The original goal of this notebook was to predict the existing balancing behaviour of Citibike.

In [125]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from IPython.display import clear_output

import keras
from keras.models import Sequential
from keras.layers import Dense, Dropout, Activation, Input
from keras.optimizers import Adam, SGD
from keras.regularizers import l1, l2
from keras.metrics import categorical_accuracy
```

In [126]:
```
# Callback to plot model loss + accuracy during training
class PlotLosses(keras.callbacks.Callback):
    def on_train_begin(self, logs={}):
        self.i = 0
        self.x = []
        self.losses = []
        self.accuracy = []

        self.fig = plt.figure()

        self.logs = []

    def on_epoch_end(self, epoch, logs={}):
        self.logs.append(logs)
        self.x.append(self.i)
        self.losses.append(logs.get('loss'))
        self.accuracy.append(logs.get('categorical_accuracy'))
        self.i += 1

        clear_output(wait=True)
        plt.plot(self.x, self.losses, label="loss")
        plt.xlabel("Epoch")
        plt.ylabel("Loss")
        plt.legend()
        plt.show()

        plt.plot(self.x, self.accuracy, label="accuracy")
        plt.xlabel("Epoch")
        plt.ylabel("Accuracy")
        plt.legend()
        plt.show()

def read_csv(fname, base_path='../data/'):
    return pd.read_csv(f'{base_path}{fname}', index_col=0)

plot_losses = PlotLosses()
```

The rebalanced trips dataset will be used for base features.

In [127]:
```
trips = read_csv('rebalanced_bikes.csv.zip')
trips = trips.drop(['birth year', 'gender', 'tripduration', 'usertype'
], axis=1)

trips['next starttime'] = pd.to_datetime(trips['next starttime'])
trips['stoptime'] = pd.to_datetime(trips['stoptime'])
trips['next start station id'] = pd.to_numeric(trips['next start stati
on id'], downcast='unsigned')
```

In [128]:
```
trips['balancing delta'] = trips['next starttime'] - trips['stoptime']
trips['balancing delta'] = trips['balancing delta'].astype(np.int64) #
Convert to nanoseconds

trips['stoptime hour'] = trips['stoptime'].apply(lambda x: x.hour)
trips['next starttime hour'] = trips['next starttime'].apply(lambda x:
x.hour)
```

In [129]:
```
trips.head()
```

Out[129]:

	bikeid	end station id	end station latitude	end station longitude	end station name	next start station id	next starttime	start station id	sta static latitu
0	25542	3341	40.795346	-73.961860	central park west & w 102 st	3289	2017-01-11 21:36:50	3292	40.7857
1	25542	324	40.689888	-73.981013	dekalb ave & hudson ave	532	2017-01-25 19:24:13	399	40.6885
2	25542	248	40.721854	-74.007718	laight st & hudson st	3064	2017-02-04 02:01:01	417	40.7129
3	25542	497	40.737050	-73.990093	e 17 st & broadway	2003	2017-02-08 13:14:33	527	40.7440
4	25542	447	40.763707	-73.985162	8 ave & w 52 st	517	2017-02-08 22:27:53	446	40.7448

In [130]:
```
avg_balancing_delta = trips.groupby('bikeid')['balancing delta'].agg('
mean')
avg_balancing_delta = pd.to_timedelta(avg_balancing_delta)
avg_balancing_delta.head()
```

Out[130]:
```
bikeid
14529   1 days 15:59:53.702127
14530   1 days 19:40:35.777777
14531   1 days 03:35:39.261904
14532   2 days 17:08:22.179487
14533   0 days 21:29:34.732142
Name: balancing delta, dtype: timedelta64[ns]
```

In [131]:
```
# Read in clusters
work_cluster = read_csv('work_cluster.csv')
work_cluster.head()
```

Out[131]:

	dock_id	dock_name	_lat	_long	hour	avail_bikes_percent
1	83	Atlantic Ave & Fort Greene Pl	40.683826	-73.976323	1	0.580645
2	83	Atlantic Ave & Fort Greene Pl	40.683826	-73.976323	2	0.338710
3	83	Atlantic Ave & Fort Greene Pl	40.683826	-73.976323	3	0.322581
4	83	Atlantic Ave & Fort Greene Pl	40.683826	-73.976323	4	0.322581
5	83	Atlantic Ave & Fort Greene Pl	40.683826	-73.976323	5	0.322581

In [132]:
```
residential_cluster = read_csv('residential_cluster.csv')
residential_cluster.head()
```

Out[132]:

	dock_id	dock_name	_lat	_long	hour	avail_bikes_percent
1	72	W 52 St & 11 Ave	40.767272	-73.993929	1	0.666667
2	72	W 52 St & 11 Ave	40.767272	-73.993929	2	0.666667
3	72	W 52 St & 11 Ave	40.767272	-73.993929	3	0.666667
4	72	W 52 St & 11 Ave	40.767272	-73.993929	4	0.666667
5	72	W 52 St & 11 Ave	40.767272	-73.993929	5	0.666667

In [133]:
```
low_cluster = read_csv('low_cluster.csv')
low_cluster.head()
```

Out[133]:

	dock_id	dock_name	_lat	_long	hour	avail_bikes_percent
1	116	W 17 St & 8 Ave	40.741776	-74.001497	1	0.512821
2	116	W 17 St & 8 Ave	40.741776	-74.001497	2	0.461538
3	116	W 17 St & 8 Ave	40.741776	-74.001497	3	0.487179
4	116	W 17 St & 8 Ave	40.741776	-74.001497	4	0.410256
5	116	W 17 St & 8 Ave	40.741776	-74.001497	5	0.410256

To add additional features, the station clusters can be correlated with the balancing trips.

In [134]:
```
trips['start station cluster'] = 0
trips['end station cluster'] = 0
trips['next start station cluster'] = 0

