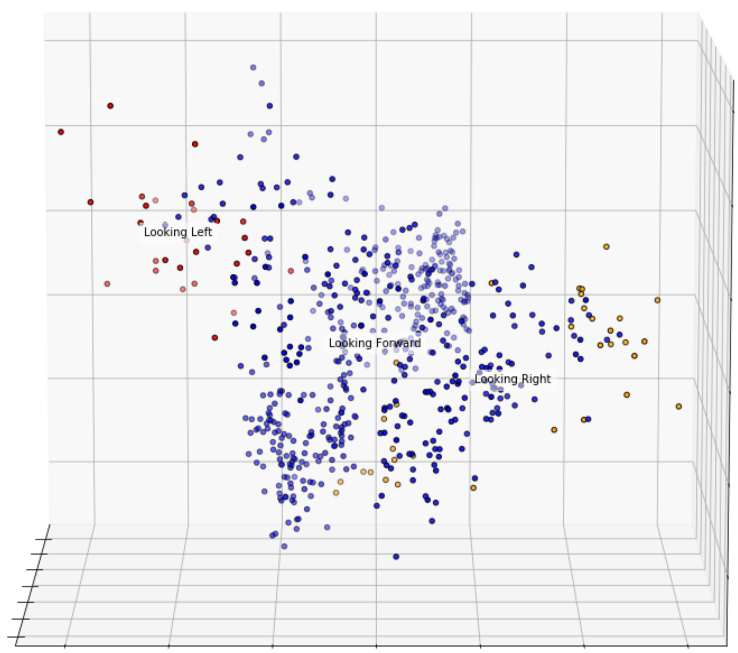
In [60]:

```
np.random.seed(5)

color_map = {1:'red', 2:'blue', 3:'orange'}
color_mapper = dataset['label'].map(lambda x: color_map.get(x))

centers = [[1, 1], [-1, -1], [1, -1]]

fig = plt.figure(1, figsize = (15, 12))
plt.clf()
ax = Axes3D(fig, rect = [0, 0, 1, 1], elev = 30, azim = 135)

for name, label in [('Looking Left', 1), ('Looking Forward', 2), ('Looking R
    ax.text3D(X_red[y == label, 0].mean(),
              X_red[y == label, 1].mean() + 1.5,
              X_red[y == label, 2].mean(), name,
              horizontalalignment = 'center',
              bbox = dict(alpha = .5, edgecolor = 'w', facecolor = 'w'))

ax.scatter(X_red[:, 0], X_red[:, 1], X_red[:, 2], c = color_mapper, edgecolo

ax.w_xaxis.set_ticklabels([])
ax.w_yaxis.set_ticklabels([])
ax.w_zaxis.set_ticklabels([])

plt.show()
```



In [61]:

```
fig = plt.figure(1, figsize = (15, 12))
plt.clf()
ax = Axes3D(fig, rect = [0, 0, 1, 1], elev = 10, azim = 180)

for name, label in [('Looking Left', 1), ('Looking Forward', 2), ('Looking R
    ax.text3D(X_red[y == label, 0].mean(),
              X_red[y == label, 1].mean() + 1.5,
              X_red[y == label, 2].mean(), name,
              horizontalalignment = 'center',
              bbox = dict(alpha = .5, edgecolor = 'w', facecolor = 'w'))

ax.scatter(X_red[:, 0], X_red[:, 1], X_red[:, 2], c = color_mapper, edgecolo

ax.w_xaxis.set_ticklabels([])
ax.w_yaxis.set_ticklabels([])
ax.w_zaxis.set_ticklabels([])

plt.show()
```



In [62]:

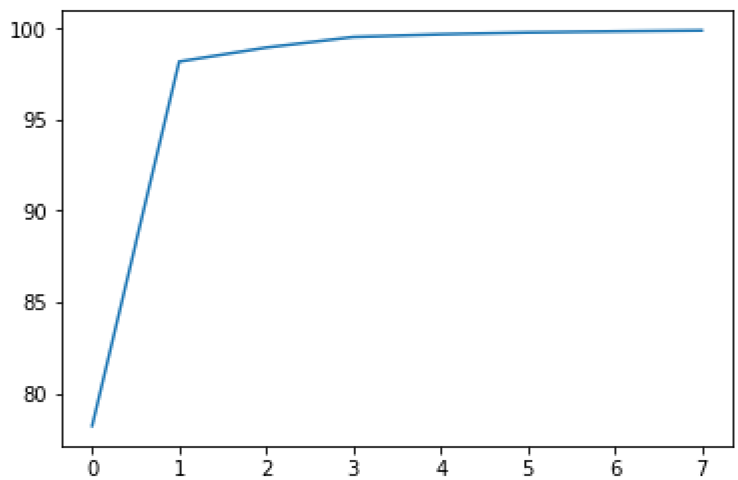
```
# We can see clear groupings after pca, with "looking forward" concentrated
# into the central region and "looking left" and "looking right" to the left
# Can see some minor "looking right" data points within the central region h
```

In [63]:
```
X = df.values
pca_1 = PCA(n_components = 8)
pca_1.fit(X)
```

Out[63]:
```
PCA(copy=True, iterated_power='auto', n_components=8, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)
```

In [64]:
```
var_Data = pca_1.explained_variance_ratio_
var1_Data = np.cumsum(np.round(pca_1.explained_variance_ratio_, decimals = 4
```

In [65]:
```
plt.plot(var1_Data)
plt.show()
```



Train and Test / Cross Validation

In [66]:

```
from sklearn.model_selection import train_test_split
from sklearn import tree
import graphviz

dataset = pd.read_csv('drivPoints.txt', index_col = 0)
df = dataset.copy()
df.pop('imgNum')
df.pop('subject')
df.pop('ang')
y = df.pop('label').values
df.head()
```

Out[66]:

	xF	yF	wF	hF	xRE	yRE	xLE	yLE	xN	yN	xRM	yRM	xLM	yl
fileName														
20130529_01_Driv_001_f	292	209	100	112	323	232	367	231	353	254	332	278	361	2
20130529_01_Driv_002_f	286	200	109	128	324	235	366	235	353	258	333	281	361	2
20130529_01_Driv_003_f	290	204	105	121	325	240	367	239	351	260	334	282	362	2
20130529_01_Driv_004_f	287	202	112	118	325	230	369	230	353	253	335	274	362	2
20130529_01_Driv_005_f	290	193	104	119	325	224	366	225	353	244	333	268	363	2

In [67]:
```
X = df.values
print(X)
print("")
print(y)
```

```
[[292 209 100 ... 278 361 278]
 [286 200 109 ... 281 361 281]
 [290 204 105 ... 282 362 282]
 ...
 [264 187 127 ... 272 337 270]
 [264 175 143 ... 261 351 251]
 [266 170 141 ... 255 362 247]]

[2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 1 1 1 1 2 2 2 2 2
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 3 2 2 2 2 3 3 3 3 2 2 2 2 2 2 2 2 2 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2
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 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
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 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 1 2 2 2 3 3 3 3 3 3 3 3 3 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 3 3 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 1 1 2 2]
```

In [68]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.5, r
X_train_red, X_test_red, y_train_red, y_test_red = train_test_split(X_red, y
```

Decision Tree

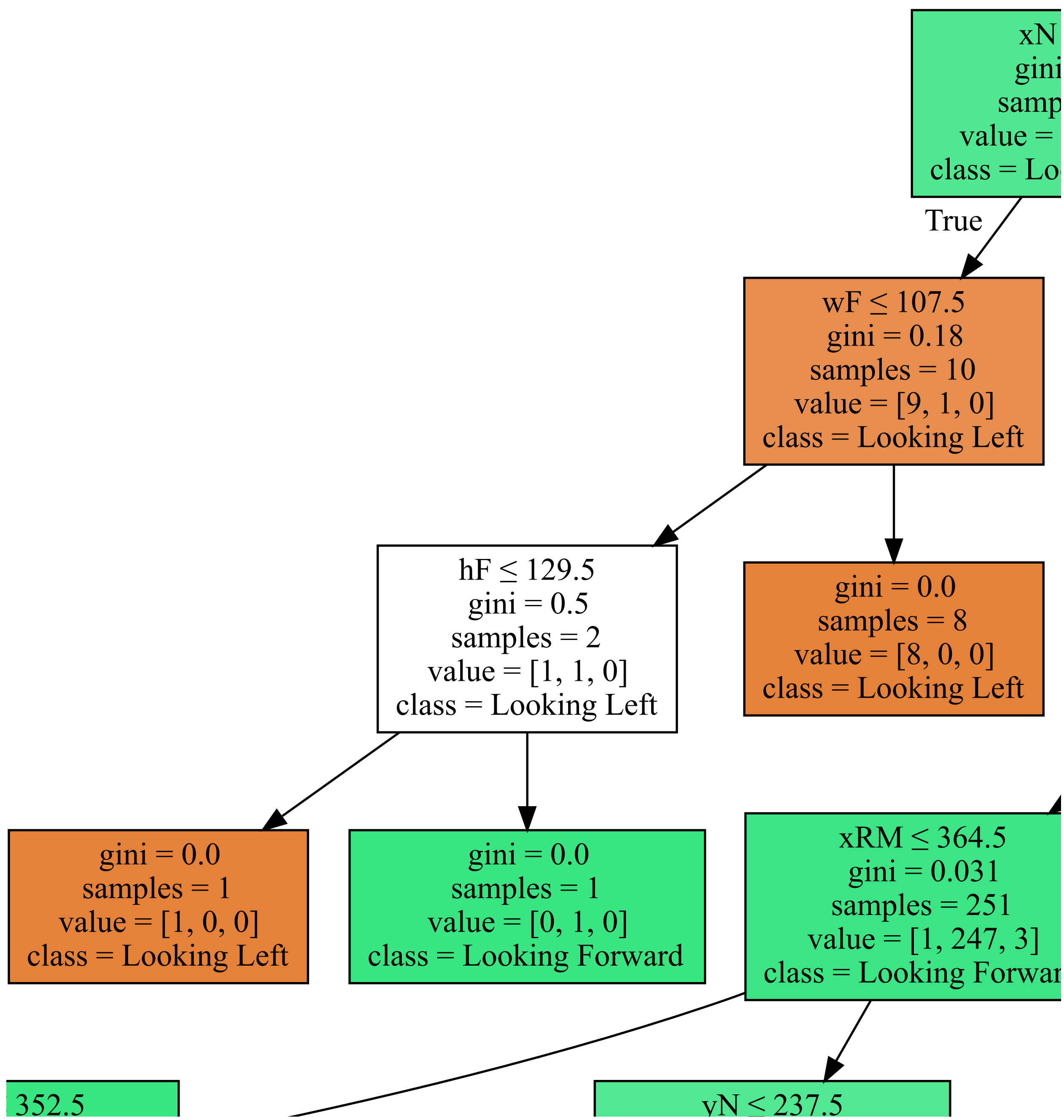
GINI

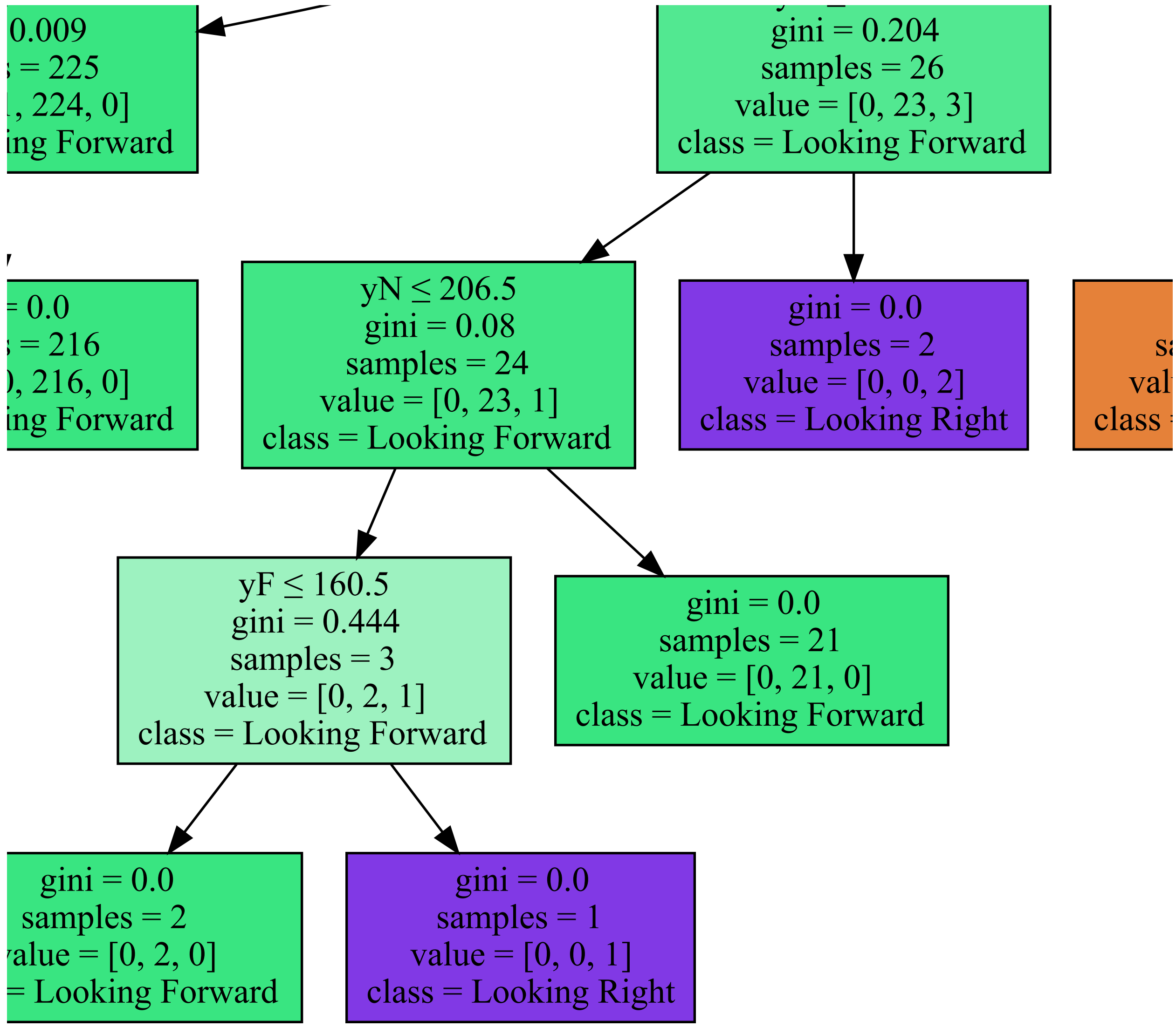
In [69]:

