Exploratory Data Analysis

In [1]:
```
# importing necessary libraries
import pandas as pd
import numpy as np
import json
import csv
import os
import cPickle as pickle
from collections import Counter

from sklearn.cluster import KMeans, SpectralClustering

import networkx as nx

from my_utilities import *

import matplotlib.pyplot as plt
%matplotlib inline
```

Reading the data (stored as dataframes in pickled files)

In [2]:
```
# Loading the pickled data frames from users, businesses, and reviews.
# Assuming these data frames were obtained already using 'make_datafra
dataframe_pickle_filename = '../data/dataframes.pkl'
with open(dataframe_pickle_filename, 'r') as f:
    (user_df, business_df, review_df) = pickle.load(f)
```

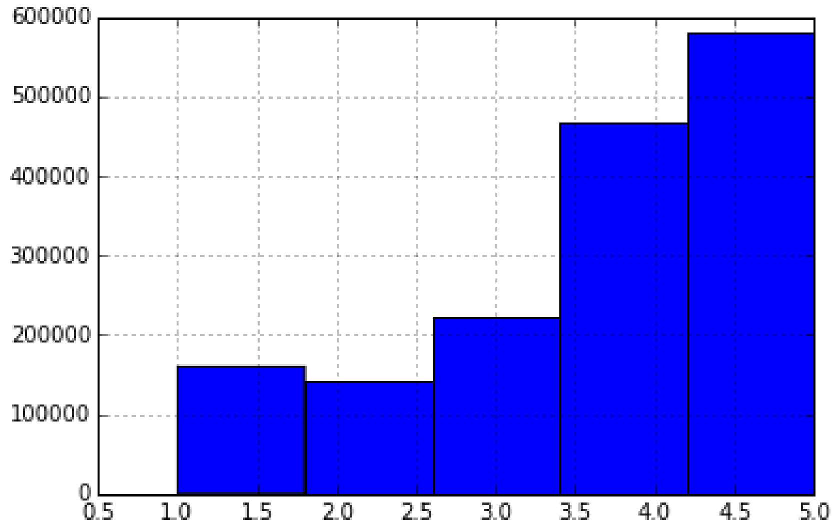
Trying to understand the data

Looking at some overall stats

In [3]:
```
# average rating
print review_df.review_stars.mean()
review_df.review_stars.hist(bins=5)
```

```
3.74265579278
```

Out[3]: <matplotlib.axes._subplots.AxesSubplot at 0x10a021790>



Ratings are skewed toward 5.

In [4]:
```
# Standard deviation of the all reviews. (This will be the baseline RM
review_df.review_stars.std()
```

Out[4]: 1.3114679041155461

Find cities for businesses using k-means.

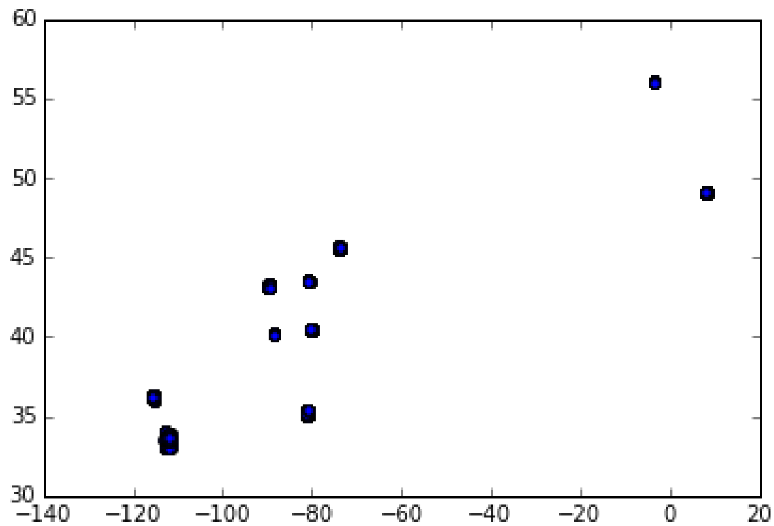
In [5]:
```
X = business_df[['business_latitude', 'business_longitude']].values
```

In [6]:
```
km = KMeans(10, n_jobs=8)
```

In [7]:
```
y = km.fit_predict(X)
```

In [8]:
```
plt.scatter(X[:,1], X[:,0])
```

Out[8]:
```
<matplotlib.collections.PathCollection at 0x10c37d210>
```



In [9]:
```
city_locations = km.cluster_centers_
```

In [10]:
```
n_businesses_per_city = Counter(y).most_common()
```

In [11]:
```
sorted_y = [c[0] for c in n_businesses_per_city]
sorted_y_map = {}
for i in range(10):
      sorted_y_map[sorted_y[i]] = i
```

In [12]:
```
business_df['business_city_int'] = map(lambda i: sorted_y_map[i], y)
```

In [13]:
```
city_names = ['Phoenix', 'Las Vegas', 'Charlotte', 'Montreal', 'Edinbu
              'Urbana-Champaign', 'Waterloo']
```

Find reviews for businesses in each city

In [14]:
```
# Dataframe with the reviews (with business city).
review_city_df = business_df[['business_id_int', 'business_city_int']]
```

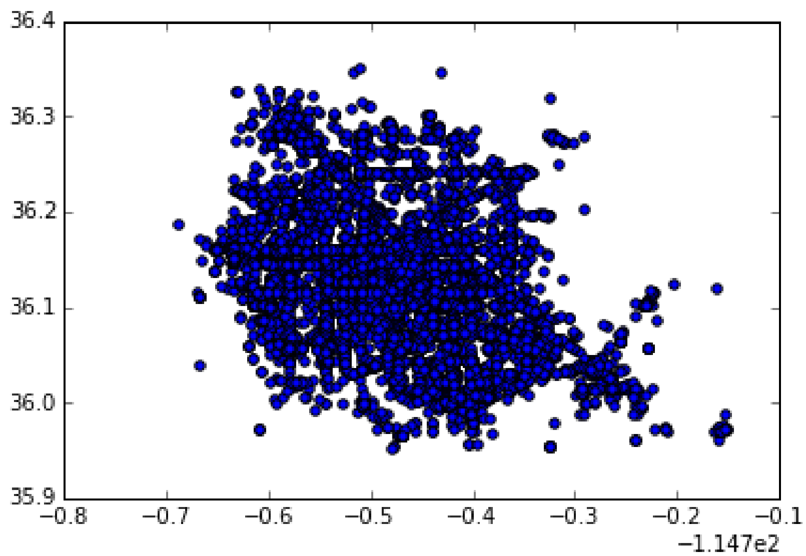
In [15]:
```
# Reviews for three specific cities.
review_phoenix = review_city_df[review_city_df.business_city_int == 0]
review_lasvegas = review_city_df[review_city_df.business_city_int == 1
review_charlotte = review_city_df[review_city_df.business_city_int ==
review_montreal = review_city_df[review_city_df.business_city_int == 3
```

In [16]:
```
len(review_phoenix.user_id_int.unique()), len(review_lasvegas.user_id_
```
Out[16]: (128330, 181712, 24649, 13861)

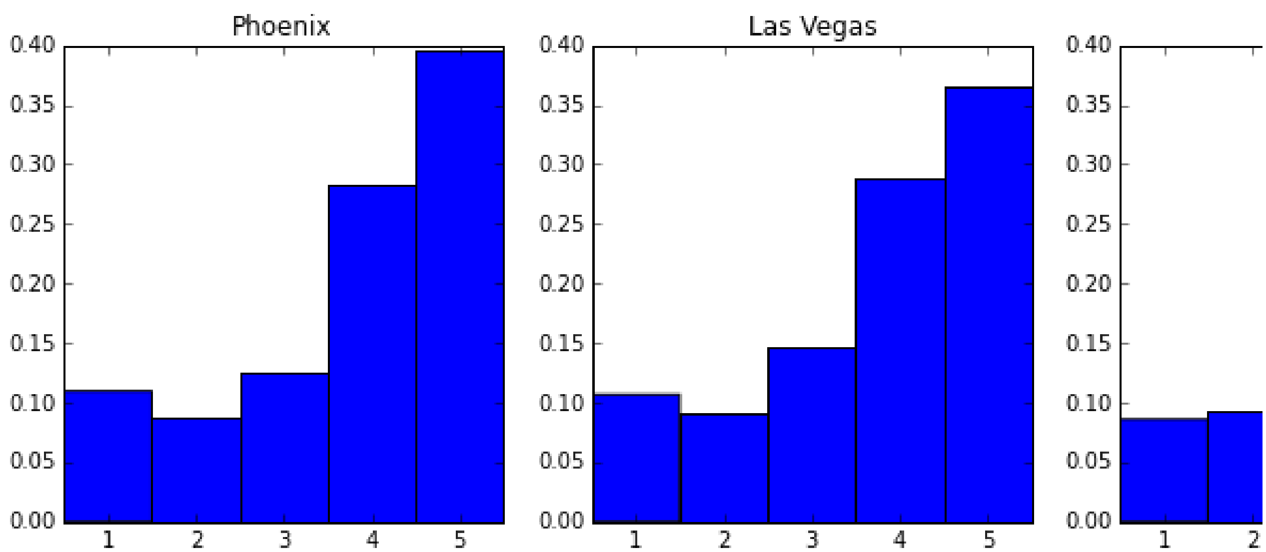
In [17]:
```
len(review_phoenix.business_id_int.unique()), len(review_lasvegas.busi
```
Out[17]: (25225, 16469, 5149, 3918)

In [18]:
```
review_phoenix.shape[0], review_lasvegas.shape[0], review_charlotte.sh
```
Out[18]: (591192, 679460, 98034, 49484)

In [19]:
```
# Check the clustering was done correctly.
X = business_df[business_df.business_city_int==1][['business_latitude'
plt.scatter(X[:,1], X[:,0])
```
Out[19]: <matplotlib.collections.PathCollection at 0x10e00e690>



In [66]:
```
# Looking at review distributions in each city (Phoenix, Las Vegas, Mc
plt.figure(figsize = (17, 4))
plt.subplot(1,4,1)
plt.title("Phoenix")
plt.xlim(0.5, 5.5)
plt.ylim(0,0.4)
plt.hist(review_phoenix.review_stars.values, range=(0.5, 5.5), normed=
plt.subplot(1,4,2)
plt.title("Las Vegas")
plt.xlim(0.5, 5.5)
plt.ylim(0,0.4)
plt.hist(review_lasvegas.review_stars.values, range=(0.5, 5.5), normed
plt.subplot(1,4,3)
plt.title("Charlotte")
plt.xlim(0.5, 5.5)
plt.ylim(0,0.4)
plt.hist(review_charlotte.review_stars.values, range=(0.5, 5.5), norme
plt.subplot(1,4,4)
plt.title("Montreal")
plt.xlim(0.5, 5.5)
plt.ylim(0,0.4)
plt.hist(review_montreal.review_stars.values, range=(0.5, 5.5), normed
plt.savefig("../fig/ratings_dist.png")
```



It is quite interesting that Montreal has quite different review distribution compared to other cities.

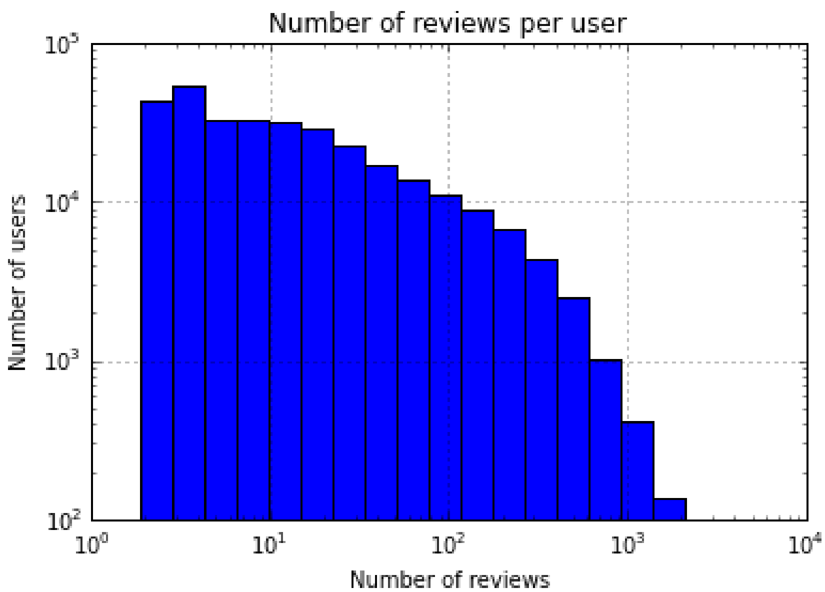
In [48]:
```
print review_phoenix.review_stars.std(), review_lasvegas.review_stars.
```

```
1.34162771089 1.32606119856 1.16331249085
```

Number of reviews per user.

In [49]:
```
plt.ylim([100,100000])
plt.gca().set_xscale("log")
plt.yscale('log')
plt.title('Number of reviews per user')
plt.xlabel('Number of reviews')
plt.ylabel('Number of users')
user_df.user_review_count.hist(bins=np.logspace(0.1, 3.5, 20))
```

Out[49]: <matplotlib.axes._subplots.AxesSubplot at 0x110844090>

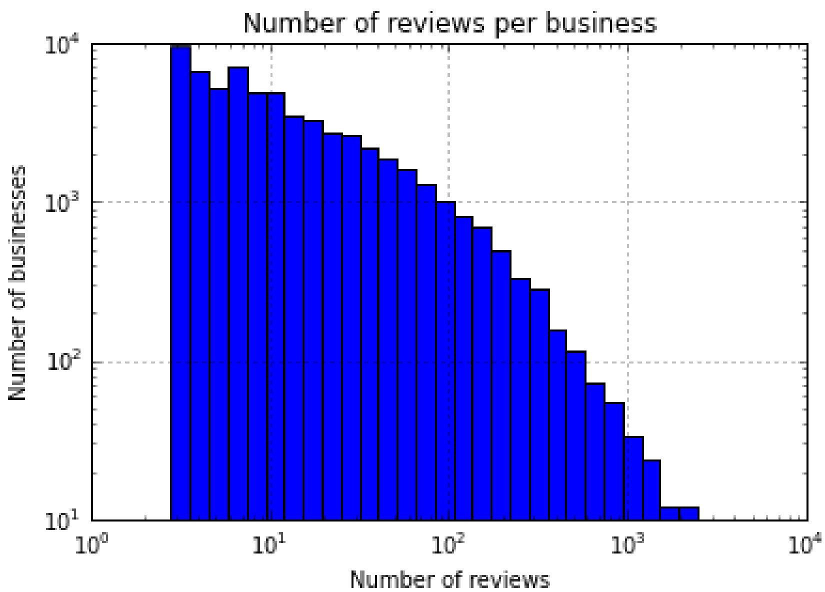


Users have at least 1 review.

Number of reviews per business.

In [50]:
```
plt.ylim([10, 10000])
plt.gca().set_xscale("log")
plt.yscale('log')
plt.title('Number of reviews per business')
plt.xlabel('Number of reviews')
plt.ylabel('Number of businesses')
business_df.business_review_count.hist(bins=np.logspace(0.45, 3.5, 30)
```

Out[50]: <matplotlib.axes._subplots.AxesSubplot at 0x10cfc8110>



In [51]:
```
business_df.business_review_count.min()
```

Out[51]: 3

Businesses have at least 3 reviews.

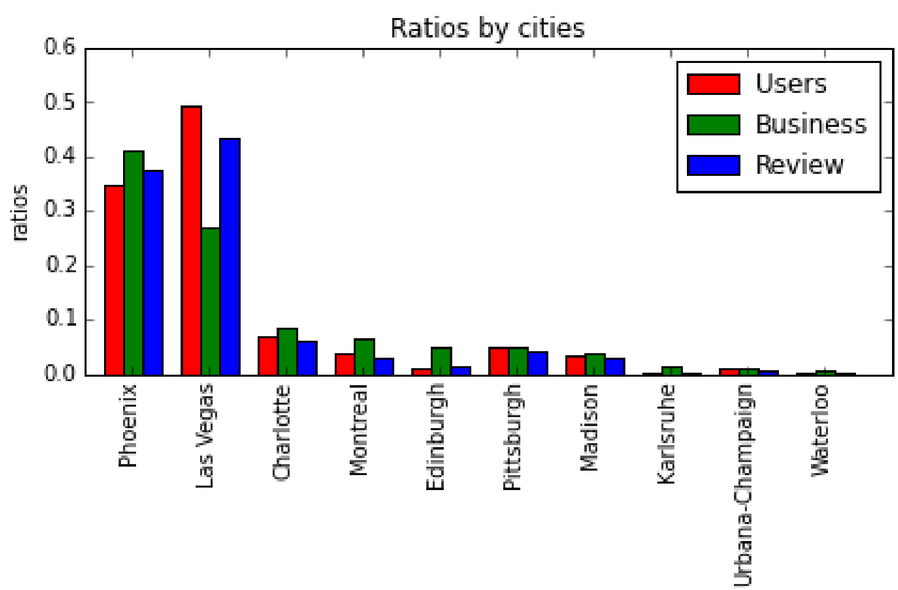
Some counts per city

In [52]:
```
n_users = float(user_df.shape[0])
n_businesses = float(business_df.shape[0])
n_reviews = float(review_df.shape[0])
users_by_city = np.array(review_city_df.groupby('business_city_int').u
businesses_by_city = np.array(review_city_df.groupby('business_city_in
reviews_by_city = np.array(review_city_df.groupby('business_city_int')
users_by_city_ratio = users_by_city / n_users
businesses_by_city_ratio = businesses_by_city / n_businesses
reviews_by_city_ratio = reviews_by_city / n_reviews
```

In [59]:
```
def plot_counts(users_by_city, businesses_by_city, reviews_by_city, ti
    fig = plt.figure()
    ax = fig.add_subplot(111)

    ind = np.arange(10) # the x locations for the groups
    width = 0.25        # the width of the bars

    ## the bars
    rects0 = ax.bar(ind, users_by_city, width, color='r')
    rects1 = ax.bar(ind + width, businesses_by_city, width, color='g')
    rects2 = ax.bar(ind + 2 * width, reviews_by_city, width, color='b'

    # axes and labels
    ax.set_xlim(-width, len(ind) + width)
    ax.set_ylim(0, ylim)
    ax.set_ylabel(ylabel)
    ax.set_title(title)
    ax.set_xticks(ind + 1.5*width)
    xtickNames = ax.set_xticklabels(city_names)
    plt.setp(xtickNames, rotation=90, fontsize=10)

    ## add a legend
    ax.legend((rects0[0], rects1[0], rects2[0]), ('Users', 'Business',
```

In [67]:
```
plt.figure(num=None, figsize=(8, 5), dpi=200)
plot_counts(users_by_city_ratio, businesses_by_city_ratio, reviews_by_
            'ratios', ylim=0.6)
plt.tight_layout()
plt.savefig('../fig/ratios_by_city.png', dpi=200)
```

<matplotlib.figure.Figure at 0x11f414350>

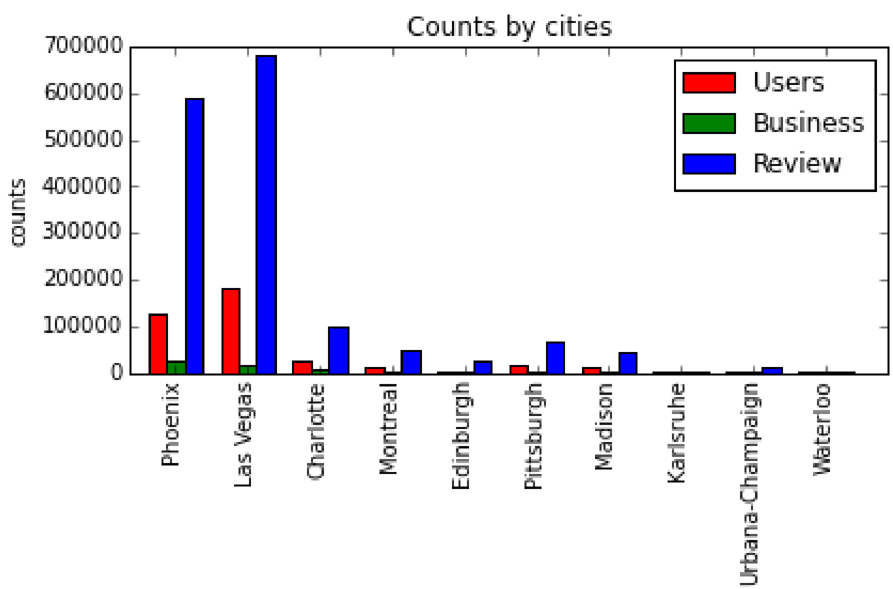


In [64]:
```
# Number of users per business
users_by_city.astype(float) / businesses_by_city
```

Out[64]:
```
array([  5.08741328,  11.03357824,   4.78714313,   3.53777437,
         1.07106426,   5.85300888,   5.06845754,   0.81084656,
         6.25199362,   3.18233618])
```

In [75]:
```
plt.figure(num=None, figsize=(8, 5), dpi=200)
plot_counts(users_by_city, businesses_by_city, reviews_by_city, 'Count
            'counts', ylim=700000)
plt.tight_layout()
plt.savefig('../fig/counts_by_city.png', dpi=160)
```

```
<matplotlib.figure.Figure at 0x11e9f9350>
```



Phoenix and Las Vegas are two biggest cities here. A unique characteristic we can see is that in Las Vegas the number of users is much greater than the number of businesses; on the other hand, in Phoenix, the number of businesses is greater than the number of users. At first, I assumed there might be many tourists in Las Vegas, but based on counts below, there are not many users who leave reviews in multiple cities (only 5%). Then two possible explanations are: (1) there are just many more users than businesses, (2) users in Las Vegas are much more active.

Number of cities per user

Here trying to find how many cities each user left reviews.

In [76]:
```
cities_by_user = np.array(review_city_df.groupby('user_id_int').busine
```

In [77]:
```
sum(cities_by_user == 1) / float(n_users)
```

Out[77]: 0.95011112171577383

In [78]:
```
sum(cities_by_user == 2) / float(n_users)
```

Out[78]: 0.045563993837176006

In [79]:
```
sum(cities_by_user > 2) / float(n_users)
```

Out[79]: 0.0043248844470501618

Most of users left reviews in only one city (95 %), and 4.56 % of users left reviews in one city. There are only 0.43 % of users who left reviews in more than two cities. Also, the earliest date and the latest date for reviews are 2004-10-12 and 2015-01-08.

In [80]:
```
print review_df.review_date.min(), review_df.review_date.max()
```

```
2004-10-12 2015-01-08
```

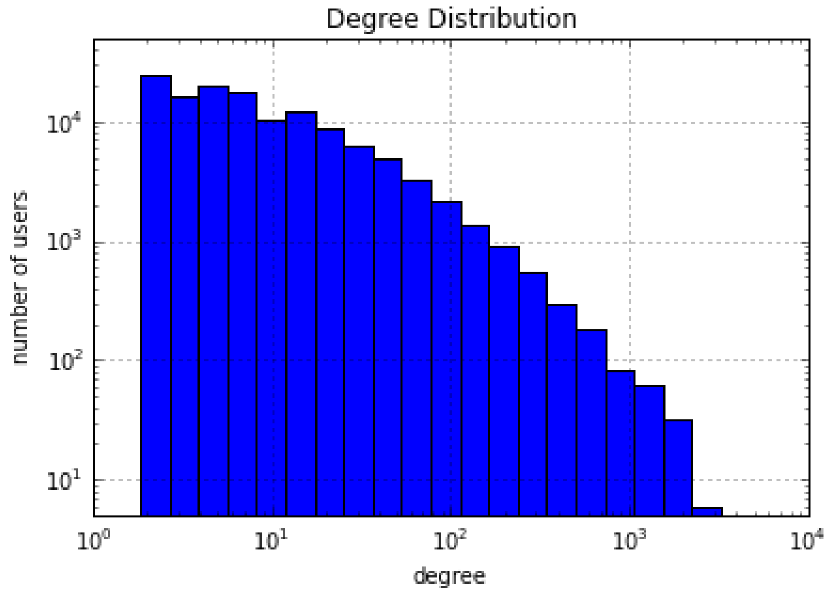
Degree distribution

Now we can look at the network structure. The easiest stat we can look is the degree distribution.

In [82]:
```
degrees = pd.read_csv("../data/degrees", names=['user_id', 'degree'],
```

In [83]:
```
def plot_degrees(degree_col, y_min, y_max):
    plt.ylim([y_min, y_max])
    plt.gca().set_xscale("log")
    plt.gca().set_yscale('log')
    plt.title('Degree Distribution')
    plt.xlabel('degree')
    plt.ylabel('number of users')
    degree_col.hist(bins=np.logspace(0.1, 4, 25))
```

In [84]:
```
plot_degrees(degrees.degree, 5, 50000)
```



Finding the number of users with at least one friend using degree info.

In [85]:
```
# A set containing users with at least one friend.
users2_set = set(degrees[degrees.degree > 0].user_id.values)
```

Create new dataframes that are reduced using only above users.

In [86]:
```
# Create all dataframes that only have data with users with at least o
# First, find users first.
user_df2 = user_df[user_df.apply(lambda x: x['user_id_int'] in users2_
# Second, find reviews done by these users.
review_df2 = review_df[review_df.apply(lambda x: x['user_id_int'] in u
# Lastly, find businesses that only these reviews are done for.
businesses2_set = set(review_df2.business_id_int.unique())
business_df2 = business_df[business_df.apply(lambda x: x['business_id_
```

In [87]:
```
# Dataframe with the reviews (with business city).
review_city_df2 = business_df2[['business_id_int', 'business_city_int'
    .merge(review_df2, on=['business_id_int'], how='inner')
```

In [88]:
```
print user_df2.shape[0], business_df2.shape[0], review_df2.shape[0]
```

```
174094 59106 1143736
```

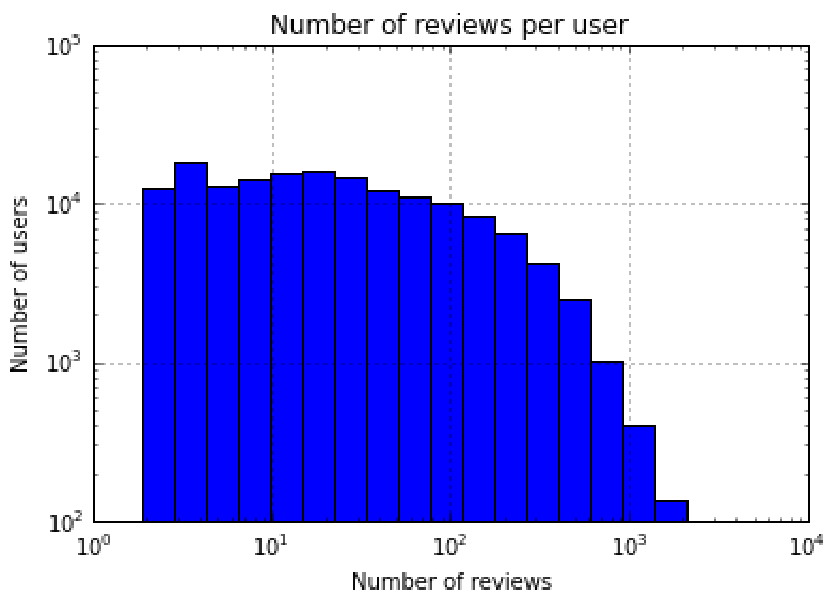
Now doing above analyses with the reduced set.

In [89]:
```
# Reviews for three specific cities.
review_phoenix2 = review_city_df2[review_city_df2.business_city_int ==
review_lasvegas2 = review_city_df2[review_city_df2.business_city_int =
review_montreal2 = review_city_df2[review_city_df2.business_city_int =
```

Number of reviews per user

In [90]:
```
plt.ylim([100,100000])
plt.gca().set_xscale("log")
plt.yscale('log')
plt.title('Number of reviews per user')
plt.xlabel('Number of reviews')
plt.ylabel('Number of users')
user_df2.user_review_count.hist(bins=np.logspace(0.1, 3.5, 20))
```

Out[90]: <matplotlib.axes._subplots.AxesSubplot at 0x11f5d23d0>

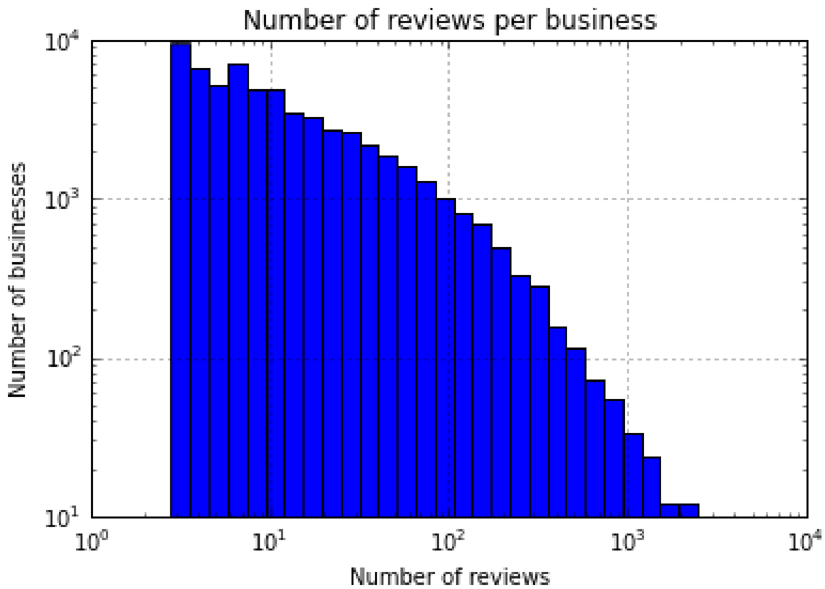


Looks different when number of reviews are small. Seems like users are more active overall.

Number of reviews per business

In [91]:
```
plt.ylim([10, 10000])
plt.gca().set_xscale("log")
plt.yscale('log')
plt.title('Number of reviews per business')
plt.xlabel('Number of reviews')
plt.ylabel('Number of businesses')
business_df.business_review_count.hist(bins=np.logspace(0.45, 3.5, 30)
```

Out[91]: <matplotlib.axes._subplots.AxesSubplot at 0x11d1833d0>

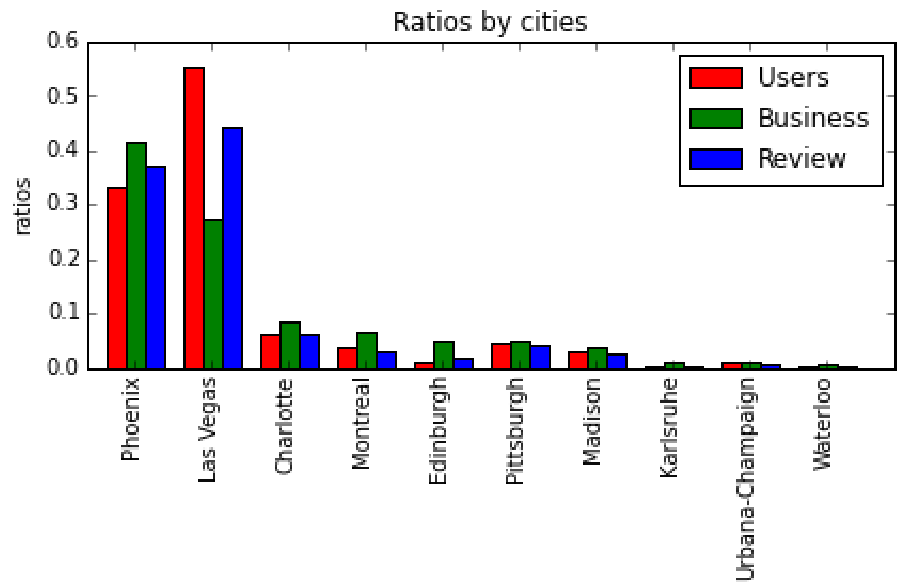


Looks almost the same as before.

Some counts per city

In [92]:
```
n_users2 = float(user_df2.shape[0])
n_businesses2 = float(business_df2.shape[0])
n_reviews2 = float(review_df2.shape[0])
users_by_city_ratio2 = np.array(review_city_df2.groupby('business_city
businesses_by_city_ratio2 = np.array(review_city_df2.groupby('business
reviews_by_city_ratio2 = np.array(review_city_df2.groupby('business_ci
```

In [93]:
```
plot_counts(users_by_city_ratio2, businesses_by_city_ratio2, reviews_b
            'ratios', ylim=0.6)
plt.tight_layout()
#plt.savefig('../fig/ratios_by_city.png', dpi=200)
```



Overall trends are the same here.

Degree distribution should be the same as before, except users with degree zero.

In [94]:
```
cities_by_user2 = np.array(review_city_df2.groupby('user_id_int').busi
```

In [95]:
```
print sum(cities_by_user2 == 1) / float(n_users2),\
    sum(cities_by_user2 == 2) / float(n_users2),\
    sum(cities_by_user2 > 2) / float(n_users2)
```

```
0.920278700013 0.0714211862557 0.00830011373166
```

User by city computed from 'find_users_by_city.py'.

Here it uses the network friends to determine the city if a user has reviews in multiple cities. If threre are ties between friends, it chooses the city randomly. As shown above, 92.1% of users have reviews in only one city, and 0.8% of users are chosen randomly, which means out of users with multiple cities, about 10% of them are chosen randomly.

In [96]:
```
user_by_city = pd.read_csv('../data/user_by_city', names=['user_id', '
user_by_city.groupby('city').count()
```

Out[96]:

	user_id
city	
0	52104
1	92761
2	9257
3	5270
4	1450
5	6928
6	4305
7	135
8	1507
9	377

Looking at subnetworks for each city.

In [97]:
```
# Dataframes for each city.
degrees_subnet = []
for i in range(10):
    degrees_subnet.append(pd.read_csv('../data/degrees%s' % i, names=[
```

In [98]:
```
# Number of edges for all subgraphs.
nedges_subnet = []
for i in range(10):
    nedges_subnet.append(degrees_subnet[i].values.sum(axis=0)[1])
    print nedges_subnet[i]/2,  nedges_subnet[i]/float(len(degrees_subn
print sum(nedges_subnet)
```

```
194968 8.5645632454
758230 17.2295631426
21541 6.04150890478
9328 5.41567489115
4524 9.35677352637
13195 5.15046838407
6950 4.64416972937
114 2.35051546392
1326 2.72
261 2.26956521739
2020876
```

In [99]:
```
# Number of edges for the total graph.
nedges = degrees.values.sum(axis=0)[1]
print nedges
```

```
2576179
```

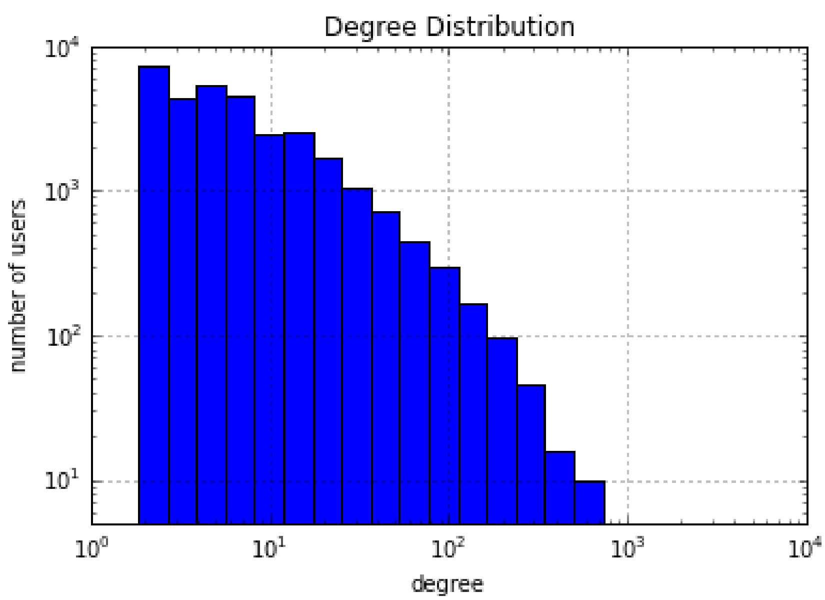
In [100]:
```
# Percentage of edges that are connecting inside communities.
sum(nedges_subnet)/float(nedges)
```

Out[100]:
```
0.78444704347019367
```

Degree distributions for subnets for three cities.

Phoenix

In [101]:
```
plot_degrees(degrees_subnet[0].degree, 5, 10000)
plt.savefig('../fig/degree_phoenix.png')
```

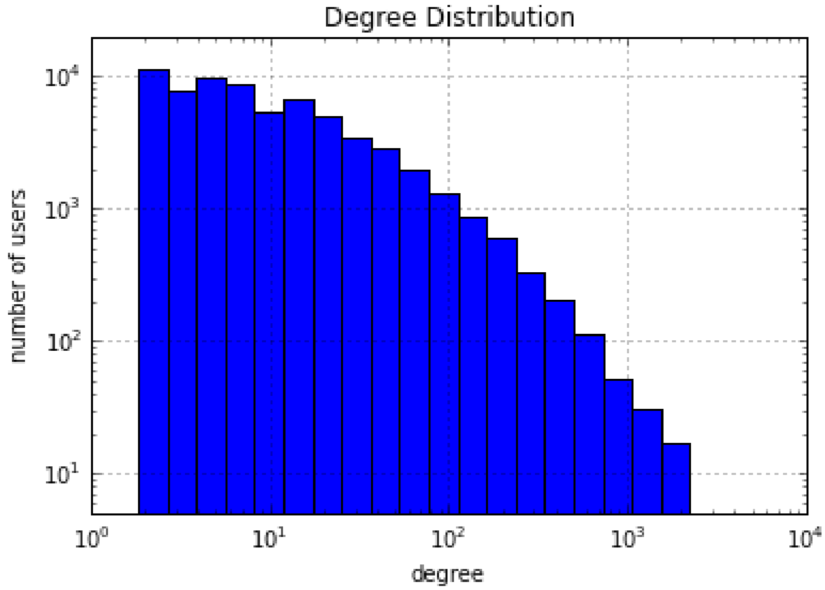


In [102]:
```
print degrees_subnet[0].degree.mean(), degrees_subnet[0].degree.median
```

```
8.5645632454 3.0
```

Las Vegas

In [103]:
```
plot_degrees(degrees_subnet[1].degree, 5, 20000)
plt.savefig('../fig/degree_lasvegas.png')
```

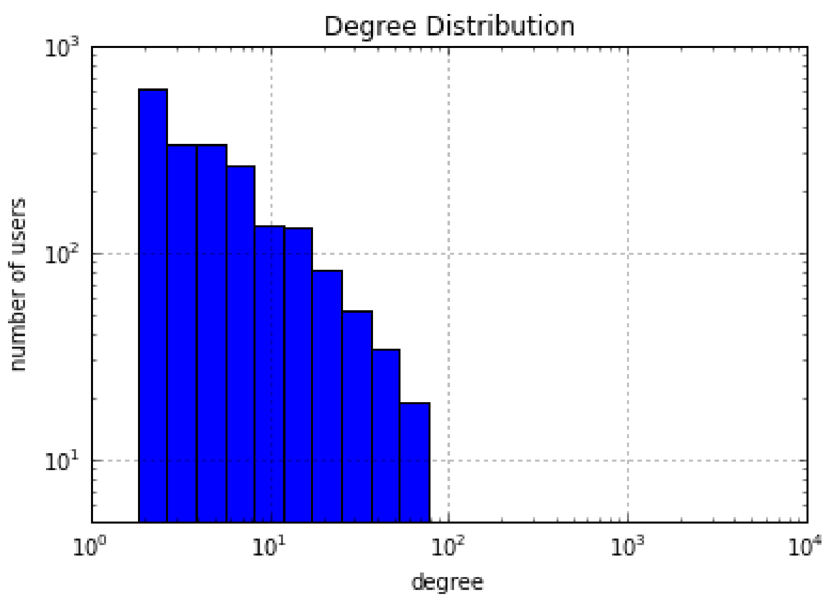


In [104]:
```
print degrees_subnet[1].degree.mean(), degrees_subnet[1].degree.median
```

```
17.2295631426 4.0
```

Montreal

In [105]:
```
plot_degrees(degrees_subnet[3].degree, 5, 1000)
plt.savefig('../fig/degree_lasvegas.png')
```



In [106]:
```
print degrees_subnet[3].degree.mean(), degrees_subnet[3].degree.median
```

```
5.41567489115 2.0
```

If we look at above results, three cities have quite different social networks. The avereage degrees are quite different. It is hard to find reasons why they are so different.

Correlation between values.

reviews per user and degrees per user

In [107]:
```
rev_count = user_df.user_review_count
deg_count = degrees.degree
```

In [108]:
```
from scipy.stats.stats import pearsonr
```

In [109]:
```
pearsonr(rev_count, deg_count)[0]
```

Out[109]:
```
0.48288144800008354
```

As expected, the more active users are in terms of writing reviews, the more friends those users have. We can clearly see that when we look at those values together.

Finding friends of friends for a network of a given city

In [112]:
```
city = 0
my_graph = read_dictlist_from_file('../data/network' + str(city) + 'b.
```

In [113]:
```
friends_of_friends = {}
for node in my_graph:
    friends_of_friends[node] = set(my_graph[node])
    for friend1 in my_graph[node]:
        for friend2 in my_graph[friend1]:
            friends_of_friends[node].add(friend2)
```

In [114]:
```
nff = []
for user in friends_of_friends:
    nff.append(len(friends_of_friends[user]))
```

In [115]:
```
plt.xlim(0,6000)
plt.hist(nff, bins=100)
```

Out[115]:
```
(array([  2.71870000e+04,   4.46000000e+03,   2.30100000e+03,
          1.48700000e+03,   1.00100000e+03,   6.47000000e+02,
          8.66000000e+02,   6.61000000e+02,   4.45000000e+02,
          3.43000000e+02,   2.68000000e+02,   4.71000000e+02,
          2.68000000e+02,   3.30000000e+02,   2.40000000e+02,
          2.26000000e+02,   2.06000000e+02,   1.60000000e+02,
          1.50000000e+02,   1.30000000e+02,   1.20000000e+02,
          1.07000000e+02,   7.80000000e+01,   9.30000000e+01,
          8.20000000e+01,   6.30000000e+01,   5.20000000e+01,
          4.00000000e+01,   5.40000000e+01,   4.40000000e+01,
          4.10000000e+01,   3.00000000e+01,   2.60000000e+01,
          3.70000000e+01,   2.20000000e+01,   2.10000000e+01,
          2.10000000e+01,   2.50000000e+01,   2.10000000e+01,
          1.50000000e+01,   1.70000000e+01,   1.10000000e+01,
          1.40000000e+01,   9.00000000e+00,   1.10000000e+01,
          1.30000000e+01,   1.10000000e+01,   6.00000000e+00,
          5.00000000e+00,   4.00000000e+00,   7.00000000e+00,
          1.00000000e+01,   4.00000000e+00,   6.00000000e+00,
          1.00000000e+00,   2.00000000e+00,   5.00000000e+00,
```

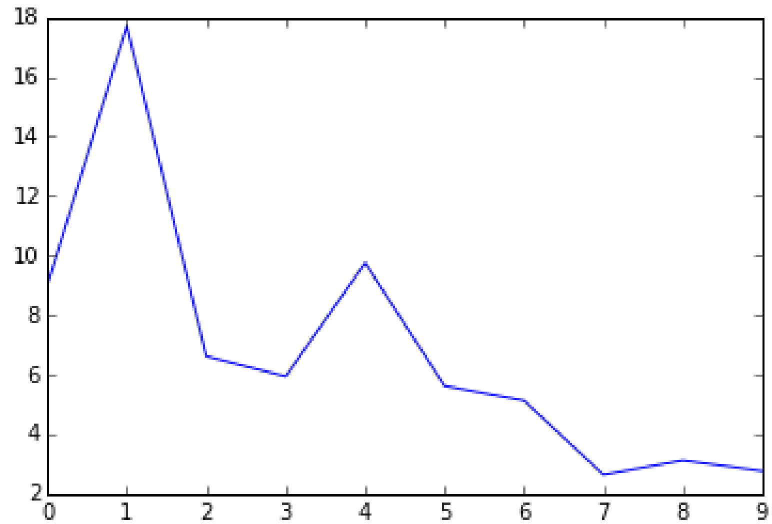
Looking at all small networks (biggest components).

In [116]:
```
# Reading the biggest component of each graph for each city.
my_nets = []  # dict of lists
my_nets_nx = []  # networkx objects
for i in range(10):
    my_nets.append(reindex_graph(read_dictlist_from_file('../data/netw
    my_nets_nx.append(convert_to_nx(my_nets[-1]))
```

Number of average degrees (for the biggest components).

In [117]:
```
average_degrees = []
for i in range(10):
    average_degrees.append(np.mean(my_nets_nx[i].degree().values()))
plt.plot(average_degrees)
```

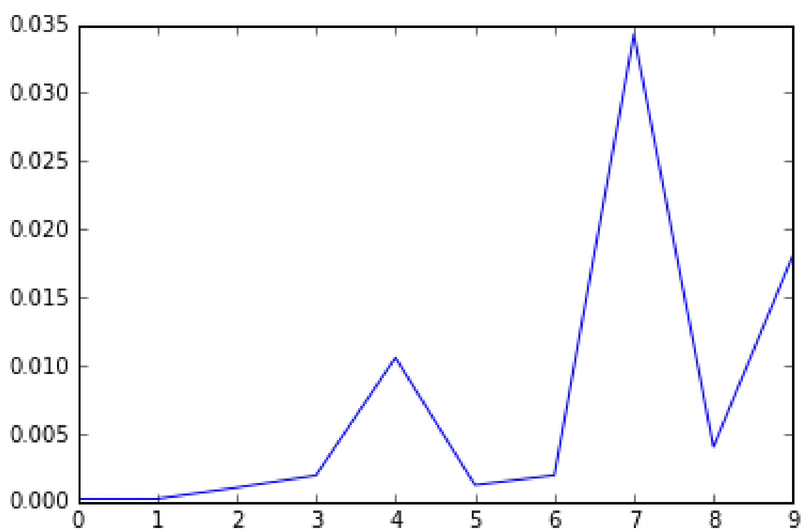
Out[117]: [<matplotlib.lines.Line2D at 0x10c3df350>]



Densities

In [118]:
```
densities = []
for i in range(10):
    densities.append(nx.density(my_nets_nx[i]))
plt.plot(densities)
```

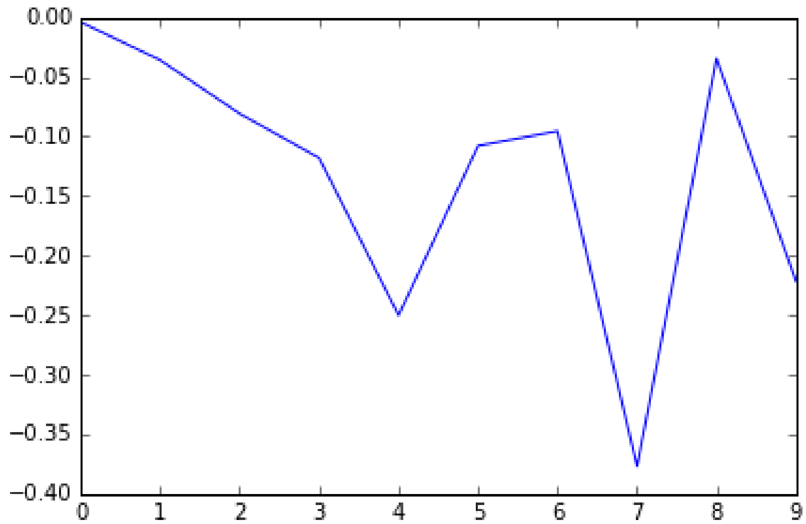
Out[118]: [<matplotlib.lines.Line2D at 0x11f4dc5d0>]



Assortativities.

In [119]:
```
assortativities = []
for i in range(10):
    assortativities.append(nx.degree_assortativity_coefficient(my_nets
plt.plot(assortativities)
```

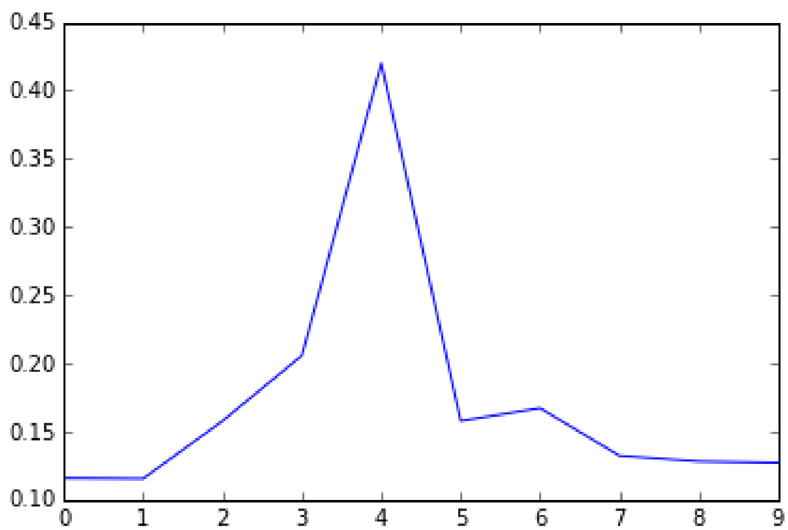
Out[119]: [<matplotlib.lines.Line2D at 0x12790d810>]



Average clustering coefficients

In [120]:
```
average_clusterings = []
for i in range(10):
    average_clusterings.append(nx.average_clustering(my_nets_nx[i]))
plt.plot(average_clusterings)
```

Out[120]: [<matplotlib.lines.Line2D at 0x1a6560a50>]



Spectral clustering for cities.

In [121]:
```
# Adjacency matrix for small cities (city number >= 2 only)
adjacency = []
for i in range(2, 10):
    adjacency.append(adjacency_matrix(my_nets[i]))
```

In [122]:
```
spectral = []
for i in range(8):
    spectral.append(SpectralClustering(n_clusters=2, eigen_solver='arp
                                        assign_labels='kmeans'))
```

In [123]:
```
for i in range(8):
    spectral[i].fit(adjacency[i])
```

In [125]:
```
n_communities = []
for i in range(5):
    n_communities.append((spectral[0].labels_ == i).sum())
print n_communities
```

```
[6385, 5, 0, 0, 0]
```

Differences between real rating and predictions.

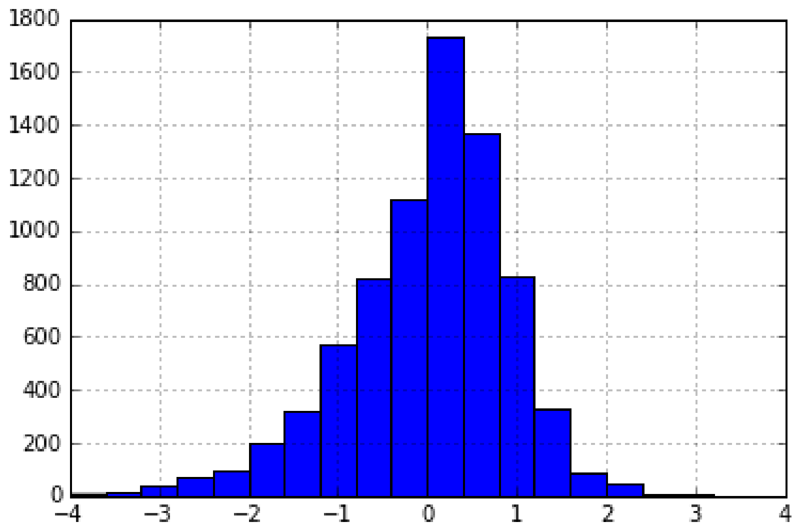
In [126]:
```
# Read the data for one run (processed to have real rating, average ra
# friends, number of friends rated, number of friends of friends ratec
# NaN will be given when there is no rating by friends and friends by
rating_diff_df = pd.read_csv('../fig/fig_data/ratings_by_item2', delim
```

In [127]:
```
ratings_diff1 = rating_diff_df[['real', 'average', 'friend', 'nfr']].d
ratings_diff2 = rating_diff_df[['real', 'average', 'friend2', 'nfr2']]
```

In [128]:
```
diff_ave1 = ratings_diff1.real - ratings_diff1.average
diff_ave2 = ratings_diff2.real - ratings_diff2.average
```

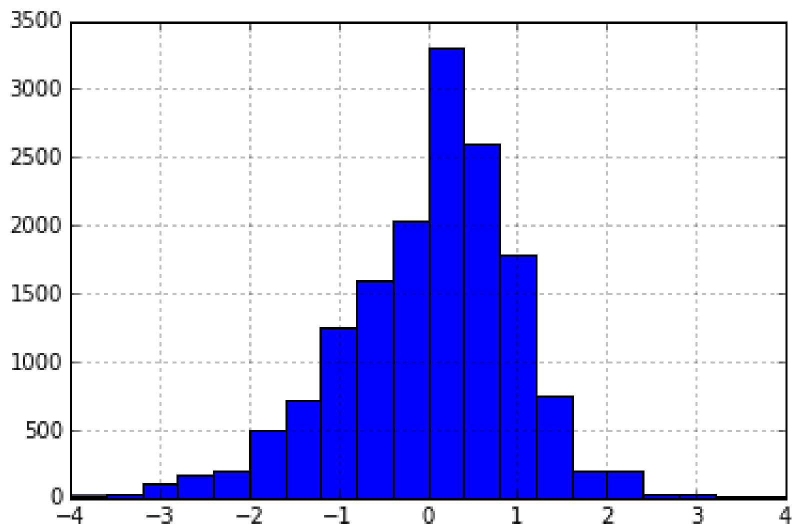
In [129]:
```
diff_ave1.hist(bins=20)
```

Out[129]: <matplotlib.axes._subplots.AxesSubplot at 0x18148bfd0>



In [130]:
```
diff_ave2.hist(bins=20)
```

Out[130]: <matplotlib.axes._subplots.AxesSubplot at 0x18152a590>

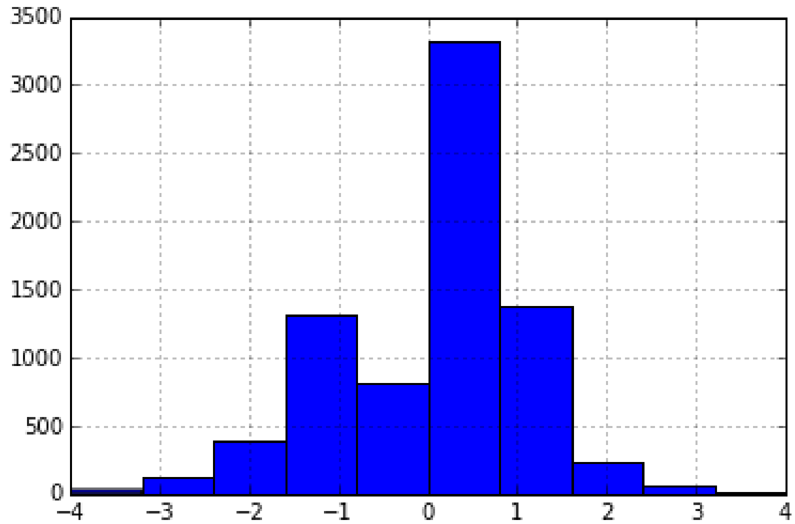


In [131]:
```
print diff_ave1.std(), diff_ave2.std()
```

```
0.910563673967 0.990802610772
```

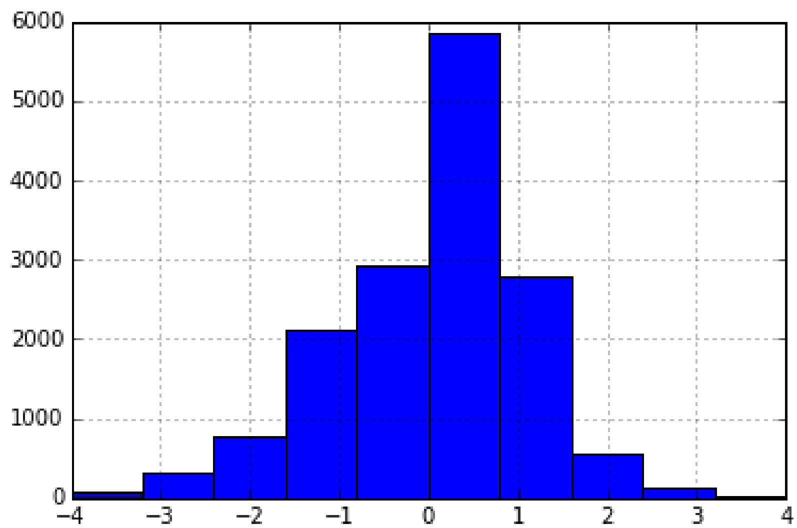
In [134]:
```
diff_fr1 = ratings_diff1.real - ratings_diff1.friend
diff_fr1.hist(bins=10)
```

Out[134]: <matplotlib.axes._subplots.AxesSubplot at 0x1affd1f90>



In [136]:
```
diff_fr2 = ratings_diff2.real - ratings_diff2.friend2
diff_fr2.hist(bins=10)
```

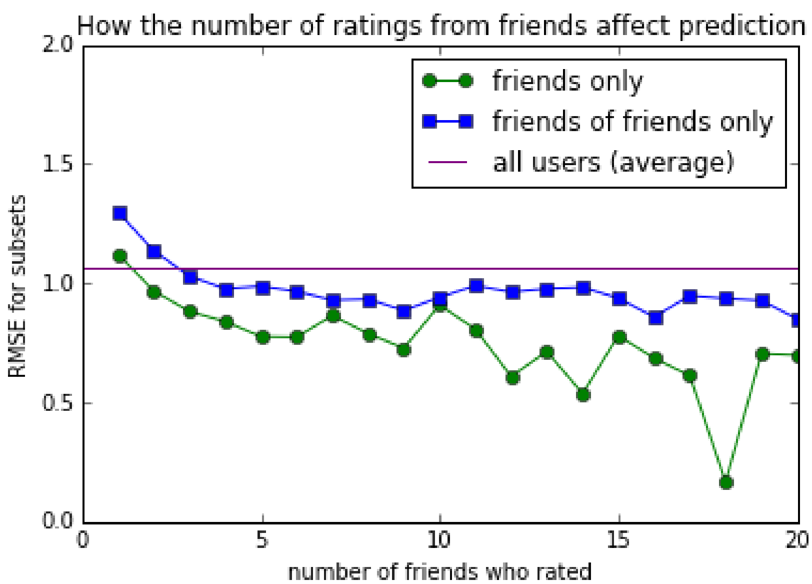
Out[136]: <matplotlib.axes._subplots.AxesSubplot at 0x1b00c5410>



In [137]:
```
stds1 = []
baseline1 = []
for n in range(1,100):
    diff_fr1 = ratings_diff1[ratings_diff1['nfr'] == n].real - \
               ratings_diff1[ratings_diff1['nfr'] == n].friend
    stds1.append(np.sqrt(np.mean(np.square(diff_fr1))))
    diff_av1 = ratings_diff1[ratings_diff1['nfr'] == n].real - \
               ratings_diff1[ratings_diff1['nfr'] == n].average
    baseline1.append(np.sqrt(np.mean(np.square(diff_av1))))
```

In [140]:
```
stds2 = []
baseline2 = []
for n in range(1,100):
    diff_fr2 = ratings_diff2[ratings_diff2['nfr2'] == n].real - \
               ratings_diff2[ratings_diff2['nfr2'] == n].friend2
    stds2.append(np.sqrt(np.mean(np.square(diff_fr2))))
    diff_av2 = ratings_diff2[ratings_diff2['nfr2'] == n].real - \
               ratings_diff2[ratings_diff2['nfr2'] == n].average
    baseline2.append(np.sqrt(np.mean(np.square(diff_av2))))
```

In [178]:
```
plt.xlabel('number of friends who rated')
plt.ylabel('RMSE for subsets')
plt.xlim(0,20)
plt.ylim(0,2)
plt.title('How the number of ratings from friends affect prediction')
fig1 = plt.plot(range(1,100), stds1, marker='o', color='g', label='fri
fig2 = plt.plot(range(1,100), stds2, marker='s', color='b', label='fri
#fig3 = plt.plot(range(1,100), baseline1, marker='D', color='g', label
#fig4 = plt.plot(range(1,100), baseline2, marker='D', color='b', label
#b1 = ratings_diff1.real.std()
#b2 = ratings_diff2.real.std()
#fig3 = plt.plot([0, 100], [b1, b1], color='g', label='baseline for fr
#fig4 = plt.plot([0, 100], [b2, b2], color='b', label='baseline for fr
b0 = 1.065 # standard deviation of ratings for the city of Montreal.
fig5 = plt.plot([0, 100], [b0, b0], color='purple', label='all users (
plt.legend()
plt.savefig('../fig/friends.png', dpi=200)
```



In [146]:
```
# Baseline is already obtained for the whole ratings of the dataset, w
# of the all ratings. But this is not to be compared with results from
# subsets (one for each city) of the whole data.
b_whole = 1.3114679041155461
```

Baseline numbers for each city was obtained using Validator.get_baseline method. Here it computes the standard deviation for the given ratings of the training set.

In [147]:
```
ba_df = np.loadtxt('../fig/fig_data/baseline_each_city')
```

CF was run using (n_feasures=2, learning_rate=0.009, regularization_parameter=0.07) and K=10 with item bias considered (not user bias).

In [168]:
```
cf = np.loadtxt('../fig/fig_data/cf_rmse')
```

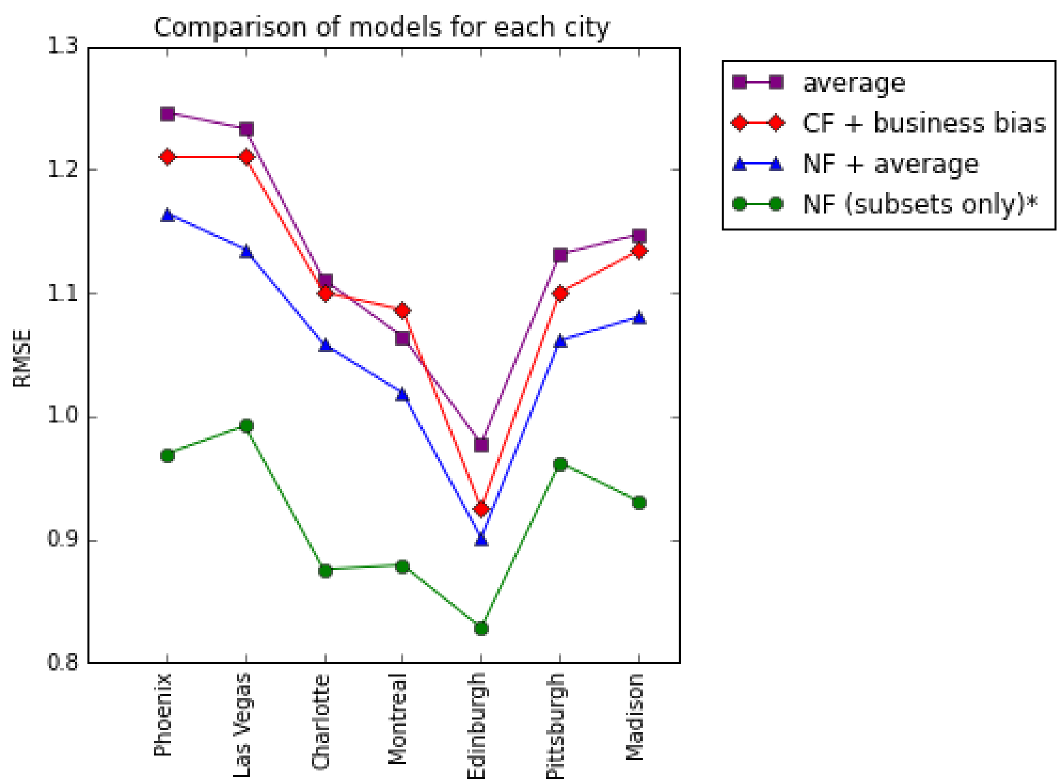
In [170]:
```
cf
```

Out[170]:
```
array([[ 0.        ,  0.011     ,  0.12      ,  1.21020065],
       [ 1.        ,  0.011     ,  0.12      ,  1.21018154],
       [ 2.        ,  0.011     ,  0.12      ,  1.10032968],
       [ 3.        ,  0.011     ,  0.12      ,  1.08628801],
       [ 4.        ,  0.011     ,  0.12      ,  0.92546796],
       [ 5.        ,  0.011     ,  0.12      ,  1.10025827],
       [ 6.        ,  0.011     ,  0.12      ,  1.1342335 ],
       [ 7.        ,  0.011     ,  0.12      ,  1.14879198],
       [ 8.        ,  0.011     ,  0.12      ,  1.21974276],
       [ 9.        ,  0.011     ,  0.12      ,  1.28382666]])
```

Using_Friends has been used to find the RMSE for the network-based model.

In [153]:
```
nf1 = np.loadtxt('../fig/fig_data/nf_rmse')
nf2 = np.loadtxt('../fig/fig_data/nf_rmse2')
```

In [181]:
```
fig = plt.figure(figsize=(8,6))
ax = fig.add_subplot(111)
plt.title('Comparison of models for each city')
plt.ylabel('RMSE')
plt.xlim(-1,6.5)
plt.ylim(0.8, 1.3)
ax.set_xticks(range(7))
xtickNames = ax.set_xticklabels(city_names)
plt.setp(xtickNames, rotation=90, fontsize=10)
ax.set_position([0.1,0.1,1.2,0.9])
#fig1 = plt.plot([-2, 100], [b, b], color='g', label='baseline (whole)
fig1 = plt.plot(ba_df[:7,0], ba_df[:7,1], marker='s', color='purple',
fig2 = plt.plot(cf[:7,0], cf[:7,3], marker='D', color='r', label='CF +
fig3 = plt.plot(nf2[:7,0], nf2[:7,1], marker='^', color='b', label='NF
fig4 = plt.plot(nf1[:7,0], nf1[:7,1], marker='o', color='g', label='NF
plt.legend(bbox_to_anchor=(1.05, 1), loc=2 )
plt.tight_layout()
plt.savefig('../fig/rmse.png', dpi=200)
```



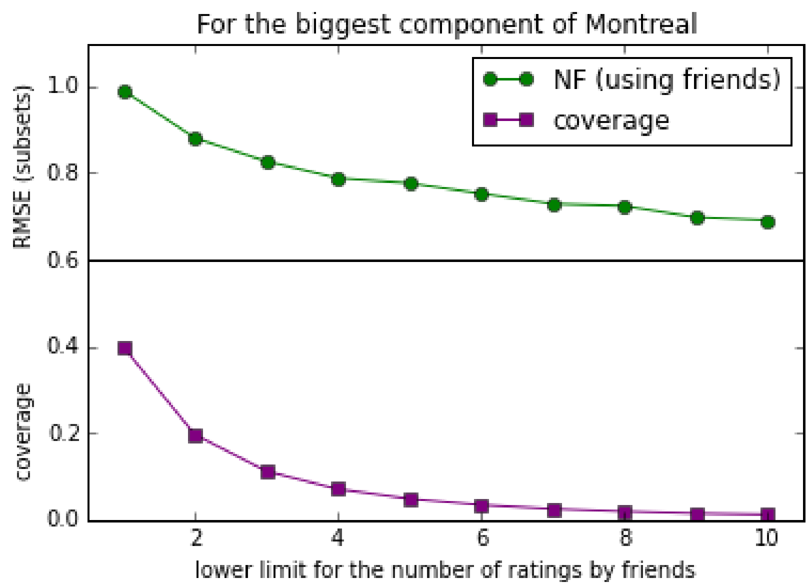
How the lower limit for the number of ratings by friends changes the RMSE and the % of predicted.

In [163]:
```
# By running the model, results are produced already: city0_limit, cit
limit0 = np.loadtxt('../fig/fig_data/city0_limit')
limit1 = np.loadtxt('../fig/fig_data/city1_limit')
limit3 = np.loadtxt('../fig/fig_data/city3_limit')
```

Seems like their behavior is almost the same.

In [167]:

```
plt.title('For the biggest component of Montreal')
plt.ylim(0, 1.1)
plt.xlim(0.5,10.5)
plt.xlabel('lower limit for the number of ratings by friends')
plt.ylabel('coverage                              RMSE (subsets)')
#plt.plot(limit0[:,0], limit0[:,1])
#plt.plot(limit1[:,0], limit1[:,1], marker='', color='b', label='Las V
plt.plot(limit3[:,0], limit3[:,2], marker='o', color='g', label='NF (u
plt.plot(limit3[:,0], limit3[:,1], marker='s', color='purple', label='
plt.plot([0,11], [0.6,0.6], color='black')
#plt.plot(limit0[:,0], limit0[:,2])
#plt.plot(limit1[:,0], limit1[:,2])
plt.legend()
plt.savefig('../fig/limit.png', dpi=200)
```



In [ ]: