Features comparison Airbnb and Pipeline

June 21, 2016

```
In [1]: %matplotlib inline

        import pandas as pd
        import matplotlib.pyplot as plt
        import numpy as np
        from __future__ import division
        from pandas.tools.plotting import autocorrelation_plot
        from scipy.stats import ks_2samp

        pd.set_option('display.mpl_style', 'default') # Make the graphs a bit prett
        plt.rcParams['figure.figsize'] = (15, 5)
        plt.rcParams['font.family'] = 'sans-serif'

        # This is necessary to show lots of columns in pandas 0.12.
        # Not necessary in pandas 0.13.
        pd.set_option('display.width', 5000)
        pd.set_option('display.max_columns', 60)
```

```
c:\python27\lib\site-packages\IPython\core\interactiveshell.py:2885: FutureWarning:
mpl_style had been deprecated and will be removed in a future version.
Use `matplotlib.pyplot.style.use` instead.

  exec(code_obj, self.user_global_ns, self.user_ns)
```

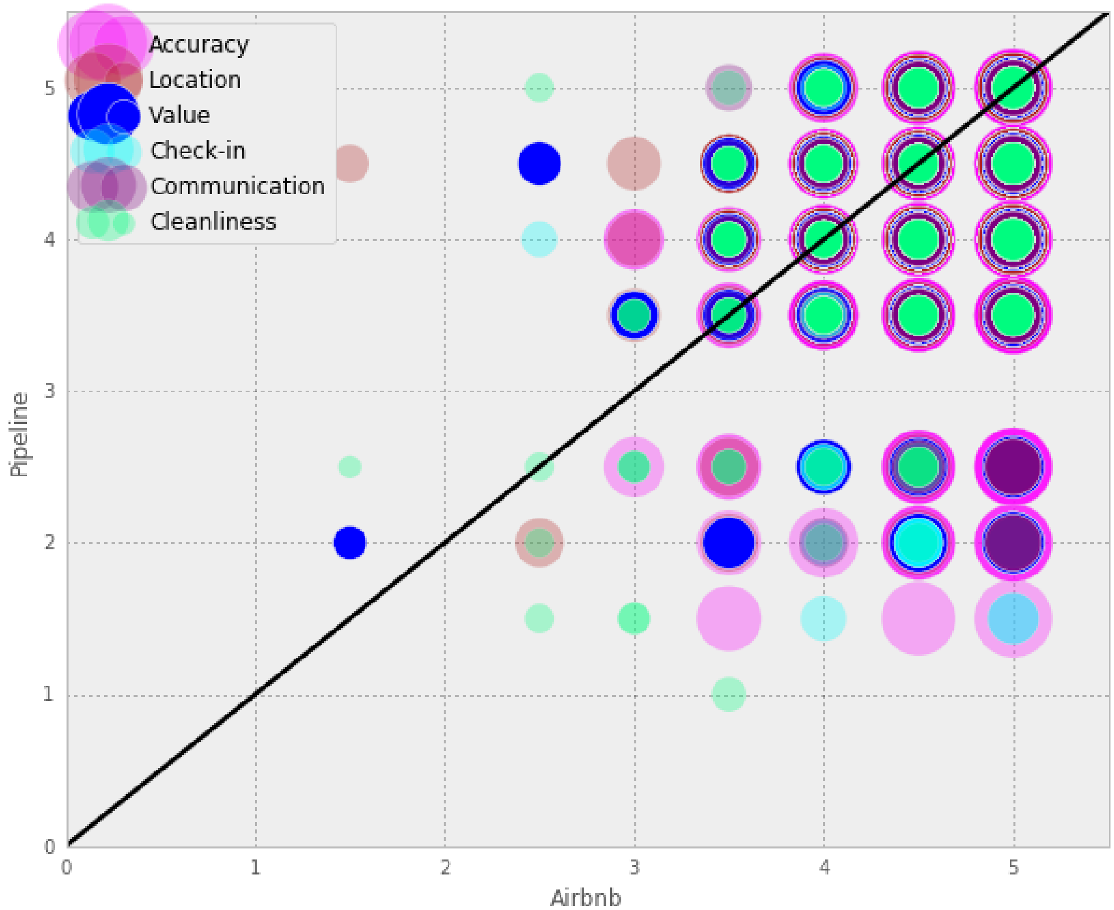
```
In [2]: comparison= pd.read_csv('C:/Python27/features_comparison.csv')
        full_content = pd.read_csv('C:/Python27/output_improved.csv')
        comparison[:2]
```

```
Out[2]:          Id  AirbnbAccuracy  AirbnbCheck-in  AirbnbCleanliness  AirbnbCommur
        0  2016430             4.5             4.5                4.5
        1    20168             4.5             4.5                4.5
```

0.1 Combinations of stars of Airbnb and Pipeline for all features

The graph shows all the possible combinations of feature stars with the Airbnb stars per feature. Each point represents a combination, the strength of the color indicates that the combination is found more often. However these frequencies will be visualized later.

In [3]:
```
ax = comparison.plot(kind='scatter', x='AirbnbAccuracy',
y='PipeAccuracy', color='Fuchsia', label='Accuracy',alpha=0.3,
 s=comparison['AirbnbAccuracy']*350)

bx = comparison.plot(kind='scatter', x='AirbnbLocation',
y='PipeLocation',color='FireBrick', label='Location', ax=ax,alpha=0.3,
s=comparison['AirbnbLocation']*280)

cx = comparison.plot(kind='scatter', x='AirbnbValue', y='PipeValue',
 color='Blue', label='Value', ax=bx,  s=comparison['AirbnbValue']*220)

dx = comparison.plot(kind='scatter', x='AirbnbCheck-in', y='PipeCheckin',
color='Aqua', label='Check-in', ax=cx,  s=comparison['AirbnbCheck-in']*150)

ex = comparison.plot(kind='scatter', x='AirbnbCommunication',
 y='PipeCommunication', color='Purple', alpha=0.3, label='Communication',
                     ax=dx,  s=comparison['AirbnbCommunication']*180)

fx = comparison.plot(kind='scatter', x='AirbnbCleanliness', y='PipeCleanlin
color='SpringGreen', label='Cleanliness', ax=ex,
s=comparison['AirbnbCleanliness']*100, alpha=0.3, figsize=(10,8)).set_xlim
line = plt.plot([0,1,2,3,4,5,6], [0,1,2,3,4,5,6])
plt.axis([0, 5.5, 0, 5.5])
plt.xlabel('Airbnb')
plt.ylabel('Pipeline')
plt.setp(line, color='Black', linewidth=2.5)
plt.show()
```



0.2 How star assignment for Accuracy are found in combination Airbnb and Pipeline

For every listing it is seen how the Pipeline assigns the value and how the corresponding star in the Airbnb system is. 26 possible combinations are found

```
In [10]: # For filling the dataframe
         i=5.0
         s0=comparison[comparison['AirbnbAccuracy']==i]
         s00=s0['PipeAccuracy'].value_counts()
         b=pd.DataFrame({'Airbnb':i, 'Pipeline':s00.index,
                         'V_Frequency': s00.values})
         i=4.5
         s1=comparison[comparison['AirbnbAccuracy']==i]
         s11=s1['PipeAccuracy'].value_counts()
         b1=pd.DataFrame({'Airbnb':i, 'Pipeline':s11.index,
                          'V_Frequency': s11.values})
         i=4.0
         s2=comparison[comparison['AirbnbAccuracy']==i]
         s22=s2['PipeAccuracy'].value_counts()
```

```
b2=pd.DataFrame({'Airbnb':i, 'Pipeline':s22.index,
                 'V_Frequency': s22.values})
i=3.5
s3=comparison[comparison['AirbnbAccuracy']==i]
s33=s3['PipeAccuracy'].value_counts()
b3=pd.DataFrame({'Airbnb':i, 'Pipeline':s33.index,
                 'V_Frequency': s33.values})
i=3.0
s4=comparison[comparison['AirbnbAccuracy']==i]
s44=s4['PipeAccuracy'].value_counts()
b4=pd.DataFrame({'Airbnb':i, 'Pipeline':s44.index,
                 'V_Frequency': s44.values})
i=2.5
s5=comparison[comparison['AirbnbAccuracy']==i]
s55=s5['PipeAccuracy'].value_counts()
b5=pd.DataFrame({'Airbnb':i, 'Pipeline':s55.index,
                 'V_Frequency': s55.values})
stars_compared=pd.concat([b,b1,b2,b3,b4,b5],ignore_index=True)
stars_compared['Percentage']=
((stars_compared['V_Frequency']/stars_compared['V_Frequency'].sum())*100)
stars_compared.columns=['Airbnb','Pipeline','Frequency','Percentage']
stars_compared
```

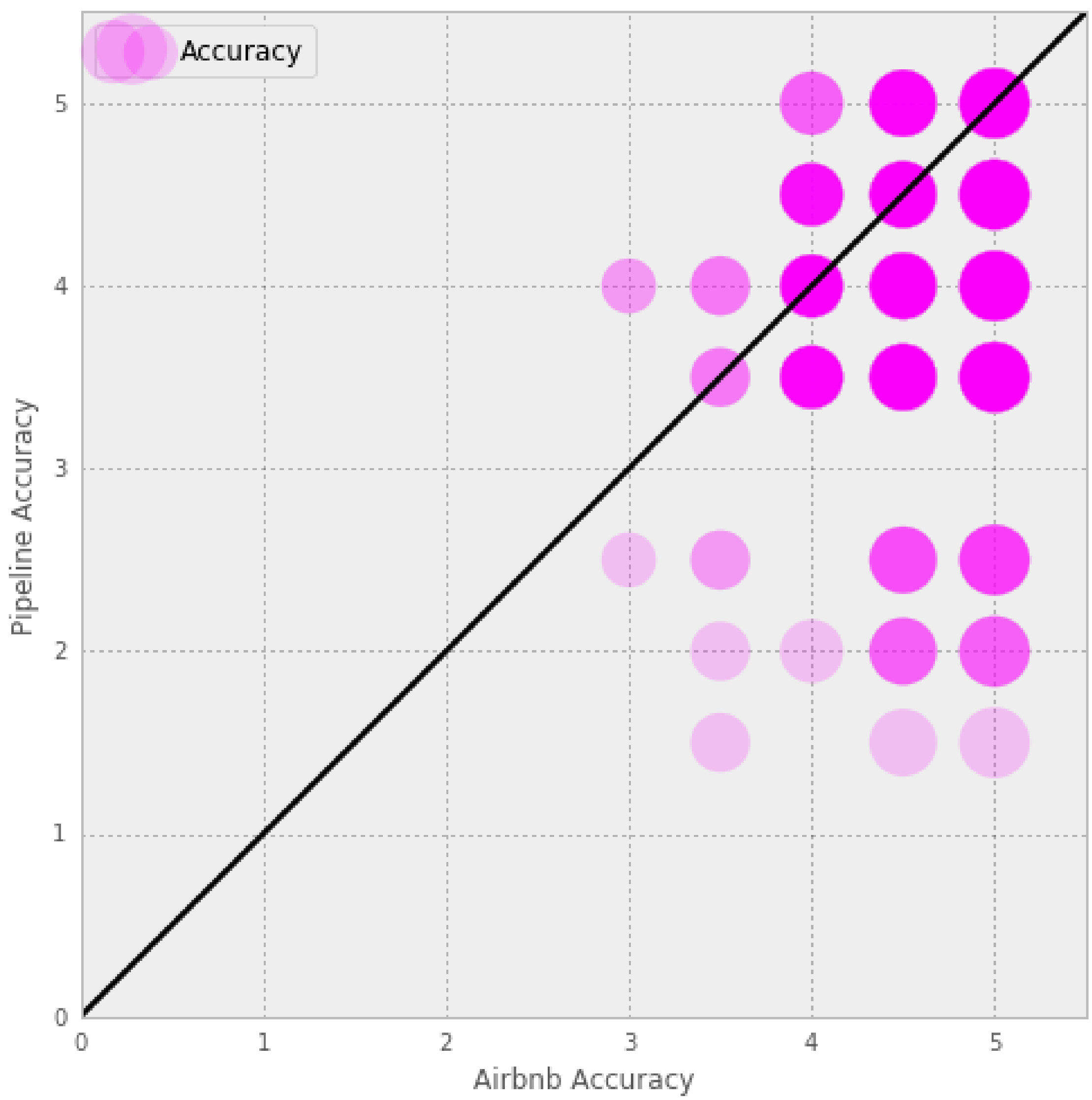
Out[10]:

	Airbnb	Pipeline	Frequency	Percentage
0	5.0	4.0	545	35.21
1	5.0	4.5	211	13.63
2	5.0	3.5	104	6.72
3	5.0	5.0	23	1.49
4	5.0	2.5	6	0.39
5	5.0	2.0	4	0.26
6	5.0	1.5	1	0.06
7	4.5	4.0	343	22.16
8	4.5	3.5	102	6.59
9	4.5	4.5	94	6.07
10	4.5	5.0	17	1.10
11	4.5	2.5	5	0.32
12	4.5	2.0	4	0.26
13	4.5	1.5	1	0.06
14	4.0	4.0	42	2.71
15	4.0	3.5	16	1.03
16	4.0	4.5	12	0.78
17	4.0	5.0	4	0.26
18	4.0	2.0	1	0.06
19	3.5	4.0	3	0.19
20	3.5	3.5	3	0.19
21	3.5	2.5	2	0.13
22	3.5	2.0	1	0.06
23	3.5	1.5	1	0.06

```
24      3.0        4.0            2          0.13
25      3.0        2.5            1          0.06
```

