In [139]:
```
import pandas as pd
import numpy as np
import seaborn as sns
%pylab inline
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
from sklearn.model_selection import train_test_split
from collections import defaultdict
from math import sqrt
from  sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from operator import itemgetter
```

```
Populating the interactive namespace from numpy and matplotlib
```

```
/Users/jonathanhilgart/anaconda/lib/python3.5/site-packages/IPython/core/
magics/pylab.py:161: UserWarning: pylab import has clobbered these variab
les: ['sqrt']
`%matplotlib` prevents importing * from pylab and numpy
  "\n`%matplotlib` prevents importing * from pylab and numpy"
```

Assume we pulled the data on 7/01/2002. We will do all calculations relative to this date.

In [4]:
```
df_data_pt_1 = pd.read_csv("Nomis Solutions_Data Part I.csv")
df_data_pt_1['car_type']=df_data_pt_1['Car  Type']
df_data_pt_1['previous_rate']=df_data_pt_1['Previous Rate']
df_data_pt_1['approve_date']=df_data_pt_1['Approve Date']
df_data_pt_1['competition_rate']=df_data_pt_1['Competition rate']
df_data_pt_1['cost_of_funds']=df_data_pt_1['Cost of Funds']


df_data_pt_1.drop(['Car  Type','Previous Rate','Approve Date','Competition r
df_data_pt_1.approve_date= pd.to_datetime(df_data_pt_1.approve_date)
df_data_pt_1.previous_rate = df_data_pt_1.previous_rate.apply(lambda x:0 if 
df_data_pt_2 = pd.read_csv("Nomis Solutions Part II.csv",skiprows=1)

## add in the year , month, and date to cluster against
df_data_pt_1['year'] = df_data_pt_1.approve_date.apply( lambda x: x.year)
df_data_pt_1['month'] = df_data_pt_1.approve_date.apply( lambda x: x.month)
df_data_pt_1['day'] = df_data_pt_1.approve_date.apply( lambda x: x.day)

## fix the naming with tier
df_data_pt_1['tier'] = df_data_pt_1.iloc[:,0]
df_data_pt_1 = df_data_pt_1.iloc[:,1:]
```

In [5]:
```
# conver the data column to the
df_data_pt_1.approve_date = pd.to_datetime(df_data_pt_1.approve_date)
```

In [6]:
```
## create a dataframe without data to cluster against
df_data_copy = df_data_pt_1.copy()
df_data_pt_1_no_date = df_data_copy.loc[:,('tier', 'FICO', 'Term', 'Amount',
       'car_type', 'previous_rate', 'competition_rate',\
       'cost_of_funds', 'year', 'month', 'day')]
```

In [7]:
```
# Drop NA columns
df_data_pt_1.dropna(inplace=True)
```

In [8]:
```
 #Drop na columns
df_data_pt_2.dropna(inplace=True)
```

In [9]:
```
df_data_pt_1_no_date.dropna(inplace=True)
```

In [10]:
```
df_data_pt_1.approve_date.describe()
```

Out[10]:
```
count                  208077
unique                    861
top       2003-07-28 00:00:00
freq                      718
first     2002-07-01 00:00:00
last      2004-11-16 00:00:00
Name: approve_date, dtype: object
```

In [11]:
```
df_data_no_date_dummy = pd.get_dummies(df_data_pt_1_no_date)
```

In [12]:
```
## round our values to four places
df_data_no_date_dummy = df_data_no_date_dummy.apply(lambda x:x.astype(float)
```

In [13]:
```
df_data_no_date_dummy[df_data_no_date_dummy.tier==None]
```

Out[13]:

	tier	FICO	Term	Amount	Outcome	Rate	Partner Bin	previous_rate	competition_rate	cost_

In [14]:
```
df_data_no_date_dummy.columns
```

Out[14]:
```
Index(['tier', 'FICO', 'Term', 'Amount', 'Outcome', 'Rate', 'Partner Bi
n',
       'previous_rate', 'competition_rate', 'cost_of_funds', 'year', 'mon
th',
       'day', 'car_type_N', 'car_type_R', 'car_type_U'],
      dtype='object')
```

In [15]:
```
## drop year, month, day from df_data no date
df_data_no_date_dummy = df_data_no_date_dummy.loc[:,('tier', 'FICO', 'Term',
       'previous_rate', 'competition_rate', 'cost_of_funds', \
       'car_type_N', 'car_type_R', 'car_type_U')]
# we will create a flag that looks at cost of funds to find the year the loa
```

