Section 4: Yelp Data Challenge - Restaurant Recommender

Yiting Luo | Data Science Applied Research - 4

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In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
% matplotlib inline
plt.style.use("ggplot")
```

```
/Users/luoyiting/anaconda/envs/gl-env/lib/python2.7/site-packages/ma
tplotlib/font_manager.py:273: UserWarning: Matplotlib is building th
e font cache using fc-list. This may take a moment.
  warnings.warn('Matplotlib is building the font cache using fc-list
. This may take a moment.')
```

In [2]:
```
df = pd.read_csv('dataset/last_2_years_restaurant_reviews.csv')
```

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

Out[3]:

	business_id	name	categories	avg_stars	cool	date	funny	review_id
0	--9e1ONYQuAa-CB_Rrw7Tw	Delmonico Steakhouse	['Cajun/Creole', 'Steakhouses', 'Restaurants']	4.0	0	2016-03-31	0	6SgvNWJl
1	--9e1ONYQuAa-CB_Rrw7Tw	Delmonico Steakhouse	['Cajun/Creole', 'Steakhouses', 'Restaurants']	4.0	0	2015-06-29	0	iwx6s6yQx
2	--9e1ONYQuAa-CB_Rrw7Tw	Delmonico Steakhouse	['Cajun/Creole', 'Steakhouses', 'Restaurants']	4.0	0	2015-03-16	0	UVUMu_b
3	--9e1ONYQuAa-CB_Rrw7Tw	Delmonico Steakhouse	['Cajun/Creole', 'Steakhouses', 'Restaurants']	4.0	0	2016-02-10	0	UxFpgng8
4	--9e1ONYQuAa-CB_Rrw7Tw	Delmonico Steakhouse	['Cajun/Creole', 'Steakhouses', 'Restaurants']	4.0	0	2017-02-14	0	Xp3ppynE

1. Clean data and get rating data

Select relevant columns in the original dataframe

In [4]:

```
# Get business_id, user_id, stars for recommender

df_stars = df[['business_id', 'user_id', 'stars']]
```

In [5]:
```
df_stars['stars'].value_counts()
```

Out[5]:
```
5    239295
4    110642
1     65552
3     57420
2     42843
Name: stars, dtype: int64
```

In [6]:
```
df_stars['business_id'].nunique() # number of unique business_id
```

Out[6]:
```
4832
```

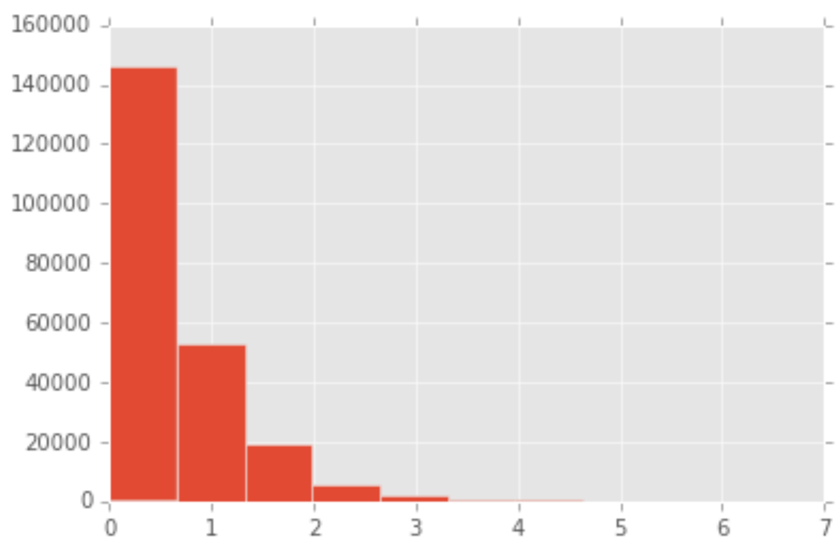
In [7]:
```
df_stars['user_id'].nunique()
```

Out[7]:
```
227241
```

In [8]:
```
df_user_counts = df_stars['user_id'].value_counts()
df_user_counts.head()
```

Out[8]:
```
bLbSNkLggFnqwNNzzq-Ijw    748
JaqcCU3nxReTW2cBLHounA    330
PKEzKWv_FktMm2mGPjwd0Q    276
B1829_hxXSEpDPEDJtYeIw    244
U4INQZOPSUaj8hMjLlZ3KA    232
Name: user_id, dtype: int64
```

In [9]:
```
# display log histogram
df_user_counts.apply(np.log).hist()
plt.show()
```



There are many users that haven't given many reviews, exclude these users from the item-item similarity recommender

In [10]:
```
# how many users only comments once
df_user_counts[df_user_counts == 1].sum()
```

Out[10]:
```
145721
```

In [11]:
```
# user comment over 5 times
df_users = df_user_counts[df_user_counts >5]
```

In [12]:
```
# count users comment over 5 times as active user
df_users.count()
```

Out[12]:
```
14675
```

In [13]:
```
# sum of all comments
df_users.sum()
```

Out[13]:
```
187598
```

In [14]:
```
# display active user id
df_users.index
```

Out[14]:
```
Index([u'bLbSNkLggFnqwNNzzq-Ijw', u'JaqcCU3nxReTW2cBLHounA',
       u'PKEzKWv_FktMm2mGPjwd0Q', u'B1829_hxXSEpDPEDJtYeIw',
       u'U4INQZOPSUaj8hMjLlZ3KA', u'3nIuSCZk5f_2WWYMLN7h3w',
       u'qPVtjjp8sNQ32p9860SR9Q', u'OXSJCjKtvZPf-YPDCXcWZg',
       u'JYcCYNWs8Ul6ewG5kCYW4Q', u'fVILhIglx6RNOXQba5t4kQ',
       ...
       u'dqdTYDRYyo1CPfkQzQmSRw', u'1FdoUP8a1Q54XPduwUouYA',
       u'z044R1luJTuVtzUGUA9d-A', u'FQsbJx12jvFYxzKy6RdPSw',
       u'XC6xHcptE6RB4f7gu692-A', u'0GTanD35lGadNgiDp_a8cQ',
       u'ezIORV7xsOnbfyGAEaQCag', u'WUE6G4OdTkIdrhqK0blrOg',
       u'u53sKuzUuiV1xH1QzKmb6w', u'ItSmZzoGfoJ_MOdKI4qkBQ'],
      dtype='object', length=14675)
```

In [15]:
```
# reader dataframe
df_stars_cleaned = df_stars.set_index('user_id').ix[df_users.index].re
set_index()