trips.loc[trips['start station id'].isin(work_cluster['dock_id'].unique()), 'start station cluster'] = 1
trips.loc[trips['end station id'].isin(work_cluster['dock_id'].unique()), 'end station cluster'] = 1
trips.loc[trips['next start station id'].isin(work_cluster['dock_id'].unique()), 'next start station cluster'] = 1

trips.loc[trips['start station id'].isin(residential_cluster['dock_id'].unique()), 'start station cluster'] = 2
trips.loc[trips['end station id'].isin(residential_cluster['dock_id'].unique()), 'end station cluster'] = 2
trips.loc[trips['next start station id'].isin(residential_cluster['dock_id'].unique()), 'next start station cluster'] = 2
```

Next, the average bike availability for each particular station at the relevant hour can be obtained from the cluster data.

In [135]:
```
test = low_cluster.groupby(['dock_id', 'hour'])['avail_bikes_percent'].mean()
test[116, 6]
```

Out[135]:
```
0.46520146520146516
```

In [136]:
```
def extract_avg_station_time(means, x):
    try:
        return means[x['end station id'], x['stoptime hour']+1]
    except KeyError:
        try:
            return means[x['end station id']].mean()
        except KeyError:
            return means.mean()
```

In [137]:
```
trips['avail_bikes_percent_low'] = np.float64(0)
trips['avail_bikes_percent_work'] = np.float64(0)
trips['avail_bikes_percent_res'] = np.float64(0)
trips['avail_bikes_percent'] = np.float64(0)

print("Populated initial values")
low_trips = trips.loc[trips['end station cluster'] == 0]
work_trips = trips.loc[trips['end station cluster'] == 1]
res_trips = trips.loc[trips['end station cluster'] == 2]

low_means = low_cluster.groupby('hour')['avail_bikes_percent'].mean()
work_means = work_cluster.groupby('hour')['avail_bikes_percent'].mean(
)
res_means = residential_cluster.groupby('hour')['avail_bikes_percent']
.mean()

print("Populating averages")
trips['avail_bikes_percent_low'] = trips.apply(lambda x: low_means[x['
stoptime hour']+1], axis=1)
print(" " * 4, "Low")
trips['avail_bikes_percent_work'] = trips.apply(lambda x: work_means[x
['stoptime hour']+1], axis=1)
print(" " * 4, "Work")
trips['avail_bikes_percent_res'] = trips.apply(lambda x: res_means[x['
stoptime hour']+1], axis=1)
print(" " * 4, "Res")
print("Populated averages")


trips.loc[trips['end station cluster'] == 0, 'avail_bikes_percent'] =
low_trips.apply(lambda x: low_cluster[(low_cluster['dock_id'] == x['en
d station id']) & (low_cluster['hour'] == (x['stoptime hour'] + 1))]['
avail_bikes_percent'].agg('mean'), axis=1)
print("Populated specifics for low")

trips.loc[trips['end station cluster'] == 1, 'avail_bikes_percent'] =
work_trips.apply(lambda x: work_cluster[(work_cluster['dock_id'] == x[
'end station id']) & (work_cluster['hour'] == (x['stoptime hour'] + 1)
)]['avail_bikes_percent'].agg('mean'), axis=1)
print("Populated specifics for work")

trips.loc[trips['end station cluster'] == 2, 'avail_bikes_percent'] =
res_trips.apply(lambda x: residential_cluster[(residential_cluster['do
ck_id'] == x['end station id']) & (residential_cluster['hour'] == (x['
stoptime hour'] + 1))]['avail_bikes_percent'].agg('mean'), axis=1)
print("Populated specifics for res")
```

```
Populated initial values
Populating averages
     Low
     Work
     Res
Populated averages
Populated specifics for low
Populated specifics for work
Populated specifics for res
```

In [138]:

```python
# trips = trips.drop(['avail_bikes_percent'], axis=1)
print(trips.shape)
trips.head()
```

```
(479801, 23)
```

Out[138]:

	bikeid	end station id	end station latitude	end station longitude	end station name	next start station id	next starttime	start station id	sta statio latitu
0	25542	3341	40.795346	-73.961860	central park west & w 102 st	3289	2017-01-11 21:36:50	3292	40.78578
1	25542	324	40.689888	-73.981013	dekalb ave & hudson ave	532	2017-01-25 19:24:13	399	40.68851
2	25542	248	40.721854	-74.007718	laight st & hudson st	3064	2017-02-04 02:01:01	417	40.71291
3	25542	497	40.737050	-73.990093	e 17 st & broadway	2003	2017-02-08 13:14:33	527	40.74402
4	25542	447	40.763707	-73.985162	8 ave & w 52 st	517	2017-02-08 22:27:53	446	40.74487

5 rows × 23 columns

In [139]:
```
# trips[trips.isnull().any()] = 0.5
trips = trips.dropna()
```

In [140]:
```
trips['weekday'] = trips['stoptime'].apply(lambda x: x.weekday())
trips['is_weekday'] = trips['weekday'].apply(lambda x: x < 5)