```python
# Original Data

from sklearn import metrics

dec_tree = tree.DecisionTreeClassifier()
dec_tree.fit(X_train, y_train)
print('Decision tree accuracy GINI (Original Data) is: ',dec_tree.score(X_te
cls_names = ['Looking Left', 'Looking Forward', 'Looking Right']
graphData = tree.export_graphviz(dec_tree, out_file = None,
                                feature_names = list(df.columns),
                                class_names = cls_names,
                                filled = True,
                                special_characters = True)
graphDraw = graphviz.Source(graphData)
graphDraw
```

```
Decision tree accuracy GINI (Original Data) is:  0.9108910891089109
```

Out[69]:



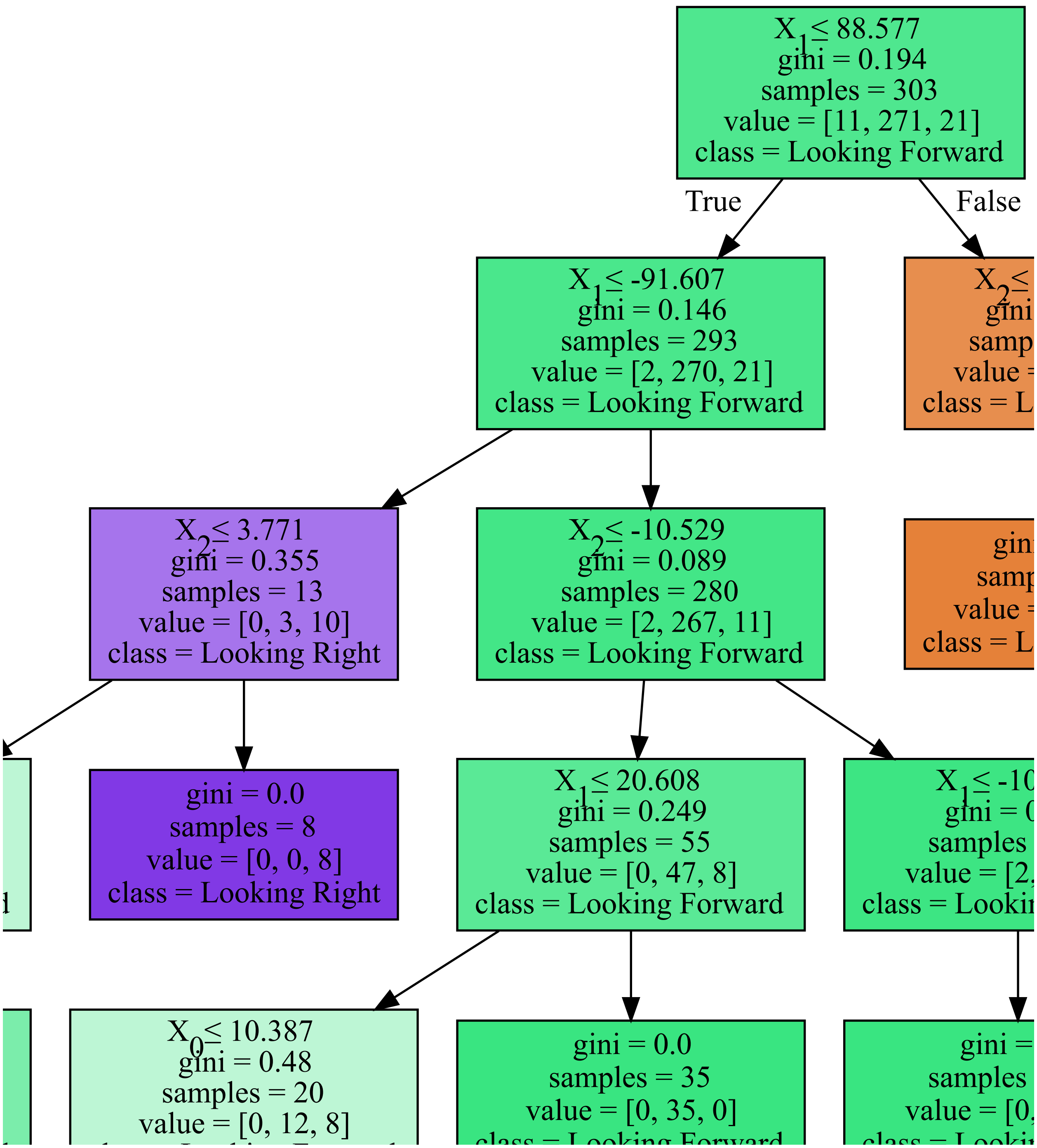

0.009
s = 225
, 224, 0]
ing Forward
gini = 0.204
samples = 26
value = [0, 23, 3]
class = Looking Forward
= 0.0
s = 216
), 216, 0]
ing Forward
yN ≤ 206.5
gini = 0.08
samples = 24
value = [0, 23, 1]
class = Looking Forward
gini = 0.0
samples = 2
value = [0, 0, 2]
class = Looking Right
yF ≤ 160.5
gini = 0.444
samples = 3
value = [0, 2, 1]
class = Looking Forward
gini = 0.0
samples = 21
value = [0, 21, 0]
class = Looking Forward
gini = 0.0
samples = 2
value = [0, 2, 0]
= Looking Forward
gini = 0.0
samples = 1
value = [0, 0, 1]
class = Looking Right

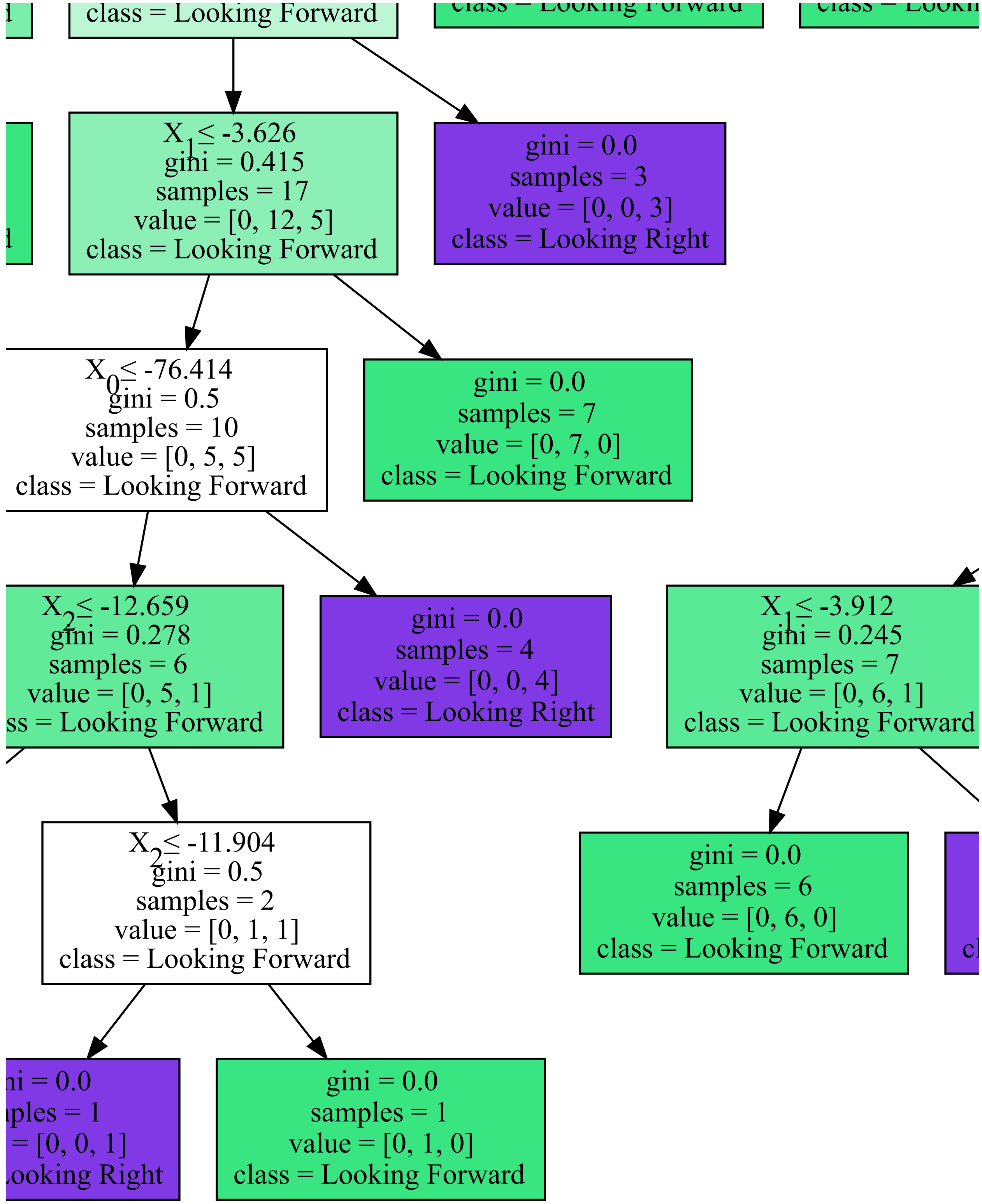
In [70]:

```python
# PCA data

dec_tree_red = tree.DecisionTreeClassifier()
dec_tree_red.fit(X_train_red, y_train_red)
#prediction_red = dec_tree_red.predict(X_test_red)
print('Decision tree accuracy GINI (Reduced Data) is: ', dec_tree_red.score(
cls_names = ['Looking Left', 'Looking Forward', 'Looking Right']
graphData = tree.export_graphviz(dec_tree_red, out_file = None,
                                 class_names = cls_names,
                                 filled = True,
                                 special_characters = True)
graphDraw = graphviz.Source(graphData)
graphDraw
```

```
Decision tree accuracy GINI (Reduced Data) is:  0.9207920792079208
```

Out[70]:




class = Looking Forward
X1 ≤ -3.626
gini = 0.415
samples = 17
value = [0, 12, 5]
class = Looking Forward
gini = 0.0
samples = 3
value = [0, 0, 3]
class = Looking Right
X0 ≤ -76.414
gini = 0.5
samples = 10
value = [0, 5, 5]
class = Looking Forward
gini = 0.0
samples = 7
value = [0, 7, 0]
class = Looking Forward
X2 ≤ -12.659
gini = 0.278
samples = 6
value = [0, 5, 1]
gini = 0.0
samples = 4
value = [0, 0, 4]
class = Looking Right
X1 ≤ -3.912
gini = 0.245
samples = 7
value = [0, 6, 1]
class = Looking Forward
X2 ≤ -11.904
gini = 0.5
samples = 2
value = [0, 1, 1]
class = Looking Forward
gini = 0.0
samples = 6
value = [0, 6, 0]
class = Looking Forward
gini = 0.0
samples = 1
value = [0, 1, 0]
class = Looking Forward

In [71]:
```
# evalute each decision tree

from sklearn.metrics import classification_report,confusion_matrix

predictions = dec_tree.predict(X_test)
predictions_red = dec_tree_red.predict(X_test_red)

print(classification_report(y_test, predictions))
print("")
print(classification_report(y_test_red, predictions_red))
```

```
              precision    recall  f1-score   support

           1       0.56      0.56      0.56        16
           2       0.96      0.94      0.95       275
           3       0.47      0.67      0.55        12

   micro avg       0.91      0.91      0.91       303
   macro avg       0.66      0.72      0.69       303
weighted avg       0.92      0.91      0.91       303


              precision    recall  f1-score   support

           1       0.57      0.81      0.67        16
           2       0.98      0.93      0.96       275
           3       0.53      0.75      0.62        12

   micro avg       0.92      0.92      0.92       303
   macro avg       0.69      0.83      0.75       303
weighted avg       0.94      0.92      0.93       303
```

In [72]:
```
print('Decision tree GINI accuracy (Original Data) is: ', metrics.accuracy_s
print("")
print('Decision tree GINI accuracy (Reduced Data) is: ', metrics.accuracy_sc
```

```
Decision tree GINI accuracy (Original Data) is:  0.9108910891089109

Decision tree GINI accuracy (Reduced Data) is:  0.9207920792079208
```

Entropy

In [73]:
```
dec_tree = tree.DecisionTreeClassifier(criterion = 'entropy')
dec_tree.fit(X_train,y_train)

dec_tree_red = tree.DecisionTreeClassifier(criterion = 'entropy')
dec_tree_red.fit(X_train_red,y_train_red)
```

Out[73]:
```
DecisionTreeClassifier(class_weight=None, criterion='entropy', max_depth=None,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=None,
            splitter='best')
```

In [74]:
```
predictions = dec_tree.predict(X_test)
predictions_red = dec_tree_red.predict(X_test_red)
```

In [75]:
```
print(confusion_matrix(y_test, predictions))
print("")
print(confusion_matrix(y_test_red, predictions_red))
```

```
[[ 11   5   0]
 [  4 263   8]
 [  0   2  10]]

[[ 12   4   0]
 [  1 265   9]
 [  0   3   9]]
```

In [76]:
```
featureNames = df.columns
```

In [77]:
```
featureNames
```

Out[77]:
```
Index(['xF', 'yF', 'wF', 'hF', 'xRE', 'yRE', 'xLE', 'yLE', 'xN', 'yN', 'xRM',
       'yRM', 'xLM', 'yLM'],
      dtype='object')
```

In [78]:
```
target_names = ['1', '2' ,'3']
target_names
```

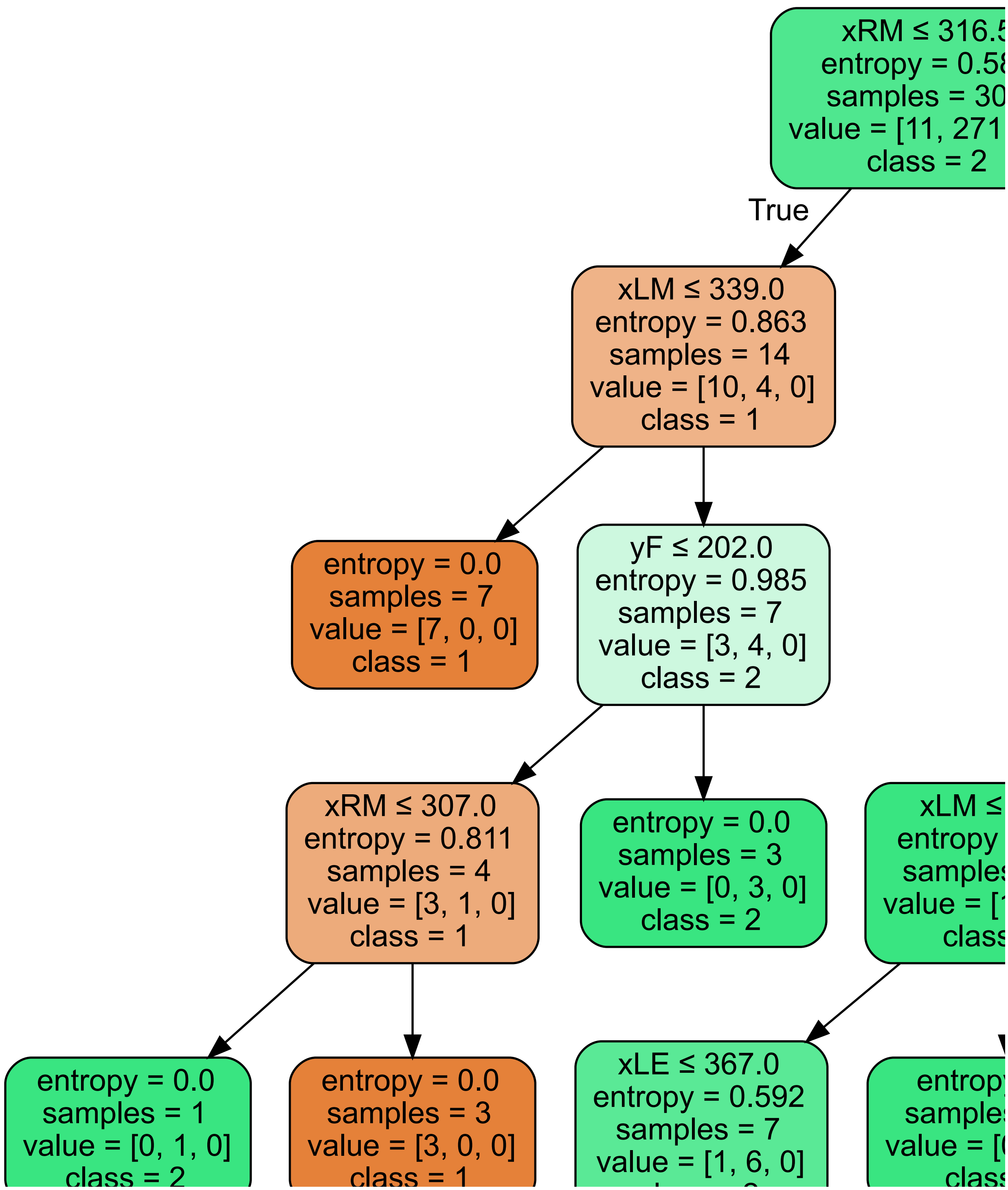
Out[78]:
```
['1', '2', '3']
```

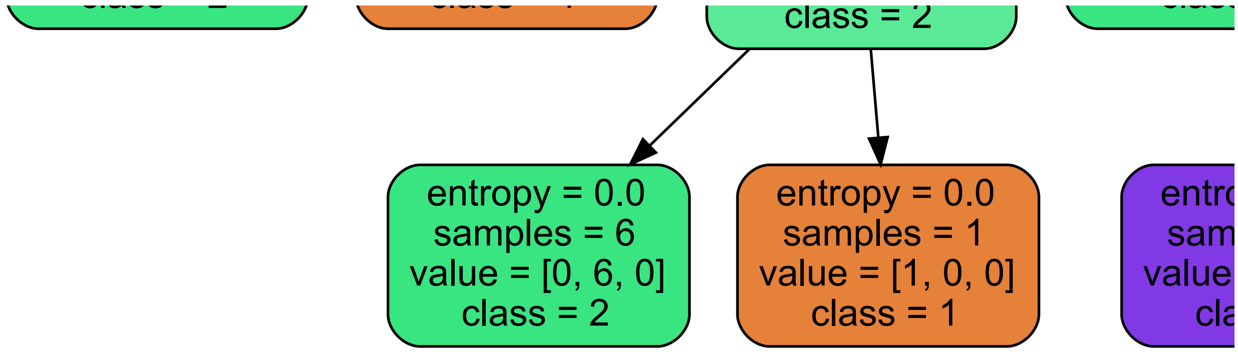
In [79]:

```python
# Original Data

print('Decision tree Entropy accuracy (Original Data) is: ', dec_tree.score(

dot_data = tree.export_graphviz(dec_tree, out_file = None,
                                feature_names = featureNames,
                                class_names = target_names,
                                filled = True, rounded = True,
                                special_characters = True)
graph = graphviz.Source(dot_data)
graph
```

```
Decision tree Entropy accuracy (Original Data) is:  0.9372937293729373
```

Out[79]:



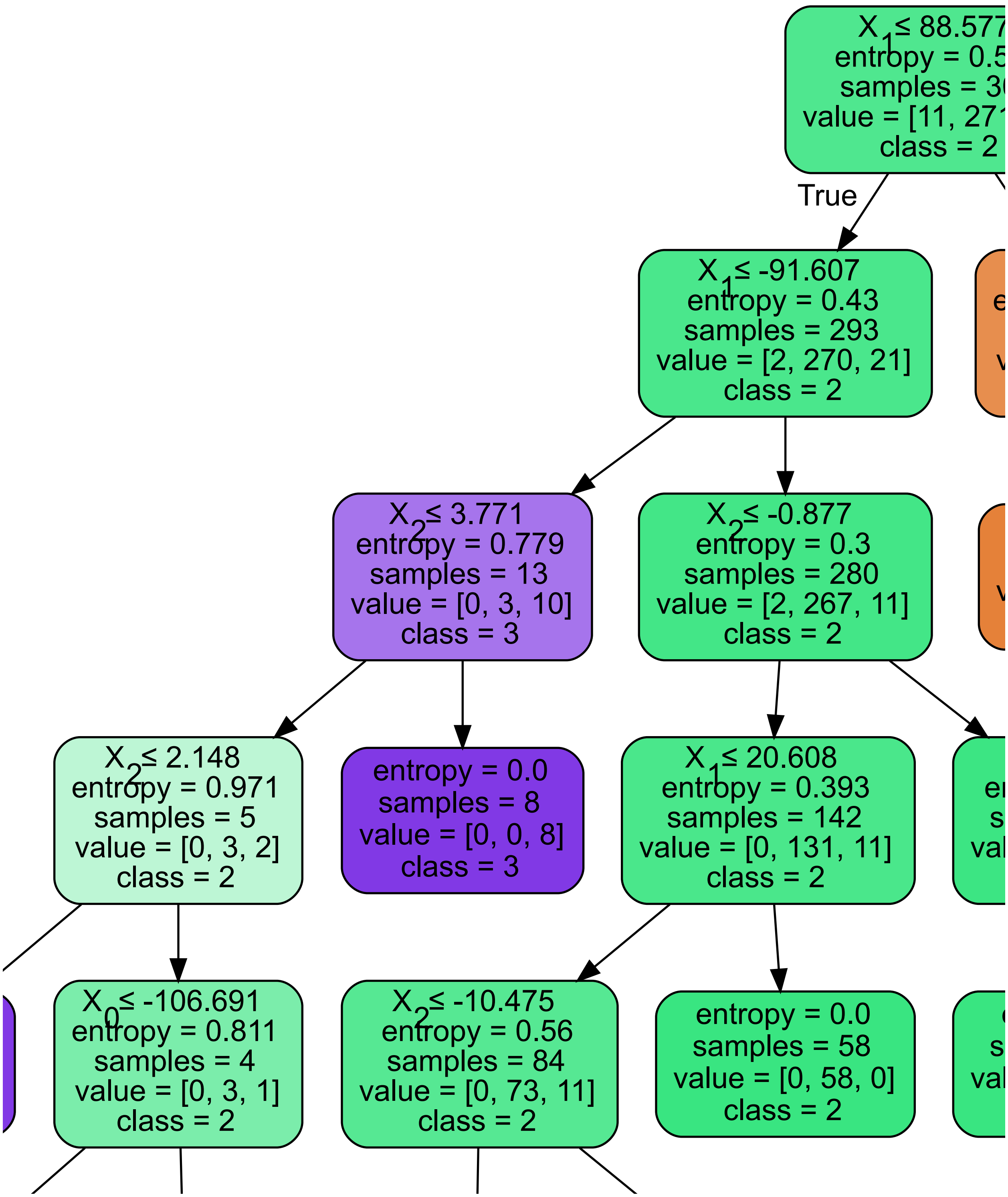

class = 2
entropy = 0.0
samples = 6
value = [0, 6, 0]
class = 2
entropy = 0.0
samples = 1
value = [1, 0, 0]
class = 1

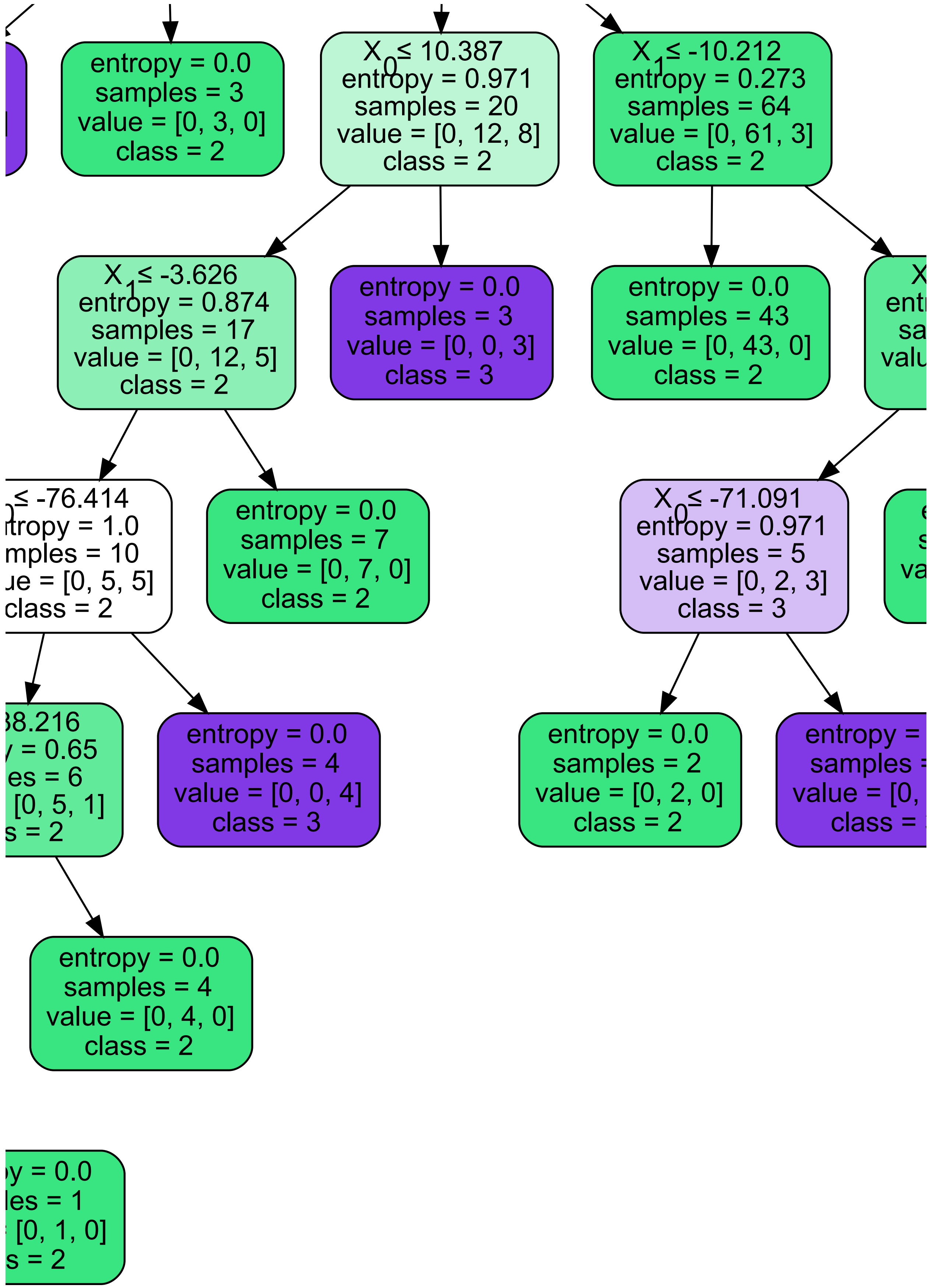
In [80]:

```python
# Reduced Data
print('Decision tree Entropy accuracy (Reduced Data) is: ', dec_tree_red.sco

dot_data = tree.export_graphviz(dec_tree_red, out_file = None,
                                #feature_names = featureNames,
                                class_names = target_names,
                                filled = True, rounded = True,
                                special_characters = True)
graph = graphviz.Source(dot_data)
graph
```

```
Decision tree Entropy accuracy (Reduced Data) is:  0.9438943894389439
```

Out[80]:




entropy = 0.0
samples = 3
value = [0, 3, 0]
class = 2
X_0 ≤ 10.387
entropy = 0.971
samples = 20
value = [0, 12, 8]
class = 2
X_1 ≤ -10.212
entropy = 0.273
samples = 64
value = [0, 61, 3]
class = 2
X_1 ≤ -3.626
entropy = 0.874
samples = 17
value = [0, 12, 5]
class = 2
entropy = 0.0
samples = 3
value = [0, 0, 3]
class = 3
entropy = 0.0
samples = 43
value = [0, 43, 0]
class = 2
entropy = 0.0
samples = 7
value = [0, 7, 0]
class = 2
X_0 ≤ -71.091
entropy = 0.971
samples = 5
value = [0, 2, 3]
class = 3
entropy = 0.0
samples = 4
value = [0, 0, 4]
class = 3
entropy = 0.0
samples = 2
value = [0, 2, 0]
class = 2
entropy = 0.0
samples = 4
value = [0, 4, 0]
class = 2

In [81]:
```
# evalute each decision tree

predictions = dec_tree.predict(X_test)
predictions_red = dec_tree_red.predict(X_test_red)

print(classification_report(y_test, predictions))
print("")
print(classification_report(y_test_red, predictions_red))
```

```
              precision    recall  f1-score   support

           1       0.73      0.69      0.71        16
           2       0.97      0.96      0.97       275
           3       0.56      0.83      0.67        12

   micro avg       0.94      0.94      0.94       303
   macro avg       0.75      0.83      0.78       303
weighted avg       0.94      0.94      0.94       303


              precision    recall  f1-score   support

           1       0.92      0.75      0.83        16
           2       0.97      0.96      0.97       275
           3       0.50      0.75      0.60        12

   micro avg       0.94      0.94      0.94       303
   macro avg       0.80      0.82      0.80       303
weighted avg       0.95      0.94      0.95       303
```

In [82]:
```
print('Decision tree ENTROPY accuracy (Original Data) is: ', metrics.accurac
print("")
print('Decision tree ENTROPY accuracy (Reduced Data) is: ', metrics.accuracy
```

```
Decision tree ENTROPY accuracy (Original Data) is:  0.9372937293729373

Decision tree ENTROPY accuracy (Reduced Data) is:  0.9438943894389439
```

K - Nearest Neighbours

In [83]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn import metrics
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import LinearRegression
```

In [84]:
```
knn = KNeighborsClassifier(n_neighbors = 5)
knn_red = KNeighborsClassifier(n_neighbors = 5)

knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
print(metrics.accuracy_score(y_test, y_pred))

knn_red.fit(X_train_red, y_train_red)
y_pred_red = knn_red.predict(X_test_red)
print(metrics.accuracy_score(y_test_red, y_pred_red))
```

```
0.9372937293729373
0.9306930693069307
```

In [85]:
```
scores = cross_val_score(knn, X, y, cv = 10, scoring = "accuracy")
print(scores)
print(scores.mean())

scores_red = cross_val_score(knn_red, X_red, y, cv = 10, scoring = "accuracy
print(scores_red)
print(scores_red.mean())
```

```
[0.90322581 0.9516129  0.96774194 0.96721311 0.95081967 0.62295082
 0.96666667 0.96610169 0.93220339 0.77966102]
0.900819702008025
[0.88709677 0.96774194 0.9516129  0.96721311 0.95081967 0.62295082
 0.93333333 0.96610169 0.91525424 0.79661017]
0.8958734654488852
```

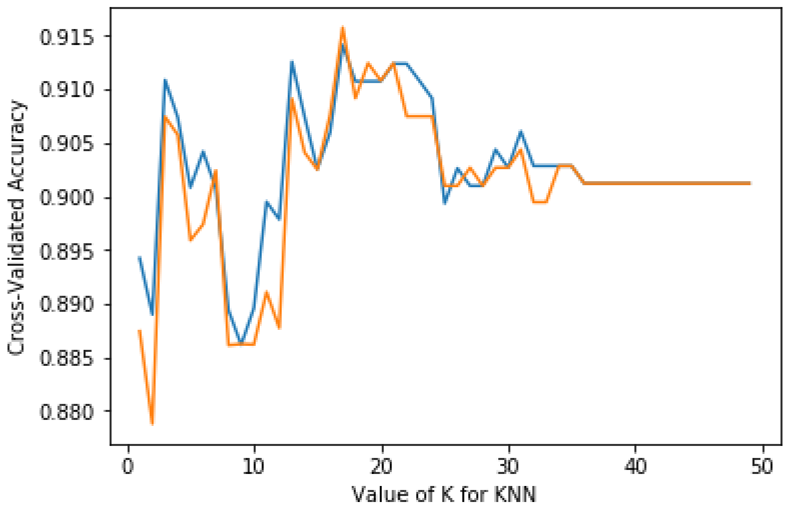
In [86]:

```
k_range = list(range(1, 50))

k_scores = []
for item in k_range:
    knn = KNeighborsClassifier(n_neighbors = item)
    scores = cross_val_score(knn, X, y, cv = 10, scoring = "accuracy")
    k_scores.append(scores.mean())
print(k_scores)

print(" ")

k_scores_red = []
for item in k_range:
    knn_red = KNeighborsClassifier(n_neighbors = item)
    scores_red = cross_val_score(knn_red, X_red, y, cv = 10, scoring = "accu
    k_scores_red.append(scores_red.mean())
print(k_scores)
```

```
[0.8942578284887978, 0.8889862327348993, 0.9108798591006462, 0.907382456895135
2, 0.900819702008025, 0.9041830914800111, 0.9007103675752225, 0.889390915039123
8, 0.8861386675510223, 0.889584069051439, 0.8994757056171517, 0.897836361354856
4, 0.9125895783476293, 0.9074228205564866, 0.9025576698425788, 0.90594750035105
33, 0.914144221662528 6, 0.9107553173372531, 0.9107553173372531, 0.9107553173372
531, 0.9123946615995482, 0.9123946615995482, 0.9108108883291953, 0.909171544066
9003, 0.8993354784931297, 0.9026141670177198, 0.9009748227554247, 0.90097482275
54247, 0.9043646532638994, 0.9026697380096621, 0.9060595685181367, 0.9028364509
854887, 0.9028364509854887, 0.9028364509854887, 0.9028364509854887, 0.901197106
7231936, 0.9011971067231936, 0.9011971067231936, 0.9011971067231936, 0.90119710
67231936, 0.9011971067231936, 0.9011971067231936, 0.9011971067231936, 0.9011971
067231936, 0.9011971067231936, 0.9011971067231936, 0.9011971067231936, 0.901197
1067231936, 0.9011971067231936]

[0.8942578284887978, 0.8889862327348993, 0.9108798591006462, 0.907382456895135
2, 0.900819702008025, 0.9041830914800111, 0.9007103675752225, 0.889390915039123
8, 0.8861386675510223, 0.889584069051439, 0.8994757056171517, 0.897836361354856
4, 0.9125895783476293, 0.9074228205564866, 0.9025576698425788, 0.90594750035105
33, 0.914144221662528 6, 0.9107553173372531, 0.9107553173372531, 0.9107553173372
531, 0.9123946615995482, 0.9123946615995482, 0.9108108883291953, 0.909171544066
9003, 0.8993354784931297, 0.9026141670177198, 0.9009748227554247, 0.90097482275
54247, 0.9043646532638994, 0.9026697380096621, 0.9060595685181367, 0.9028364509
854887, 0.9028364509854887, 0.9028364509854887, 0.9028364509854887, 0.901197106
7231936, 0.9011971067231936, 0.9011971067231936, 0.9011971067231936, 0.90119710
67231936, 0.9011971067231936, 0.9011971067231936, 0.9011971067231936, 0.9011971
067231936, 0.9011971067231936, 0.9011971067231936, 0.9011971067231936, 0.901197
1067231936, 0.9011971067231936]
```

In [87]:
```
plt.plot(k_range, k_scores)
plt.xlabel("Value of K for KNN")
plt.ylabel("Cross-Validated Accuracy")

plt.plot(k_range, k_scores_red)
```

Out[87]:
```
[<matplotlib.lines.Line2D at 0x2279f0a36a0>]
```



In [88]:
```
knn = KNeighborsClassifier(n_neighbors = 17)
knn_red = KNeighborsClassifier(n_neighbors = 17)

knn.fit(X_train, y_train)
knn_red.fit(X_train_red, y_train_red)

prediction = knn.predict(X_test)
prediction_red = knn_red.predict(X_test_red)

print(cross_val_score(knn, X, y, cv = 10, scoring = "accuracy").mean())
print(cross_val_score(knn_red, X_red, y, cv = 10, scoring = "accuracy").mean

print('With KNN (k = 17) accuracy is: ',knn.score(X_test, y_test)) # accurac
print('With KNN (k = 17) accuracy is: ',knn_red.score(X_test_red, y_test_red

# KNN = 17 is best, and as seen below the reduced data offers slightly highe
```

```
0.9141442216625286
0.9157835659248237
With KNN (k = 17) accuracy is:  0.9174917491749175
With KNN (k = 17) accuracy is:  0.9174917491749175
```

In [89]:

```
# sample readout to check out of interest
print('True:', y_test[0:50])
print('Pred:', y_pred[0:50])
```

```
True: [1 1 2 2 2 2 2 2 2 2 2 2 2 1 2 3 2 2 2 2 2 2 2 2 2 2 2 2 3 2 2 2 2 2 2 2
2
 2 2 2 2 2 2 3 2 3 2 2 2 2]
Pred: [2 2 2 2 2 2 2 2 2 2 2 2 2 1 2 3 2 2 2 2 2 2 2 2 2 3 2 3 3 2 2 2 2 2 2 2
2
 2 2 2 2 2 2 3 2 3 2 2 2 2]
```

In [90]:

```
confusion = metrics.confusion_matrix(y_test, y_pred)
confusion_red = metrics.confusion_matrix(y_test_red, y_pred_red)

print(confusion)
print("")
print(confusion_red)
```

```
[[  7   9   0]
 [  0 267   8]
 [  0   2  10]]

[[  6  10   0]
 [  0 266   9]
 [  0   2  10]]
```

In [91]:
```
print(classification_report(y_test, prediction))
print(" ")
print(classification_report(y_test_red, prediction_red))
```

```
              precision    recall  f1-score   support

           1       0.00      0.00      0.00        16
           2       0.92      1.00      0.96       275
           3       1.00      0.25      0.40        12

   micro avg       0.92      0.92      0.92       303
   macro avg       0.64      0.42      0.45       303
weighted avg       0.87      0.92      0.88       303


              precision    recall  f1-score   support

           1       0.00      0.00      0.00        16
           2       0.92      1.00      0.96       275
           3       0.80      0.33      0.47        12

   micro avg       0.92      0.92      0.92       303
   macro avg       0.57      0.44      0.48       303
weighted avg       0.87      0.92      0.89       303


C:\Users\jstos\Anaconda3\lib\site-packages\sklearn\metrics\classification.py:11
43: UndefinedMetricWarning: Precision and F-score are ill-defined and being set
to 0.0 in labels with no predicted samples.
  'precision', 'predicted', average, warn_for)
C:\Users\jstos\Anaconda3\lib\site-packages\sklearn\metrics\classification.py:11
43: UndefinedMetricWarning: Precision and F-score are ill-defined and being set
to 0.0 in labels with no predicted samples.
  'precision', 'predicted', average, warn_for)
C:\Users\jstos\Anaconda3\lib\site-packages\sklearn\metrics\classification.py:11
43: UndefinedMetricWarning: Precision and F-score are ill-defined and being set
to 0.0 in labels with no predicted samples.
  'precision', 'predicted', average, warn_for)
C:\Users\jstos\Anaconda3\lib\site-packages\sklearn\metrics\classification.py:11
43: UndefinedMetricWarning: Precision and F-score are ill-defined and being set
to 0.0 in labels with no predicted samples.
  'precision', 'predicted', average, warn_for)
C:\Users\jstos\Anaconda3\lib\site-packages\sklearn\metrics\classification.py:11
43: UndefinedMetricWarning: Precision and F-score are ill-defined and being set
to 0.0 in labels with no predicted samples.
  'precision', 'predicted', average, warn_for)
C:\Users\jstos\Anaconda3\lib\site-packages\sklearn\metrics\classification.py:11
43: UndefinedMetricWarning: Precision and F-score are ill-defined and being set
to 0.0 in labels with no predicted samples.
  'precision', 'predicted', average, warn_for)
```

In [92]:
```
print('KNN accuracy (Original Data) is: ', metrics.accuracy_score(y_test, pr
print("")
print('KNN accuracy (Reduced Data) is: ', metrics.accuracy_score(y_test_red,
```

```
KNN accuracy (Original Data) is:  0.9174917491749175

KNN accuracy (Reduced Data) is:  0.9174917491749175
```

Random Forest

In [93]:
```
from sklearn.ensemble import RandomForestClassifier

rfc = RandomForestClassifier(n_estimators = 600)
rfc_red = RandomForestClassifier(n_estimators = 600)

rfc.fit(X_train, y_train)
rfc_red.fit(X_train_red, y_train_red)
```

Out[93]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=600, n_jobs=None,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)
```

In [94]:
```
predictions = rfc.predict(X_test)
predictions_red = rfc_red.predict(X_test_red)
```

In [95]:
```
print(classification_report(y_test, predictions))
print("")
print(classification_report(y_test_red, predictions_red))
```

```
              precision    recall  f1-score   support

           1       0.90      0.56      0.69        16
           2       0.96      0.97      0.97       275
           3       0.60      0.75      0.67        12

   micro avg       0.94      0.94      0.94       303
   macro avg       0.82      0.76      0.78       303
weighted avg       0.95      0.94      0.94       303


              precision    recall  f1-score   support

           1       0.91      0.62      0.74        16
           2       0.95      0.98      0.97       275
           3       0.50      0.42      0.45        12

   micro avg       0.94      0.94      0.94       303
   macro avg       0.79      0.67      0.72       303
weighted avg       0.93      0.94      0.93       303
```

In [96]:
```
print('Random Forest accuracy (Original Data) is: ', metrics.accuracy_score(
print("")
print('Random Forest accuracy (Reduced Data) is: ', metrics.accuracy_score(y
```

```
Random Forest accuracy (Original Data) is:  0.9438943894389439

Random Forest accuracy (Reduced Data) is:  0.9372937293729373
```

In [97]:
```
print(confusion_matrix(y_test, predictions))
print("")
print(confusion_matrix(y_test_red, predictions_red))
```

```
[[  9   7   0]
 [  1 268   6]
 [  0   3   9]]

[[ 10   6   0]
 [  1 269   5]
 [  0   7   5]]
```

In [98]:
```
# The performance for the original and reduced data are very close.  Likely
# to save computing time.
```

SVM Classification

In [99]:

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
scaler_red = StandardScaler()

X_train = scaler.fit_transform(X_train)
X_train_red = scaler_red.fit_transform(X_train_red)

X_test = scaler.transform(X_test)
X_test_red = scaler_red.transform(X_test_red)

classifier = SVC(kernel = 'linear', random_state = 5)
classifier_red = SVC(kernel = 'linear', random_state = 5)

classifier.fit(X_train, y_train)
classifier_red.fit(X_train_red, y_train_red)

y_pred = classifier.predict(X_test)
y_pred_red = classifier_red.predict(X_test_red)
```

```
C:\Users\jstos\Anaconda3\lib\site-packages\sklearn\utils\validation.py:595: Dat
aConversionWarning: Data with input dtype int64 was converted to float64 by Sta
ndardScaler.
  warnings.warn(msg, DataConversionWarning)
C:\Users\jstos\Anaconda3\lib\site-packages\sklearn\utils\validation.py:595: Dat
aConversionWarning: Data with input dtype int64 was converted to float64 by Sta
ndardScaler.
  warnings.warn(msg, DataConversionWarning)
C:\Users\jstos\Anaconda3\lib\site-packages\sklearn\utils\validation.py:595: Dat
aConversionWarning: Data with input dtype int64 was converted to float64 by Sta
ndardScaler.
  warnings.warn(msg, DataConversionWarning)
```

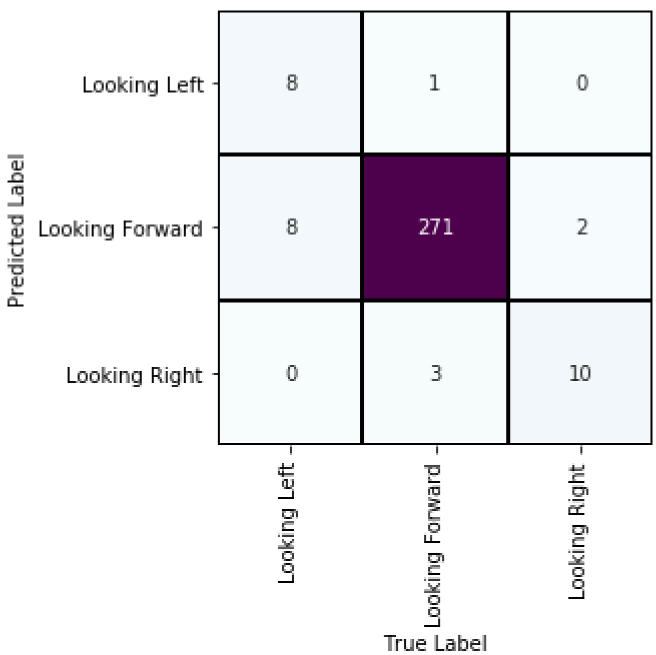
In [100]:

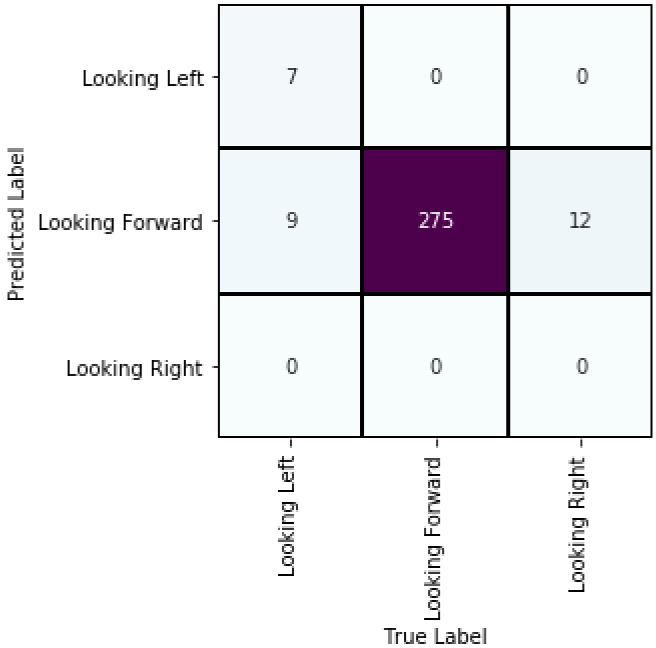
```
print(confusion_matrix(y_test, y_pred))
print("")
print(confusion_matrix(y_test_red, y_pred_red))
```

```
[[  8   8   0]
 [  1 271   3]
 [  0   2  10]]

[[  7   9   0]
 [  0 275   0]
 [  0  12   0]]
```

In [101]:

```
face_labels = ['Looking Left','Looking Forward', 'Looking Right']

matrix = confusion_matrix(y_test, y_pred)
matrix_red = confusion_matrix(y_test_red, y_pred_red)

sea.heatmap(matrix.T, square = True, annot = True, fmt = 'd', cbar = False,
            xticklabels = face_labels, cmap = "BuPu", linecolor = 'black', l
            yticklabels = face_labels)
plt.xlabel('True Label')
plt.ylabel('Predicted Label');
plt.show()

sea.heatmap(matrix_red.T, square = True, annot = True, fmt = 'd', cbar = Fal
            xticklabels = face_labels, cmap = "BuPu", linecolor = 'black', l
            yticklabels = face_labels)
plt.xlabel('True Label')
plt.ylabel('Predicted Label');
plt.show()
```





In [102]:
```
print('SVM accuracy (Original Data) is: ', classifier.score(X_test, y_test))
print('SVM accuracy (Reduced Data) is: ', classifier_red.score(X_test_red, y
```

```
SVM accuracy (Original Data) is:  0.9537953795379538
SVM accuracy (Reduced Data) is:  0.9306930693069307
```

In [103]:
```
print(classification_report(y_test, y_pred))
print(" ")
print(classification_report(y_test_red, y_pred_red))
```

```
              precision    recall  f1-score   support

           1       0.89      0.50      0.64        16
           2       0.96      0.99      0.97       275
           3       0.77      0.83      0.80        12

   micro avg       0.95      0.95      0.95       303
   macro avg       0.87      0.77      0.80       303
weighted avg       0.95      0.95      0.95       303


              precision    recall  f1-score   support

           1       1.00      0.44      0.61        16
           2       0.93      1.00      0.96       275
           3       0.00      0.00      0.00        12

   micro avg       0.93      0.93      0.93       303
   macro avg       0.64      0.48      0.52       303
```

In [104]:
```
print('SVM Classification accuracy (Original Data) is: ', metrics.accuracy_s
print("")
print('SVM Classification accuracy (Reduced Data) is: ', metrics.accuracy_sc
```

```
SVM Classification accuracy (Original Data) is:  0.9537953795379538

SVM Classification accuracy (Reduced Data) is:  0.9306930693069307
```

SVM Regression

In [105]:
```
from sklearn.svm import SVR
from sklearn.preprocessing import StandardScaler

regression = SVR(kernel = 'rbf', gamma = 'auto')
regression_red = SVR(kernel = 'rbf', gamma = 'auto')

regression.fit(X, y)
regression_red.fit(X_red, y)
```

Out[105]:
```
SVR(C=1.0, cache_size=200, coef0=0.0, degree=3, epsilon=0.1, gamma='auto',
  kernel='rbf', max_iter=-1, shrinking=True, tol=0.001, verbose=False)
```

In [106]:
```
y = np.reshape(y, (-1,1))
```

In [107]:
```
print(dataset[-20:][0:])
```

```
                          subject  imgNum  label  ang   xF   yF   wF   hF  xRE  \
fileName                                                                          
20130530_04_Driv_071_f         4      71      2   15  325  175  111  138  361   
20130530_04_Driv_072_f         4      72      2   15  324  178  107  131  358   
20130530_04_Driv_073_f         4      73      2    0  310  177  121  137  346   
20130530_04_Driv_074_f         4      74      2    0  302  175  128  136  337   
20130530_04_Driv_075_f         4      75      2    0  298  172  121  143  324   
20130530_04_Driv_076_f         4      76      2  -15  290  178  120  144  319   
20130530_04_Driv_077_f         4      77      2  -15  288  181  119  141  316   
20130530_04_Driv_078_f         4      78      2  -15  288  180  111  123  315   
20130530_04_Driv_079_f         4      79      2  -15  280  175  120  149  313   
20130530_04_Driv_080_f         4      80      2  -15  282  189  116  131  313   
20130530_04_Driv_081_f         4      81      2  -15  282  186  120  129  311   
20130530_04_Driv_082_f         4      82      2  -15  282  183  124  131  312   
20130530_04_Driv_083_f         4      83      2  -15  282  181  120  140  312   
20130530_04_Driv_084_f         4      84      2  -15  279  185  125  133  310   
20130530_04_Driv_085_f         4      85      2  -15  281  181  127  140  311   
20130530_04_Driv_086_f         4      86      2  -15  278  183  128  141  307   
20130530_04_Driv_087_lr        4      87      1  -30  268  186  128  134  296   
20130530_04_Driv_088_lr        4      88      1  -30  264  187  127  131  287   
20130530_04_Driv_089_f         4      89      2  -15  264  175  143  136  295   
20130530_04_Driv_090_f         4      90      2    0  266  170  141  139  303   

                          yRE  xLE  yLE   xN   yN  xRM  yRM  xLM  yLM  
fileName                                                               
20130530_04_Driv_071_f    198  406  198  393  225  368  253  403  251  
20130530_04_Driv_072_f    200  407  201  389  225  364  258  405  253  
20130530_04_Driv_073_f    205  397  200  376  228  355  257  395  258  
20130530_04_Driv_074_f    207  390  202  367  229  347  257  388  255  
20130530_04_Driv_075_f    206  378  199  352  229  335  258  377  252  
20130530_04_Driv_076_f    212  370  207  342  237  327  266  370  258  
20130530_04_Driv_077_f    212  367  207  337  238  328  259  373  260  
20130530_04_Driv_078_f    209  365  206  339  237  329  261  370  259  
20130530_04_Driv_079_f    213  366  206  333  240  325  265  369  258  
20130530_04_Driv_080_f    219  362  212  330  246  326  274  367  265  
20130530_04_Driv_081_f    215  363  210  335  243  329  271  366  261  
20130530_04_Driv_082_f    215  364  209  337  243  330  269  361  261  
20130530_04_Driv_083_f    214  360  206  335  241  327  269  361  261  
20130530_04_Driv_084_f    213  359  209  338  241  322  264  359  264  
20130530_04_Driv_085_f    216  360  207  336  241  324  264  363  264  
20130530_04_Driv_086_f    218  354  210  330  247  324  273  356  266  
20130530_04_Driv_087_lr   222  344  212  319  247  316  274  347  269  
20130530_04_Driv_088_lr   220  334  211  304  247  305  272  337  270  
20130530_04_Driv_089_f    207  345  200  320  234  314  261  351  251  
20130530_04_Driv_090_f    206  354  198  331  229  319  255  362  247  
```

In [108]:
```
print(X_red[-20:][:])
```

```
[[-84.00253959 -57.0805435    5.57792248]
 [-77.8104238  -53.13734536   1.62702648]
 [-72.36765624 -25.54447557   9.85528829]
 [-71.44456477  -5.50489891  11.04964754]
 [-73.98081655  21.54131243  20.31838816]
 [-55.94152588  39.31990825  22.33687789]
 [-56.23157408  43.61667484  19.538421  ]
 [-58.00148363  45.57818687   3.80064555]
 [-55.8603768   52.26569173  27.91804563]
 [-36.02209906  55.23539011  12.79240184]
 [-43.79761978  53.17601118   9.76978859]
 [-46.05464292  53.0047717   10.98666823]
 [-49.29078018  55.97372504  18.70755811]
 [-47.28260754  60.05026168  10.80967569]
 [-48.85227538  56.90935088  19.16849319]
 [-38.4823047   67.13408147  21.87030792]
 [-31.96731054  91.38591918  16.57322672]
 [-31.95085066 115.98117104  17.35342064]
 [-65.46335867  93.97339745  18.32652384]
 [-75.89991244  75.11178559  17.6630584 ]]
```

In [109]:
```
# Predict for imgNum 90 for original and reduced data.  Expecting label = 2
y_pred = regression.predict([[266, 170, 141, 139, 303, 206, 354, 198, 331, 2
y_pred_red = regression_red.predict([[-75.89991244, 75.11178559, 17.6630584]

print(y_pred)
print(y_pred_red)
```

```
[2.08165714]
[2.07873515]
```

In [110]:
```
# Predict for imgNum 88 for original and reduced data. Expecting label = 1
y_pred = regression.predict([[268, 186, 128, 134, 296, 222, 344, 212, 319, 2
y_pred_red = regression_red.predict([[-31.96731054, 91.38591918, 16.57322672

print(y_pred)
print(y_pred_red)
```

```
[1.09964487]
[1.09992151]
```

In [111]:
```
print('SVR accuracy (Original Data) is: ', regression.score(X_test, y_test))
print('SVR accuracy (Reduced Data) is: ', regression_red.score(X_test_red, y
```

```
SVR accuracy (Original Data) is:  -0.09755658003981038
SVR accuracy (Reduced Data) is:  -0.09163894002575668
```

In [112]:
```
y = y.reshape(-1, 1)

import warnings
warnings.filterwarnings('ignore')
```

In [113]:
```
log_regression = LogisticRegression()
print(cross_val_score(log_regression, X_train, y_train, cv = 10, scoring = "
```

```
0.9275757575757575
```

Linear Regression

In [114]:
```
from sklearn import datasets
from sklearn import preprocessing

diabetes = datasets.load_diabetes()
diabetes.keys()
```

Out[114]:
```
dict_keys(['data', 'target', 'DESCR', 'feature_names', 'data_filename', 'target
_filename'])
```

In [115]:
```
diabetes.data
```

Out[115]:
```
array([[ 0.03807591,  0.05068012,  0.06169621, ..., -0.00259226,
         0.01990842, -0.01764613],
       [-0.00188202, -0.04464164, -0.05147406, ..., -0.03949338,
        -0.06832974, -0.09220405],
       [ 0.08529891,  0.05068012,  0.04445121, ..., -0.00259226,
         0.00286377, -0.02593034],
       ...,
       [ 0.04170844,  0.05068012, -0.01590626, ..., -0.01107952,
        -0.04687948,  0.01549073],
       [-0.04547248, -0.04464164,  0.03906215, ...,  0.02655962,
         0.04452837, -0.02593034],
       [-0.04547248, -0.04464164, -0.0730303 , ..., -0.03949338,
        -0.00421986,  0.00306441]])
```

In [116]:
```
diabetes.feature_names
```

Out[116]:
```
['age', 'sex', 'bmi', 'bp', 's1', 's2', 's3', 's4', 's5', 's6']
```

In [117]:
```
# Pick 'bp'
X = diabetes.data[:, np.newaxis, 3]
y = diabetes.target
print(X)
print(y)
```

```
[-2.22773986e-03]
[ 4.94153205e-02]
[-3.66564468e-02]
[-9.86281193e-02]
[ 8.10087222e-03]
[-5.67061055e-03]
[-4.35421882e-02]
[-2.63278347e-02]
[ 3.90867085e-02]
[-2.51802112e-02]
[-2.63278347e-02]
[-1.25563519e-02]
[ 3.56438378e-02]
[-5.38708003e-02]
[ 5.63010619e-02]
[ 6.31868033e-02]
[-2.28849640e-02]
[ 8.10087222e-03]
[-1.94420933e-02]
[-2.63278347e-02]
```

In [118]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.5, r
```

In [119]:
```
lin_reg = LinearRegression()
```

In [120]:
```
lin_reg.fit(X_train, y_train)
```

Out[120]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
         normalize=False)
```

In [121]:
```
y_pred = lin_reg.predict(X_test)
```

In [122]:
```
print('Linear Regression accuracy (Original Data, bp) is: ', lin_reg.score(X
print('RMSE: {}'.format(np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

```
Linear Regression accuracy (Original Data, bp) is:  0.14171660665368413
RMSE: 71.75023012151485
```

In [123]:

```
# Try for 'bmi' instead.
X = diabetes.data[:, np.newaxis, 2]
y = diabetes.target
print(X)
print(y)
```

```
[[ 0.06169621]
 [-0.05147406]
 [ 0.04445121]
 [-0.01159501]
 [-0.03638469]
 [-0.04069594]
 [-0.04716281]
 [-0.00189471]
 [ 0.06169621]
 [ 0.03906215]
 [-0.08380842]
 [ 0.01750591]
 [-0.02884001]
 [-0.00189471]
 [-0.02560657]
 [-0.01806189]
 [ 0.04229559]
 [ 0.01211685]
 [-0.0105172 ]
```

In [124]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.5, r
lin_reg = LinearRegression()
lin_reg.fit(X_train, y_train)
y_pred = lin_reg.predict(X_test)
print('Linear Regression accuracy (Original Data, bmi) is: ', lin_reg.score(
print('RMSE: {}'.format(np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

```
Linear Regression accuracy (Original Data, bmi) is:  0.3440122223004842
RMSE: 62.727187769740894
```

In [125]:
```
count = 0
for elem in diabetes.feature_names:
    X = diabetes.data[:, np.newaxis, count]
    y = diabetes.target
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.
    lin_reg = LinearRegression()
    lin_reg.fit(X, y)
    y_pred = lin_reg.predict(X_test)
    print("Linear Regression accuracy (Original Data, {}) is: {}".format(ele
    count = count + 1
```

```
Linear Regression accuracy (Original Data, age) is: 0.016632047556654705
Linear Regression accuracy (Original Data, sex) is: -0.0010208521499910361
Linear Regression accuracy (Original Data, bmi) is: 0.3455707299904237
Linear Regression accuracy (Original Data, bp) is: 0.14991957789063814
Linear Regression accuracy (Original Data, s1) is: 0.03785372894007688
Linear Regression accuracy (Original Data, s2) is: 0.024069411698512955
Linear Regression accuracy (Original Data, s3) is: 0.14500106975582294
Linear Regression accuracy (Original Data, s4) is: 0.17555246008621506
Linear Regression accuracy (Original Data, s5) is: 0.3288109714910701
Linear Regression accuracy (Original Data, s6) is: 0.149391121627106
```

In [126]:
```
# bmi returns the best linear regression accuracy @ 0.3455707299904237
```

In [127]:
```
feature_cols = ['age', 'sex', 'bmi', 'bp']
```

In [128]:
```
X = diabetes.data[:,[0,1,2,3]]
X
```

Out[128]:
```
array([[ 0.03807591,  0.05068012,  0.06169621,  0.02187235],
       [-0.00188202, -0.04464164, -0.05147406, -0.02632783],
       [ 0.08529891,  0.05068012,  0.04445121, -0.00567061],
       ...,
       [ 0.04170844,  0.05068012, -0.01590626,  0.01728186],
       [-0.04547248, -0.04464164,  0.03906215,  0.00121513],
       [-0.04547248, -0.04464164, -0.0730303 , -0.08141377]])
```

In [129]:
```
y = diabetes.target
```

In [130]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 5)
```

In [131]:
```
lin_reg.fit(X_train, y_train)
```

Out[131]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
         normalize=False)
```

In [132]:
```
y_pred = lin_reg.predict(X_test)
```

In [133]:
```
print("Linear Regression accuracy (Reduced Features: 'age', 'sex', 'bmi', 'b
print('RMSE: {}'.format(np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

```
Linear Regression accuracy (Reduced Features: 'age', 'sex', 'bmi', 'bp') is:
0.37983776564636873
RMSE: 63.410445412891725
```

In [134]:
```
# Removing all but 'age', 'sex', 'bmi', 'bp' we were able to achieve a lower
# square error.
```

Logistic Regression

In [135]:
```
diabetes.data
```

Out[135]:
```
array([[ 0.03807591,  0.05068012,  0.06169621, ..., -0.00259226,
         0.01990842, -0.01764613],
       [-0.00188202, -0.04464164, -0.05147406, ..., -0.03949338,
        -0.06832974, -0.09220405],
       [ 0.08529891,  0.05068012,  0.04445121, ..., -0.00259226,
         0.00286377, -0.02593034],
       ...,
       [ 0.04170844,  0.05068012, -0.01590626, ..., -0.01107952,
        -0.04687948,  0.01549073],
       [-0.04547248, -0.04464164,  0.03906215, ...,  0.02655962,
         0.04452837, -0.02593034],
       [-0.04547248, -0.04464164, -0.0730303 , ..., -0.03949338,
        -0.00421986,  0.00306441]])
```

In [136]:
```
diabetes.keys()
```

Out[136]:
```
dict_keys(['data', 'target', 'DESCR', 'feature_names', 'data_filename', 'target
_filename'])
```

In [137]:
```
diabetes.feature_names
```

Out[137]:
```
['age', 'sex', 'bmi', 'bp', 's1', 's2', 's3', 's4', 's5', 's6']
```

In [138]:

```
# Pick 'bp'
X = diabetes.data[:, np.newaxis, 3]
y = diabetes.target
print(X)
print(y)
```

```
[[ 2.18723550e-02]
 [-2.63278347e-02]
 [-5.67061055e-03]
 [-3.66564468e-02]
 [ 2.18723550e-02]
 [-1.94420933e-02]
 [-1.59992226e-02]
 [ 6.66296740e-02]
 [-4.00993175e-02]
 [-3.32135761e-02]
 [ 8.10087222e-03]
 [-3.32135761e-02]
 [-9.11348125e-03]
 [ 8.10087222e-03]
 [-1.25563519e-02]
 [ 8.04011568e-02]
 [ 4.94153205e-02]
 [ 5.63010619e-02]
 [-3.66564468e-02]
```

In [139]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.5, r
log_reg = LogisticRegression()
log_reg.fit(X_train, y_train)
y_pred = log_reg.predict(X_test)
print('Logistic Regression accuracy (Original Data, bp) is: ', log_reg.score
print('RMSE: {}'.format(np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

```
Logistic Regression accuracy (Original Data, bp) is:  0.0
RMSE: 114.76832851779811
```

In [140]:

```
# Try for 'bmi'.
X = diabetes.data[:, np.newaxis, 2]
y = diabetes.target
print(X)
print(y)
```

```
[[ 0.06169621]
 [-0.05147406]
 [ 0.04445121]
 [-0.01159501]
 [-0.03638469]
 [-0.04069594]
 [-0.04716281]
 [-0.00189471]
 [ 0.06169621]
 [ 0.03906215]
 [-0.08380842]
 [ 0.01750591]
 [-0.02884001]
 [-0.00189471]
 [-0.02560657]
 [-0.01806189]
 [ 0.04229559]
 [ 0.01211685]
 [-0.0105172 ]
```

In [141]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.5, r
log_reg = LogisticRegression()
log_reg.fit(X_train, y_train)
y_pred = log_reg.predict(X_test)
print('Logistic Regression accuracy (Original Data, bmi) is: ', log_reg.scor
print('RMSE: {}'.format(np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

```
Logistic Regression accuracy (Original Data, bmi) is:  0.00904977375565611
RMSE: 117.77194389679899
```

In [142]:

```
feature_cols = ['age', 'sex', 'bmi', 'bp']
```

In [143]:

```
X = diabetes.data[:,[0,1,2,3]]
X
```

Out[143]:

```
array([[ 0.03807591,  0.05068012,  0.06169621,  0.02187235],
       [-0.00188202, -0.04464164, -0.05147406, -0.02632783],
       [ 0.08529891,  0.05068012,  0.04445121, -0.00567061],
       ...,
       [ 0.04170844,  0.05068012, -0.01590626,  0.01728186],
       [-0.04547248, -0.04464164,  0.03906215,  0.00121513],
       [-0.04547248, -0.04464164, -0.0730303 , -0.08141377]])
```

In [144]:

```
y = diabetes.target
```

In [145]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 5)
```

In [146]:
```
log_reg.fit(X_train, y_train)
```

Out[146]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False)
```

In [147]:
```
y_pred = log_reg.predict(X_test)
```

In [148]:
```
print("Logistic Regression accuracy (Reduced Features: 'age', 'sex', 'bmi',
print('RMSE: {}'.format(np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

```
Logistic Regression accuracy (Reduced Features: 'age', 'sex', 'bmi', 'bp') is:
0.0
RMSE: 118.92105034944913
```

Results

In [149]:
```
Summary of Classification Results:
```

```
  File "<ipython-input-149-605a9f9aab1c>", line 1
    Summary of Classification Results:
             ^
SyntaxError: invalid syntax
```

```
Decision Tree GINI

Original
               precision    recall  f1-score   support

           1       0.56      0.56      0.56        16
           2       0.96      0.94      0.95       275
           3       0.47      0.67      0.55        12

   micro avg       0.91      0.91      0.91       303
   macro avg       0.66      0.72      0.69       303
weighted avg       0.92      0.91      0.91       303

Reduced
              precision    recall  f1-score   support

           1       0.57      0.81      0.67        16
           2       0.98      0.93      0.96       275
           3       0.53      0.75      0.62        12

   micro avg       0.92      0.92      0.92       303
```

```
   macro avg       0.69      0.83      0.75       303
weighted avg       0.94      0.92      0.93       303

Decision tree GINI accuracy (Original Data) is:  0.9108910891089109
Decision tree GINI accuracy (Reduced Data) is:  0.9207920792079208
```

```
Decision Tree ENTROPY

Original
               precision    recall  f1-score   support

           1       0.73      0.69      0.71        16
           2       0.97      0.96      0.97       275
           3       0.56      0.83      0.67        12

   micro avg       0.94      0.94      0.94       303
   macro avg       0.75      0.83      0.78       303
weighted avg       0.94      0.94      0.94       303

Reduced
                precision    recall  f1-score   support

           1       0.92      0.75      0.83        16
           2       0.97      0.96      0.97       275
           3       0.50      0.75      0.60        12

   micro avg       0.94      0.94      0.94       303
   macro avg       0.80      0.82      0.80       303
weighted avg       0.95      0.94      0.95       303

Decision tree ENTROPY accuracy (Original Data) is:  0.9372937293729373
Decision tree ENTROPY accuracy (Reduced Data) is:  0.9438943894389439
```

```
K - Nearest Neighbours

Original
               precision    recall  f1-score   support

           1       0.00      0.00      0.00        16
           2       0.92      1.00      0.96       275
           3       1.00      0.25      0.40        12

   micro avg       0.92      0.92      0.92       303
   macro avg       0.64      0.42      0.45       303
weighted avg       0.87      0.92      0.88       303

Reduced
              precision    recall  f1-score   support

           1       0.00      0.00      0.00        16
           2       0.92      1.00      0.96       275
           3       0.80      0.33      0.47        12

   micro avg       0.92      0.92      0.92       303
   macro avg       0.57      0.44      0.48       303
```

```
weighted avg       0.87      0.92      0.89       303

KNN accuracy (Original Data) is:  0.9174917491749175
KNN accuracy (Reduced Data) is:  0.9174917491749175
```

```
Random Forest

Original
               precision    recall  f1-score   support

           1       0.90      0.56      0.69        16
           2       0.96      0.97      0.97       275
           3       0.60      0.75      0.67        12

   micro avg       0.94      0.94      0.94       303
   macro avg       0.82      0.76      0.78       303
weighted avg       0.95      0.94      0.94       303

Reduced
              precision    recall  f1-score   support

           1       0.91      0.62      0.74        16
           2       0.95      0.98      0.97       275
           3       0.50      0.42      0.45        12

   micro avg       0.94      0.94      0.94       303
   macro avg       0.79      0.67      0.72       303
weighted avg       0.93      0.94      0.93       303

Random Forest accuracy (Original Data) is:  0.9438943894389439
Random Forest accuracy (Reduced Data) is:  0.9372937293729373
```

```
SVM Classification

Original
               precision    recall  f1-score   support

           1       0.89      0.50      0.64        16
           2       0.96      0.99      0.97       275
           3       0.77      0.83      0.80        12

   micro avg       0.95      0.95      0.95       303
   macro avg       0.87      0.77      0.80       303
weighted avg       0.95      0.95      0.95       303

Reduced
              precision    recall  f1-score   support

           1       1.00      0.44      0.61        16
           2       0.93      1.00      0.96       275
           3       0.00      0.00      0.00        12

   micro avg       0.93      0.93      0.93       303
   macro avg       0.64      0.48      0.52       303
weighted avg       0.90      0.93      0.91       303
```

```
SVM Classification accuracy (Original Data) is:  0.9537953795379538
SVM Classification accuracy (Reduced Data) is:  0.9306930693069307
```

```
The best performing classification algorithm looks to be SVM classification on the original data, with an
accuracy of 0.9538, and weighted avgs for precision and recall @ 0.95 and 0.95 respectively
```

```
SVM Regression

SVR accuracy (Original Data) is:  -0.09755658003981038
SVR accuracy (Reduced Data) is:  -0.09163894002575668
```

```
Linear Regression

Linear Regression accuracy (Original Data, bmi) is:  0.3455707299904237
RMSE: 62.65262926241338

Linear Regression accuracy (Reduced Features: 'age', 'sex', 'bmi', 'bp') is:  0.37983776564636873
RMSE: 63.410445412891725
```

```
Logistic Regression

Logistic Regression accuracy (Original Data, bmi) is:  0.00904977375565611
RMSE: 117.77194389679899

Logistic Regression accuracy (Reduced Features: 'age', 'sex', 'bmi', 'bp') is:  0.0
RMSE: 118.92105034944913
```

```
The best performing regression algorithm looks to be Linear Regression on the Reduced Feature Data where accuracy is 0.37983776564636873.  However, RMSE is slightly elevated in comparison to Linear Regression with the original data.  Note SVM Regression returned negative results.  I could not figure out why but it must be an error as sample predictions came out somewhat accurate.
```