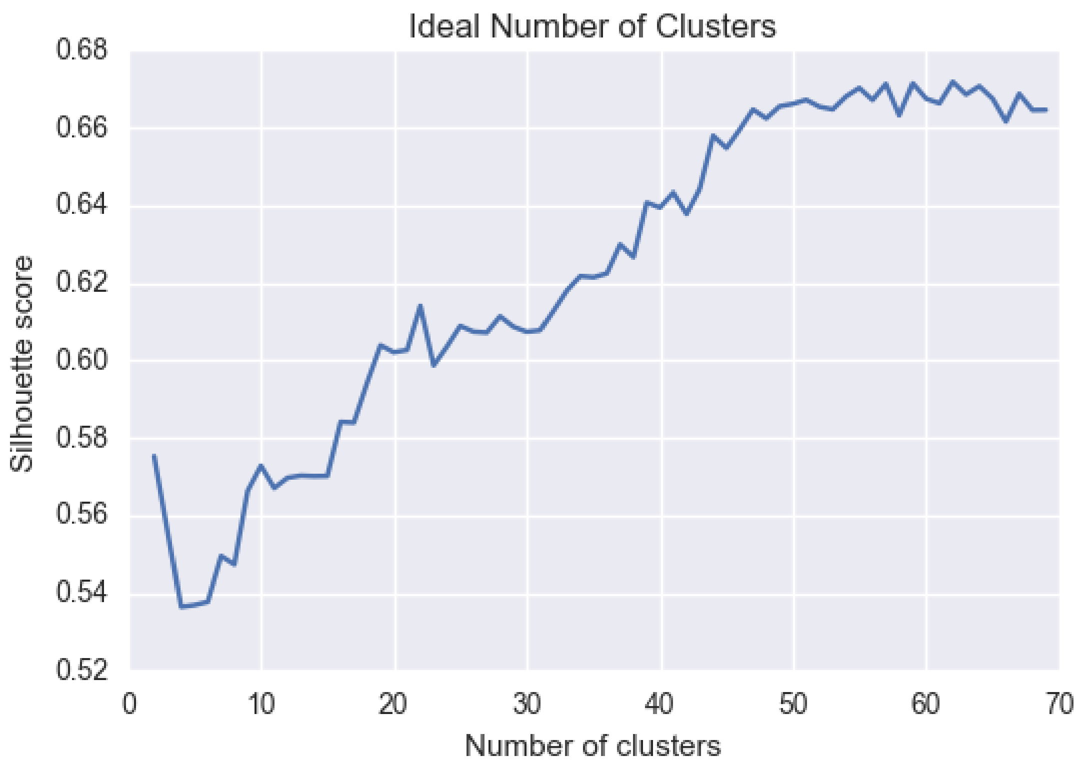
In [401]:

```
def sample_silhouette_score(dataframe_input,max_size=20):
    """Run a three fold CV on 10,000 samples from the dataframe to determine
    Output is the ideal number of clusters of 3 CV folds with 10k samples."'
    silhouette_score_l = []
    for clusters in range(2,70):
        knn_classifier = KMeans(clusters)
        silhouette_scores_for_this_cluster = []
        for _ in range(3): ## CV for samples
            sample = dataframe_input.sample(10000)
            fit_knn = knn_classifier.fit(X=sample.values)
            predicted_labels = fit_knn.labels_
            silhouette_scores_for_this_cluster.append(silhouette_score(X=sar
        silhouette_score_l.append(np.mean(silhouette_scores_for_this_cluster
        print('Finished iteration {}'.format(clusters))
    number_of_clusters = [i for i in range(2,70)]
    plt.plot([i for i in range(2,70)],silhouette_score_l)
    plt.title('Ideal Number of Clusters')
    plt.ylabel('Silhouette score')
    plt.xlabel('Number of clusters')
    print('The best number of clusters is {}'.format(number_of_clusters[np.a
```

In [402]:
```
# This takes ~30 minutes to run
sample_silhouette_score(df_data_no_date_dummy)
```

```
Finished iteration 2
Finished iteration 3
Finished iteration 4
Finished iteration 5
Finished iteration 6
Finished iteration 7
Finished iteration 8
Finished iteration 9
Finished iteration 10
Finished iteration 11
Finished iteration 12
Finished iteration 13
Finished iteration 14
Finished iteration 15
Finished iteration 16
Finished iteration 17
Finished iteration 18
Finished iteration 19
Finished iteration 20
Finished iteration 21
Finished iteration 22
Finished iteration 23
Finished iteration 24
Finished iteration 25
Finished iteration 26
Finished iteration 27
Finished iteration 28
Finished iteration 29
Finished iteration 30
Finished iteration 31
Finished iteration 32
Finished iteration 33
Finished iteration 34
Finished iteration 35
Finished iteration 36
Finished iteration 37
Finished iteration 38
Finished iteration 39
Finished iteration 40
Finished iteration 41
Finished iteration 42
Finished iteration 43
Finished iteration 44
Finished iteration 45
Finished iteration 46
Finished iteration 47
Finished iteration 48
Finished iteration 49
Finished iteration 50
Finished iteration 51
Finished iteration 52
Finished iteration 53
Finished iteration 54
Finished iteration 55
```

```
Finished iteration 56
Finished iteration 57
Finished iteration 58
Finished iteration 59
Finished iteration 60
Finished iteration 61
Finished iteration 62
Finished iteration 63
Finished iteration 64
Finished iteration 65
Finished iteration 66
Finished iteration 67
Finished iteration 68
Finished iteration 69
The best number of clusters is 62
```



- ~ Sixty is the ideal nuber of clusters here

In [16]:
```
def find_avg_centroid(dataframe_input,cluster_size=60):
    """Using the cluster size for the number of centers, find the centers ir
    sample = dataframe_input
    knn_classifier = KMeans(cluster_size)
    fit_knn = knn_classifier.fit(X=sample.values)
    predicted_labels = fit_knn.labels_
    centers = fit_knn.cluster_centers_
    return centers
```

In [17]:
```
## store the cluster centers
average_cluster_centers = find_avg_centroid(df_data_no_date_dummy)
```

Now, find the center that each row is closest to and assign to that cluster number.

- Define a euclidean distance function.

In [18]:
```
def euclidean_distance(a,b):
    """Expects numpy array and returns the euclidan distance between them""'
    return sqrt(sum((a-b)**2))
```

In [19]:
```

def assign_cluster_center(dataframe_input,centroids):
    """Take in a dataframe, iterate through the rows and find the closest ce
    Returns the same dataframe with a new column indicating the closest clus
    dataframe_input = dataframe_input.copy()
    list_of_min_distances = []
    list_of_cluster_numbers = []
    for row in dataframe_input.iterrows():
        row_array=np.array(row[1])
        min_distance = 9999999999999999
        min_distance_cluster_number = 0
        for center_number,center in enumerate(centroids):
            center = np.array(center)
            distance = euclidean_distance(center, row_array)
            if distance < min_distance:
                min_distance = distance
                min_distance_cluster_number = center_number
        list_of_min_distances.append(min_distance)
        list_of_cluster_numbers.append(min_distance_cluster_number)
    dataframe_input['cluster_number']=list_of_cluster_numbers
    return dataframe_input
```