print(df_stars.head())
print(df_stars_cleaned.head())
```

```
              business_id                 user_id  stars
0  --9e1ONYQuAa-CB_Rrw7Tw  oFyOUOeGTRZhFPF9uTqrTQ      5
1  --9e1ONYQuAa-CB_Rrw7Tw  2aeNFntqY2QDZLADNo8iQQ      4
2  --9e1ONYQuAa-CB_Rrw7Tw  gmPP4YFrgYsYQqPYokMgFA      5
3  --9e1ONYQuAa-CB_Rrw7Tw  aVOGlN9fZ-BXcbtj6dbf0g      5
4  --9e1ONYQuAa-CB_Rrw7Tw  KC8H7qTZVPIEnanw9fG43g      5
                  user_id             business_id  stars
0  bLbSNkLggFnqwNNzzq-Ijw  -BS4aZAQm9u41YnB9MUASA      4
1  bLbSNkLggFnqwNNzzq-Ijw  -C8sSrFqaCxp51pyo-fQLQ      4
2  bLbSNkLggFnqwNNzzq-Ijw  -CQokjildrY7UZezXCdEBw      5
3  bLbSNkLggFnqwNNzzq-Ijw  -FcZY7a7qgxTUlTvwuyJnQ      3
4  bLbSNkLggFnqwNNzzq-Ijw  -IWsoxH7mLJTTpU5MmWY4w      4
```

Create utility matrix from records

In [16]:
```
df_utility = pd.pivot_table(data = df_stars_cleaned,
                            values ='stars', # fill with stars
                            index = 'user_id', # rows
                            columns = 'business_id', #columns
                            fill_value = 0 # fill missings
                            )
```

In [17]:
```
df_utility.head()
```

Out[17]:

business_id	--9e1ONYQuAa-CB_Rrw7Tw	-1m9o3vGRA8IBPNvNqKLmA	-1vfRrlnNnN
user_id			
--LUapetRSkZpFZ2d-MXLQ	0	0	0
--RlSfc-QmcHFGHyX6aVjA	0	0	0
--ZNfWKj1VyVElRx6-g1fg	0	0	0
-00kdEIhCt-ODaV4BS-EAg	0	0	0
-05XqtNjcBq19vh2CVJN8g	0	0	0

5 rows × 4558 columns

In [18]:
```
# get the list of user id by checking out the index of the utility mat
rix
user_id_list = df_utility.index
user_id_list.shape
```

Out[18]: (14675,)

In [19]:
```
# get the list of item id by checking out the columns of the utility m
atrix
item_id_list = df_utility.columns
item_id_list.shape
```

Out[19]: (4558,)

2. Item-Item similarity recommender

In [20]:
```
import graphlab
```

In [23]:
```
sf_stars = graphlab.SFrame(df_stars)
sf_stars
```

```
[INFO] graphlab.cython.cy_server: GraphLab Create v2.1 started. Logg
ing: /tmp/graphlab_server_1525723753.log
```

```
This non-commercial license of GraphLab Create for academic use is a
ssigned to luoyiting68@hotmail.com and will expire on May 08, 2019.
```

Out[23]:

business_id	user_id	stars
--9e1ONYQuAa-CB_Rrw7Tw	oFyOUOeGTRZhFPF9uTqrTQ	5
--9e1ONYQuAa-CB_Rrw7Tw	2aeNFntqY2QDZLADNo8iQQ	4
--9e1ONYQuAa-CB_Rrw7Tw	gmPP4YFrgYsYQqPYokMgFA	5
--9e1ONYQuAa-CB_Rrw7Tw	aVOGlN9fZ-BXcbtj6dbf0g	5
--9e1ONYQuAa-CB_Rrw7Tw	KC8H7qTZVPIEnanw9fG43g	5
--9e1ONYQuAa-CB_Rrw7Tw	3RTesI_MAwct13LWm4rhLw	4
--9e1ONYQuAa-CB_Rrw7Tw	EAOt1UQhJD0GG3I_jv7rWA	5
--9e1ONYQuAa-CB_Rrw7Tw	C6kw0Rny7jZAGjTj0MWA3Q	5
--9e1ONYQuAa-CB_Rrw7Tw	tTifjrXIRrUme-4c0UW9Bw	5
--9e1ONYQuAa-CB_Rrw7Tw	OtKA03ALQQ1CBhtaJod_Jw	2

[515752 rows x 3 columns]
Note: Only the head of the SFrame is printed.
You can use print_rows(num_rows=m, num_columns=n) to print more rows and columns.

In [24]:
```
# item item recommender
item_item_rec = graphlab.recommender.item_similarity_recommender.creat
e(sf_stars,

user_id = 'user_id',

item_id = 'business_id',

target = 'stars')
```

```
Recsys training: model = item_similarity

Preparing data set.

    Data has 515752 observations with 227241 users and 4832 items.

    Data prepared in: 0.931662s

Training model from provided data.

Gathering per-item and per-user statistics.

+--------------------------------+------------+

| Elapsed Time (Item Statistics) | % Complete |

+--------------------------------+------------+

| 7.459ms                        | 3.5        |

| 86.608ms                       | 100        |

+--------------------------------+------------+

Setting up lookup tables.

Processing data in one pass using dense lookup tables.

+-------------------------------------+------------------+----------
-------+

| Elapsed Time (Constructing Lookups) | Total % Complete | Items Pro
cessed |

+-------------------------------------+------------------+----------
-------+

| 174.748ms                           | 0                | 0
|

| 638.675ms                           | 100              | 4832
|

+-------------------------------------+------------------+----------
-------+

Finalizing lookup tables.

Generating candidate set for working with new users.

Finished training in 1.72294s
```

In [25]:

```
item_item_rec_result = item_item_rec.recommend(k = 3, verbose = False)
```

In [26]:
```
item_item_rec_result
```

Out[26]:

user_id	business_id	score
oFyOUOeGTRZhFPF9uTqrTQ	BhueLLvA0k9G1Lr0WeZX9w	0.0054555649453
oFyOUOeGTRZhFPF9uTqrTQ	4mb32UmQULqg7IMck28vog	0.00528274064368
oFyOUOeGTRZhFPF9uTqrTQ	6fz0hnNIVpLF5v2NqJfA9w	0.0052772303845
2aeNFntqY2QDZLADNo8iQQ	rcaPajgKOJC2vo_I3xa42A	0.0165879130363
2aeNFntqY2QDZLADNo8iQQ	faPVqws-x-5k2CQKDNtHxw	0.016526311636
2aeNFntqY2QDZLADNo8iQQ	KXITXbKuE60WSUDs7NZVLQ	0.0158300697803
gmPP4YFrgYsYQqPYokMgFA	rcaPajgKOJC2vo_I3xa42A	0.0144976079464
gmPP4YFrgYsYQqPYokMgFA	faPVqws-x-5k2CQKDNtHxw	0.0140542984009
gmPP4YFrgYsYQqPYokMgFA	XZbuPXdyA0ZtTu3AzqtQhg	0.0136348605156
aVOGIN9fZ-BXcbtj6dbf0g	Fi-2ruy5x600SX4avnrFuA	0.0113100707531

[681723 rows x 4 columns]
Note: Only the head of the SFrame is printed.
You can use print_rows(num_rows=m, num_columns=n) to print more rows and columns.

3. Content-based recommender

In [28]:
```
# group by business_id, then average numerical features