0.3 Plot of star combinations only for feature Accuracy

```
In [11]: ax = comparison.plot(kind='scatter', x='AirbnbAccuracy', y='PipeAccuracy',
         color='Fuchsia', label='Accuracy', s=comparison['AirbnbAccuracy']*200,
                                     alpha=0.2, figsize=(8,8))

         line = plt.plot([0,1,2,3,4,5,6], [0,1,2,3,4,5,6])
         plt.axis([0, 5.5, 0, 5.5])
         plt.ylabel('Pipeline Accuracy')
         plt.xlabel('Airbnb Accuracy')
         plt.setp(line, color='Black', linewidth=2.5)
         plt.show()
```



0.4 Group rare combinations under the category "OTHERS"

```
In [12]: ot=stars_compared[stars_compared['Percentage']<5]
         other=ot['Percentage'].sum()
         other
         freq=ot['Frequency'].sum()
         main=stars_compared[stars_compared['Percentage']>=5]
         main.loc[26]=['Other','Other',freq,other]
         main
```

```
c:\python27\lib\site-packages\ipykernel\__main__.py:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/i
```

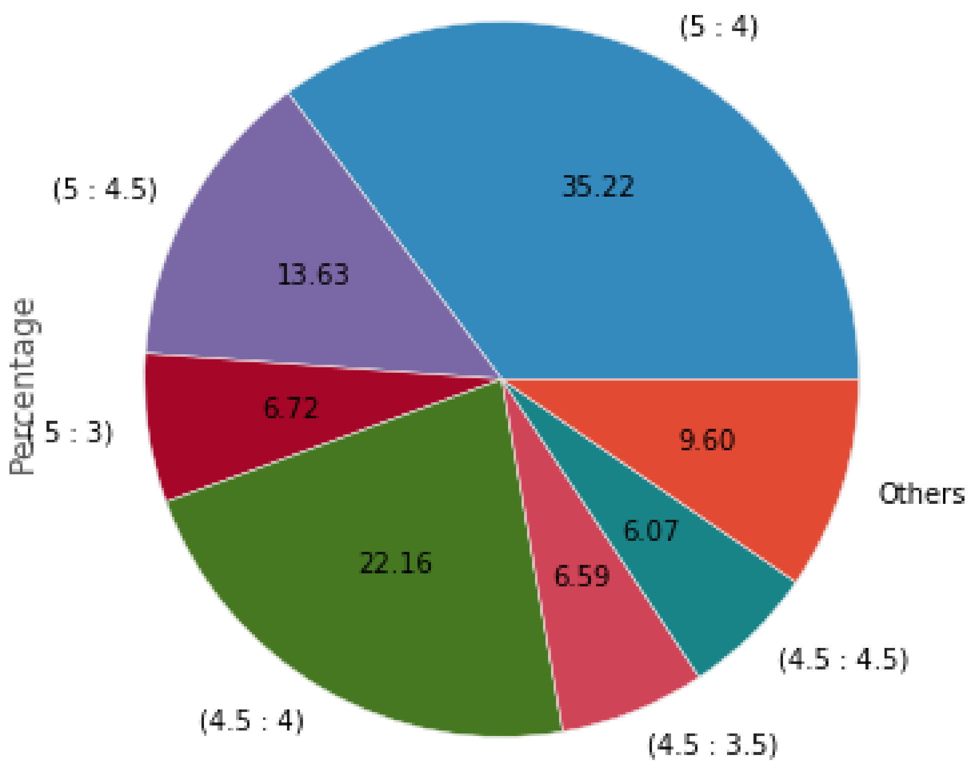
Out[12]:

	Airbnb	Pipeline	Frequency	Percentage
0	5	4	545	35.21
1	5	4.5	211	13.63
2	5	3.5	104	6.72
7	4.5	4	343	22.16
8	4.5	3.5	102	6.59
9	4.5	4.5	94	6.07
26	Other	Other	149	9.60

0.5 Visualization of all the combinations found for Feature: Accuracy

```
In [13]: main['Percentage'].plot(kind='pie', labels=['(5 : 4)', '(5 : 4.5)', '( 5 :
           '(4.5 : 4)', '(4.5 : 3.5)', '(4.5 : 4.5)', 'Others'],
            autopct='%.2f', fontsize=10, figsize=(6, 6))
```

```
Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0xcb85390>
```



0.6 Differences between the Airbnb stars and the pipeline

```
In [14]: comparison['DiffAccuracy']=comparison['AirbnbAccuracy']-comparison['PipeAc
         dfr=comparison['DiffAccuracy'].value_counts()
         norm= comparison['DiffAccuracy'].value_counts(normalize=True)
         dfrf=dfr.to_frame()
         dfrf['Normalized']=norm
         dfrf.columns=['Frequency','Normalized']
         dfrf
```

Out[14]:

	Frequency	Normalized
1.0	649	0.419251
0.5	571	0.368863
0.0	162	0.104651
1.5	105	0.067829
-0.5	32	0.020672
2.5	10	0.006460
2.0	7	0.004522

```
-1.0           6    0.003876
 3.0           5    0.003230
 3.5           1    0.000646
```

0.7 Get the IDs of listings which have big difference in stars between pipeline and Airbnb

In [15]:
```
bg1=comparison[comparison['DiffAccuracy']>1.5]
ls1=comparison[comparison['DiffAccuracy']<-1.5]
weird=pd.concat([bg1,ls1])
weird_listing=weird['Id']
weird[['Id','AirbnbAccuracy','PipeAccuracy']]
```

Out[15]:

	Id	AirbnbAccuracy	PipeAccuracy
15	2030718	4.5	2.5
138	2148498	4.5	2.5
165	2176762	5.0	2.5
237	2279998	5.0	1.5
327	2383331	5.0	2.0
485	2545716	3.5	1.5
744	2813439	4.5	2.0
778	2841577	5.0	2.0
870	293190	4.5	2.0
889	2955330	4.5	2.5
928	2985952	5.0	2.5
945	3005180	5.0	2.0
946	3007461	5.0	2.5
947	3008108	5.0	2.0
985	3040374	4.5	2.5
1047	3107052	4.0	2.0
1184	3236227	5.0	2.5
1325	3385173	4.5	2.0
1342	3401648	5.0	2.5
1379	3437051	4.5	1.5
1557	3649042	4.5	2.5
1665	3739928	5.0	2.5
1746	3814846	4.5	2.0

0.8 Check some of the cases

Here we see that the listing has feature **Accuracy** mentioned in only 2 sentences, thus it is not very accurate on generating a sentiment score for this feature

In [16]:
```
acy=full_content[full_content['Listing ID']== 2176762]
acy[acy['Feature: Accuracy']!=0]
```

Out[16]:

	Listing ID	Review ID	Ser
23614	2176762	13669114	Even when we arrived two hours earlier than
23667	2176762	10723997	The apartement is like descr

0.9 Exclude from the analysis listing with less than 3 reviews about the feature

In order to be more reliable, the cases where about a feature we have less than 3 reviews, are excluded

In [17]:
```
a=full_content[['Listing ID','Review ID','Feature: Accuracy']]
ap=a[a['Feature: Accuracy']!=0]
a_nodup=ap.drop_duplicates()
count=a_nodup.groupby('Listing ID').count()
count['Listing ID']=count.index
d = count[count['Review ID']<3]
less_3 = d[['Listing ID']]
less_3[:5]
```

Out[17]:

	Listing ID
Listing ID	
3209	3209
23651	23651
27886	27886
30431	30431
31080	31080

In [18]:
```
mutual=comparison[comparison['Id'].isin(less_3['Listing ID'])]
indexes_ID=mutual.index
for i in less_3['Listing ID']:
    new_comparison1=comparison.drop(indexes_ID)
```

0.10 Check the differences within the filtered set

Now we see that for the highest differences are 2.0 and 2.5 in only two cases

In [21]:
```
new_comparison1['DifferenceAccuracy']=
new_comparison1['AirbnbAccuracy']-new_comparison1['PipeAccuracy']

dfr_new=new_comparison1['DifferenceAccuracy'].value_counts()
norm_new = new_comparison1['DifferenceAccuracy'].value_counts(normalize=Tr
dfrf_new=dfr_new.to_frame()
dfrf_new['Normalized']=norm_new
dfrf_new.columns=['New_Frequency','New_Normalized']
dfrf_new
```

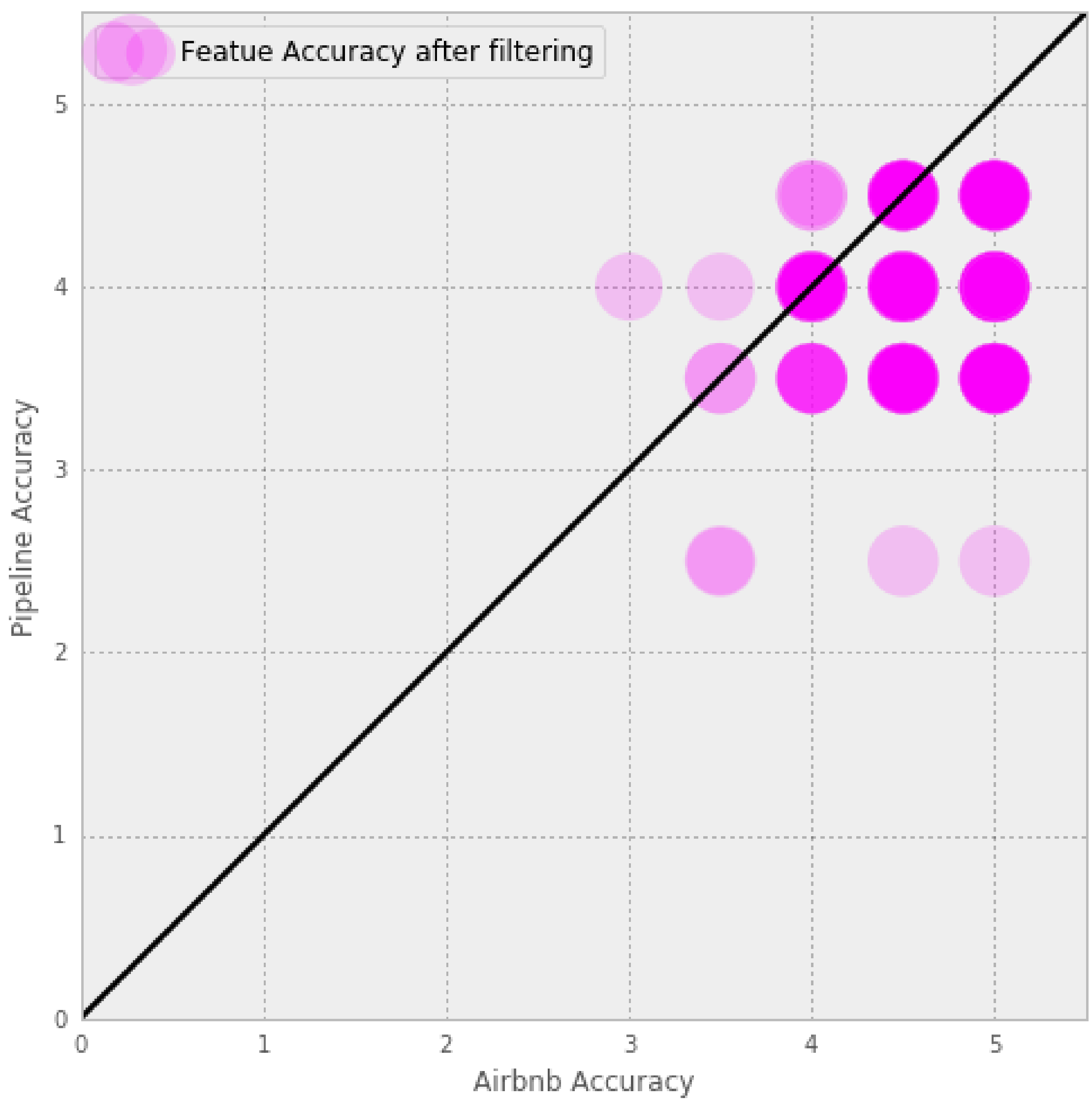
Out[21]:

	New_Frequency	New_Normalized
1.0	387	0.456368
0.5	355	0.418632
0.0	74	0.087264
1.5	25	0.029481
-0.5	4	0.004717
-1.0	1	0.001179
2.0	1	0.001179
2.5	1	0.001179

0.11 Visualization of combinations

The noise in the data is cleaned up

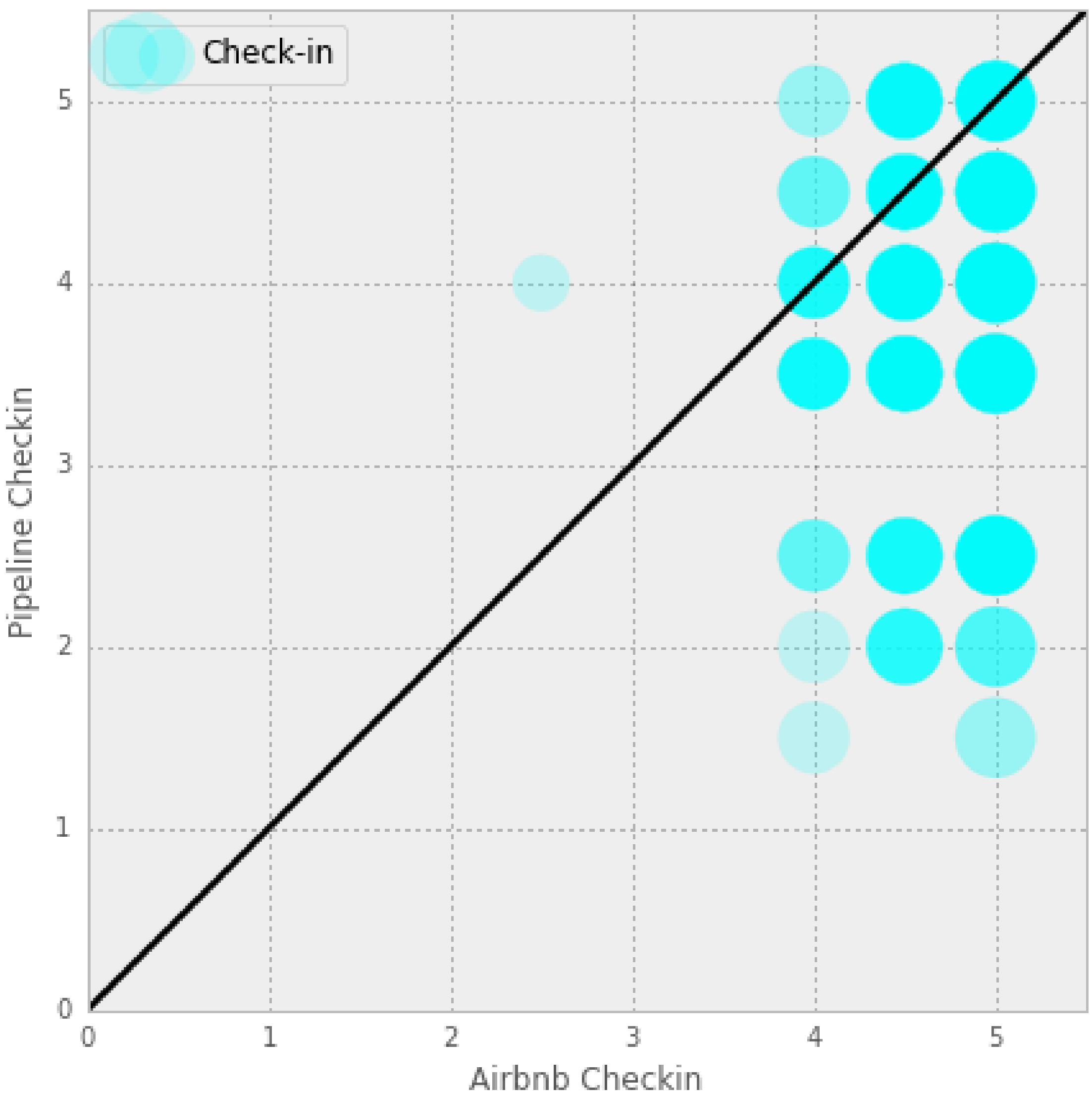
In [20]:
```
ax = new_comparison1.plot(kind='scatter', x='AirbnbAccuracy', y='PipeAccur
color='Fuchsia',label='Featue Accuracy after filtering',
                                    s=comparison['AirbnbAccuracy']*200,alpha=0.2, fi
line = plt.plot([0,1,2,3,4,5,6], [0,1,2,3,4,5,6])
plt.axis([0, 5.5, 0, 5.5])
plt.ylabel('Pipeline Accuracy')
plt.xlabel('Airbnb Accuracy')
plt.setp(line, color='Black', linewidth=2.5)
plt.show()
```



1 The same process is repeated for all the other features

1.1 Feature: Check-in

```
In [22]: dx = comparison.plot(kind='scatter', x='AirbnbCheck-in', y='PipeCheckin',
         color='Aqua',label='Check-in',s=comparison['AirbnbCheck-in']*200,alpha=0.2
                                 figsize=(7,7)).set_xlim(0,7)

         line = plt.plot([0,1,2,3,4,5,6], [0,1,2,3,4,5,6])
         plt.axis([0, 5.5, 0, 5.5])
         plt.ylabel('Pipeline Checkin')
         plt.xlabel('Airbnb Checkin')
         plt.setp(line, color='Black', linewidth=2.5)
         plt.show()
```



```
In [23]: # For filling the dataframe
         i=5.0
         s0=comparison[comparison['AirbnbCheck-in']==i]
         s00=s0['PipeCheckin'].value_counts()
         b=pd.DataFrame({'Airbnb':i, 'Pipeline':s00.index,
                        'V_Frequency': s00.values})
         i=4.5
         s1=comparison[comparison['AirbnbCheck-in']==i]
         s11=s1['PipeCheckin'].value_counts()
         b1=pd.DataFrame({'Airbnb':i, 'Pipeline':s11.index,
                         'V_Frequency': s11.values})
         i=4.0
         s2=comparison[comparison['AirbnbCheck-in']==i]
         s22=s2['PipeCheckin'].value_counts()
         b2=pd.DataFrame({'Airbnb':i, 'Pipeline':s22.index,
                         'V_Frequency': s22.values})
         i=3.5
         s3=comparison[comparison['AirbnbCheck-in']==i]
         s33=s3['PipeCheckin'].value_counts()
         b3=pd.DataFrame({'Airbnb':i, 'Pipeline':s33.index,
                         'V_Frequency': s33.values})
         i=3.0
         s4=comparison[comparison['AirbnbCheck-in']==i]
         s44=s4['PipeCheckin'].value_counts()
         b4=pd.DataFrame({'Airbnb':i, 'Pipeline':s44.index,
                         'V_Frequency': s44.values})
         stars_compared=pd.concat([b,b1,b2,b3,b4],ignore_index=True)
         stars_compared['Percentage']=
         ((stars_compared['V_Frequency']/stars_compared['V_Frequency'].sum())*100)
         stars_compared.columns=['Airbnb','Pipeline','Frequency','Percentage']
         stars_compared
```

Out[23]:

	Airbnb	Pipeline	Frequency	Percentage
0	5.0	4.0	515	36.79
1	5.0	4.5	228	16.29
2	5.0	3.5	166	11.86
3	5.0	5.0	62	4.43
4	5.0	2.5	18	1.29
5	5.0	2.0	5	0.36
6	5.0	1.5	2	0.14
7	4.5	4.0	176	12.57
8	4.5	3.5	97	6.93
9	4.5	4.5	60	4.29
10	4.5	5.0	17	1.21
11	4.5	2.5	11	0.79
12	4.5	2.0	8	0.57
13	4.0	3.5	13	0.93
14	4.0	4.0	10	0.71

```
15      4.0       4.5          4         0.29
16      4.0       2.5          4         0.29
17      4.0       5.0          2         0.14
18      4.0       2.0          1         0.07
19      4.0       1.5          1         0.07
```

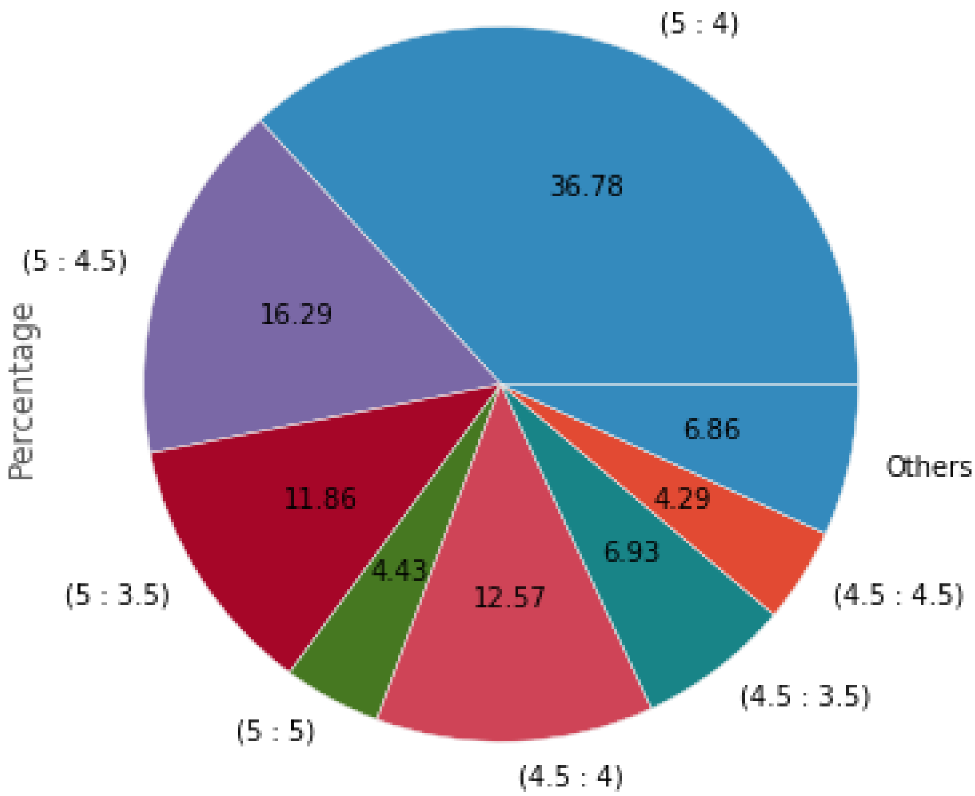
```
In [24]: ot=stars_compared[stars_compared['Percentage']<4]
         other=ot['Percentage'].sum()
         other
         freq=ot['Frequency'].sum()
         main=stars_compared[stars_compared['Percentage']>=4]
         main.loc[26]=['Other','Other',freq,other]
         main
```

```
c:\python27\lib\site-packages\ipykernel\__main__.py:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/i
```

Out[24]:

	Airbnb	Pipeline	Frequency	Percentage
0	5	4	515	36.79
1	5	4.5	228	16.29
2	5	3.5	166	11.86
3	5	5	62	4.43
7	4.5	4	176	12.57
8	4.5	3.5	97	6.93
9	4.5	4.5	60	4.29
26	Other	Other	96	6.86

```
In [25]: main['Percentage'].plot(kind='pie', labels=['(5 : 4)', '(5 : 4.5)',
         '(5 : 3.5)', ' (5 : 5)','(4.5 : 4)', '(4.5 : 3.5)', '(4.5 : 4.5)' ,'Others
                                  autopct='%.2f', fontsize=10, figsize=(6, 6))

Out[25]: <matplotlib.axes._subplots.AxesSubplot at 0xd1b28b0>
```




```
In [26]: comparison['DiffCheckin']=comparison['AirbnbCheck-in']-comparison['PipeChe
         dfr=comparison['DiffCheckin'].value_counts()
         norm= comparison['DiffCheckin'].value_counts(normalize=True)
         dfrf=dfr.to_frame()
         dfrf['Normalized']=norm
         dfrf.columns=['Frequency','Normalized']
         dfrf
```

Out[26]:

	Frequency	Normalized
1.0	612	0.436831
0.5	417	0.297645
1.5	170	0.121342
0.0	132	0.094218
2.5	27	0.019272
-0.5	21	0.014989
2.0	12	0.008565
3.0	5	0.003569
-1.0	2	0.001428

```
 3.5           2    0.001428
-1.5           1    0.000714
```

In [27]:
```
bg1=comparison[comparison['DiffCheckin']>1.5]
ls1=comparison[comparison['DiffCheckin']<-1.5]
weird=pd.concat([bg1,ls1])
weird_listing=weird['Id']
weird[['Id','AirbnbCheck-in','PipeCheckin']]
```

Out[27]:

	Id	AirbnbCheck-in	PipeCheckin
32	2047376	5.0	2.5
195	2218464	5.0	1.5
257	2304806	4.5	2.5
288	2343032	4.5	2.0
397	2470214	5.0	2.5
399	2470646	4.5	2.0
403	2476882	5.0	2.5
450	2519425	4.5	2.5
455	2529643	5.0	1.5
465	2534324	4.5	2.5
542	2603354	4.5	2.5
543	260362	5.0	2.5
572	2632165	4.5	2.0
616	2682581	4.5	2.0
620	2691833	4.5	2.5
720	2789134	5.0	2.5
736	2805366	4.5	2.0
872	2936383	5.0	2.5
883	2947585	4.5	2.5
899	2962310	4.5	2.0
1054	3109338	4.5	2.5
1063	3113368	5.0	2.5
1121	3171348	4.0	2.0
1142	3190091	4.5	2.0
1153	3203283	5.0	2.5
1265	3328384	4.5	2.5
1324	3383871	5.0	2.0
1340	3399014	5.0	2.5
1344	3403331	5.0	2.5
1415	3483681	5.0	2.5
1458	352886	5.0	2.5
1518	3592814	4.5	2.5
1521	3594030	5.0	2.5
1531	3608501	4.5	2.5
1545	362418	5.0	2.0
1550	3628018	5.0	2.5
1581	3664531	5.0	2.5
1625	3708427	5.0	2.0

```
1683  3754415            5.0          2.5
1775  3841266            5.0          2.0
1784  3847123            5.0          2.5
1793  3851423            5.0          2.0
1807  3863795            4.5          2.0
1862  3915382            4.0          1.5
1917  3957927            4.5          2.5
1923  3965319            5.0          2.5
```

In [28]:
```
acy=full_content[full_content['Listing ID']== 2529643]
acy[acy['Feature: Check-in']!=0]
```

Out[28]:
```
       Listing ID  Review ID                                        Se
65492     2529643   12012600  Notably our arrival, we had a delay in the p
```

In [29]:
```
acy=full_content[full_content['Listing ID']== 2218464]
acy[acy['Feature: Check-in']!=0]
```

Out[29]:
```
       Listing ID  Review ID                                        Se
27433     2218464   51685180  The host canceled this reservation 187 days
```

In [30]:
```
a=full_content[['Listing ID','Review ID','Feature: Check-in']]
ap=a[a['Feature: Check-in']!=0]
a_nodup=ap.drop_duplicates()
count=a_nodup.groupby('Listing ID').count()
count['Listing ID']=count.index
d = count[count['Review ID']<3]
less_3 = d[['Listing ID']]

# Drop from the dataframe these cases
mutual=comparison[comparison['Id'].isin(less_3['Listing ID'])]
indexes_ID=mutual.index
for i in less_3['Listing ID']:
    new_comparison2=comparison.drop(indexes_ID)
```

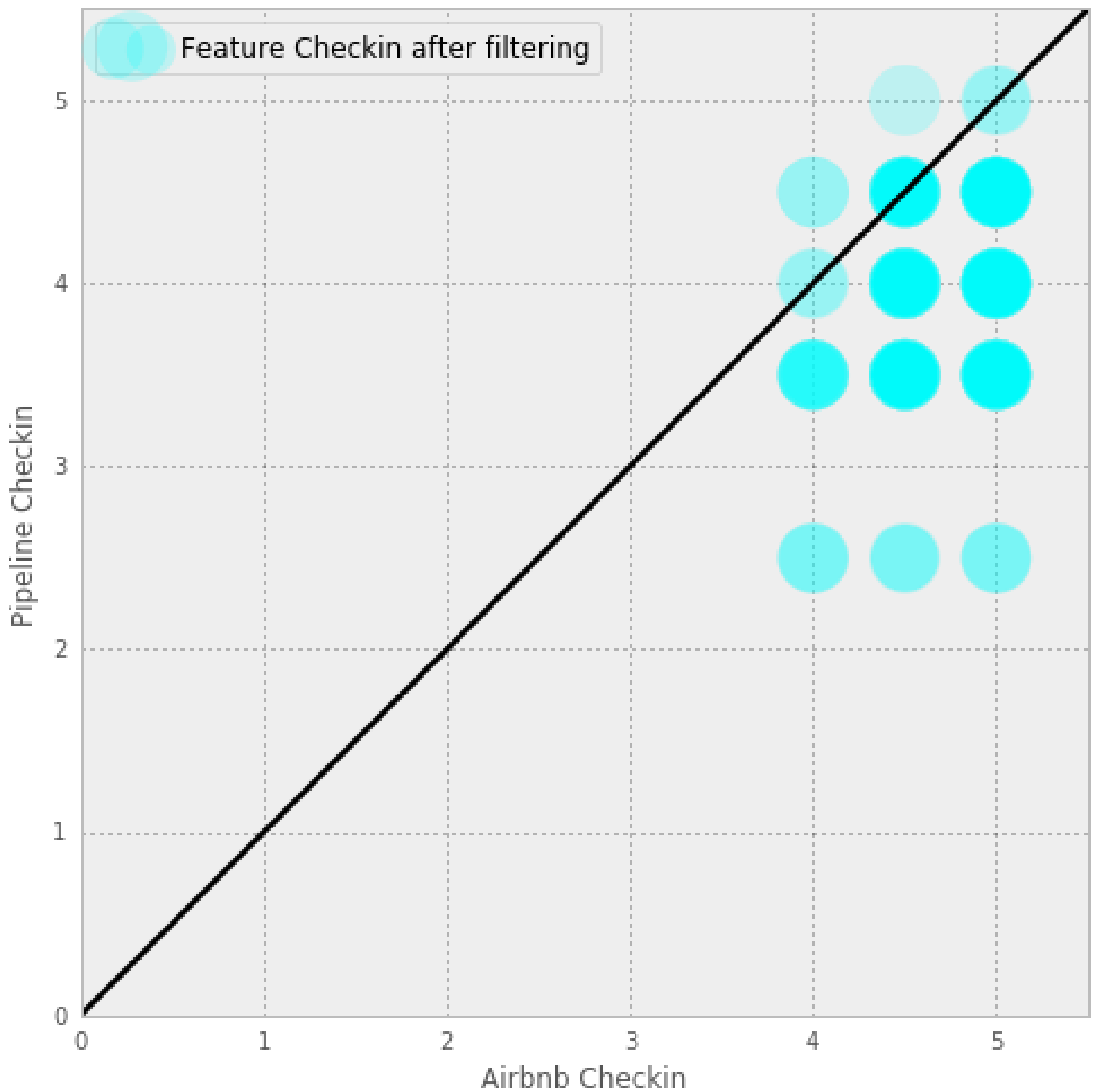
In [31]:
```
new_comparison2['DifferenceCheckin']=
new_comparison2['AirbnbCheck-in']-new_comparison2['PipeCheckin']
dfr_new=new_comparison2['DifferenceCheckin'].value_counts()
norm_new = new_comparison2['DifferenceCheckin'].value_counts(normalize=Tru
dfrf_new=dfr_new.to_frame()
dfrf_new['Normalized']=norm_new
dfrf_new.columns=['New_Frequency','New_Normalized']
dfrf_new
```

Out[31]:

	New_Frequency	New_Normalized
1.0	313	0.515651
0.5	208	0.342669
1.5	55	0.090610
0.0	22	0.036244

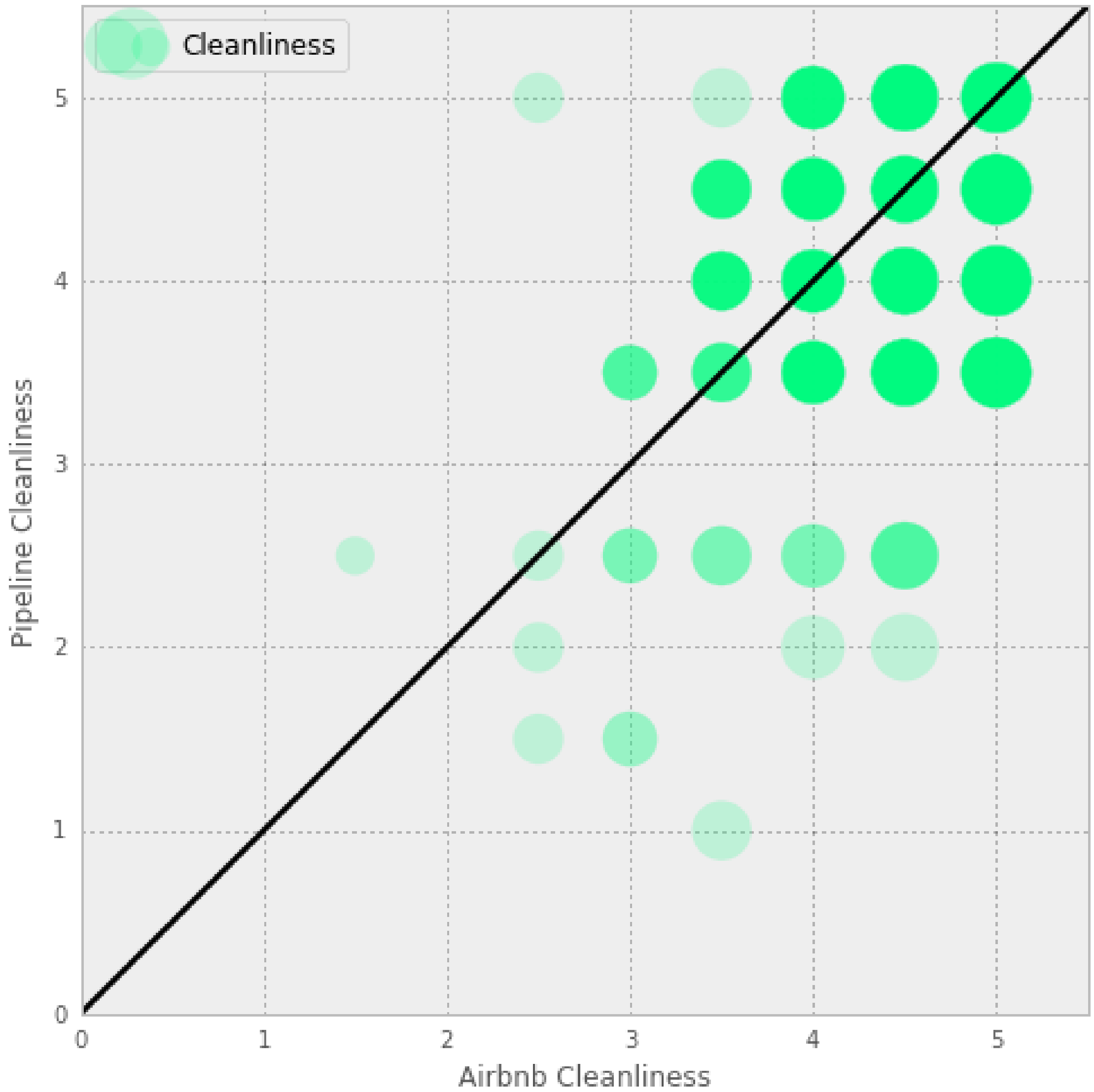
```
 2.0              3        0.004942
-0.5              3        0.004942
 2.5              3        0.004942
```

```
In [32]: ax = new_comparison2.plot(kind='scatter', x='AirbnbCheck-in', y='PipeCheck
          color='Aqua', label='Feature Checkin after filtering',
                                    s=comparison['AirbnbCheck-in']*200,alpha=0.2, fi

         line = plt.plot([0,1,2,3,4,5,6], [0,1,2,3,4,5,6])
         plt.axis([0, 5.5, 0, 5.5])
         plt.ylabel('Pipeline Checkin')
         plt.xlabel('Airbnb Checkin')
         plt.setp(line, color='Black', linewidth=2.5)
         plt.show()
```



1.2 Feature: Cleanliness

```
In [33]: ax = comparison.plot(kind='scatter', x='AirbnbCleanliness', y='PipeCleanli
         color='SpringGreen',label='Cleanliness',
                                     s=comparison['AirbnbCleanliness']*200,alpha=0.2, figs

         line = plt.plot([0,1,2,3,4,5,6], [0,1,2,3,4,5,6])
         plt.axis([0, 5.5, 0, 5.5])
         plt.ylabel('Pipeline Cleanliness')
         plt.xlabel('Airbnb Cleanliness')
         plt.setp(line, color='Black', linewidth=2.5)
         plt.show()
```




```
In [34]: # For filling the dataframe
```

```python
i=5.0
s0=comparison[comparison['AirbnbCleanliness']==i]
s00=s0['PipeCleanliness'].value_counts()
b=pd.DataFrame({'Airbnb':i, 'Pipeline':s00.index,
                'V_Frequency': s00.values})
i=4.5
s1=comparison[comparison['AirbnbCleanliness']==i]
s11=s1['PipeCleanliness'].value_counts()
b1=pd.DataFrame({'Airbnb':i, 'Pipeline':s11.index,
                 'V_Frequency': s11.values})
i=4.0
s2=comparison[comparison['AirbnbCleanliness']==i]
s22=s2['PipeCleanliness'].value_counts()
b2=pd.DataFrame({'Airbnb':i, 'Pipeline':s22.index,
                 'V_Frequency': s22.values})
i=3.5
s3=comparison[comparison['AirbnbCleanliness']==i]
s33=s3['PipeCleanliness'].value_counts()
b3=pd.DataFrame({'Airbnb':i, 'Pipeline':s33.index,
                 'V_Frequency': s33.values})
i=3.0
s4=comparison[comparison['AirbnbCleanliness']==i]
s44=s4['PipeCleanliness'].value_counts()
b4=pd.DataFrame({'Airbnb':i, 'Pipeline':s44.index,
                 'V_Frequency': s44.values})
i=2.5
s5=comparison[comparison['AirbnbCleanliness']==i]
s55=s5['PipeCleanliness'].value_counts()
b5=pd.DataFrame({'Airbnb':i, 'Pipeline':s55.index,
                 'V_Frequency': s55.values})
i=1.5
s6=comparison[comparison['AirbnbCleanliness']==i]
s66=s6['PipeCleanliness'].value_counts()
b6=pd.DataFrame({'Airbnb':i, 'Pipeline':s66.index,
                 'V_Frequency': s66.values})

stars_compared=pd.concat([b,b1,b2,b3,b4,b5,b6],ignore_index=True)
stars_compared['Percentage']=
((stars_compared['V_Frequency']/stars_compared['V_Frequency'].sum())*100).
stars_compared.columns=['Airbnb','Pipeline','Frequency','Percentage']
stars_compared
```

Out[34]:

	Airbnb	Pipeline	Frequency	Percentage
0	5.0	4.5	540	30.32
1	5.0	4.0	259	14.54
2	5.0	5.0	67	3.76
3	5.0	3.5	17	0.95
4	4.5	4.5	330	18.53

```
5       4.5        4.0         275        15.44
6       4.5        5.0          45         2.53
7       4.5        3.5          23         1.29
8       4.5        2.5           5         0.28
9       4.5        2.0           1         0.06
10      4.0        4.0          81         4.55
11      4.0        4.5          48         2.70
12      4.0        3.5          20         1.12
13      4.0        5.0          15         0.84
14      4.0        2.5           3         0.17
15      4.0        2.0           1         0.06
16      3.5        4.0          13         0.73
17      3.5        4.5          11         0.62
18      3.5        3.5           7         0.39
19      3.5        2.5           3         0.17
20      3.5        1.0           1         0.06
21      3.5        5.0           1         0.06
22      3.0        3.5           5         0.28
23      3.0        2.5           3         0.17
24      3.0        1.5           2         0.11
25      2.5        5.0           1         0.06
26      2.5        2.0           1         0.06
27      2.5        1.5           1         0.06
28      2.5        2.5           1         0.06
29      1.5        2.5           1         0.06
```

```
In [35]: ot=stars_compared[stars_compared['Percentage']<4]
         other=ot['Percentage'].sum()
         other
         freq=ot['Frequency'].sum()
         main=stars_compared[stars_compared['Percentage']>=4]
         main.loc[26]=['Other','Other',freq,other]
         main
```

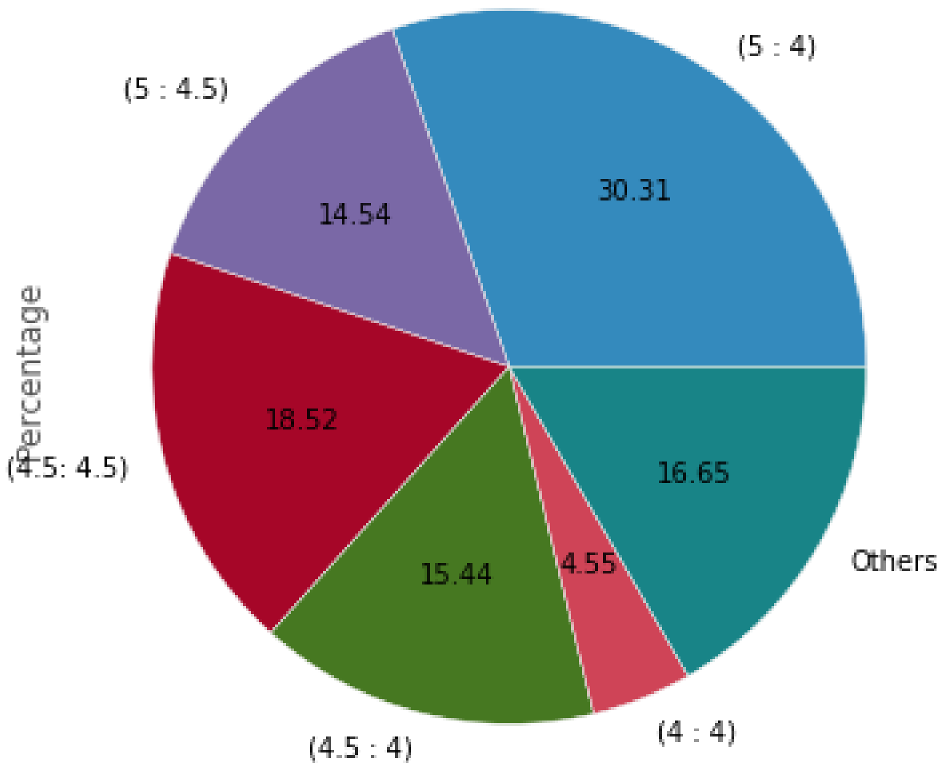
```
c:\python27\lib\site-packages\ipykernel\__main__.py:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/i
```

Out[35]:

	Airbnb	Pipeline	Frequency	Percentage
0	5	4.5	540	30.32
1	5	4	259	14.54
4	4.5	4.5	330	18.53
5	4.5	4	275	15.44
10	4	4	81	4.55
26	Other	Other	296	16.65

```
In [36]: main['Percentage'].plot(kind='pie', labels=['(5 : 4)', '(5 : 4.5)', '(4.5:
           ' (4.5 : 4)', '(4 : 4)','Others'], autopct='%.2f', fontsize=10, figsize=
```

Out[36]: <matplotlib.axes._subplots.AxesSubplot at 0xd54d0d0>




```
In [37]: comparison['DiffCleanliness']=comparison['AirbnbCleanliness']-comparison['
         dfr=comparison['DiffCleanliness'].value_counts()
         norm= comparison['DiffCleanliness'].value_counts(normalize=True)
         dfrf=dfr.to_frame()
         dfrf['Normalized']=norm
         dfrf.columns=['Frequency','Normalized']
         dfrf
```

Out[37]:

	Frequency	Normalized
0.5	839	0.471084
0.0	486	0.272880
1.0	286	0.160584
-0.5	111	0.062325
-1.0	27	0.015160
1.5	22	0.012353
2.0	6	0.003369
2.5	2	0.001123

```
-2.5          1    0.000561
-1.5          1    0.000561
```

```
In [38]: bg1=comparison[comparison['DiffCleanliness']>1.5]
         ls1=comparison[comparison['DiffCleanliness']<-1.5]
         weird=pd.concat([bg1,ls1])
         weird_listing=weird['Id']
         weird[['Id','AirbnbCleanliness','PipeCleanliness']]
```

```
Out[38]:            Id  AirbnbCleanliness  PipeCleanliness
         161   2174515                4.5              2.5
         653   2722090                4.5              2.5
         725   2796412                4.5              2.5
         942   3003133                4.5              2.0
         1482  3565067                4.5              2.5
         1554  3641523                4.0              2.0
         1692  3760214                4.5              2.5
         1719  3786601                3.5              1.0
         1820  3877186                2.5              5.0
```

```
In [39]: acy=full_content[full_content['Listing ID']== 3877186]
         acy[acy['Feature: Cleanliness']!=0]
```

```
Out[39]:         Listing ID  Review ID                                          Se
         225688     3877186   29455957  The room we stayed in, at the houses top fl
         225689     3877186   29455957  It is a student house very fun indeed but c
```

```
In [40]: acy=full_content[full_content['Listing ID']==  3786601]
         acy[acy['Feature: Cleanliness']!=0]
```

```
Out[40]:         Listing ID  Review ID                                          Se
         217781     3786601   26333387  The apartment however was not that clean (f
```

```
In [41]: a=full_content[['Listing ID','Review ID','Feature: Cleanliness']]
         ap=a[a['Feature: Cleanliness']!=0]
         a_nodup=ap.drop_duplicates()
         count=a_nodup.groupby('Listing ID').count()
         count['Listing ID']=count.index
         d = count[count['Review ID']<3]
         less_3 = d[['Listing ID']]

         # Drop from the dataframe these cases
         mutual=comparison[comparison['Id'].isin(less_3['Listing ID'])]
         indexes_ID=mutual.index
         for i in less_3['Listing ID']:
             new_comparison3=comparison.drop(indexes_ID)
```

```
In [42]: new_comparison3['DifferenceCleanliness']=
         new_comparison3['AirbnbCleanliness']-new_comparison3['PipeCleanliness']
```

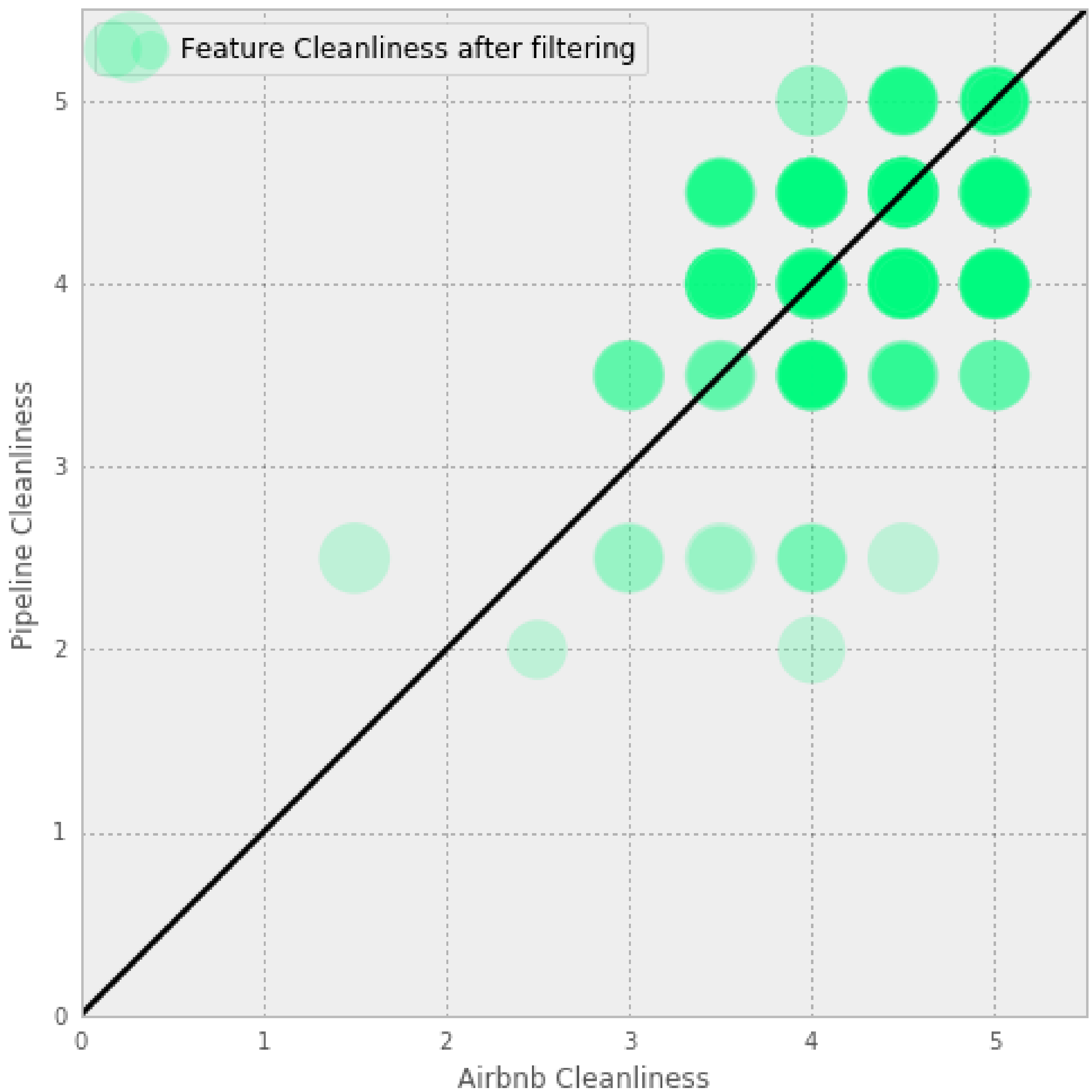
```
dfr_new=new_comparison3['DifferenceCleanliness'].value_counts()
norm_new = new_comparison3['DifferenceCleanliness'].value_counts(normalize
dfrf_new=dfr_new.to_frame()
dfrf_new['Normalized']=norm_new
dfrf_new.columns=['New_Frequency','New_Normalized']
dfrf_new
```

Out[42]:

	New_Frequency	New_Normalized
0.5	692	0.534363
0.0	348	0.268726
1.0	176	0.135907
-0.5	58	0.044788
-1.0	12	0.009266
1.5	7	0.005405
2.0	2	0.001544

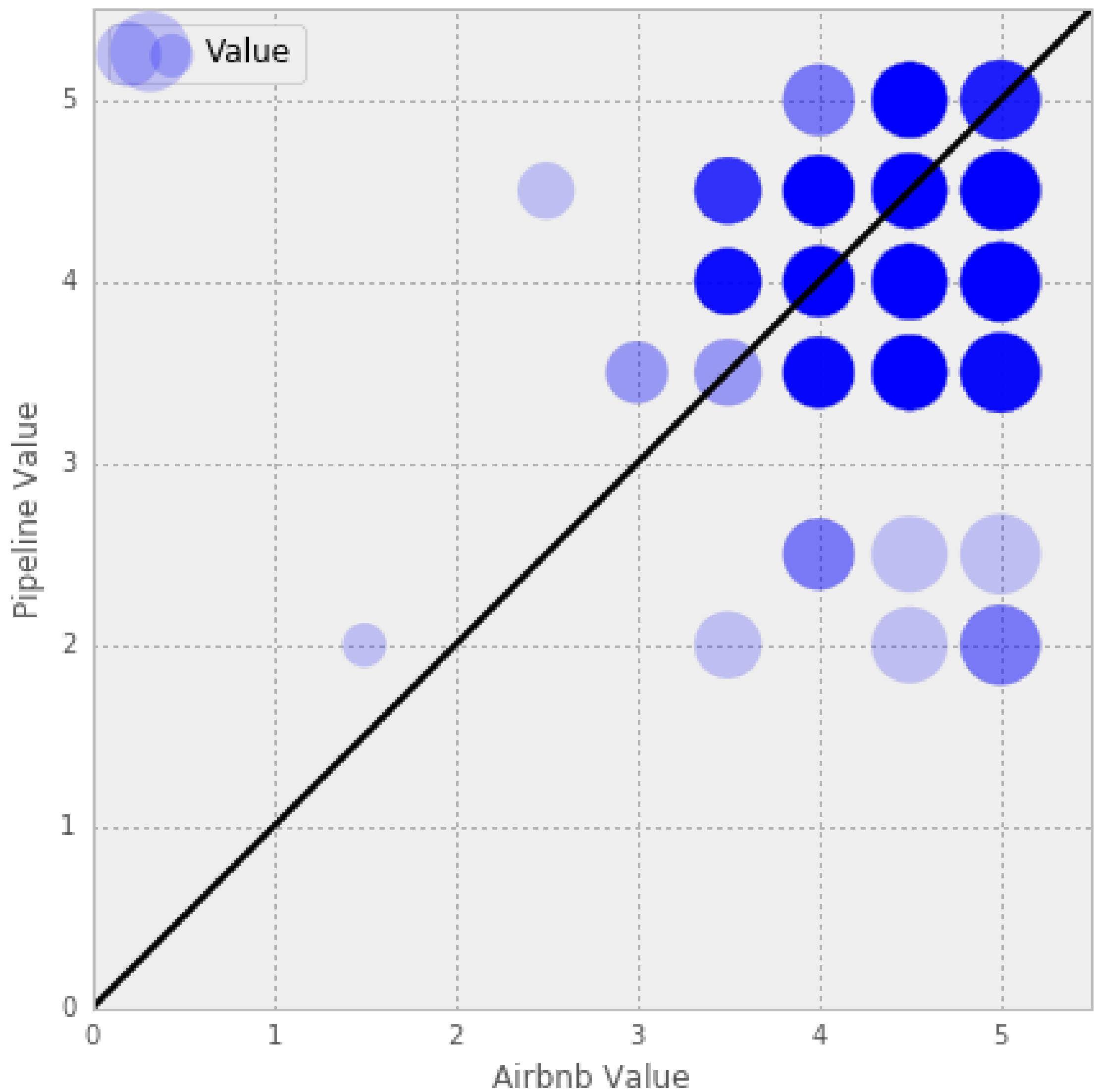
In [43]:

```
ax = new_comparison3.plot(kind='scatter', x='AirbnbCleanliness', y='PipeCl
color='SpringGreen',label='Feature Cleanliness after filtering',
                          s=comparison['AirbnbCleanliness']*200,alpha=0.2,
line = plt.plot([0,1,2,3,4,5,6], [0,1,2,3,4,5,6])
plt.axis([0, 5.5, 0, 5.5])
plt.ylabel('Pipeline Cleanliness')
plt.xlabel('Airbnb Cleanliness')
plt.setp(line, color='Black', linewidth=2.5)
plt.show()
```



1.3 Feature: Value

```
In [44]: dx = comparison.plot(kind='scatter', x='AirbnbValue', y='PipeValue',
         color='Blue',label='Value', s=comparison['AirbnbValue']*200,alpha=0.2,
                                   figsize=(7,7)).set_xlim(0,7)

         line = plt.plot([0,1,2,3,4,5,6], [0,1,2,3,4,5,6])
         plt.axis([0, 5.5, 0, 5.5])
         plt.ylabel('Pipeline Value')
         plt.xlabel('Airbnb Value')
         plt.setp(line, color='Black', linewidth=2.5)
         plt.show()
```




```
In [45]: a=full_content[['Listing ID','Review ID','Feature: Value']]
         ap=a[a['Feature: Value']!=0]
         a_nodup=ap.drop_duplicates()
         count=a_nodup.groupby('Listing ID').count()
         count['Listing ID']=count.index
         d = count[count['Review ID']<3]
         less_3 = d[['Listing ID']]

         # Drop from the dataframe these cases
         mutual=comparison[comparison['Id'].isin(less_3['Listing ID'])]
         indexes_ID=mutual.index
         for i in less_3['Listing ID']:
             new_comparison4=comparison.drop(indexes_ID)
```

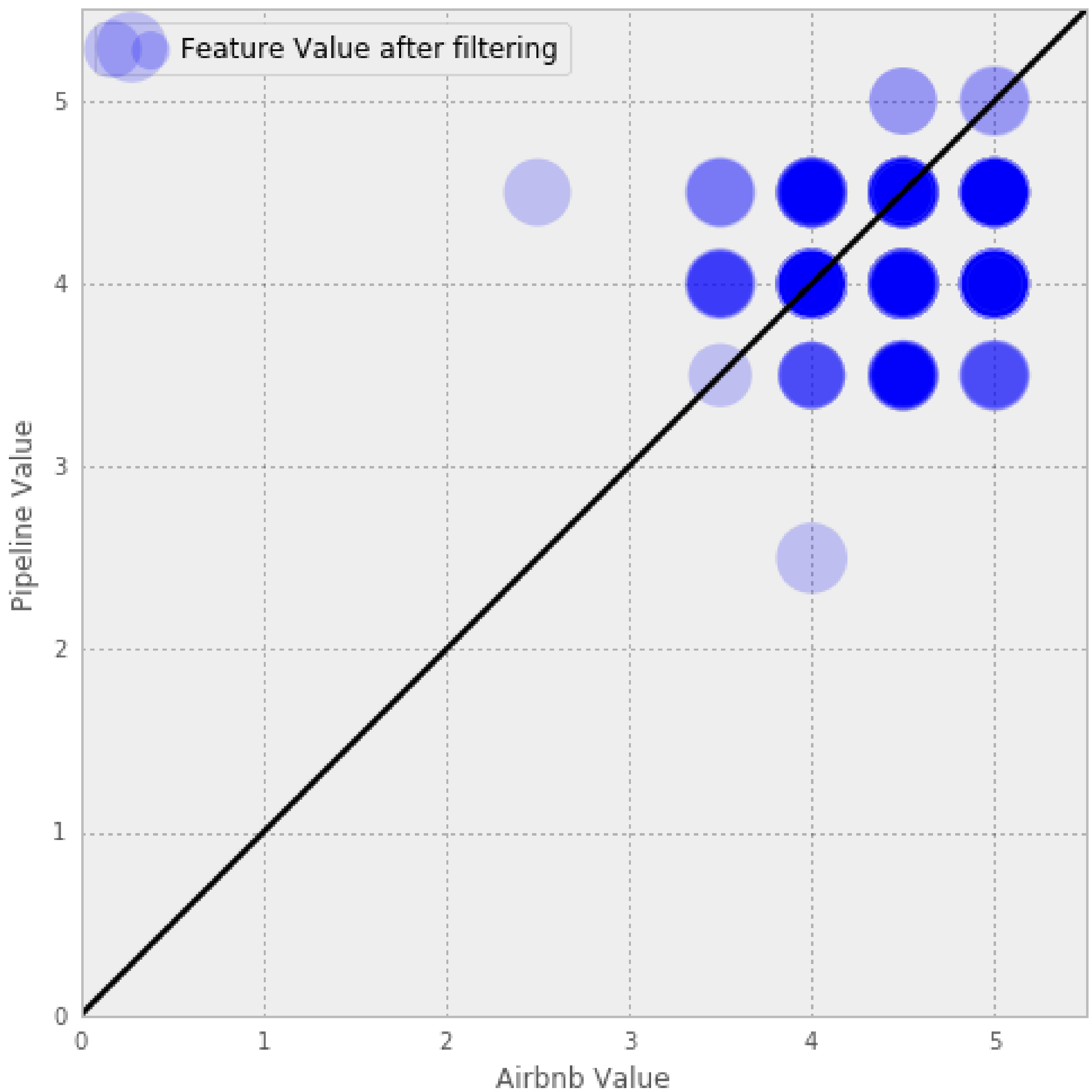
```
new_comparison4['DifferenceValue']=
new_comparison4['AirbnbValue']-new_comparison4['PipeValue']

dfr_new=new_comparison4['DifferenceValue'].value_counts()
norm_new = new_comparison4['DifferenceValue'].value_counts(normalize=True)
dfrf_new=dfr_new.to_frame()
dfrf_new['Normalized']=norm_new
dfrf_new.columns=['New_Frequency','New_Normalized']
dfrf_new
```

Out[45]:

	New_Frequency	New_Normalized
0.5	753	0.537090
0.0	384	0.273894
1.0	211	0.150499
-0.5	44	0.031384
1.5	6	0.004280
-1.0	3	0.002140
-2.0	1	0.000713

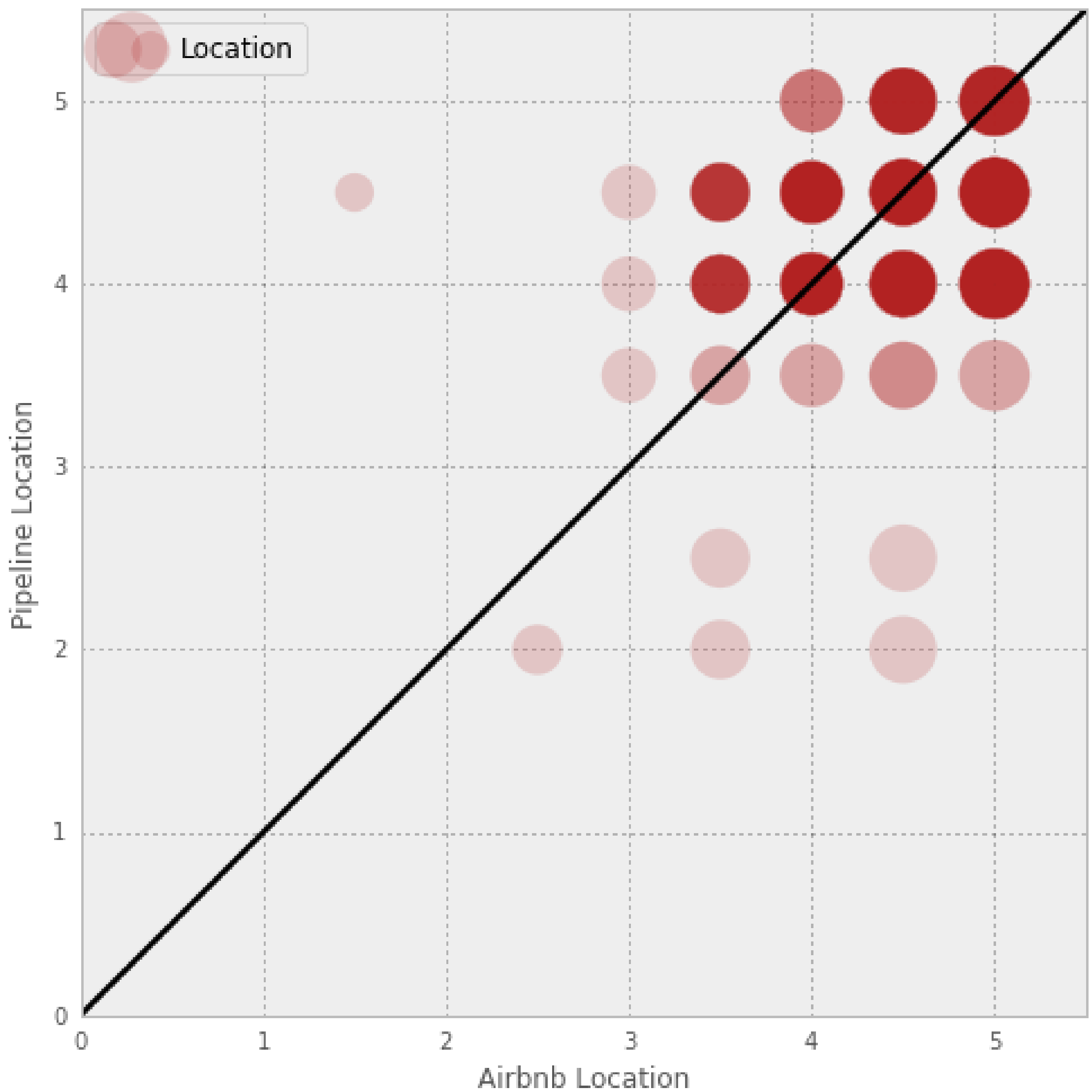
In [46]:

```
ax = new_comparison4.plot(kind='scatter', x='AirbnbValue', y='PipeValue',
color='Blue',label='Feature Value after filtering',
              s=comparison['AirbnbValue']*200,alpha=0.2, figsize=(8,8))

line = plt.plot([0,1,2,3,4,5,6], [0,1,2,3,4,5,6])
plt.axis([0, 5.5, 0, 5.5])
plt.ylabel('Pipeline Value')
plt.xlabel('Airbnb Value')
plt.setp(line, color='Black', linewidth=2.5)
plt.show()
```



1.4 Feature Location

```
In [47]: ax = comparison.plot(kind='scatter', x='AirbnbLocation', y='PipeLocation',
         color='FireBrick', label='Location', s=comparison['AirbnbLocation']*200,
                                  alpha=0.2, figsize=(8,8))

         line = plt.plot([0,1,2,3,4,5,6], [0,1,2,3,4,5,6])
         plt.axis([0, 5.5, 0, 5.5])
         plt.ylabel('Pipeline Location')
         plt.xlabel('Airbnb Location')
         plt.setp(line, color='Black', linewidth=2.5)
         plt.show()
```



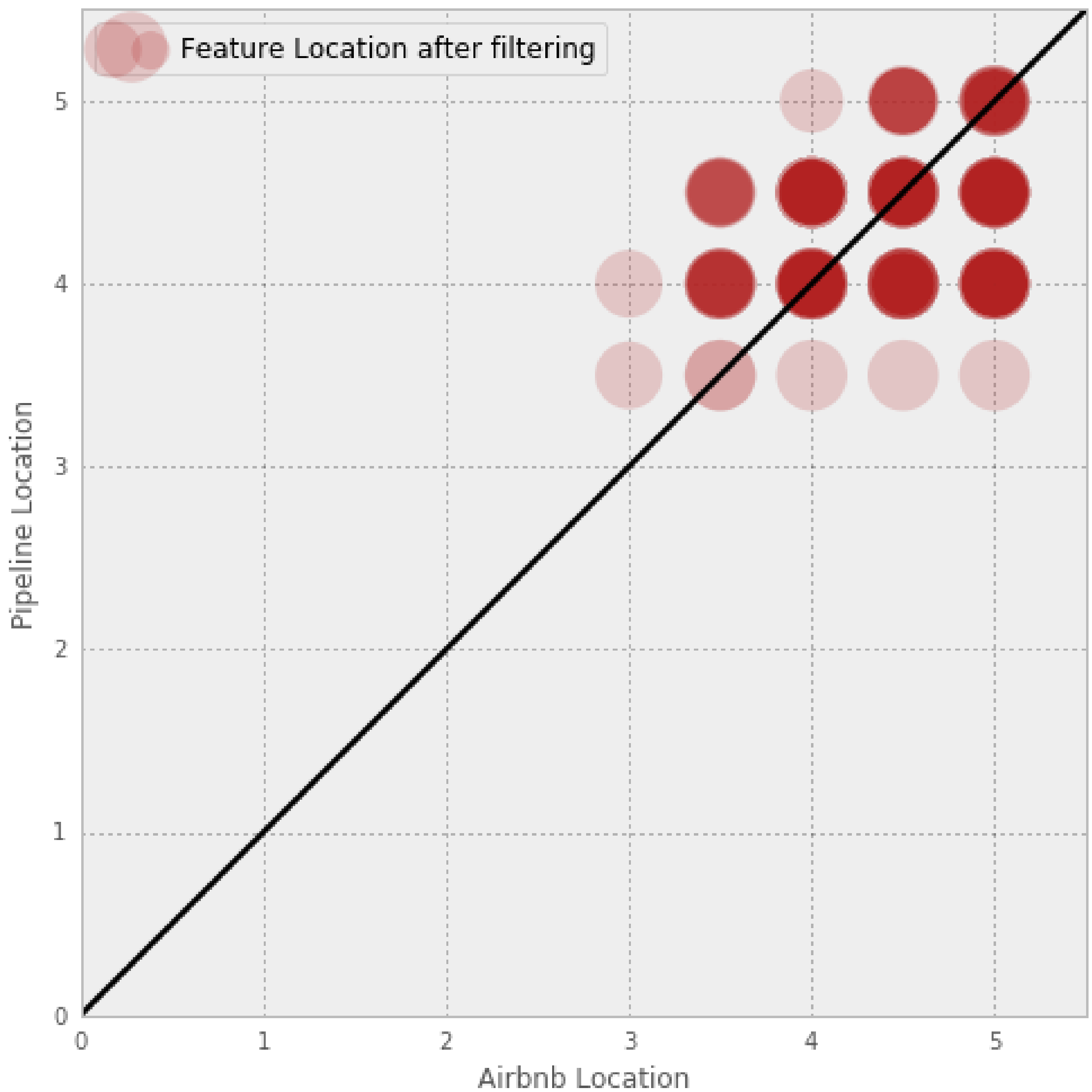

```
In [48]: a=full_content[['Listing ID','Review ID','Feature: Location']]
         ap=a[a['Feature: Location']!=0]
         a_nodup=ap.drop_duplicates()
         count=a_nodup.groupby('Listing ID').count()
         count['Listing ID']=count.index
         d = count[count['Review ID']<3]
         less_3 = d[['Listing ID']]

         # Drop from the dataframe these cases
         mutual=comparison[comparison['Id'].isin(less_3['Listing ID'])]
         indexes_ID=mutual.index
         for i in less_3['Listing ID']:
             new_comparison5=comparison.drop(indexes_ID)
```

```
new_comparison5['DifferenceLocation']=
new_comparison5['AirbnbLocation']-new_comparison5['PipeLocation']

dfr_new=new_comparison5['DifferenceLocation'].value_counts()
norm_new = new_comparison5['DifferenceLocation'].value_counts(normalize=Tr
dfrf_new=dfr_new.to_frame()
dfrf_new['Normalized']=norm_new
dfrf_new.columns=['New_Frequency','New_Normalized']
dfrf_new
```

Out[48]:

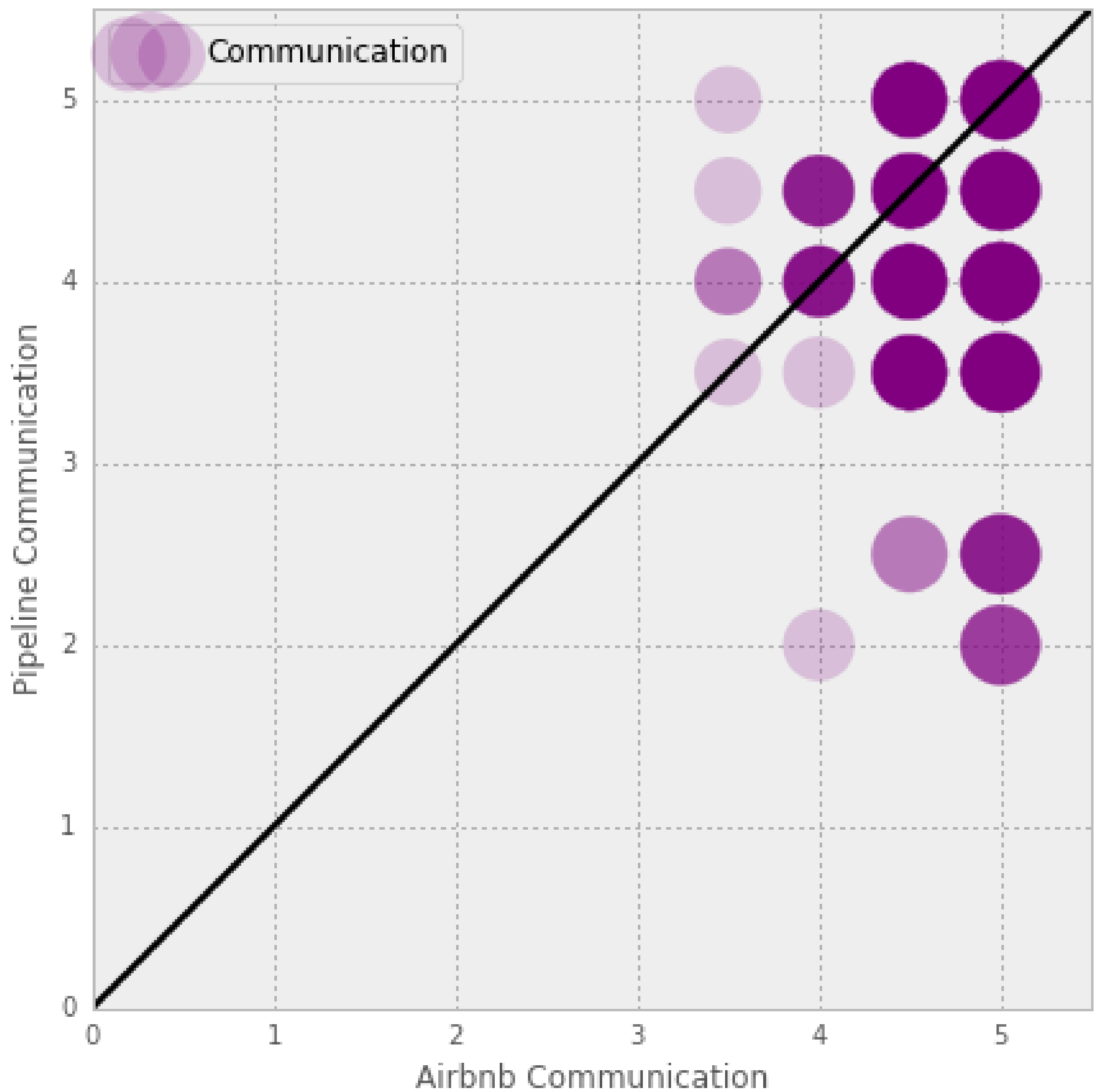
	New_Frequency	New_Normalized
0.5	960	0.512000
0.0	681	0.363200
1.0	121	0.064533
-0.5	103	0.054933
-1.0	9	0.004800
1.5	1	0.000533

In [49]:
```
ax = new_comparison5.plot(kind='scatter', x='AirbnbLocation', y='PipeLocat
color='FireBrick',label='Feature Location after filtering',
        s=comparison['AirbnbLocation']*200,alpha=0.2, figsize=(8,8))

line = plt.plot([0,1,2,3,4,5,6], [0,1,2,3,4,5,6])
plt.axis([0, 5.5, 0, 5.5])
plt.ylabel('Pipeline Location')
plt.xlabel('Airbnb Location')
plt.setp(line, color='Black', linewidth=2.5)
plt.show()
```



1.5 Feature Communication

```
In [50]: dx = comparison.plot(kind='scatter', x='AirbnbCommunication', y='PipeCommu
          color='Purple',label='Communication', s=comparison['AirbnbCommunication']
                                    alpha=0.2, figsize=(7,7)).set_xlim(1,7)

         line = plt.plot([0,1,2,3,4,5,6], [0,1,2,3,4,5,6])
         plt.axis([0, 5.5, 0, 5.5])
         plt.xlabel('Airbnb Communication')
         plt.ylabel('Pipeline Communication')
         plt.setp(line, color='Black', linewidth=2.5)
         plt.show()
```



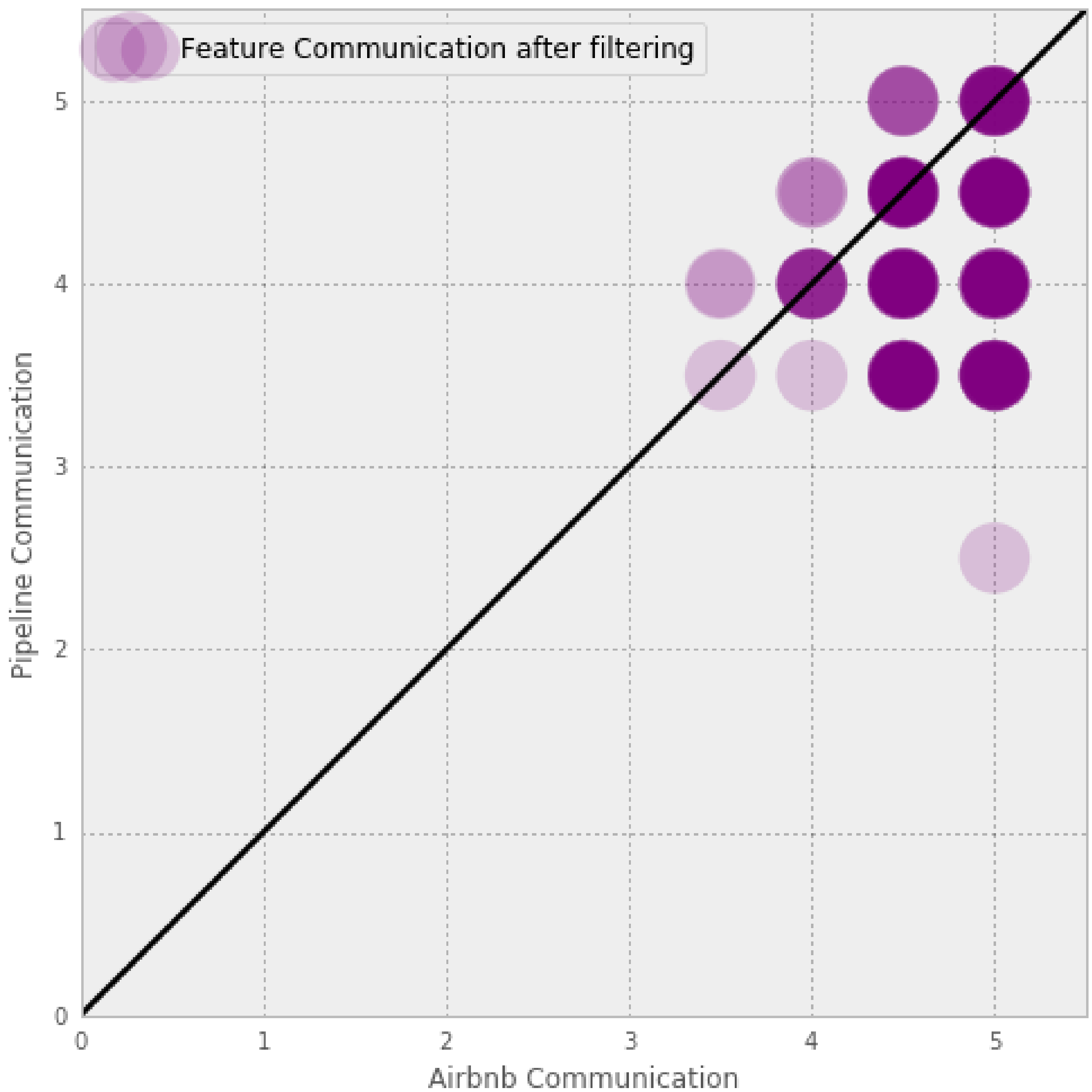

```
In [51]: a=full_content[['Listing ID','Review ID','Feature: Communication']]
         ap=a[a['Feature: Communication']!=0]
         a_nodup=ap.drop_duplicates()
         count=a_nodup.groupby('Listing ID').count()
         count['Listing ID']=count.index
         d = count[count['Review ID']<3]
         less_3 = d[['Listing ID']]

         # Drop from the dataframe these cases
         mutual=comparison[comparison['Id'].isin(less_3['Listing ID'])]
         indexes_ID=mutual.index
         for i in less_3['Listing ID']:
             new_comparison6=comparison.drop(indexes_ID)
```

```
new_comparison6['DifferenceCommunication']=
new_comparison6['AirbnbCommunication']-new_comparison6['PipeCommunication'

dfr_new=new_comparison6['DifferenceCommunication'].value_counts()
norm_new = new_comparison6['DifferenceCommunication'].value_counts(normali
dfrf_new=dfr_new.to_frame()
dfrf_new['Normalized']=norm_new
dfrf_new.columns=['New_Frequency','New_Normalized']
dfrf_new
```

Out[51]:

	New_Frequency	New_Normalized
0.5	683	0.535266
1.0	406	0.318182
0.0	152	0.119122
1.5	24	0.018809
-0.5	10	0.007837
2.5	1	0.000784

In [52]:
```
ax = new_comparison6.plot(kind='scatter', x='AirbnbCommunication', y='Pipe
color='Purple',label='Feature Communication after filtering',
                          s=comparison['AirbnbCommunication']*200,alpha=0.
line = plt.plot([0,1,2,3,4,5,6], [0,1,2,3,4,5,6])
plt.axis([0, 5.5, 0, 5.5])
plt.ylabel('Pipeline Communication')
plt.xlabel('Airbnb Communication')
plt.setp(line, color='Black', linewidth=2.5)
plt.show()
```

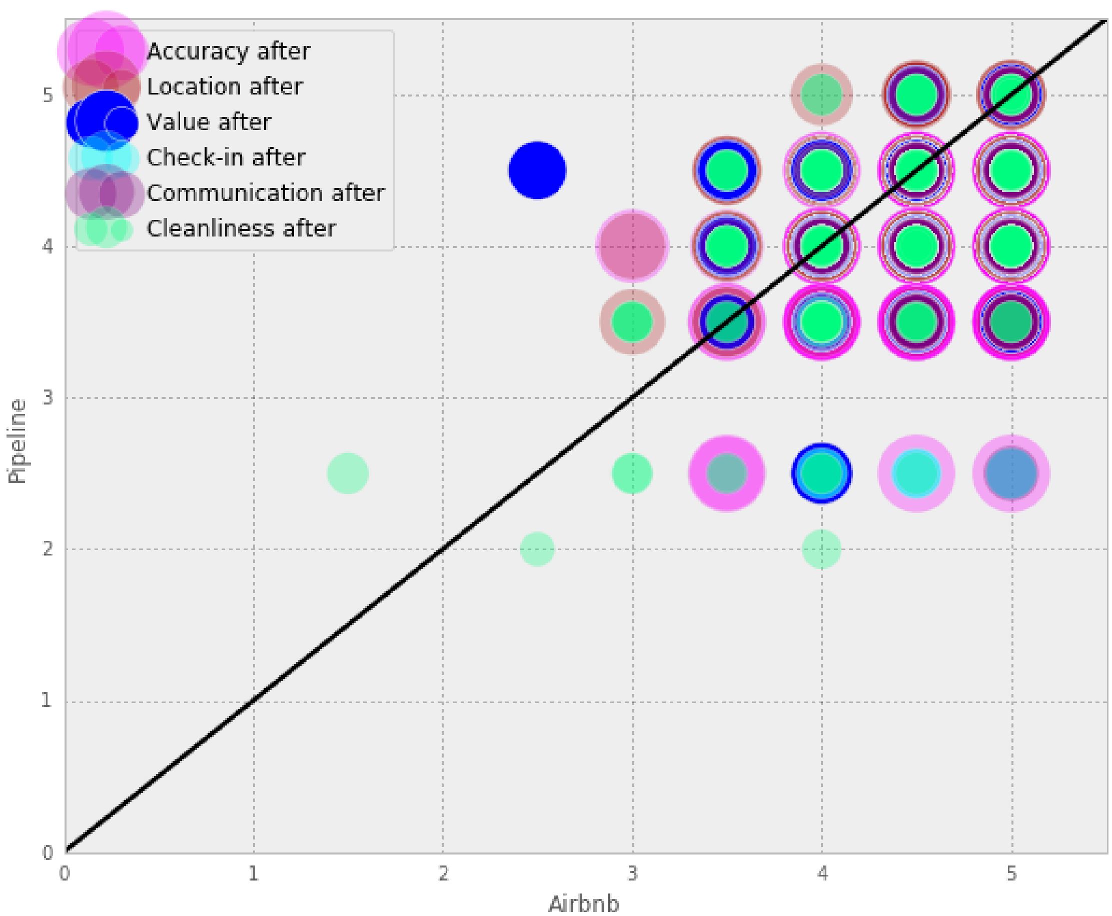


2 Visualization of combinations for all features after filtering them all

Here the combinations of stars of features given by the pipeline and compared once again with the values of Airbnb, but this time we compare the filtered set. So, all the listings which do not have enough reviews to generate a star per feature are exculded from the certain feature. We see that the combinations are much more concentrated now.

```
In [53]: ax = new_comparison1.plot(kind='scatter', x='AirbnbAccuracy', y='PipeAccur
         color='Fuchsia', label='Accuracy after',alpha=0.3, s=comparison['AirbnbAcc

         bx = new_comparison5.plot(kind='scatter', x='AirbnbLocation', y='PipeLocat
         color='FireBrick', label='Location after', ax=ax,alpha=0.3, s=comparison['
```

```
cx = new_comparison4.plot(kind='scatter', x='AirbnbValue', y='PipeValue',
                          label='Value after', ax=bx,  s=comparison['Airbn

dx = new_comparison2.plot(kind='scatter', x='AirbnbCheck-in', y='PipeCheck
 label='Check-in after', alpha=0.3, ax=cx,  s=comparison['AirbnbCheck-in']

ex = new_comparison6.plot(kind='scatter', x='AirbnbCommunication', y='Pipe
color='Purple', alpha=0.3, label='Communication after', ax=dx,  s=comparis

fx = new_comparison3.plot(kind='scatter', x='AirbnbCleanliness', y='PipeCl
 color='SpringGreen',label='Cleanliness after', ax=ex,  s=comparison['Airb
                          alpha=0.3, figsize=(10,8)).set_xlim(0,8)

line = plt.plot([0,1,2,3,4,5,6], [0,1,2,3,4,5,6])
plt.axis([0, 5.5, 0, 5.5])
plt.xlabel('Airbnb')
plt.ylabel('Pipeline')
plt.setp(line, color='Black', linewidth=2.5)
plt.show()
```



3 SOME STATISTICS

3.1 Calculate the Root Mean Squared Error (RMSE) in star difference before and after the filtering

The table and the plot shows how the RMSE changed after conditioning the number of reviews to 3 per each feature

In [54]:
```
SSD1=(comparison['AirbnbAccuracy']-comparison['PipeAccuracy'])
SSD1.pow(2).sum()
MSE_Accuracy=SSD1/new_comparison1['DifferenceAccuracy'].count()

SSD2=(comparison['AirbnbCheck-in']-comparison['PipeCheckin'])
SSD2.pow(2).sum()
MSE_Checkin=SSD2/new_comparison2['DifferenceCheckin'].count()

SSD3=(comparison['AirbnbCleanliness']-comparison['PipeCleanliness'])
SSD3.pow(2).sum()
MSE_Cleanliness=SSD3/new_comparison3['DifferenceCleanliness'].count()

SSD4=(comparison['AirbnbValue']-comparison['PipeValue']).pow(2).sum()
MSE_Value=SSD4/new_comparison4['DifferenceValue'].count()

SSD5=(comparison['AirbnbLocation']-comparison['PipeLocation'])
SSD4.pow(2).sum()
MSE_Location=SSD5/new_comparison5['DifferenceLocation'].count()

SSD6=(comparison['AirbnbValue']-comparison['PipeValue'])
SSD6.pow(2).sum()
MSE_Communication=SSD6/new_comparison6['DifferenceCommunication'].count()

values=[MSE_Accuracy, MSE_Checkin,MSE_Cleanliness,MSE_Value,
        MSE_Location, MSE_Communication]
mse=pd.DataFrame(data=values, index=['Accuracy','Checkin',
                  'Cleanliness','Value','Location','Communication'])
mse.columns=['MSE']
```

In [55]:
```
SSD1=new_comparison1['DifferenceAccuracy'].pow(2).sum()
MSE_Accuracy=SSD1/new_comparison1['DifferenceAccuracy'].count()

SSD2=new_comparison2['DifferenceCheckin'].pow(2).sum()
MSE_Checkin=SSD2/new_comparison2['DifferenceCheckin'].count()

SSD3=new_comparison3['DifferenceCleanliness'].pow(2).sum()
MSE_Cleanliness=SSD3/new_comparison3['DifferenceCleanliness'].count()
```

```
SSD4=new_comparison4['DifferenceValue'].pow(2).sum()
MSE_Value=SSD4/new_comparison4['DifferenceValue'].count()

SSD5=new_comparison5['DifferenceLocation'].pow(2).sum()
MSE_Location=SSD5/new_comparison5['DifferenceLocation'].count()

SSD6=new_comparison6['DifferenceCommunication'].pow(2).sum()
MSE_Communication=SSD6/new_comparison6['DifferenceCommunication'].count()

values=[MSE_Accuracy, MSE_Checkin,MSE_Cleanliness,MSE_Value,
        MSE_Location, MSE_Communication]
mse_re=pd.DataFrame(data=np.sqrt(values), index=['Accuracy',
      'Checkin','Cleanliness','Value','Location','Communication'])

mse_re['MSE']=np.sqrt(mse['MSE'])
mse_re.columns=['RMSE_After','RMSE']
mse_re['# in RMSE']=mse_re['RMSE_After'] - mse_re['RMSE']
mse_re
```

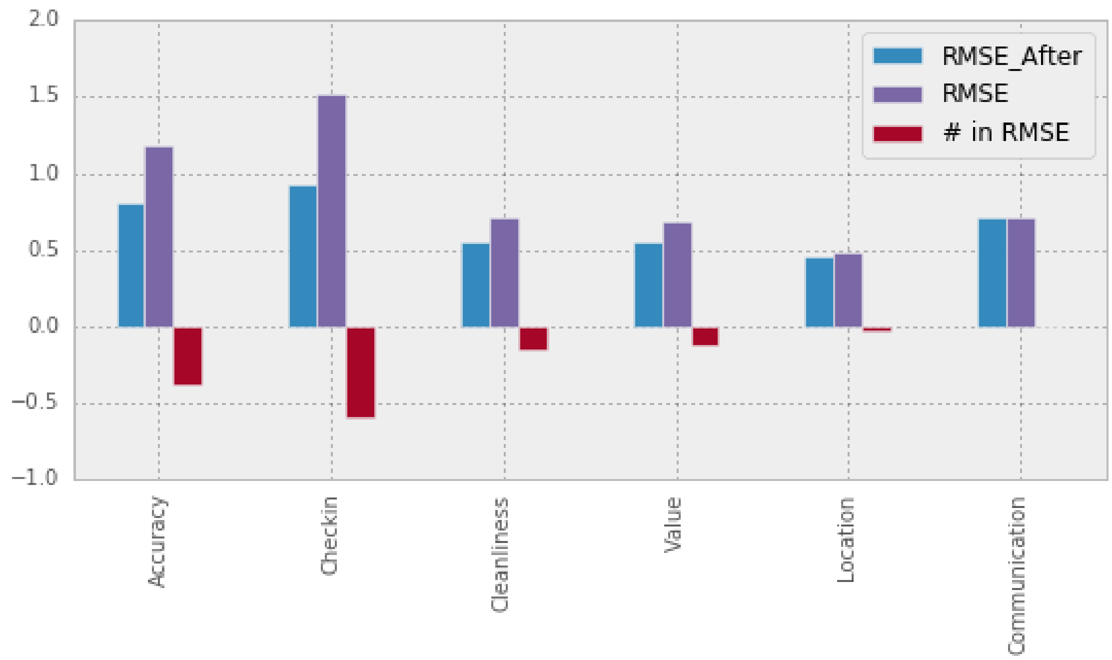
Out[55]:

	RMSE_After	RMSE	# in RMSE
Accuracy	0.801127	1.184486	-0.383359
Checkin	0.925788	1.515706	-0.589917
Cleanliness	0.555249	0.705740	-0.150492
Value	0.554292	0.678538	-0.124246
Location	0.460724	0.487032	-0.026308
Communication	0.707938	0.711251	-0.003313

3.2 Visualization of RMSE and how it changed

In [56]:
```
mse_re.plot(kind='bar',figsize=(9,4))
```

Out[56]: <matplotlib.axes._subplots.AxesSubplot at 0xa8297b0>



4 OCCURRENCE AND CO-OCCURRENCE OF FEATURES

In [57]:
```
f1=new_comparison1[['Id','DifferenceAccuracy']]
f2=new_comparison2[['Id','DifferenceCheckin']]
f3=new_comparison3[['Id','DifferenceCleanliness']]
f4=new_comparison4[['Id','DifferenceValue']]
f5=new_comparison5[['Id','DifferenceLocation']]
f6=new_comparison6[['Id','DifferenceCommunication']]
m1=pd.merge(f1, f2, how='outer', on='Id')
m2=pd.merge(m1, f3, how='outer', on='Id')
m3=pd.merge(m2, f4, how='outer', on='Id')
m4=pd.merge(m3, f5, how='outer', on='Id')
all_diff=pd.merge(m4, f6, how='outer', on='Id')
```

4.1 Number of listings where at least one feature is mentioned in more than 3 reviews

In **83.4%** of listings we will find features mentioned more than 3 times

In [58]:
```
total=full_content['Listing ID'].drop_duplicates().count()
n_listings=all_diff['Id'].count()
print n_listings
print ((n_listings/total)*100).round(1),'%'
```

```
1950
83.5 %
```

4.2 Number of listing where NONE of these 6 features is mentioned

In **16.5%** of the listings none of the features is mentioned in more than 3 reviews. This makes these listings to be excluded from the analysis of feature scores, as they wouldn't be reliable.

```
In [59]: no_feature=total-n_listings
         print no_feature
         print ((no_feature/total)*100).round(1),'%'
```

```
384
16.5 %
```

4.3 Find listing where ALL features are mentioned in more than 3 reviews

There are 473 listing that all the features are mentioned in more than 3 reviews. So, in other words in **24.3%** of the listings we can calculate the sentiment scores of the features mentioned in them.

```
In [60]: listings_with_all_features = all_diff.dropna(axis=0, how='any')
         n_all= listings_with_all_features['Id'].count()
         print 'Number of listings with all features with +3 reviews: ', n_all
         print ((n_all/1950)*100).round(2)
```

```
Number of listings with all features with more than 3 reviews:  473
Compared to the overall number of listings:  24.26
```

4.4 Number of listing with more than 3 reviews per feature

The table shows per each feature how many listings have more than three reviews. So for example we see that for feature **location** we can calculate its value in **96.15%** of the cases (so almost always). Howevwe, that will not be the case for feature **check-in** as its value will be calculated in less than a half of the listings, so in only **31.13%**

```
In [61]: a=all_diff.count()
         b=a.to_frame()
         b.columns=['Number']
         b['Percentage']=((b['Number']/1950)*100).round(2)
         b
```

Out[61]:

	Number	Percentage
Id	1950	100.00
DifferenceAccuracy	848	43.49
DifferenceCheckin	607	31.13
DifferenceCleanliness	1295	66.41
DifferenceValue	1402	71.90
DifferenceLocation	1875	96.15
DifferenceCommunication	1276	65.44