In [20]:
```
# create a new DF with added columns for the cluster it belongs to as well a
df_data_clusters_dummy_no_date = assign_cluster_center(df_data_no_date_dummy
```

In [21]:
```
df_data_clusters_dummy_no_date.head()
```

Out[21]:

	tier	FICO	Term	Amount	Outcome	Rate	Partner Bin	previous_rate	competition_rate	cos
0	3.0	695.0	72.0	35000.0	0.0	7.49	1.0	0.0	6.25	1.83
1	1.0	751.0	60.0	40000.0	0.0	5.49	3.0	0.0	5.65	1.83
2	1.0	731.0	60.0	18064.0	0.0	5.49	3.0	0.0	5.65	1.83
3	4.0	652.0	72.0	15415.0	0.0	8.99	3.0	0.0	6.25	1.83
4	1.0	730.0	48.0	32000.0	0.0	5.49	1.0	0.0	5.65	1.83

Next, create a random forest prediction of

outcome per cluster_number

In [23]:
```
list_of_centroids = [i for i in range(60)]
```

In [124]:
```
def create_model_per_cluster(dataframe_in,list_of_clusters):
    """Create a classifier model for each cluster with 300 trees. Return a d
    is the cluster number and the value is the trained model. Also returns a
    rmse_per_cluster = {}
    list_of_models_per_cluster = {}
    for cluster in list_of_clusters:
        cluster_df = dataframe_in[dataframe_in.cluster_number==cluster]

        df_X =cluster_df.loc[:,('tier', 'FICO', 'Term', 'Amount', 'Rate', 'P
       'previous_rate', 'competition_rate', 'cost_of_funds',\
        'car_type_N', 'car_type_R', 'car_type_U')]
        df_y = cluster_df['Outcome']
        # train test split
        X_train, X_test, y_train, y_test = train_test_split(
        df_X, df_y, test_size=0.33)
        # create the classifier
        Log_classifier_model = LogisticRegression()
        Log_classifier_model .fit(X_train,y_train)
        classifier_predictions = Log_classifier_model .predict(X_test)
        precent_predictions = Log_classifier_model .predict_proba(X_test)
        rmse = np.linalg.norm(y_test - classifier_predictions)/sqrt(len(y_te
        rmse_per_cluster[cluster]=rmse
        list_of_models_per_cluster[cluster]=Log_classifier_model
    return rmse_per_cluster,list_of_models_per_cluster
```

In [125]:
```
rmse_per_cluster, dict_of_models_per_cluster = create_model_per_cluster(df_c
```

In [26]:
```
df_data_clusters_dummy_no_date.head()
```

Out[26]:

	tier	FICO	Term	Amount	Outcome	Rate	Partner Bin	previous_rate	competition_rate	cos
0	3.0	695.0	72.0	35000.0	0.0	7.49	1.0	0.0	6.25	1.83
1	1.0	751.0	60.0	40000.0	0.0	5.49	3.0	0.0	5.65	1.83
2	1.0	731.0	60.0	18064.0	0.0	5.49	3.0	0.0	5.65	1.83
3	4.0	652.0	72.0	15415.0	0.0	8.99	3.0	0.0	6.25	1.83
4	1.0	730.0	48.0	32000.0	0.0	5.49	1.0	0.0	5.65	1.83

In [126]:
```
dict_of_models_per_cluster
```

```
1,
           verbose=0, warm_start=False),
 30: LogisticRegression(C=1.0, class_weight=None, dual=False, fit_interce
pt=True,
           intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=
1,
           penalty='l2', random_state=None, solver='liblinear', tol=0.000
1,
           verbose=0, warm_start=False),
 31: LogisticRegression(C=1.0, class_weight=None, dual=False, fit_interce
pt=True,
           intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=
1,
           penalty='l2', random_state=None, solver='liblinear', tol=0.000
1,
           verbose=0, warm_start=False),
 32: LogisticRegression(C=1.0, class_weight=None, dual=False, fit_interce
pt=True,

           intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=
```

Next, change the rate offered to each cluster, and see what the impact on prediction is.

- Start at APR of 1% and go up to 10%
- Assume all loans start at the same time

In [243]:
```
apr_rate = [i for i in np.linspace(3,15,15)]
```

In [255]:
```
# Define a NPV function
def npv_loan_amount(loan, term, APR, cost_of_capital):
    """Return the npv given the parameters above"""
    interest = loan*APR # http://mathforum.org/dr.math/faq/faq.interest.html
    Cfs = []
    Cfs.append(-loan)
    for i in range(1,int(term/12)+1):
        Cfs.append(interest)
    Cfs[-1] += loan

    disc_Cfs = []
    for t,cf in enumerate(Cfs):
         disc_Cfs.append(cf / (1+cost_of_capital)**t)
    return sum(disc_Cfs)

npv_loan_amount(1000, 60, 0.07, 0.01)
```