df_average = df.groupby(['business_id']).mean()
df_average.head()
```

Out[28]:

	avg_stars	cool	funny	stars	useful
business_id					
--9e1ONYQuAa-CB_Rrw7Tw	4.0	0.706263	0.578834	4.159827	1.010799
-1m9o3vGRA8IBPNvNqKLmA	4.5	1.000000	0.631579	4.736842	1.315789
-1vfRrlnNnNJ5boOVghMPA	3.0	0.428571	0.642857	3.000000	0.428571
-3zffZUHoY8bQjGfPSoBKQ	4.0	0.534483	0.454023	3.867816	1.091954
-8R_-EkGpUhBk55K9Dd4mg	3.5	0.761905	0.650794	3.841270	0.968254

In [29]:
```
# group by business_id, extract categories data

categories_series = df.groupby(['business_id']).categories.apply(np.un
ique)
categories_series.head()
```

Out[29]:
```
business_id
--9e1ONYQuAa-CB_Rrw7Tw     [['Cajun/Creole', 'Steakhouses', 'Restaur
ants']]
-1m9o3vGRA8IBPNvNqKLmA    [['African', 'Restaurants', 'Nightlife', '
Bars...
-1vfRrlnNnNJ5boOVghMPA            [['Sushi Bars', 'Korean', 'Restaur
ants']]
-3zffZUHoY8bQjGfPSoBKQ    [['Seafood', 'Bars', 'Nightlife', 'America
n (N...
-8R_-EkGpUhBk55K9Dd4mg                            [['Thai', 'Restaur
ants']]
Name: categories, dtype: object
```

In [30]:
```
# convert categories data to string remove '[]'

categories_series = categories_series.str.join('').apply(lambda x: x[1
:-1])
```

In [31]:

```
# business_id, categories table
# a sparse matrix
from sklearn.feature_extraction.text import CountVectorizer

vectorizer = CountVectorizer()

# get a ndarray with no index or column names
categories_mat = vectorizer.fit_transform(categories_series).toarray()
categories = vectorizer.get_feature_names()

#transform it to pandas df with column and index names
df_categories = pd.DataFrame(categories_mat,
                             columns=categories,
                             index=categories_series.index)
df_categories.head()
```

Out[31]:

	acai	active	activities	acupuncture	adoption	adult	afg
business_id							
--9e1ONYQuAa-CB_Rrw7Tw	0	0	0	0	0	0	0
-1m9o3vGRA8IBPNvNqKLmA	0	0	0	0	0	0	0
-1vfRrlnNnNJ5boOVghMPA	0	0	0	0	0	0	0
-3zffZUHoY8bQjGfPSoBKQ	0	0	0	0	0	0	0
-8R_-EkGpUhBk55K9Dd4mg	0	0	0	0	0	0	0

5 rows × 469 columns

In [32]:
```
# use svd to reduce dimension
# only retain 150 components
from sklearn.decomposition import TruncatedSVD
svd = TruncatedSVD(n_components=150,
                   random_state=42)

svd.fit(categories_mat)
categories_svd = svd.transform(categories_mat)
df_categories_svd = pd.DataFrame(categories_svd,
                                 index=categories_series.index)

print(svd.explained_variance_ratio_.sum()) # total variance explained
df_categories_svd.head()
```

```
0.978568848534
```

Out[32]:

	0	1	2	3	4	5
business_id						
--9e1ONYQuAa-CB_Rrw7Tw	0.729615	0.048135	-0.449471	-0.432830	0.022885	0.02
-1m9o3vGRA8IBPNvNqKLmA	1.831809	2.004849	0.609203	0.020579	-0.122700	-0.1
-1vfRrlnNnNJ5boOVghMPA	1.019308	0.614910	0.163117	-0.705667	-0.085955	0.12
-3zffZUHoY8bQjGfPSoBKQ	1.496075	1.358226	0.002296	0.196015	-0.049401	-0.1
-8R_-EkGpUhBk55K9Dd4mg	0.706684	0.010360	-0.445351	-0.452623	0.015391	0.05

5 rows × 150 columns

In [33]:
```
# display feature matrix dimension

print 'df_average : ', df_average.shape   # to be joined
print 'df_categories : ', df_categories.shape
print 'df_categories_svd : ', df_categories_svd.shape  # to be joined
```

```
df_average :  (4832, 5)
df_categories :  (4832, 469)
df_categories_svd :  (4832, 150)
```

In [34]:
```
# join two to generate feature data for each business_id
df_business = df_average.join(df_categories_svd)
```

In [35]:
```
df_business.shape, df_business.head()
```

Out[35]:
```
((4832, 155),
                          avg_stars      cool     funny     stars
useful  \
 business_id
 --9e1ONYQuAa-CB_Rrw7Tw        4.0  0.706263  0.578834  4.159827  1.
010799
 -1m9o3vGRA8IBPNvNqKLmA        4.5  1.000000  0.631579  4.736842  1.
```

```
315789
 -1vfRrlnNnNJ5boOVghMPA        3.0  0.428571  0.642857  3.000000  0.
428571
 -3zffZUHoY8bQjGfPSoBKQ        4.0  0.534483  0.454023  3.867816  1.
091954
 -8R_-EkGpUhBk55K9Dd4mg        3.5  0.761905  0.650794  3.841270  0.
968254

                                0         1         2         3
4  \
 business_id
 --9e1ONYQuAa-CB_Rrw7Tw  0.729615  0.048135 -0.449471 -0.432830  0.0
22885
 -1m9o3vGRA8IBPNvNqKLmA  1.831809  2.004849  0.609203  0.020579 -0.1
22700
 -1vfRrlnNnNJ5boOVghMPA  1.019308  0.614910  0.163117 -0.705667 -0.0
85955
 -3zffZUHoY8bQjGfPSoBKQ  1.496075  1.358226  0.002296  0.196015 -0.0
49401
 -8R_-EkGpUhBk55K9Dd4mg  0.706684  0.010360 -0.445351 -0.452623  0.0
15391

                           ...       140       141       142
143  \
 business_id               ...
 --9e1ONYQuAa-CB_Rrw7Tw    ...  0.006637  0.007949  0.007346  0.0
12538
 -1m9o3vGRA8IBPNvNqKLmA    ... -0.051330  0.033400  0.034054 -0.0
55641
 -1vfRrlnNnNJ5boOVghMPA    ...  0.003058 -0.009049 -0.006594 -0.0
07373
 -3zffZUHoY8bQjGfPSoBKQ    ... -0.002457 -0.007027 -0.011435 -0.0
15463
 -8R_-EkGpUhBk55K9Dd4mg    ...  0.000442 -0.002289 -0.002723  0.0
01286

                              144       145       146       147
148  \
 business_id
 --9e1ONYQuAa-CB_Rrw7Tw  0.004413 -0.010007  0.002728  0.001197 -0.0
01293
 -1m9o3vGRA8IBPNvNqKLmA -0.058839  0.075682  0.019001 -0.025338  0.0
64974
 -1vfRrlnNnNJ5boOVghMPA -0.006259  0.006767  0.002197 -0.000847  0.0
00545
 -3zffZUHoY8bQjGfPSoBKQ -0.011692 -0.005671 -0.002791 -0.005562 -0.0
01172
 -8R_-EkGpUhBk55K9Dd4mg -0.003358  0.006847  0.000040  0.003044 -0.0
02073

                              149
 business_id
 --9e1ONYQuAa-CB_Rrw7Tw  0.005149
```

```
 -1m9o3vGRA8IBPNvNqKLmA  0.054436
 -1vfRrlnNnNJ5boOVghMPA -0.004172
 -3zffZUHoY8bQjGfPSoBKQ  0.008745
 -8R_-EkGpUhBk55K9Dd4mg -0.000813

 [5 rows x 155 columns])
```

In [36]:
```
# prepare data

item_data = graphlab.SFrame(df_business.reset_index())
```

In [37]:
```
# build content based recommender

content_rec = graphlab.recommender.item_content_recommender.create(ite
m_data, "business_id")
```

```
WARNING: The ItemContentRecommender model is still in beta.
WARNING: This feature transformer is still in beta, and some interpr
etation rules may change in the future.
('Applying transform:\n', Class              : AutoVectorizer

Model Fields
------------
Features          : ['avg_stars', 'cool', 'funny', 'stars', 'useful'
, '0', '1', '2', '3', '4', '5', '6', '7', '8', '9', '10', '11', '12'
, '13', '14', '15', '16', '17', '18', '19', '20', '21', '22', '23',
'24', '25', '26', '27', '28', '29', '30', '31', '32', '33', '34', '3
5', '36', '37', '38', '39', '40', '41', '42', '43', '44', '45', '46'
, '47', '48', '49', '50', '51', '52', '53', '54', '55', '56', '57',
'58', '59', '60', '61', '62', '63', '64', '65', '66', '67', '68', '6
9', '70', '71', '72', '73', '74', '75', '76', '77', '78', '79', '80'
, '81', '82', '83', '84', '85', '86', '87', '88', '89', '90', '91',
'92', '93', '94', '95', '96', '97', '98', '99', '100', '101', '102',
'103', '104', '105', '106', '107', '108', '109', '110', '111', '112'
, '113', '114', '115', '116', '117', '118', '119', '120', '121', '12
2', '123', '124', '125', '126', '127', '128', '129', '130', '131', '
132', '133', '134', '135', '136', '137', '138', '139', '140', '141',
'142', '143', '144', '145', '146', '147', '148', '149']
Excluded Features : ['business_id']

Column     Type   Interpretation  Transforms  Output Type
---------  -----  --------------  ----------  -----------
avg_stars  float  numerical       None        float
cool       float  numerical       None        float
funny      float  numerical       None        float
stars      float  numerical       None        float
useful     float  numerical       None        float
0          float  numerical       None        float
1          float  numerical       None        float
2          float  numerical       None        float
3          float  numerical       None        float
4          float  numerical       None        float
5          float  numerical       None        float
```

6	float	numerical	None	float
7	float	numerical	None	float
8	float	numerical	None	float
9	float	numerical	None	float
10	float	numerical	None	float
11	float	numerical	None	float
12	float	numerical	None	float
13	float	numerical	None	float
14	float	numerical	None	float
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42	float	numerical	None	float
43	float	numerical	None	float
44	float	numerical	None	float
45	float	numerical	None	float
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48	float	numerical	None	float
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103	float	numerical	None	float
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106	float	numerical	None	float
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108	float	numerical	None	float
109	float	numerical	None	float
110	float	numerical	None	float
111	float	numerical	None	float

```
112         float  numerical       None        float
113         float  numerical       None        float
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148         float  numerical       None        float
149         float  numerical       None        float

)

Recsys training: model = item_content_recommender

Defaulting to brute force instead of ball tree because there are mul
tiple distance components.

Starting brute force nearest neighbors model training.

Starting pairwise querying.

+--------------+---------+-------------+--------------+

| Query points | # Pairs | % Complete. | Elapsed Time |
```

1	4832	0.0206954	227.573ms
39	188448	0.807119	1.25s
80	386560	1.65563	2.25s
126	608832	2.60762	3.23s
164	792448	3.39404	4.28s
193	932576	3.99421	5.23s
240	1159680	4.96689	6.27s
294	1420608	6.08444	7.24s
348	1681536	7.20199	8.24s
405	1956960	8.38162	9.27s
458	2213056	9.47848	10.24s
527	2546464	10.9065	11.25s
594	2870208	12.293	12.24s
663	3203616	13.721	13.27s
716	3459712	14.8179	14.24s
748	3614336	15.4801	15.27s
790	3817280	16.3493	16.24s
835	4034720	17.2806	17.23s
890	4300480	18.4189	18.24s
954	4609728	19.7434	19.26s
1024	4947968	21.1921	20.23s
1059	5117088	21.9164	21.23s
1095	5291040	22.6614	22.26s
1126	5440832	23.303	23.26s
1157	5590624	23.9445	24.27s
1193	5764576	24.6896	25.24s
1233	5957856	25.5174	26.24s
1291	6238112	26.7177	27.23s

1361	6576352	28.1664	28.25s
1416	6842112	29.3046	29.33s
1451	7011232	30.029	30.30s
1492	7209344	30.8775	31.27s
1537	7426784	31.8088	32.25s
1576	7615232	32.6159	33.27s
1615	7803680	33.423	34.23s
1677	8103264	34.7061	35.25s
1741	8412512	36.0306	36.23s
1807	8731424	37.3965	37.24s
1858	8977856	38.452	38.26s
1905	9204960	39.4247	39.24s
1962	9480384	40.6043	40.26s
2008	9702656	41.5563	41.23s
2077	1e+07	42.9843	42.27s
2136	1e+07	44.2053	43.25s
2196	1.1e+07	45.447	44.25s
2261	1.1e+07	46.7922	45.23s
2324	1.1e+07	48.096	46.23s
2396	1.2e+07	49.5861	47.26s
2466	1.2e+07	51.0348	48.23s
2542	1.2e+07	52.6076	49.24s
2612	1.3e+07	54.0563	50.25s
2682	1.3e+07	55.505	51.23s
2746	1.3e+07	56.8295	52.25s
2812	1.4e+07	58.1954	53.26s
2878	1.4e+07	59.5613	54.29s
2942	1.4e+07	60.8858	55.23s
3015	1.5e+07	62.3965	56.27s

3089	1.5e+07	63.928	57.28s
3154	1.5e+07	65.2732	58.23s
3206	1.5e+07	66.3493	59.25s
3271	1.6e+07	67.6945	1m 0s
3343	1.6e+07	69.1846	1m 1s
3418	1.7e+07	70.7368	1m 2s
3494	1.7e+07	72.3096	1m 3s
3536	1.7e+07	73.1788	1m 4s
3597	1.7e+07	74.4412	1m 5s
3644	1.8e+07	75.4139	1m 6s
3701	1.8e+07	76.5935	1m 7s
3763	1.8e+07	77.8767	1m 8s
3841	1.9e+07	79.4909	1m 9s
3916	1.9e+07	81.043	1m 10s
3990	1.9e+07	82.5745	1m 11s
4063	2e+07	84.0853	1m 12s
4135	2e+07	85.5753	1m 13s
4206	2e+07	87.0447	1m 14s
4271	2.1e+07	88.3899	1m 15s
4333	2.1e+07	89.673	1m 16s
4389	2.1e+07	90.832	1m 17s
4429	2.1e+07	91.6598	1m 18s
4487	2.2e+07	92.8601	1m 19s
4542	2.2e+07	93.9983	1m 20s
4601	2.2e+07	95.2194	1m 21s
4663	2.3e+07	96.5025	1m 22s
4716	2.3e+07	97.5993	1m 23s
4771	2.3e+07	98.7376	1m 24s
4831	2.3e+07	99.9793	1m 25s

```
| Done          |         | 100        | 1m 25s       |
+--------------+---------+------------+--------------+
Preparing data set.
    Data has 0 observations with 0 users and 4832 items.
    Data prepared in: 0.763917s
Loading user-provided nearest items.
Generating candidate set for working with new users.
Finished training in 0.039033s
```

In [38]:

```
# make recommendation for a single item
# essentially make recommendation based on businiess_id(155 features)
similarities
sample_item = [df_stars.iloc[0].business_id]
content_rec.recommend_from_interactions(sample_item)
```

Out[38]:

business_id	score	rank
TT658qQinO6MBHP9q7rJ8w	0.939524710178	1
uWECX6-Uq9n8v5ipk9R29A	0.937774240971	2
AT1bODcrWTKTRNZKRxO-cA	0.894924402237	3
zcScEL0WEdFkROcnz5379g	0.893789052963	4
p3YqOYELqXtLyHz9T49p_w	0.891371250153	5
5TY6bUT3bbl9aHItilXXqw	0.888443648815	6
L2W0QLXIIR5MEmhQwZk-iA	0.887454330921	7
UNI1agsPX2k3eJSJVB91nw	0.859774649143	8
VPO8pBUwYz1u6GoG0d2U-Q	0.859451830387	9
KXITXbKuE60WSUDs7NZVLQ	0.836147964001	10

[10 rows x 3 columns]

In [39]:
```
# similar items per item

similar_items_df = content_rec.get_similar_items().to_dataframe()
similar_items_df.head(20) # each business_id with 10 most similar ones
```

Out[39]:

	business_id	similar	score	rank
0	--9e1ONYQuAa-CB_Rrw7Tw	TT658qQinO6MBHP9q7rJ8w	0.939525	1
1	--9e1ONYQuAa-CB_Rrw7Tw	uWECX6-Uq9n8v5ipk9R29A	0.937774	2
2	--9e1ONYQuAa-CB_Rrw7Tw	AT1bODcrWTKTRNZKRxO-cA	0.894924	3
3	--9e1ONYQuAa-CB_Rrw7Tw	zcScEL0WEdFkROcnz5379g	0.893789	4
4	--9e1ONYQuAa-CB_Rrw7Tw	p3YqOYELqXtLyHz9T49p_w	0.891371	5
5	--9e1ONYQuAa-CB_Rrw7Tw	5TY6bUT3bbl9aHItiIXXqw	0.888444	6
6	--9e1ONYQuAa-CB_Rrw7Tw	L2W0QLXIIR5MEmhQwZk-iA	0.887454	7
7	--9e1ONYQuAa-CB_Rrw7Tw	UNI1agsPX2k3eJSJVB91nw	0.859775	8
8	--9e1ONYQuAa-CB_Rrw7Tw	VPO8pBUwYz1u6GoG0d2U-Q	0.859452	9
9	--9e1ONYQuAa-CB_Rrw7Tw	KXITXbKuE60WSUDs7NZVLQ	0.836148	10
10	-1m9o3vGRA8IBPNvNqKLmA	FhIeCF6QrsLaRvAeu0oEPQ	0.688294	1
11	-1m9o3vGRA8IBPNvNqKLmA	6MpOzb5ImLdDXHsn4HwI-Q	0.680585	2
12	-1m9o3vGRA8IBPNvNqKLmA	bpRo8L8dkhgbJhdIKa9mwA	0.678564	3
13	-1m9o3vGRA8IBPNvNqKLmA	Q5oIb1x6FGk2oLAIc9p5Lg	0.663660	4
14	-1m9o3vGRA8IBPNvNqKLmA	HhVmDybpU7L50Kb5A0jXTg	0.661209	5
15	-1m9o3vGRA8IBPNvNqKLmA	dTsyfvRfN-zFdsgIDuQIlQ	0.646282	6
16	-1m9o3vGRA8IBPNvNqKLmA	dubu2kN3Y9EB4uYGFWa0MQ	0.639656	7
17	-1m9o3vGRA8IBPNvNqKLmA	JRh14J_be0jI7Wbt412vDA	0.636291	8
18	-1m9o3vGRA8IBPNvNqKLmA	wkKIpSx3OcoGJiv7p8VZzw	0.631747	9
19	-1m9o3vGRA8IBPNvNqKLmA	PsdWWQE_9GrfmCNfz2yW4g	0.630566	10

In [40]:
```
# make recommendation for a sample user
df_favored = df_stars[df_stars.stars > 4] # select favored restuarants
bid_favored = df_favored[df_favored.user_id == df_favored.user_id.iloc
[0]] # retain only one user's ratings

# first select favored restaurants' similar items
# each store rated by this user has 10 most similar stores
# hence there will be 50 candidates
# second sort those restaurants, then got top 10
similar_items_df[similar_items_df['business_id'].isin(bid_favored.busi
ness_id)].sort('score',ascending=False).similar[:10]
```

```
/Users/luoyiting/anaconda/envs/gl-env/lib/python2.7/site-packages/ip
ykernel/__main__.py:9: FutureWarning: sort(columns=....) is deprecat
ed, use sort_values(by=.....)
```

Out[40]:
```
31140    GkRF8rSvh9cOQuuPeDh9bg
24650    kiweDovyXezj-ZMpB1tlXg
31141    Bm8nRUsZ-dK6g2eJLxMTOw
38170    wAQr_GVUNFSvqFfr3cC9kA
42780    KQoeETpQ1nBEQ6fVOtFgWQ
25810    80Lkm305ZOkQdMEIvOy_lw
31142    TCWMgOiV0PxQkWE1SyBIWQ
14010    GU0zNpgisY-pV3U2Sfdp6A
31143    MXC9pwIxovWUc9yu1F8OxA
31144    KVsv8wRGnLX8QWoNZKNMQA
Name: similar, dtype: object
```

5. Popularity based recommender

In [41]:
```
# data
sf_stars
```

Out[41]:

business_id	user_id	stars
--9e1ONYQuAa-CB_Rrw7Tw	oFyOUOeGTRZhFPF9uTqrTQ	5
--9e1ONYQuAa-CB_Rrw7Tw	2aeNFntqY2QDZLADNo8iQQ	4
--9e1ONYQuAa-CB_Rrw7Tw	gmPP4YFrgYsYQqPYokMgFA	5
--9e1ONYQuAa-CB_Rrw7Tw	aVOGlN9fZ-BXcbtj6dbf0g	5
--9e1ONYQuAa-CB_Rrw7Tw	KC8H7qTZVPIEnanw9fG43g	5
--9e1ONYQuAa-CB_Rrw7Tw	3RTesI_MAwct13LWm4rhLw	4
--9e1ONYQuAa-CB_Rrw7Tw	EAOt1UQhJD0GG3I_jv7rWA	5
--9e1ONYQuAa-CB_Rrw7Tw	C6kw0Rny7jZAGjTj0MWA3Q	5
--9e1ONYQuAa-CB_Rrw7Tw	tTifjrXIRrUme-4c0UW9Bw	5
--9e1ONYQuAa-CB_Rrw7Tw	OtKA03ALQQ1CBhtaJod_Jw	2

[515752 rows x 3 columns]
Note: Only the head of the SFrame is printed.
You can use print_rows(num_rows=m, num_columns=n) to print more rows and columns.

In [42]:
```
# build recommendation system
pop_rec = graphlab.popularity_recommender.create(sf_stars,
                                                 user_id = 'user_id',
                                                 item_id = 'business_i
d',
                                                 target = 'stars')
```

```
Recsys training: model = popularity

Preparing data set.

    Data has 515752 observations with 227241 users and 4832 items.

    Data prepared in: 1.02208s

515752 observations to process; with 4832 unique items.
```

In [43]:
```
# get recommendation
pop_result = pop_rec.recommend()
```

```
recommendations finished on 1000/227241 queries. users per second: 3
5095.1

recommendations finished on 2000/227241 queries. users per second: 3
6412.6
```

```
recommendations finished on 3000/227241 queries. users per second: 3
4396.6

recommendations finished on 4000/227241 queries. users per second: 3
2934

recommendations finished on 5000/227241 queries. users per second: 3
3285.2

recommendations finished on 6000/227241 queries. users per second: 3
4294.7

recommendations finished on 7000/227241 queries. users per second: 3
4530

recommendations finished on 8000/227241 queries. users per second: 3
4314.4

recommendations finished on 9000/227241 queries. users per second: 3
4810.3

recommendations finished on 10000/227241 queries. users per second:
34992

recommendations finished on 11000/227241 queries. users per second:
35182.7

recommendations finished on 12000/227241 queries. users per second:
34813

recommendations finished on 13000/227241 queries. users per second:
34710

recommendations finished on 14000/227241 queries. users per second:
34770.5

recommendations finished on 15000/227241 queries. users per second:
34778.4

recommendations finished on 16000/227241 queries. users per second:
34750.3

recommendations finished on 17000/227241 queries. users per second:
34947.1

recommendations finished on 18000/227241 queries. users per second:
34511.7

recommendations finished on 19000/227241 queries. users per second:
34052.4
```

recommendations finished on 20000/227241 queries. users per second: 33684.1

recommendations finished on 21000/227241 queries. users per second: 33748

recommendations finished on 22000/227241 queries. users per second: 33601.1

recommendations finished on 23000/227241 queries. users per second: 33780.2

recommendations finished on 24000/227241 queries. users per second: 34036

recommendations finished on 25000/227241 queries. users per second: 34125.1

recommendations finished on 26000/227241 queries. users per second: 34299.2

recommendations finished on 27000/227241 queries. users per second: 34162

recommendations finished on 28000/227241 queries. users per second: 34124.5

recommendations finished on 29000/227241 queries. users per second: 34140.1

recommendations finished on 30000/227241 queries. users per second: 34313.4

recommendations finished on 31000/227241 queries. users per second: 34270.5

recommendations finished on 32000/227241 queries. users per second: 34072.5

recommendations finished on 33000/227241 queries. users per second: 33635.4

recommendations finished on 34000/227241 queries. users per second: 33489.8

recommendations finished on 35000/227241 queries. users per second: 33233.1

recommendations finished on 36000/227241 queries. users per second: 32988.7

recommendations finished on 37000/227241 queries. users per second: 32561.4

recommendations finished on 38000/227241 queries. users per second: 32440.6

recommendations finished on 39000/227241 queries. users per second: 32377.5

recommendations finished on 40000/227241 queries. users per second: 32431

recommendations finished on 41000/227241 queries. users per second: 32535.9

recommendations finished on 42000/227241 queries. users per second: 32651.5

recommendations finished on 43000/227241 queries. users per second: 32686.7

recommendations finished on 44000/227241 queries. users per second: 32822.1

recommendations finished on 45000/227241 queries. users per second: 32890.5

recommendations finished on 46000/227241 queries. users per second: 33033.4

recommendations finished on 47000/227241 queries. users per second: 33016.9

recommendations finished on 48000/227241 queries. users per second: 33057.4

recommendations finished on 49000/227241 queries. users per second: 33085.5

recommendations finished on 50000/227241 queries. users per second: 33149.2

recommendations finished on 51000/227241 queries. users per second: 33052.3

recommendations finished on 52000/227241 queries. users per second: 32441.8

recommendations finished on 53000/227241 queries. users per second: 32411.4

```
recommendations finished on 54000/227241 queries. users per second: 32236.9
recommendations finished on 55000/227241 queries. users per second: 32183.2
recommendations finished on 56000/227241 queries. users per second: 32032.7
recommendations finished on 57000/227241 queries. users per second: 31920.3
recommendations finished on 58000/227241 queries. users per second: 31933.9
recommendations finished on 59000/227241 queries. users per second: 32036
recommendations finished on 60000/227241 queries. users per second: 32082.1
recommendations finished on 61000/227241 queries. users per second: 32107.8
recommendations finished on 62000/227241 queries. users per second: 32202
recommendations finished on 63000/227241 queries. users per second: 32271.3
recommendations finished on 64000/227241 queries. users per second: 32381
recommendations finished on 65000/227241 queries. users per second: 32452.9
recommendations finished on 66000/227241 queries. users per second: 32547
recommendations finished on 67000/227241 queries. users per second: 32594.5
recommendations finished on 68000/227241 queries. users per second: 32611.1
recommendations finished on 69000/227241 queries. users per second: 32718.2
recommendations finished on 70000/227241 queries. users per second: 32793.6
```

recommendations finished on 71000/227241 queries. users per second: 32878.6

recommendations finished on 72000/227241 queries. users per second: 32930.3

recommendations finished on 73000/227241 queries. users per second: 33024.7

recommendations finished on 74000/227241 queries. users per second: 32912.9

recommendations finished on 75000/227241 queries. users per second: 33013.2

recommendations finished on 76000/227241 queries. users per second: 33023.9

recommendations finished on 77000/227241 queries. users per second: 33126.4

recommendations finished on 78000/227241 queries. users per second: 33184.8

recommendations finished on 79000/227241 queries. users per second: 33272.6

recommendations finished on 80000/227241 queries. users per second: 33330.4

recommendations finished on 81000/227241 queries. users per second: 33320.2

recommendations finished on 82000/227241 queries. users per second: 33364.1

recommendations finished on 83000/227241 queries. users per second: 33392.7

recommendations finished on 84000/227241 queries. users per second: 33415

recommendations finished on 85000/227241 queries. users per second: 33405.3

recommendations finished on 86000/227241 queries. users per second: 33427

recommendations finished on 87000/227241 queries. users per second: 33404.6

```
recommendations finished on 88000/227241 queries. users per second:
33319.3

recommendations finished on 89000/227241 queries. users per second:
33363.7

recommendations finished on 90000/227241 queries. users per second:
33373

recommendations finished on 91000/227241 queries. users per second:
33379.3

recommendations finished on 92000/227241 queries. users per second:
33330.3

recommendations finished on 93000/227241 queries. users per second:
33328.3

recommendations finished on 94000/227241 queries. users per second:
33314.1

recommendations finished on 95000/227241 queries. users per second:
33353.6

recommendations finished on 96000/227241 queries. users per second:
33420.6

recommendations finished on 97000/227241 queries. users per second:
33463.4

recommendations finished on 98000/227241 queries. users per second:
33536.5

recommendations finished on 99000/227241 queries. users per second:
33544.4

recommendations finished on 100000/227241 queries. users per second:
33587.5

recommendations finished on 101000/227241 queries. users per second:
33565.9

recommendations finished on 102000/227241 queries. users per second:
33611.2

recommendations finished on 103000/227241 queries. users per second:
33469.5

recommendations finished on 104000/227241 queries. users per second:
33376.1
```

recommendations finished on 105000/227241 queries. users per second: 33262.4

recommendations finished on 106000/227241 queries. users per second: 33283.8

recommendations finished on 107000/227241 queries. users per second: 33314.8

recommendations finished on 108000/227241 queries. users per second: 33271.6

recommendations finished on 109000/227241 queries. users per second: 33310.9

recommendations finished on 110000/227241 queries. users per second: 33253.4

recommendations finished on 111000/227241 queries. users per second: 33175.9

recommendations finished on 112000/227241 queries. users per second: 32883.1

recommendations finished on 113000/227241 queries. users per second: 32757

recommendations finished on 114000/227241 queries. users per second: 32674.2

recommendations finished on 115000/227241 queries. users per second: 32607.3

recommendations finished on 116000/227241 queries. users per second: 32389

recommendations finished on 117000/227241 queries. users per second: 32377.7

recommendations finished on 118000/227241 queries. users per second: 32425.9

recommendations finished on 119000/227241 queries. users per second: 32422.1

recommendations finished on 120000/227241 queries. users per second: 32401.5

recommendations finished on 121000/227241 queries. users per second: 32402

```
recommendations finished on 122000/227241 queries. users per second:
32406.2

recommendations finished on 123000/227241 queries. users per second:
32393.4

recommendations finished on 124000/227241 queries. users per second:
32410.9

recommendations finished on 125000/227241 queries. users per second:
32369.5

recommendations finished on 126000/227241 queries. users per second:
32384.9

recommendations finished on 127000/227241 queries. users per second:
32412.7

recommendations finished on 128000/227241 queries. users per second:
32438.8

recommendations finished on 129000/227241 queries. users per second:
32466.5

recommendations finished on 130000/227241 queries. users per second:
32480.8

recommendations finished on 131000/227241 queries. users per second:
32490.9

recommendations finished on 132000/227241 queries. users per second:
32510.1

recommendations finished on 133000/227241 queries. users per second:
32495.4

recommendations finished on 134000/227241 queries. users per second:
32457.9

recommendations finished on 135000/227241 queries. users per second:
32382

recommendations finished on 136000/227241 queries. users per second:
32296

recommendations finished on 137000/227241 queries. users per second:
32266.1

recommendations finished on 138000/227241 queries. users per second:
32185.7
```

```
recommendations finished on 139000/227241 queries. users per second:
32152.1

recommendations finished on 140000/227241 queries. users per second:
32110.3

recommendations finished on 141000/227241 queries. users per second:
32046.5

recommendations finished on 142000/227241 queries. users per second:
32009.5

recommendations finished on 143000/227241 queries. users per second:
32035

recommendations finished on 144000/227241 queries. users per second:
32045.1

recommendations finished on 145000/227241 queries. users per second:
32004.6

recommendations finished on 146000/227241 queries. users per second:
31971.5

recommendations finished on 147000/227241 queries. users per second:
31921.4

recommendations finished on 148000/227241 queries. users per second:
31951.2

recommendations finished on 149000/227241 queries. users per second:
31999

recommendations finished on 150000/227241 queries. users per second:
32005.6

recommendations finished on 151000/227241 queries. users per second:
31979.6

recommendations finished on 152000/227241 queries. users per second:
31866.4

recommendations finished on 153000/227241 queries. users per second:
31820.8

recommendations finished on 154000/227241 queries. users per second:
31806.7

recommendations finished on 155000/227241 queries. users per second:
31780.5
```

recommendations finished on 156000/227241 queries. users per second: 31756.2

recommendations finished on 157000/227241 queries. users per second: 31687.5

recommendations finished on 158000/227241 queries. users per second: 31644.9

recommendations finished on 159000/227241 queries. users per second: 31577.7

recommendations finished on 160000/227241 queries. users per second: 31541.6

recommendations finished on 161000/227241 queries. users per second: 31523.8

recommendations finished on 162000/227241 queries. users per second: 31529.4

recommendations finished on 163000/227241 queries. users per second: 31503.2

recommendations finished on 164000/227241 queries. users per second: 31509.1

recommendations finished on 165000/227241 queries. users per second: 31482.7

recommendations finished on 166000/227241 queries. users per second: 31486.6

recommendations finished on 167000/227241 queries. users per second: 31492.4

recommendations finished on 168000/227241 queries. users per second: 31501.3

recommendations finished on 169000/227241 queries. users per second: 31538.9

recommendations finished on 170000/227241 queries. users per second: 31547.7

recommendations finished on 171000/227241 queries. users per second: 31566.4

recommendations finished on 172000/227241 queries. users per second: 31592.8

```
recommendations finished on 173000/227241 queries. users per second:
31624.5

recommendations finished on 174000/227241 queries. users per second:
31580.8

recommendations finished on 175000/227241 queries. users per second:
31558.2

recommendations finished on 176000/227241 queries. users per second:
31552.3

recommendations finished on 177000/227241 queries. users per second:
31555.2

recommendations finished on 178000/227241 queries. users per second:
31551.7

recommendations finished on 179000/227241 queries. users per second:
31545.7

recommendations finished on 180000/227241 queries. users per second:
31528.1

recommendations finished on 181000/227241 queries. users per second:
31539.6

recommendations finished on 182000/227241 queries. users per second:
31534.3

recommendations finished on 183000/227241 queries. users per second:
31484.7

recommendations finished on 184000/227241 queries. users per second:
31462.6

recommendations finished on 185000/227241 queries. users per second:
31428.6

recommendations finished on 186000/227241 queries. users per second:
31408.6

recommendations finished on 187000/227241 queries. users per second:
31376.9

recommendations finished on 188000/227241 queries. users per second:
31371.3

recommendations finished on 189000/227241 queries. users per second:
31362.1
```

recommendations finished on 190000/227241 queries. users per second: 31324.1

recommendations finished on 191000/227241 queries. users per second: 31331.5

recommendations finished on 192000/227241 queries. users per second: 31339.8

recommendations finished on 193000/227241 queries. users per second: 31337

recommendations finished on 194000/227241 queries. users per second: 31339.4

recommendations finished on 195000/227241 queries. users per second: 31321.2

recommendations finished on 196000/227241 queries. users per second: 31324.5

recommendations finished on 197000/227241 queries. users per second: 31341.7

recommendations finished on 198000/227241 queries. users per second: 31348.9

recommendations finished on 199000/227241 queries. users per second: 31374.9

recommendations finished on 200000/227241 queries. users per second: 31402.3

recommendations finished on 201000/227241 queries. users per second: 31435.1

recommendations finished on 202000/227241 queries. users per second: 31468.1

recommendations finished on 203000/227241 queries. users per second: 31487.5

recommendations finished on 204000/227241 queries. users per second: 31515.2

recommendations finished on 205000/227241 queries. users per second: 31490.9

recommendations finished on 206000/227241 queries. users per second: 31485.5

recommendations finished on 207000/227241 queries. users per second: 31454.7

recommendations finished on 208000/227241 queries. users per second: 31381.2

recommendations finished on 209000/227241 queries. users per second: 31244

recommendations finished on 210000/227241 queries. users per second: 31190.7

recommendations finished on 211000/227241 queries. users per second: 31217.1

recommendations finished on 212000/227241 queries. users per second: 31257

recommendations finished on 213000/227241 queries. users per second: 31301.8

recommendations finished on 214000/227241 queries. users per second: 31341.9

recommendations finished on 215000/227241 queries. users per second: 31369

recommendations finished on 216000/227241 queries. users per second: 31400.7

recommendations finished on 217000/227241 queries. users per second: 31442.7

recommendations finished on 218000/227241 queries. users per second: 31484.4

recommendations finished on 219000/227241 queries. users per second: 31514.8

recommendations finished on 220000/227241 queries. users per second: 31554.1

recommendations finished on 221000/227241 queries. users per second: 31551.7

recommendations finished on 222000/227241 queries. users per second: 31536.9

recommendations finished on 223000/227241 queries. users per second: 31540.2

```
recommendations finished on 224000/227241 queries. users per second:
31477.8

recommendations finished on 225000/227241 queries. users per second:
31324.4

recommendations finished on 226000/227241 queries. users per second:
31242.9

recommendations finished on 227000/227241 queries. users per second:
31125.4
```

In [45]:
```
pop_result.print_rows(num_rows=30, num_columns=3) # everyone is recomm
ended with the most popular business_id
```

```
+------------------------+------------------------+-------+-----+
|        user_id         |      business_id       | score | ... |
+------------------------+------------------------+-------+-----+
| oFyOUOeGTRZhFPF9uTqrTQ | irVqdCcmeO_Qhz8YcwaxOA |  5.0  | ... |
| oFyOUOeGTRZhFPF9uTqrTQ | ikR7b7j-Dw8VOEztNT4oLw |  5.0  | ... |
| oFyOUOeGTRZhFPF9uTqrTQ | V9eIbZwaOJ7YeMy5bPVm6w |  5.0  | ... |
| oFyOUOeGTRZhFPF9uTqrTQ | V6u7__4jbEDOgWR8K6qUSw |  5.0  | ... |
| oFyOUOeGTRZhFPF9uTqrTQ | U4ZvCExEi8Chtzu9IVrkCg |  5.0  | ... |
| oFyOUOeGTRZhFPF9uTqrTQ | iQOjQH30LFsj6aO3wJG7nQ |  5.0  | ... |
| oFyOUOeGTRZhFPF9uTqrTQ | i5vy3X8WBjQ-F7P8HqC7KA |  5.0  | ... |
| oFyOUOeGTRZhFPF9uTqrTQ | hkbZCioL7TkHLZuTXf-5fQ |  5.0  | ... |
| oFyOUOeGTRZhFPF9uTqrTQ | 096iGHoQ-UImxUExuyqlZA |  5.0  | ... |
| oFyOUOeGTRZhFPF9uTqrTQ | -UtYWvCnUppcSaC_u1pTYQ |  5.0  | ... |
| 2aeNFntqY2QDZLADNo8iQQ | irVqdCcmeO_Qhz8YcwaxOA |  5.0  | ... |
| 2aeNFntqY2QDZLADNo8iQQ | ikR7b7j-Dw8VOEztNT4oLw |  5.0  | ... |
| 2aeNFntqY2QDZLADNo8iQQ | V9eIbZwaOJ7YeMy5bPVm6w |  5.0  | ... |
| 2aeNFntqY2QDZLADNo8iQQ | V6u7__4jbEDOgWR8K6qUSw |  5.0  | ... |
| 2aeNFntqY2QDZLADNo8iQQ | U4ZvCExEi8Chtzu9IVrkCg |  5.0  | ... |
| 2aeNFntqY2QDZLADNo8iQQ | iQOjQH30LFsj6aO3wJG7nQ |  5.0  | ... |
| 2aeNFntqY2QDZLADNo8iQQ | i5vy3X8WBjQ-F7P8HqC7KA |  5.0  | ... |
| 2aeNFntqY2QDZLADNo8iQQ | hkbZCioL7TkHLZuTXf-5fQ |  5.0  | ... |
| 2aeNFntqY2QDZLADNo8iQQ | 096iGHoQ-UImxUExuyqlZA |  5.0  | ... |
| 2aeNFntqY2QDZLADNo8iQQ | -UtYWvCnUppcSaC_u1pTYQ |  5.0  | ... |
| gmPP4YFrgYsYQqPYokMgFA | irVqdCcmeO_Qhz8YcwaxOA |  5.0  | ... |
| gmPP4YFrgYsYQqPYokMgFA | ikR7b7j-Dw8VOEztNT4oLw |  5.0  | ... |
| gmPP4YFrgYsYQqPYokMgFA | V9eIbZwaOJ7YeMy5bPVm6w |  5.0  | ... |
| gmPP4YFrgYsYQqPYokMgFA | V6u7__4jbEDOgWR8K6qUSw |  5.0  | ... |
| gmPP4YFrgYsYQqPYokMgFA | U4ZvCExEi8Chtzu9IVrkCg |  5.0  | ... |
| gmPP4YFrgYsYQqPYokMgFA | iQOjQH30LFsj6aO3wJG7nQ |  5.0  | ... |
| gmPP4YFrgYsYQqPYokMgFA | i5vy3X8WBjQ-F7P8HqC7KA |  5.0  | ... |
| gmPP4YFrgYsYQqPYokMgFA | hkbZCioL7TkHLZuTXf-5fQ |  5.0  | ... |
| gmPP4YFrgYsYQqPYokMgFA | 096iGHoQ-UImxUExuyqlZA |  5.0  | ... |
| gmPP4YFrgYsYQqPYokMgFA | -UtYWvCnUppcSaC_u1pTYQ |  5.0  | ... |
+------------------------+------------------------+-------+-----+
[2272410 rows x 4 columns]
```

In [ ]:
```

```

In [ ]:
```

```