trips.head()
```

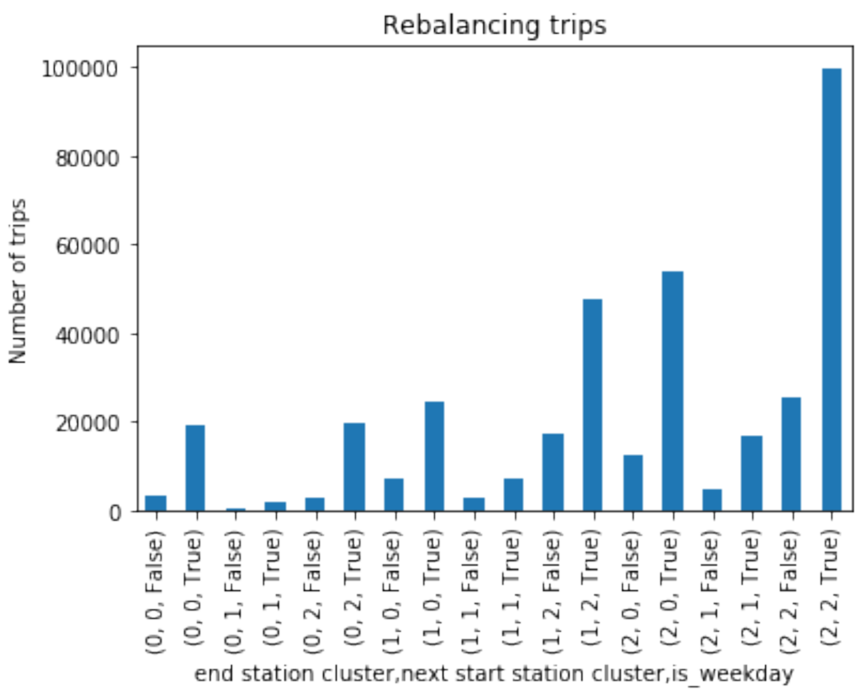
Out[140]:

	bikeid	end station id	end station latitude	end station longitude	end station name	next start station id	next starttime	start station id	st stat latitu
0	25542	3341	40.795346	-73.961860	central park west & w 102 st	3289	2017-01-11 21:36:50	3292	40.7857
1	25542	324	40.689888	-73.981013	dekalb ave & hudson ave	532	2017-01-25 19:24:13	399	40.6885
4	25542	447	40.763707	-73.985162	8 ave & w 52 st	517	2017-02-08 22:27:53	446	40.7448
5	25542	3058	40.692371	-73.937054	lewis ave & kosciuszko st	530	2017-02-28 08:30:49	3064	40.6968
6	25542	412	40.715816	-73.994224	forsyth st & canal st	532	2017-03-21 09:46:27	241	40.6898

5 rows × 25 columns

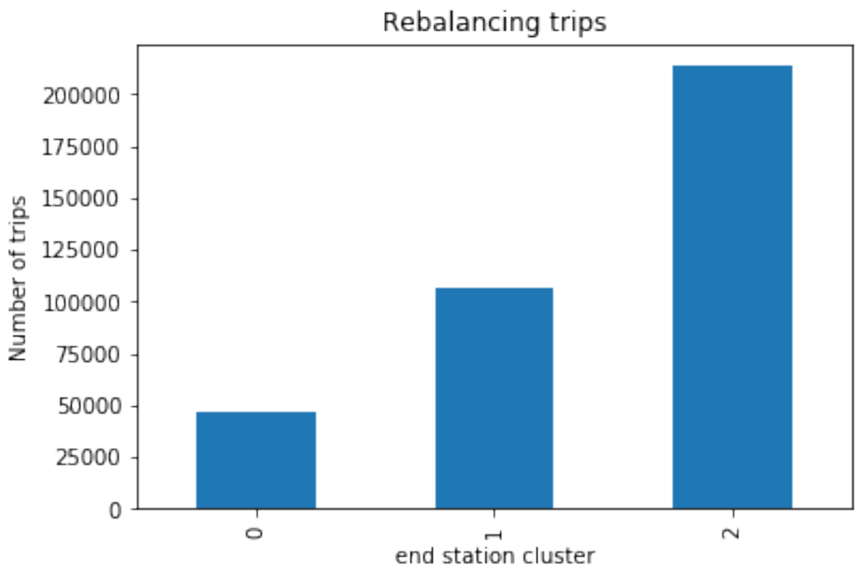
After correlating the clusters with the trips, we can see the balancing behaviour in terms of the clusters.

In [141]:
```
rebalancing_clusters = trips.groupby(['end station cluster', 'next sta
rt station cluster', 'is_weekday'])['bikeid'].agg('count')

rebalancing_clusters.plot(kind='bar')
plt.ylabel("Number of trips")
plt.title("Rebalancing trips")
plt.show()

print("Percentage of bike rebalancing during the week", trips[trips['i
s_weekday'] == True]['bikeid'].agg('count') / trips.shape[0])
print("Percentage of bike rebalancing to work cluster", trips[trips['e
nd station cluster'] == 1]['bikeid'].agg('count') / trips.shape[0])
print("Percentage of bike rebalancing to residential cluster", trips[t
rips['end station cluster'] == 2]['bikeid'].agg('count') / trips.shape
[0])
print("Percentage of bike rebalancing to residential cluster (from oth
er clusters)", trips[(trips['end station cluster'] == 2) & (trips['sta
rt station cluster'] != 2)]['bikeid'].agg('count') / trips.shape[0])
```




```
Percentage of bike rebalancing during the week 0.7909035957589322
Percentage of bike rebalancing to work cluster 0.29085186213806885
Percentage of bike rebalancing to residential cluster 0.581232676044
0661
Percentage of bike rebalancing to residential cluster (from other cl
usters) 0.28748100831549883
```

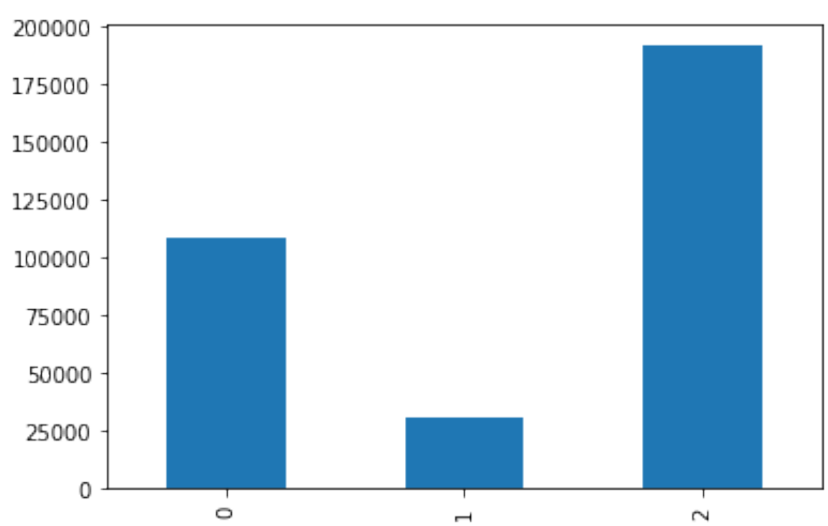
In [142]:
```
rebalancing_clusters = trips.groupby(['end station cluster'])['bikeid'
].agg('count')

rebalancing_clusters.plot(kind='bar')
plt.ylabel("Number of trips")
plt.title("Rebalancing trips")
plt.show()
```

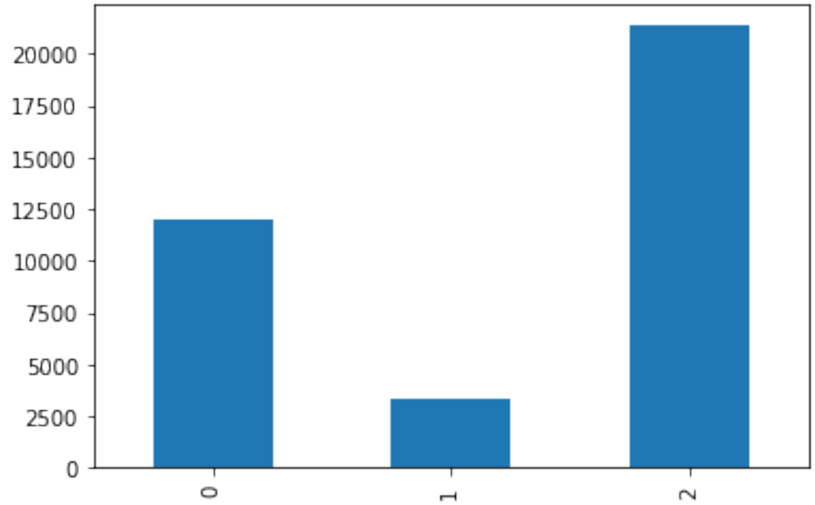


This next block will extract individual parts from the dates and build one hot vectors for these features. Then the data can be split into training and testing sets. The goal of a classifier is: given the ending month, day, hour, if the day is a workday, and the end station cluster, predict the cluster that the bike should be moved to.

In [143]:
```
from sklearn.model_selection import train_test_split
# 'end station id',
balancing_features = trips[['stoptime', 'stoptime hour', 'avail_bikes_
percent', 'avail_bikes_percent_low', 'avail_bikes_percent_work', 'avai
l_bikes_percent_res', 'end station cluster']]
# end_station_cluster_feature = pd.get_dummies(trips['end station clus
ter'])
balancing_features['stopmonth'] = balancing_features['stoptime'].apply
(lambda x: x.month)
balancing_features['stopday'] = balancing_features['stoptime'].apply(l
ambda x: x.day)
balancing_features['stophour'] = balancing_features['stoptime'].apply(
lambda x: x.hour)
balancing_features['stop weekday'] = balancing_features['stoptime'].ap
ply(lambda x: x.weekday() < 5)

balancing_features = balancing_features.drop(['stoptime', 'stoptime ho
ur'], axis=1)
# balancing_features = pd.concat([balancing_features, end_station_clus
ter_feature], axis=1, join='inner')

categorial = ['stopmonth', 'stopday', 'stophour', 'end station cluster
']

for c in categorial:
    balancing_features = pd.concat([balancing_features.drop([c], axis=
1), pd.get_dummies(balancing_features[c], prefix=c)], axis=1)

balancing_labels = pd.get_dummies(trips['next start station cluster'])
# Encode as a 1-hot vector
balancing_delta_label = trips['balancing delta']

X_train, X_test, Y_train, Y_test = train_test_split(balancing_features
, balancing_labels, train_size=0.9)
features = X_train.shape[1]

Y_train.agg('sum').plot(kind='bar')
plt.show()

Y_test.agg('sum').plot(kind='bar')
plt.show()
```

```
/usr/local/lib/python3.6/site-packages/ipykernel_launcher.py:5: Sett
ingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/panda
s-docs/stable/indexing.html#indexing-view-versus-copy
  """
/usr/local/lib/python3.6/site-packages/ipykernel_launcher.py:6: Sett
ingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/panda
s-docs/stable/indexing.html#indexing-view-versus-copy

/usr/local/lib/python3.6/site-packages/ipykernel_launcher.py:7: Sett
ingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/panda
s-docs/stable/indexing.html#indexing-view-versus-copy
  import sys
/usr/local/lib/python3.6/site-packages/ipykernel_launcher.py:8: Sett
ingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/panda
s-docs/stable/indexing.html#indexing-view-versus-copy
```





In [144]:
```
X_train.head()
```

Out[144]:

	avail_bikes_percent	avail_bikes_percent_low	avail_bikes_percent_work	avail_
449518	0.426667	0.371603	0.488629	0.492
304750	0.489198	0.400225	0.517372	0.452
440370	0.451049	0.384404	0.478100	0.490
82537	0.499962	0.371688	0.483512	0.496
272736	0.500000	0.370378	0.477908	0.502

5 rows × 75 columns

As the majority of the balancing trips had a target in the residential cluster (number 2), I will drop 50% of these to make the dataset more balanced. Otherwise, I found that the classifier would learn to always predict cluster 2.

In [712]:
```
drop_rows = Y_train[Y_train[2] == 1].sample(frac=0.5).index
X_train = X_train.drop(drop_rows)
Y_train = Y_train.drop(drop_rows)

Y_train.agg('sum')
```

Out[712]:
```
0    118794
1     71942
2    120542
dtype: int64
```

In [17]:
```
print(X_train[X_train.isnull().any(axis=1)].shape)
print(X_test[X_test.isnull().any(axis=1)].shape)

drop_train_rows = X_train[X_train.isnull().any(axis=1)].index
drop_test_rows = X_test[X_test.isnull().any(axis=1)].index

X_train = X_train.drop(drop_train_rows)
Y_train = Y_train.drop(drop_train_rows)
X_test = X_test.drop(drop_test_rows)
Y_test = Y_test.drop(drop_test_rows)
```

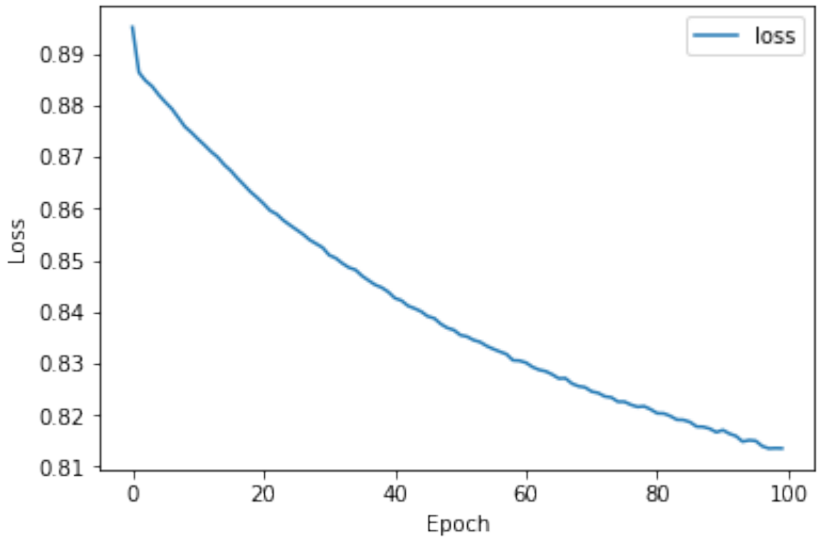
```
(104448, 72)
(11813, 72)
```

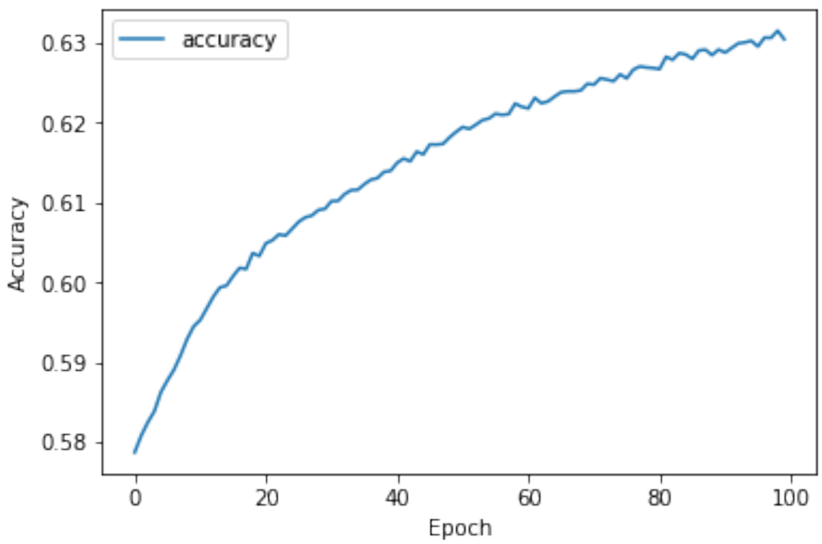
Neural Network Model

This model will predict a probability distribution of balancing to each cluster. After experimenting with various iterations, I was able to gain a maximum test accuracy of ~62%.

In [161]:
```
#     Dense(20, activation='tanh', kernel_regularizer=l2(0.01), activi
ty_regularizer=l1(0.01)),
model = Sequential([
    Dense(300, input_shape=(features,), activation='sigmoid'),
    Dropout(0.15),
    Dense(100, activation='sigmoid'),
    Dropout(0.10),
    Dense(3),
    Activation('softmax')
])
#     Dense(806),


optimizer = Adam(lr=0.01)
model.compile(loss='categorical_crossentropy', optimizer='nadam', metr
ics=[categorical_accuracy])
```

In [162]:
```
model.fit(x=X_train.values, y=Y_train.values, epochs=100, batch_size=500, shuffle=True, validation_split=0.2, callbacks=[plot_losses])
```





Out[162]: <keras.callbacks.History at 0x124d45d68>

In [163]:
```
model.evaluate(X_test, Y_test)
```

```
36727/36727 [==============================] - 2s 41us/step
```

Out[163]: [0.8337671695479503, 0.6222125411968427]

In [148]:
```
for i in range(0, 20):
    d = X_test.values[i].reshape(1, features)
    prediction = model.predict(d)
    target = Y_test.iloc[i]
    print(d, '-> station:', prediction.argmax())
    print('target station: ', target.values.argmax())
```

```
[[0.4769680505521763 0.4073227094684509 0.5131014889589844
  0.45120305516014625 False 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1
0 0 0
  0 0 0 0 0 0 0 0 0 0 1]] -> station: 2
target station:  2
[[0.5 0.4025284046109517 0.5130300795967859 0.45419965681899493 True
0 0
  0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1]]
-> station: 2
target station:  0
[[0.4952015496998195 0.3844042862932431 0.47809991990436757
  0.4901574440273738 False 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0
0 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 0 1 0]] -> station: 2
target station:  1
[[0.5 0.4073227094684509 0.5131014889589844 0.45120305516014625 Fals
e 0 0
  0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
  0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1]]
-> station: 2
target station:  1
[[0.42116095286827 0.38444673734846374 0.49037858808443086
  0.47819764029413137 True 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1
0 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 1 0 0]] -> station: 0
target station:  0
[[0.2581296992481203 0.4073227094684509 0.5131014889589844
  0.45120305516014625 True 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0
0 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1
0 0 0
  0 0 0 0 0 0 0 0 1 0 0]] -> station: 0
target station:  2
```

```
[[0.589958737593398 0.3768886287476546 0.4997808975313007
  0.47852731872942195 True 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0
  0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
  0 1 0 0 0 0 0 0 0 1 0]] -> station: 0
target station:  2
[[0.4838709677419355 0.367065949258832 0.4836096490580789
  0.49951339587790167 True 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0
0 0
  0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 1 0 0 0 1]] -> station: 2
target station:  2
[[0.4883203559510568 0.37160316078987193 0.4886294570278699
  0.4928761340792226 True 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
  0 0 1 0 0 0 0 0 0 1]] -> station: 2
target station:  0
[[0.45037220843672454 0.3855412122116808 0.5086832813212849
  0.46412237630167813 True 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 1
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
  1 0 0 0 0 0 0 0 0 0 1]] -> station: 2
target station:  2
[[0.5092592592592593 0.3997941198846534 0.5101799924608992
  0.4612801699694579 True 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 1 0]] -> station: 2
target station:  0
[[0.4904761904761905 0.3716876766656343 0.48351200696350066
  0.496193443426428 False 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
  0 0 0 1 0 0 0 0 1 0]] -> station: 2
target station:  2
[[0.5000000000000001 0.37160316078987193 0.4886294570278699
  0.4928761340792226 True 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
  0 0 1 0 0 0 0 0 0 1]] -> station: 2
target station:  2
[[0.5 0.3676911159185694 0.4839193165396441 0.4972944393389463 False
```

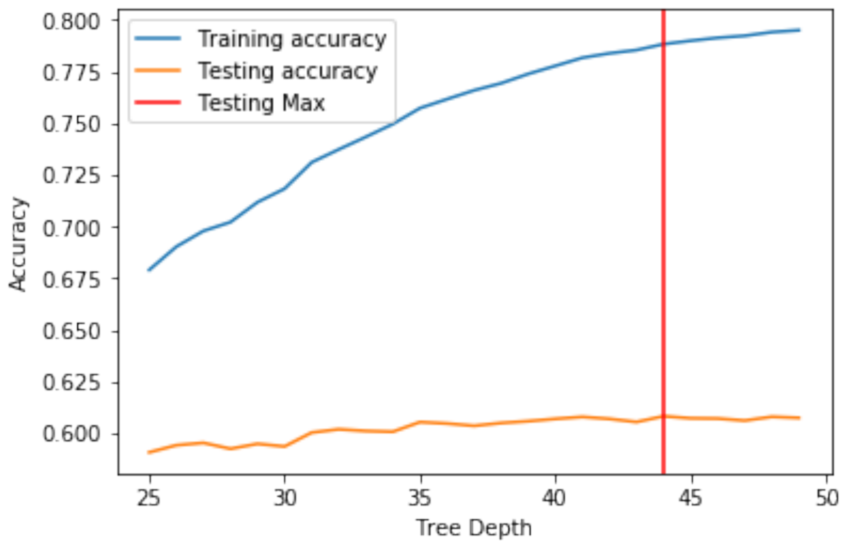
```
0 0
  0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1]]
-> station: 2
target station:  2
[[0.4686609686609687 0.4002250453211441 0.5173724223517082
  0.45236837007578 True 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
  1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1
0 0 0
  0 0 0 0 0 0 0 0 1]] -> station: 2
target station:  2
[[0.5160680529300568 0.3711393373237767 0.4804075030049398
  0.5001426230589271 True 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 1 0 0 1]] -> station: 2
target station:  0
[[0.4832562496340963 0.3855412122116808 0.5086832813212849
  0.46412237630167813 True 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0
  0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
  1 0 0 0 0 0 0 0 0 1 0]] -> station: 2
target station:  0
[[0.531584062196307 0.367065949258832 0.4836096490580789
  0.49951339587790167 True 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0
1 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 1 0 0 0 1]] -> station: 2
target station:  2
[[0.5 0.37051577277473485 0.49299695793787174 0.48828999786427507 Tr
ue 0
  0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 1]
] -> station: 2
target station:  2
[[0.4983388704318936 0.37051577277473485 0.49299695793787174
  0.48828999786427507 True 0 0 0 0 0 1 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0
0 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
  0 0 1 0 0 0 0 0 0 0 1]] -> station: 0
target station:  0
```

Decision Tree Model

I also created a decision tree classifier, this performed in a similar manner to the neural network model. I experimented by limiting the depth of the tree of prevent overfitting.

In [153]:
```
from sklearn import tree

min_depth, max_depth = 25, 50
train_acc = []
test_acc = []
for depth in range(min_depth, max_depth):
    print("Current Depth: ", depth)

    tree_model = tree.DecisionTreeClassifier(max_depth=depth, criterio
n='entropy')
    tree_model.fit(X_train, Y_train)
    train_acc.append(tree_model.score(X_train, Y_train))
    test_acc.append(tree_model.score(X_test, Y_test))

print(train_acc)
print(test_acc)
test_max = np.argmax(test_acc)

print("Best depth:", min_depth + test_max)

plt.plot(range(min_depth, max_depth), train_acc, label="Training accur
acy")
plt.plot(range(min_depth, max_depth), test_acc, label="Testing accurac
y")
plt.axvline(x=min_depth + test_max, label='Testing Max', color='r')
plt.xlabel("Tree Depth")
plt.ylabel("Accuracy")
plt.legend()
plt.show()
```

```
Current Depth:  25
Current Depth:  26
Current Depth:  27
Current Depth:  28
Current Depth:  29
Current Depth:  30
Current Depth:  31
Current Depth:  32
Current Depth:  33
Current Depth:  34
Current Depth:  35
Current Depth:  36
Current Depth:  37
Current Depth:  38
Current Depth:  39
Current Depth:  40
Current Depth:  41
Current Depth:  42
Current Depth:  43
Current Depth:  44
Current Depth:  45
Current Depth:  46
Current Depth:  47
Current Depth:  48
Current Depth:  49
[0.679021235013115, 0.6902634787422967, 0.6978631870974378, 0.702134
9976855984, 0.7117828758482357, 0.718290428663486, 0.731042327834234
4, 0.7372775981049134, 0.7433283213176055, 0.7495726676731036, 0.757
2449847067971, 0.7615894039735099, 0.7658612145616704, 0.76928289853
84478, 0.7737937126935097, 0.7776752516344516, 0.781605196361095, 0.
7837532031016007, 0.7853354672217197, 0.788206535386142, 0.789840230
6535689, 0.7912530745237325, 0.7922363170457949, 0.7940273311167517,
0.7949288888754429]
[0.5908187437035424, 0.5942494622484821, 0.5953930350967953, 0.59253
41029760122, 0.594930160372478, 0.5936504478993656, 0.60037574536444
58, 0.6019549650121164, 0.6011381272633213, 0.6007841642388434, 0.60
54401394069758, 0.6047594412829799, 0.6036430963596264, 0.6050044926
076183, 0.6058757862063332, 0.6069921311296866, 0.607945108503281, 0
.6069921311296866, 0.6054945952568954, 0.6082718436027991, 0.6072916
383042448, 0.6071554986794456, 0.6061752933808915, 0.607999564353200
7, 0.6074822337789637]
Best depth: 44
```



In [154]:
```
for i in [0, 2, 10, 15, 25, 11]:
    d = X_test.values[i].reshape(1, features)
    prediction = tree_model.predict(d)
    target = Y_test.iloc[i]
    print(d, '->', prediction, '-> Cluster:', prediction.argmax())
    print(target.values, '-> Cluster: ', target.values.argmax())
```

```
[[0.4769680505521763 0.4073227094684509 0.5131014889589844
  0.45120305516014625 False 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1
0 0 0
  0 0 0 0 0 0 0 0 0 0 1]] -> [[0. 0. 1.]] -> Cluster: 2
[0 0 1] -> Cluster:  2
[[0.4952015496998195 0.3844042862932431 0.47809991990436757
  0.4901574440273738 False 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0
0 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 0 1 0]] -> [[0. 1. 0.]] -> Cluster: 1
[0 1 0] -> Cluster:  1
[[0.5092592592592593 0.3997941198846534 0.5101799924608992
  0.4612801699694579 True 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 1 0]] -> [[1. 0. 0.]] -> Cluster: 0
[1 0 0] -> Cluster:  0
[[0.5160680529300568 0.3711393373237767 0.4804075030049398
  0.5001426230589271 True 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 1 0 0 1]] -> [[0. 0. 1.]] -> Cluster: 2
[1 0 0] -> Cluster:  0
[[0.542825361512792 0.3926057008980605 0.5049940386663777
  0.4658517639344532 True 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1
0 0 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 1 0]] -> [[0. 0. 1.]] -> Cluster: 2
[0 0 1] -> Cluster:  2
[[0.4904761904761905 0.3716876766656343 0.48351200696350066
  0.496193443426428 False 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
  0 0 0 1 0 0 0 0 1 0]] -> [[0. 0. 1.]] -> Cluster: 2
[0 0 1] -> Cluster:  2
```

Gradient Boosting Classifier

I also tried an ensemble tree classifier, using gradient boosting. This classifier was only able to gain a test accuracy of 60%.

In [155]:
```
from sklearn.ensemble import GradientBoostingClassifier

boost_model = GradientBoostingClassifier()
boost_model.fit(X_train.values, Y_train.apply(lambda y: y.argmax(), ax
is=1))
print("Test acc:", boost_model.score(X_test, Y_test.apply(lambda y: y.
argmax(), axis=1)))
```

```
Test acc: 0.6057124186565742
```

In [156]:
```
for i in [0, 2, 10, 15, 25, 11]:
    d = X_test.values[i].reshape(1, features)
    prediction = boost_model.predict(d)
    target = Y_test.iloc[i]
    print(d, '->', prediction)
    print(target.values, '-> Cluster: ', target.values.argmax())
```

```
[[0.4769680505521763 0.4073227094684509 0.5131014889589844
  0.45120305516014625 False 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1
0 0 0
  0 0 0 0 0 0 0 0 0 1]] -> [2]
[0 0 1] -> Cluster:  2
[[0.4952015496998195 0.3844042862932431 0.47809991990436757
  0.4901574440273738 False 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0
0 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 0 1 0]] -> [2]
[0 1 0] -> Cluster:  1
[[0.5092592592592593 0.3997941198846534 0.5101799924608992
  0.4612801699694579 True 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 1 0]] -> [2]
[1 0 0] -> Cluster:  0
[[0.5160680529300568 0.3711393373237767 0.4804075030049398
  0.5001426230589271 True 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 1 0 0 1]] -> [2]
[1 0 0] -> Cluster:  0
[[0.542825361512792 0.3926057008980605 0.5049940386663777
  0.4658517639344532 True 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1
0 0 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 1 0]] -> [2]
[0 0 1] -> Cluster:  2
[[0.4904761904761905 0.3716876766656343 0.48351200696350066
  0.496193443426428 False 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
  0 0 0 1 0 0 0 0 1 0]] -> [2]
[0 0 1] -> Cluster:  2
```

Logistic Classifier

Finally, I built a logistic classifier. This model could only gain approximately 58% test accuracy.

In [157]:
```
from sklearn.linear_model import SGDClassifier

lin_model = SGDClassifier(loss='log', shuffle=True)
lin_model.fit(X_train.values, Y_train.apply(lambda y: y.argmax(), axis
=1))


print("train acc", lin_model.score(X_train.values, Y_train.apply(lambd
a y: y.argmax(), axis=1)))
print("test acc", lin_model.score(X_test.values, Y_test.apply(lambda y
: y.argmax(), axis=1)))
```

```
train acc 0.5805094103872765
test acc 0.5798731178696872
```

In [158]:
```
for i in [0, 2, 10, 15, 25, 11]:
    d = X_test.values[i].reshape(1, features)
    prediction = lin_model.predict(d)
    target = Y_test.iloc[i]
    print(d, '->', prediction)
    print(target.values.argmax())
```

```
[[0.4769680505521763 0.4073227094684509 0.5131014889589844
  0.45120305516014625 False 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1
0 0 0
  0 0 0 0 0 0 0 0 0 0 1]] -> [2]
2
[[0.4952015496998195 0.3844042862932431 0.47809991990436757
  0.4901574440273738 False 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1 0
0 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 0 1 0]] -> [2]
1
[[0.5092592592592593 0.3997941198846534 0.5101799924608992
  0.4612801699694579 True 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 1 0]] -> [2]
0
[[0.5160680529300568 0.3711393373237767 0.4804075030049398
  0.5001426230589271 True 0 0 0 0 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 1 0 0 1]] -> [2]
0
[[0.542825361512792 0.3926057008980605 0.5049940386663777
  0.4658517639344532 True 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 1
0 0 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 1 0]] -> [2]
2
[[0.4904761904761905 0.3716876766656343 0.48351200696350066
  0.496193443426428 False 0 0 0 0 0 0 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0
0 0 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0
  0 0 0 1 0 0 0 0 1 0]] -> [2]
2
```

In [159]:
```
X_train.to_csv('~/Downloads/x_train.csv')
Y_train.to_csv('~/Downloads/y_train.csv')
X_test.to_csv('~/Downloads/x_test.csv')
Y_test.to_csv('~/Downloads/y_test.csv')

# Y_train[Y_train[2] == 1].sample(frac=0.4).index

# X_train.head()
```

In [160]:
```
trips.shape
```

Out[160]:
```
(367266, 25)
```

Summary

After experiementing with various classifiers, I wasn't able to construct one with high accuracy. I believe that using more specific features, such as the availability of each station at the time the bike was docked. These more specific features would require more computational resources.