Out[255]: 291.20587435950711

In [244]:
```
def outcome_per_apr_rate(dataframe_in,dict_of_models,list_of_clusters,list_c
    """Change the APR per cluster and predict outcome.
    Return a dictionary of dictionaries where the initial key = cluster numb
    The second (inside) dictionary has the apr as the key and NPV and the va
    cluster_apr_npv = defaultdict(list)
    max_apr_per_cluster = defaultdict(int)
    max_npv_per_cluster = defaultdict(int)
    count = 0
    for cluster in list_of_clusters: ## which cluster are we looking at
        current_model = dict_of_models[cluster]
        apr_npv_per_cluster = []
        cluster_df = dataframe_in[dataframe_in.cluster_number==cluster]

        for apr_rate in list_of_apr:
            # Change the APR rate for the entire cluster
            cluster_df.Rate = apr_rate
            df_X =cluster_df.loc[:,('tier', 'FICO', 'Term', 'Amount', 'Rate'
           'previous_rate', 'competition_rate', 'cost_of_funds',\
            'car_type_N', 'car_type_R', 'car_type_U')]
            df_y = cluster_df.loc[:,'Outcome']
            ## NPV calculation
            ## loan = predictions * Amount
            ## term = Term (months)
            ## APR = Rate
            ## cost_of_capital = cost_of_funds

            cluster_df['predictions']=current_model.predict(df_X)
            cluster_df['npv'] = \
            cluster_df.apply(lambda x: npv_loan_amount(x['predictions']*x['A

            apr_npv_per_cluster.append((apr_rate,sum(cluster_df['npv'])))
            #print(apr_npv_per_cluster,' hereer') # this is correct
        cluster_apr_npv[cluster] = apr_npv_per_cluster
        # get max apr and max npv for each cluster
        max_apr_per_cluster[cluster] = max(cluster_apr_npv[cluster] ,key=ite
        max_npv_per_cluster[cluster] = max(cluster_apr_npv[cluster] ,key=ite

        count +=1
        print("Finished calculating NPV for cluster {}".format(cluster))

    return cluster_apr_npv, max_apr_per_cluster, max_npv_per_cluster
```

In [233]:
```
np.shape(df_data_clusters_dummy_no_date)
```

Out[233]: (208077, 14)

```
In [245]: r,max_npv = outcome_per_apr_rate(df_data_clusters_dummy_no_date,dict_of_mode
```

```
/Users/jonathanhilgart/anaconda/lib/python3.5/site-packages/pandas/core/g
eneric.py:2701: SettingWithCopyWarning:
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/pandas-doc
s/stable/indexing.html#indexing-view-versus-copy (http://pandas.pydata.or
g/pandas-docs/stable/indexing.html#indexing-view-versus-copy)
  self[name] = value
/Users/jonathanhilgart/anaconda/lib/python3.5/site-packages/ipykernel/__m
ain__.py:25: SettingWithCopyWarning:
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/pandas-doc
s/stable/indexing.html#indexing-view-versus-copy (http://pandas.pydata.or
g/pandas-docs/stable/indexing.html#indexing-view-versus-copy)
/Users/jonathanhilgart/anaconda/lib/python3.5/site-packages/ipykernel/__m
ain__.py:26: SettingWithCopyWarning:
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/pandas-doc
s/stable/indexing.html#indexing-view-versus-copy (http://pandas.pydata.or
g/pandas-docs/stable/indexing.html#indexing-view-versus-copy)
```

```
Finished calculating NPV for cluster 0
Finished calculating NPV for cluster 1
Finished calculating NPV for cluster 2
Finished calculating NPV for cluster 3
Finished calculating NPV for cluster 4
Finished calculating NPV for cluster 5
Finished calculating NPV for cluster 6
Finished calculating NPV for cluster 7
Finished calculating NPV for cluster 8
Finished calculating NPV for cluster 9
Finished calculating NPV for cluster 10
Finished calculating NPV for cluster 11
Finished calculating NPV for cluster 12
Finished calculating NPV for cluster 13
Finished calculating NPV for cluster 14
Finished calculating NPV for cluster 15
Finished calculating NPV for cluster 16
Finished calculating NPV for cluster 17
Finished calculating NPV for cluster 18
Finished calculating NPV for cluster 19
Finished calculating NPV for cluster 20
Finished calculating NPV for cluster 21
Finished calculating NPV for cluster 22
Finished calculating NPV for cluster 23
Finished calculating NPV for cluster 24
Finished calculating NPV for cluster 25
Finished calculating NPV for cluster 26
Finished calculating NPV for cluster 27
Finished calculating NPV for cluster 28
```

```
Finished calculating NPV for cluster 29
Finished calculating NPV for cluster 30
Finished calculating NPV for cluster 31
Finished calculating NPV for cluster 32
Finished calculating NPV for cluster 33
Finished calculating NPV for cluster 34
Finished calculating NPV for cluster 35
Finished calculating NPV for cluster 36
Finished calculating NPV for cluster 37
Finished calculating NPV for cluster 38
Finished calculating NPV for cluster 39
Finished calculating NPV for cluster 40
Finished calculating NPV for cluster 41
Finished calculating NPV for cluster 42
Finished calculating NPV for cluster 43
Finished calculating NPV for cluster 44
Finished calculating NPV for cluster 45
Finished calculating NPV for cluster 46
Finished calculating NPV for cluster 47
Finished calculating NPV for cluster 48
Finished calculating NPV for cluster 49
Finished calculating NPV for cluster 50
Finished calculating NPV for cluster 51
Finished calculating NPV for cluster 52
Finished calculating NPV for cluster 53
Finished calculating NPV for cluster 54
Finished calculating NPV for cluster 55
Finished calculating NPV for cluster 56
Finished calculating NPV for cluster 57
Finished calculating NPV for cluster 58
Finished calculating NPV for cluster 59
```

In [258]:

```
list_cluster_apr_npv
```

Out[258]:

```
defaultdict(list,
            {0: [(3.0, 71310648.7235485),
              (3.8571428571428572, 89526159.30260417),
              (4.7142857142857144, 91691106.10966633),
              (5.5714285714285712, 83768341.60743254),
              (6.4285714285714288, 75214012.13704154),
              (7.2857142857142856, 71440957.51243167),
              (8.1428571428571423, 64848631.281646244),
              (9.0, 32854200.807686247),
              (9.8571428571428577, 9738478.500106517),
              (10.714285714285714, 2469225.334703968),
              (11.571428571428571, 1036934.5255205629),
              (12.428571428571429, 475144.7180898124),
              (13.285714285714285, 113852.35434788359),
              (14.142857142857142, 0.0),
              (15.0, 0.0)],
             1: [(3.0, 3293163.679872714),
              (3.8571428571428572, 4694328.3302254435),
              (4.7142857142857144, 6115258.582728245),
```

In [256]:
```
max_apr
```

Out[256]:
```
defaultdict(int,
            {0: 4.7142857142857144,
             1: 15.0,
             2: 7.2857142857142856,
             3: 3.0,
             4: 3.8571428571428572,
             5: 3.0,
             6: 10.714285714285714,
             7: 3.0,
             8: 3.0,
             9: 9.8571428571428577,
             10: 13.285714285714285,
             11: 3.0,
             12: 4.7142857142857144,
             13: 3.0,
             14: 4.7142857142857144,
             15: 5.5714285714285712,
             16: 3.0,
             17: 15.0,
             18: 9.8571428571428577,
             19: 4.7142857142857144,
             20: 14.142857142857142,
             21: 3.0,
             22: 11.571428571428571,
             23: 3.0,
             24: 3.0,
             25: 4.7142857142857144,
             26: 4.7142857142857144,
             27: 6.4285714285714288,
             28: 5.5714285714285712,
             29: 11.571428571428571,
             30: 15.0,
             31: 9.0,
             32: 3.0,
             33: 3.8571428571428572,
             34: 8.1428571428571423,
             35: 3.0,
             36: 5.5714285714285712,
             37: 4.7142857142857144,
             38: 3.8571428571428572,
             39: 8.1428571428571423,
             40: 9.0,
             41: 7.2857142857142856,
             42: 4.7142857142857144,
             43: 3.8571428571428572,
             44: 7.2857142857142856,
             45: 3.0,
             46: 9.0,
             47: 4.7142857142857144,
             48: 4.7142857142857144,
             49: 3.0,
             50: 3.8571428571428572,
             51: 3.0,
             52: 3.0,
             53: 3.8571428571428572,
```

```
54: 14.142857142857142,
55: 3.0,
56: 3.0,
57: 3.0,
58: 4.7142857142857144,
59: 3.0})
```

In [257]:
```
max_npv
```

Out[257]:
```
defaultdict(int,
            {0: 91691106.10966633,
             1: 15595968.53992648,
             2: 8420462.586506061,
             3: 0.0,
             4: 5308740.438452114,
             5: 0.0,
             6: 39820146.86705119,
             7: 0.0,
             8: 0.0,
             9: 10627409.11604954,
             10: 7272416.893670261,
             11: 0.0,
             12: 43647370.69407616,
             13: 0.0,
             14: 72222717.83798762,
             15: 19503359.28068262,
             16: 0.0,
             17: 1379713.6652770662,
             18: 11782229.770685699,
             19: 94496070.85926488,
             20: 5648740.189168199,
             21: 0.0,
             22: 8116814.459297081,
             23: 0.0,
             24: 0.0,
             25: 82944798.75112428,
             26: 65834599.96100875,
             27: 9573389.459829079,
             28: 9959182.633037446,
             29: 29620597.287782613,
             30: 5440228.438762986,
             31: 12955766.682253856,
             32: 0.0,
             33: 88965826.08802874,
             34: 24615464.109269183,
             35: 0.0,
             36: 2244325.1664652876,
             37: 70106288.93821527,
             38: 98711457.64441523,
             39: 16254538.087659799,
             40: 7339154.76086993,
             41: 12137139.273080425,
             42: 48914794.698148325,
             43: 99435.88665592659,
             44: 12380711.662671484,
             45: 0.0,
             46: 4739083.179980121,
             47: 66570949.572330154,
             48: 72755201.14031167,
             49: 0.0,
             50: 67301456.96096416,
             51: 0.0,
             52: 0.0,
             53: 57937253.91783708,
```

```
54: 40078468.95649977,
55: 0.0,
56: 0.0,
57: 0.0,
58: 43180262.9834815,
59: 0.0})
```

In [252]:
```
npv_max = 0
for k,v in max_npv.items():
    npv_max +=v
```

In [253]:
```
npv_max
```

Out[253]: 1386193643.5484447

In [264]:
```
npv_loan_amount(npv_max,24,.056,.014)
```

Out[264]: 114039879.47869444

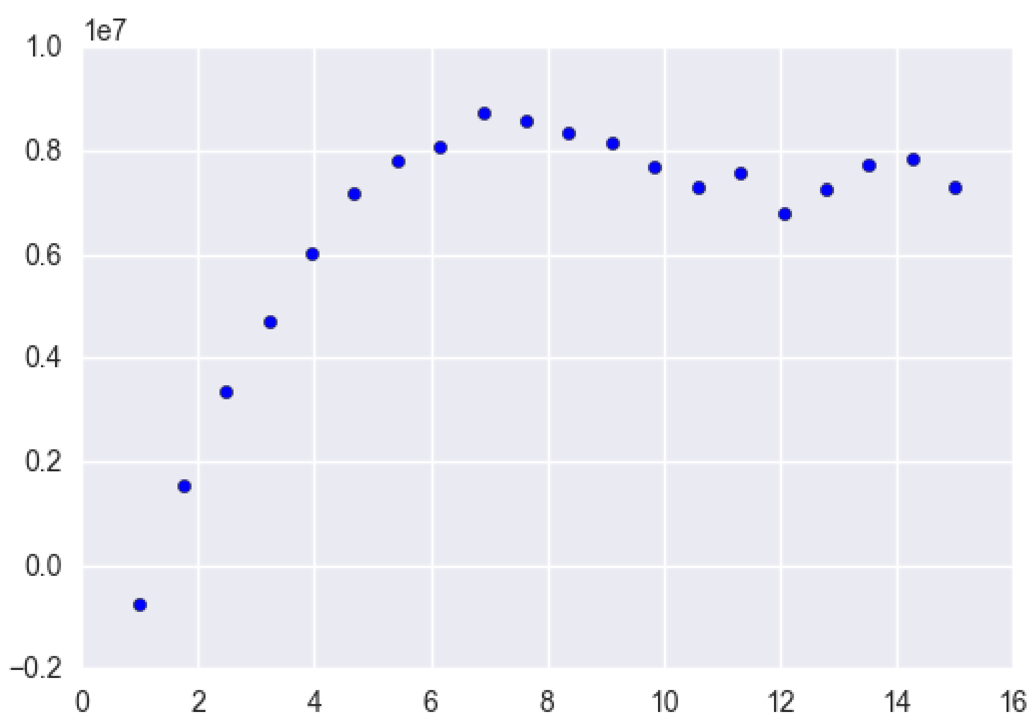
In [161]:
```


max(cluster_apr_npv[0] ,key=itemgetter(1))
```

Out[161]: (4.1666666666666661, 92101924.77954046)

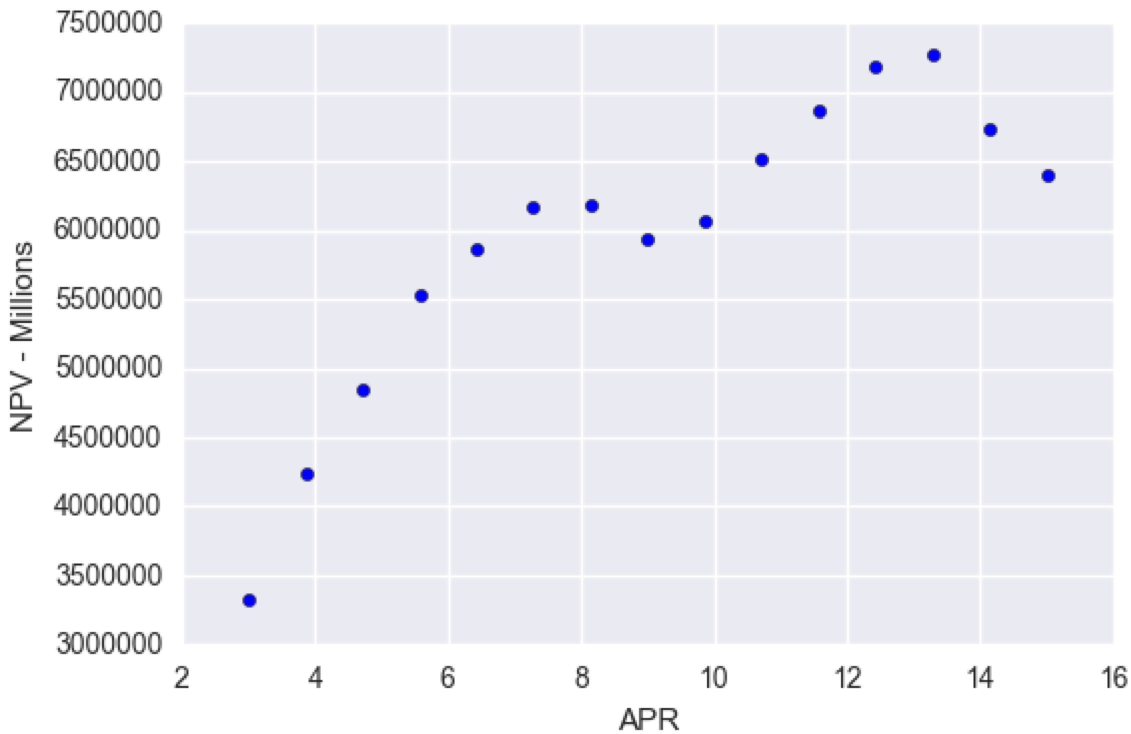
In [238]:
```
 plt.scatter(*zip(*list(list_cluster_apr_npv[2])))
    plt.ylabel('NPV - Millions')
    plt.xlabel('APR')
```

Out[238]: <matplotlib.collections.PathCollection at 0x11783e128>



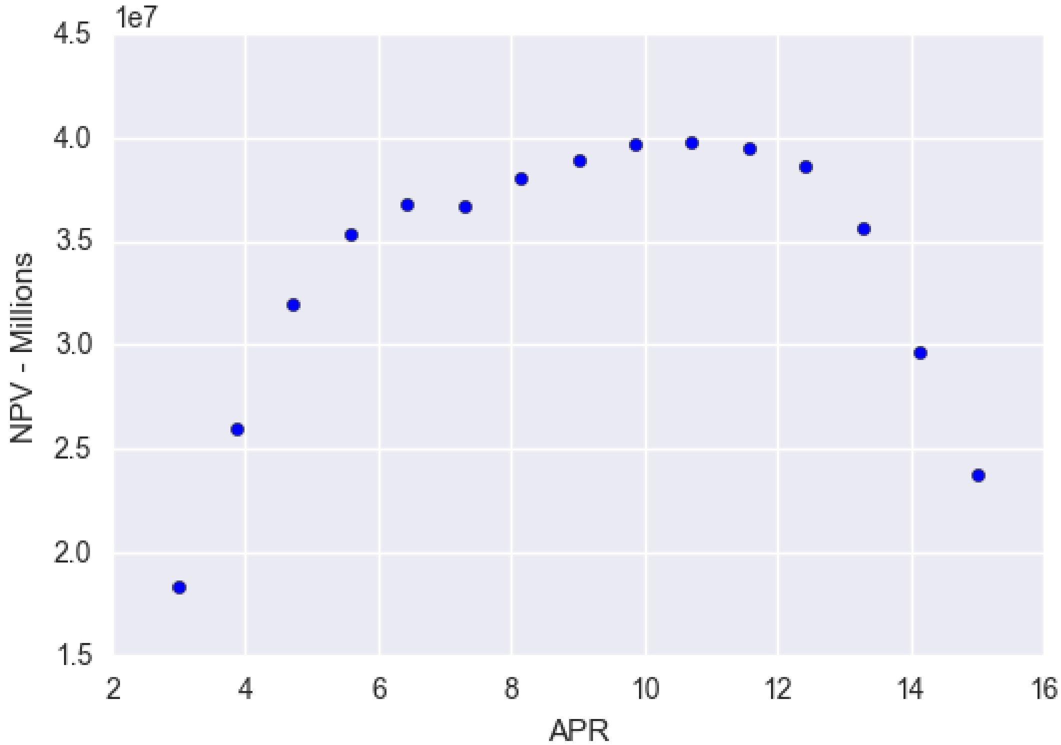
In [262]:
```
plt.scatter(*zip(*list(list_cluster_apr_npv[10])))
plt.ylabel('NPV - Millions')
plt.xlabel('APR')
```

Out[262]: <matplotlib.text.Text at 0x117e38c50>



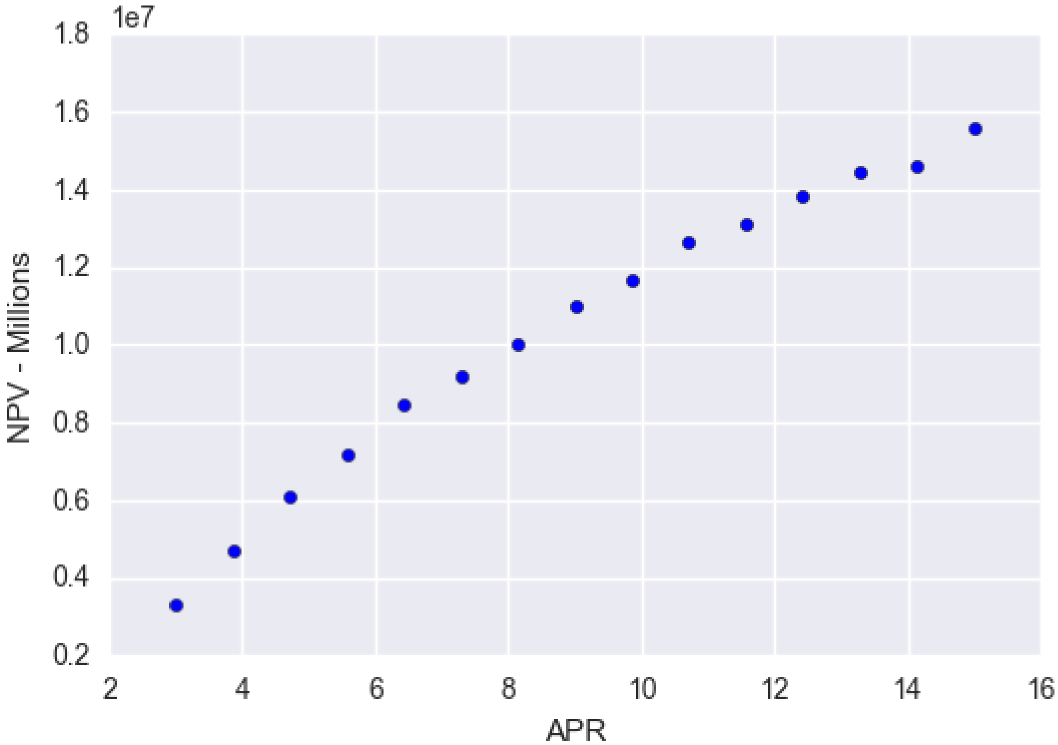
In [261]:
```
plt.scatter(*zip(*list(list_cluster_apr_npv[6])))
plt.ylabel('NPV - Millions')
plt.xlabel('APR')
```

Out[261]: <matplotlib.text.Text at 0x117e29e10>



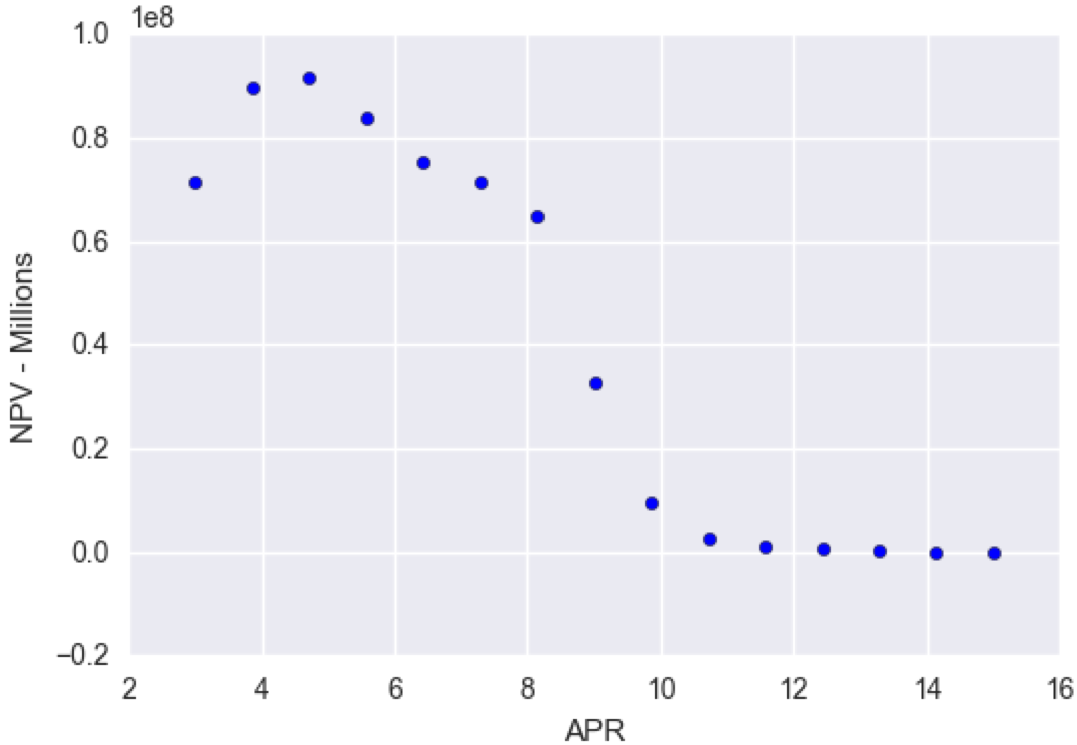
In [260]:
```
plt.scatter(*zip(*list(list_cluster_apr_npv[1])))
plt.ylabel('NPV - Millions')
plt.xlabel('APR')
```

Out[260]: <matplotlib.text.Text at 0x1178a5128>



In [267]:
```
 plt.scatter(*zip(*list(list_cluster_apr_npv[0])))
plt.ylabel('NPV - Millions')
plt.xlabel('APR')
```

Out[267]: <matplotlib.text.Text at 0x117af3f60>



Next, compare the average APR of each cluster before, and after, the optimzation to see the difference.

In [286]:
```
def avg_cluster_apr(dataframe_in,cluster_list):
    """Get avg. apr per cluster"""
    avg_apr_per_cluster = defaultdict(int)
    for cluster in cluster_list:

        df_cluster = dataframe_in[dataframe_in.cluster_number==cluster]
        avg_apr_per_cluster[cluster]=np.mean(df_cluster.Rate)

    return avg_apr_per_cluster
```

In [282]:
```
df_data_clusters_dummy_no_date.head()
```

Out[282]:

	tier	FICO	Term	Amount	Outcome	Rate	Partner Bin	previous_rate	competition_rate	cos
0	3.0	695.0	72.0	35000.0	0.0	7.49	1.0	0.0	6.25	1.83
1	1.0	751.0	60.0	40000.0	0.0	5.49	3.0	0.0	5.65	1.83
2	1.0	731.0	60.0	18064.0	0.0	5.49	3.0	0.0	5.65	1.83
3	4.0	652.0	72.0	15415.0	0.0	8.99	3.0	0.0	6.25	1.83
4	1.0	730.0	48.0	32000.0	0.0	5.49	1.0	0.0	5.65	1.83

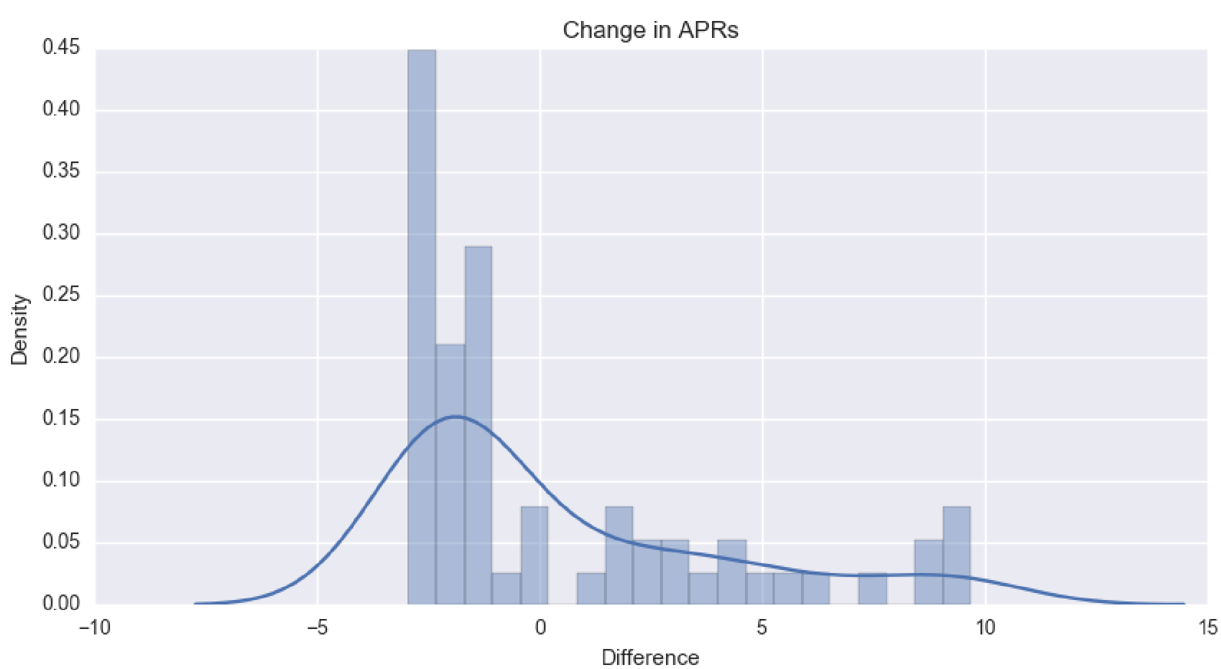
In [289]:
```
avg_apr_per_cluster_original = avg_cluster_apr(df_data_clusters_dummy_no_dat
```

In [304]:
```
difference_in_rates_new_minus_original = np.array(list(max_apr.values())) -
```

In [313]:
```
plt.figure(figsize=(10,5))
#sns.barplot(x=list_of_centroids,y=difference_in_rates_new_minus_origin
sns.distplot(difference_in_rates_new_minus_original,bins=20)
plt.ylabel('Density')
plt.title('Change in APRs')
plt.xlabel("Difference")
```

```
/Users/jonathanhilgart/anaconda/lib/python3.5/site-packages/statsmodels/n
onparametric/kdetools.py:20: VisibleDeprecationWarning: using a non-integ
er number instead of an integer will result in an error in the future
  y = X[:m/2+1] + np.r_[0,X[m/2+1:],0]*1j
```

Out[313]: <matplotlib.text.Text at 0x128af9860>



In [ ]: