Third Project: Recommender System - MovieLens

Team members:

- Harry Bhasin
- Oscar Padilla

In [54]:
```
%load_ext watermark
%watermark -u -d -v -p numpy,pandas,matplotlib,sklearn
```

```
last updated: 2017-08-10

CPython 2.7.12
IPython 5.4.1

numpy 1.11.1
pandas 0.18.1
matplotlib 1.5.3
sklearn 0.18.1
```

TOC

- Background
- Load Data & Libraries
- Exploratory Data Analysis
- Model Building
  - User-Item
  - Item-Item
  - Popularity
- Evaluation
  - Item-Item
  - User-Item
  - Grid Search
- Deployment
- References

0. Background

MovieLens collects the movie rating data through their website and, GroupLens, a research department at the University of Minnesota does further research on this collected data. For our recommender project we decided to use this data as it fits very well in recommending movies using collaborative filtering. This data set consists of the following:

- Over a million ratings from 6040 users on 3952 movies.
- Each user has rated at least 20 movies.

Description of dataset

**** users.dat***

The user data set consists of 6040 items. There are four columns: user id, gender, age, occupation, zip. In the following format:

**** UserID::Gender::Age::Occupation::Zip-code***

- Gender is denoted by a "M" for male and "F" for female
- Age is chosen from the following ranges:
  - 1: "Under 18"
  - 18: "18-24"
  - 25: "25-34"
  - 35: "35-44"
  - 45: "45-49"
  - 50: "50-55"
  - 56: "56+"
- Occupation is chosen from the following choices:
  - 0: "other" or not specified
  - 1: "academic/educator"
  - 2: "artist"
  - 3: "clerical/admin"
  - 4: "college/grad student"
  - 5: "customer service"
  - 6: "doctor/health care"
  - 7: "executive/managerial"
  - 8: "farmer"
  - 9: "homemaker"
  - 10: "K-12 student"
  - 11: "lawyer"
  - 12: "programmer"
  - 13: "retired"
  - 14: "sales/marketing"
  - 15: "scientist"
  - 16: "self-employed"
  - 17: "technician/engineer"
  - 18: "tradesman/craftsman"
  - 19: "unemployed"
  - 20: "writer"

**** ratings.dat***

The ratings dataset consists of over a million records presented in four columns in the following format:

**** UserID::MovieID::Rating::Timestamp***

- UserIDs range between 1 and 6040
- MovieIDs range between 1 and 3952
- Ratings are made on a 5-star scale (whole-star ratings only)
- Timestamp is represented in seconds since the epoch as returned by time(2)
- Each user has at least 20 ratings

**** movies.dat***

The movies dataset consists of 3952 records presented in three columns in the following format:

**** MovieID::Title::Genres***

- Titles are identical to titles provided by the IMDB (including year of release)
- Genres are pipe-separated and are selected from the following genres:
  - Action
  - Adventure

Back to Top

1. Load Data & Libraries

Import 1m MovieLens dataset as panda DataFrame

In [2]:
```
import pandas as pd
import numpy as np

path = 'data/ml-1m/'

unames = ['user_id', 'gender', 'age', 'occupation', 'zip']
users = pd.read_table(path + 'users.dat', sep = '::', header = None, names = unames, engine='
python')

rnames = ['user_id', 'movie_id', 'rating', 'timestamp']
ratings = pd.read_table(path + 'ratings.dat', sep = '::', header = None, names = rnames, engi
ne='python')

mnames = ['movie_id', 'title', 'genres']
movies = pd.read_table(path + 'movies.dat', sep = '::', header = None, names = mnames, engine
='python')

print(users.shape)
print(ratings.shape)
print(movies.shape)
```

```
(6040, 5)
(1000209, 4)
(3883, 3)
```

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

Out[3]:

	movie_id	title	genres
0	1	Toy Story (1995)	Animation|Children's|Comedy
1	2	Jumanji (1995)	Adventure|Children's|Fantasy
2	3	Grumpier Old Men (1995)	Comedy|Romance
3	4	Waiting to Exhale (1995)	Comedy|Drama
4	5	Father of the Bride Part II (1995)	Comedy

Merging *movies, users* and *ratings* (on overlapping names: user_id, movie_id)

In [4]:
```
data = pd.merge(pd.merge(ratings, users), movies)
data.tail()
```

Out[4]:

	user_id	movie_id	rating	timestamp	gender	age	occupation	zip	title	genres
1000204	5949	2198	5	958846401	M	18	17	47901	Modulations (1998)	Documentary
1000205	5675	2703	3	976029116	M	35	14	30030	Broken Vessels (1998)	Drama
1000206	5780	2845	1	958153068	M	18	17	92886	White Boys (1999)	Drama
1000207	5851	3607	5	957756608	F	18	20	55410	One Little Indian (1973)	Comedy|Drama|Western
1000208	5938	2909	4	957273353	M	25	1	35401	Five Wives, Three Secretaries and Me (1998)	Documentary

Back to Top

2. EDA

Based on Python for Data Analysis

Contents of a specific row

In [5]:
```
data.ix[1000207]
```

Out[5]:
```
user_id                            5851
movie_id                           3607
rating                                5
timestamp                     957756608
gender                                F
age                                  18
occupation                           20
zip                               55410
title         One Little Indian (1973)
genres            Comedy|Drama|Western
Name: 1000207, dtype: object
```

pivot_table function on a DataFrame will construct a movie / gender rating matrix

In [6]:
```
mean_ratings = data.pivot_table(index = ['title'], columns = ['gender'], values = 'rating', a
ggfunc = 'mean')
mean_ratings[:10]
```

Out[6]:

gender	F	M
title		
$1,000,000 Duck (1971)	3.375000	2.761905
'Night Mother (1986)	3.388889	3.352941
'Til There Was You (1997)	2.675676	2.733333
'burbs, The (1989)	2.793478	2.962085
...And Justice for All (1979)	3.828571	3.689024
1-900 (1994)	2.000000	3.000000
10 Things I Hate About You (1999)	3.646552	3.311966
101 Dalmatians (1961)	3.791444	3.500000
101 Dalmatians (1996)	3.240000	2.911215
12 Angry Men (1957)	4.184397	4.328421

In [7]:
```
ratings_by_title = data.groupby('title').size()
ratings_by_title.head(10)
```

Out[7]:
```
title
$1,000,000 Duck (1971)               37
'Night Mother (1986)                 70
'Til There Was You (1997)            52
'burbs, The (1989)                  303
...And Justice for All (1979)       199
1-900 (1994)                          2
10 Things I Hate About You (1999)   700
101 Dalmatians (1961)               565
101 Dalmatians (1996)               364
12 Angry Men (1957)                 616
dtype: int64
```

Filter movies with at least *n* ratings

In [8]:
```
n = 250
active_titles = ratings_by_title.index[ratings_by_title >= n]
active_titles
```

Out[8]:
```
Index([u''burbs, The (1989)', u'10 Things I Hate About You (1999)',
       u'101 Dalmatians (1961)', u'101 Dalmatians (1996)',
       u'12 Angry Men (1957)', u'13th Warrior, The (1999)',
       u'2 Days in the Valley (1996)', u'20,000 Leagues Under the Sea (1954)',
       u'2001: A Space Odyssey (1968)', u'2010 (1984)',
       ...
       u'X-Men (2000)', u'Year of Living Dangerously (1982)',
       u'Yellow Submarine (1968)', u'You've Got Mail (1998)',
       u'Young Frankenstein (1974)', u'Young Guns (1988)',
       u'Young Guns II (1990)', u'Young Sherlock Holmes (1985)',
       u'Zero Effect (1998)', u'eXistenZ (1999)'],
      dtype='object', name=u'title', length=1216)
```

Now we select only active titles from the pivot table created above

In [9]:
```
mean_ratings = mean_ratings.ix[active_titles]
mean_ratings[:10]
```

Out[9]:

gender	F	M
title		
'burbs, The (1989)	2.793478	2.962085
10 Things I Hate About You (1999)	3.646552	3.311966
101 Dalmatians (1961)	3.791444	3.500000
101 Dalmatians (1996)	3.240000	2.911215
12 Angry Men (1957)	4.184397	4.328421
13th Warrior, The (1999)	3.112000	3.168000
2 Days in the Valley (1996)	3.488889	3.244813
20,000 Leagues Under the Sea (1954)	3.670103	3.709205
2001: A Space Odyssey (1968)	3.825581	4.129738
2010 (1984)	3.446809	3.413712

Top movies for female viewers

In [10]:
```
top_female_ratings = mean_ratings.sort_values(by = 'F', ascending = False)
top_female_ratings[:10]
```

Out[10]:

gender	F	M
title		
Close Shave, A (1995)	4.644444	4.473795
Wrong Trousers, The (1993)	4.588235	4.478261
Sunset Blvd. (a.k.a. Sunset Boulevard) (1950)	4.572650	4.464589
Wallace & Gromit: The Best of Aardman Animation (1996)	4.563107	4.385075
Schindler's List (1993)	4.562602	4.491415
Shawshank Redemption, The (1994)	4.539075	4.560625
Grand Day Out, A (1992)	4.537879	4.293255
To Kill a Mockingbird (1962)	4.536667	4.372611
Creature Comforts (1990)	4.513889	4.272277
Usual Suspects, The (1995)	4.513317	4.518248

Ratings difference male vs. female: movies preferred by women

In [11]:
```
mean_ratings['diff'] = mean_ratings['M'] - mean_ratings['F']
sorted_by_diff = mean_ratings.sort_values(by = 'diff')
sorted_by_diff[:15]
```

Out[11]:

gender	F	M	diff
title			
Dirty Dancing (1987)	3.790378	2.959596	-0.830782
Jumpin' Jack Flash (1986)	3.254717	2.578358	-0.676359
Grease (1978)	3.975265	3.367041	-0.608224
Little Women (1994)	3.870588	3.321739	-0.548849
Steel Magnolias (1989)	3.901734	3.365957	-0.535777
Anastasia (1997)	3.800000	3.281609	-0.518391
Rocky Horror Picture Show, The (1975)	3.673016	3.160131	-0.512885
Color Purple, The (1985)	4.158192	3.659341	-0.498851
Age of Innocence, The (1993)	3.827068	3.339506	-0.487561
Free Willy (1993)	2.921348	2.438776	-0.482573
French Kiss (1995)	3.535714	3.056962	-0.478752
Little Shop of Horrors, The (1960)	3.650000	3.179688	-0.470312
Guys and Dolls (1955)	4.051724	3.583333	-0.468391
Mary Poppins (1964)	4.197740	3.730594	-0.467147
Patch Adams (1998)	3.473282	3.008746	-0.464536

Movies preferred by men

In [12]:
```
sorted_by_diff[::-1][:15]
```

Out[12]:

gender	F	M	diff
title			
Good, The Bad and The Ugly, The (1966)	3.494949	4.221300	0.726351
Kentucky Fried Movie, The (1977)	2.878788	3.555147	0.676359
Dumb & Dumber (1994)	2.697987	3.336595	0.638608
Longest Day, The (1962)	3.411765	4.031447	0.619682
Cable Guy, The (1996)	2.250000	2.863787	0.613787
Evil Dead II (Dead By Dawn) (1987)	3.297297	3.909283	0.611985
Hidden, The (1987)	3.137931	3.745098	0.607167
Rocky III (1982)	2.361702	2.943503	0.581801
Caddyshack (1980)	3.396135	3.969737	0.573602
For a Few Dollars More (1965)	3.409091	3.953795	0.544704
Porky's (1981)	2.296875	2.836364	0.539489
Animal House (1978)	3.628906	4.167192	0.538286
Exorcist, The (1973)	3.537634	4.067239	0.529605
Fright Night (1985)	2.973684	3.500000	0.526316
Barb Wire (1996)	1.585366	2.100386	0.515020

Love it or Hate it: Movies with most disagreement among viewers (as measured per standard deviation)

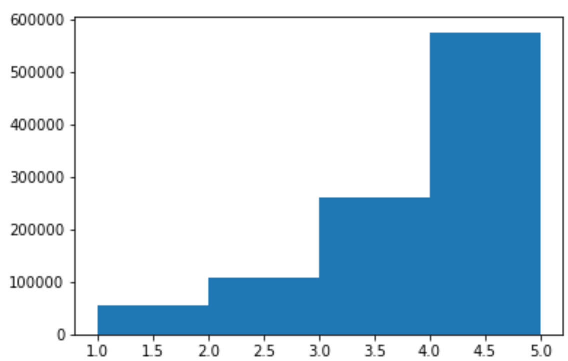
In [13]:
```
rating_std_by_title = data.groupby('title')['rating'].std()
rating_std_by_title = rating_std_by_title.ix[active_titles]
rating_std_by_title.sort_values(ascending = False)[:10]
```

Out[13]:
```
title
Dumb & Dumber (1994)                        1.321333
Blair Witch Project, The (1999)             1.316368
Natural Born Killers (1994)                 1.307198
Tank Girl (1995)                            1.277695
Rocky Horror Picture Show, The (1975)       1.260177
Eyes Wide Shut (1999)                       1.259624
Evita (1996)                                1.253631
Billy Madison (1995)                        1.249970
Fear and Loathing in Las Vegas (1998)       1.246408
Bicentennial Man (1999)                     1.245533
Name: rating, dtype: float64
```

Distribution of ratings: histogram

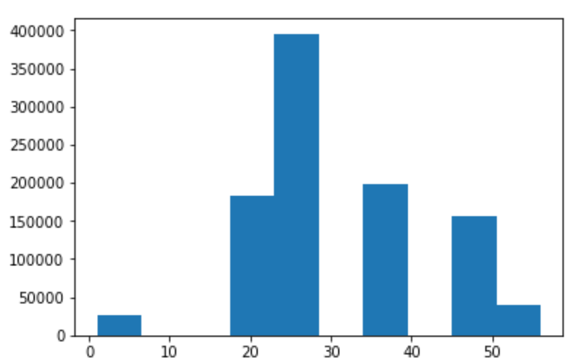
In [14]:
```
%matplotlib inline

import matplotlib.pyplot as plt

plt.hist(ratings.rating, bins = [1, 2, 3, 4, 5])
```

Out[14]:
```
(array([  56174.,  107557.,  261197.,  575281.]),
 array([1, 2, 3, 4, 5]),
 <a list of 4 Patch objects>)
```



In [15]:
```
plt.hist(data.age)
```

Out[15]:
```
(array([  27211.,       0.,       0.,  183536.,  395556.,       0.,
        199003.,       0.,  156123.,   38780.]),
 array([  1. ,   6.5,  12. ,  17.5,  23. ,  28.5,  34. ,  39.5,  45. ,
         50.5,  56. ]),
 <a list of 10 Patch objects>)
```



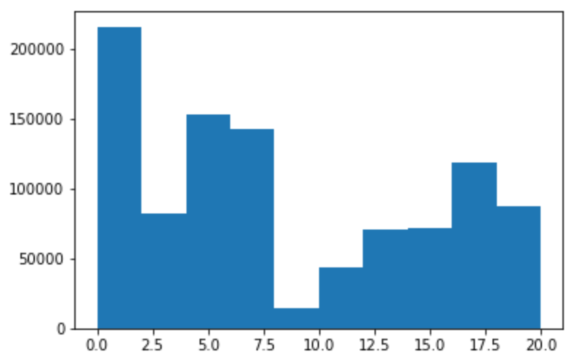
In [16]:
```
bins = [0, 25, 35, 45, 55, 100]
group_names = ['young', 'adult', 'mid-age', 'older', 'senior']

#categories = pd.cut(data['age'], bins, labels = group_names)
data['categories'] = pd.cut(data['age'], bins, labels = group_names)

data.head()
```

Out[16]:

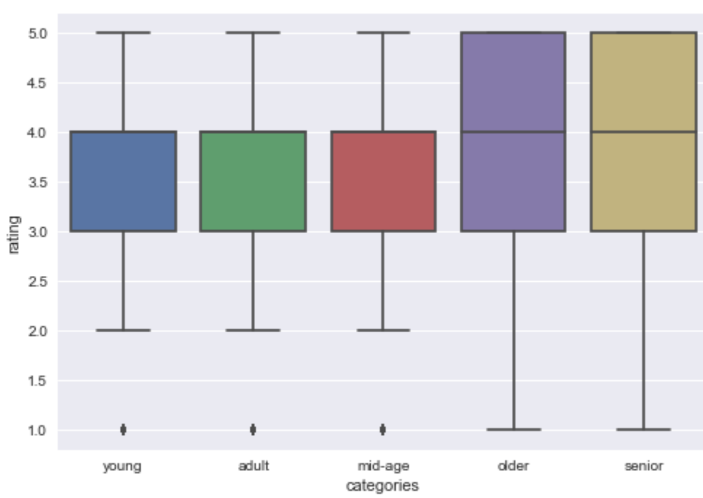
	user_id	movie_id	rating	timestamp	gender	age	occupation	zip	title	genres	categories
0	1	1193	5	978300760	F	1	10	48067	One Flew Over the Cuckoo's Nest (1975)	Drama	young
1	2	1193	5	978298413	M	56	16	70072	One Flew Over the Cuckoo's Nest (1975)	Drama	senior
2	12	1193	4	978220179	M	25	12	32793	One Flew Over the Cuckoo's Nest (1975)	Drama	young
3	15	1193	4	978199279	M	25	7	22903	One Flew Over the Cuckoo's Nest (1975)	Drama	young
4	17	1193	5	978158471	M	50	1	95350	One Flew Over the Cuckoo's Nest (1975)	Drama	older

In [17]:
```
plt.hist(data.occupation)
```

Out[17]:
```
(array([ 215850.,   81691.,  152882.,  142630.,   14051.,   43853.,
          70968.,   72060.,  118837.,   87387.]),
 array([  0.,   2.,   4.,   6.,   8.,  10.,  12.,  14.,  16.,  18.,  20.]),
 <a list of 10 Patch objects>)
```



In [18]:
```
import seaborn as sns

ax = sns.boxplot(x = "categories", y = "rating", data = data)
```



GraphLab

In [19]:
```
from os import path
import graphlab as gl
from datetime import datetime
```

```
---------------------------------------------------------------------------
ImportError                               Traceback (most recent call last)
<ipython-input-19-306b684c7233> in <module>()
      1 from os import path
----> 2 import graphlab as gl
      3 from datetime import datetime

ImportError: No module named graphlab
```

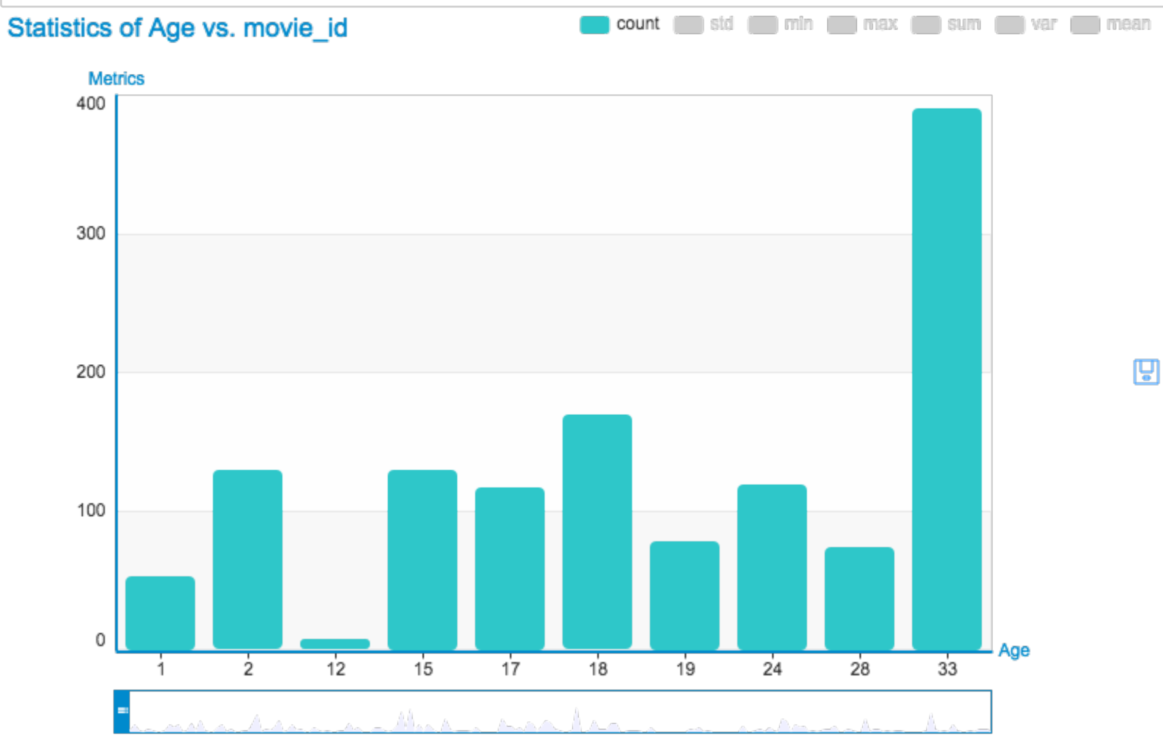
Convert Panda's DataFrames into GraphLab SFrames

In [101]:
```
items = gl.SFrame(movies)
actions = gl.SFrame(ratings)
users = gl.SFrame(users)
```

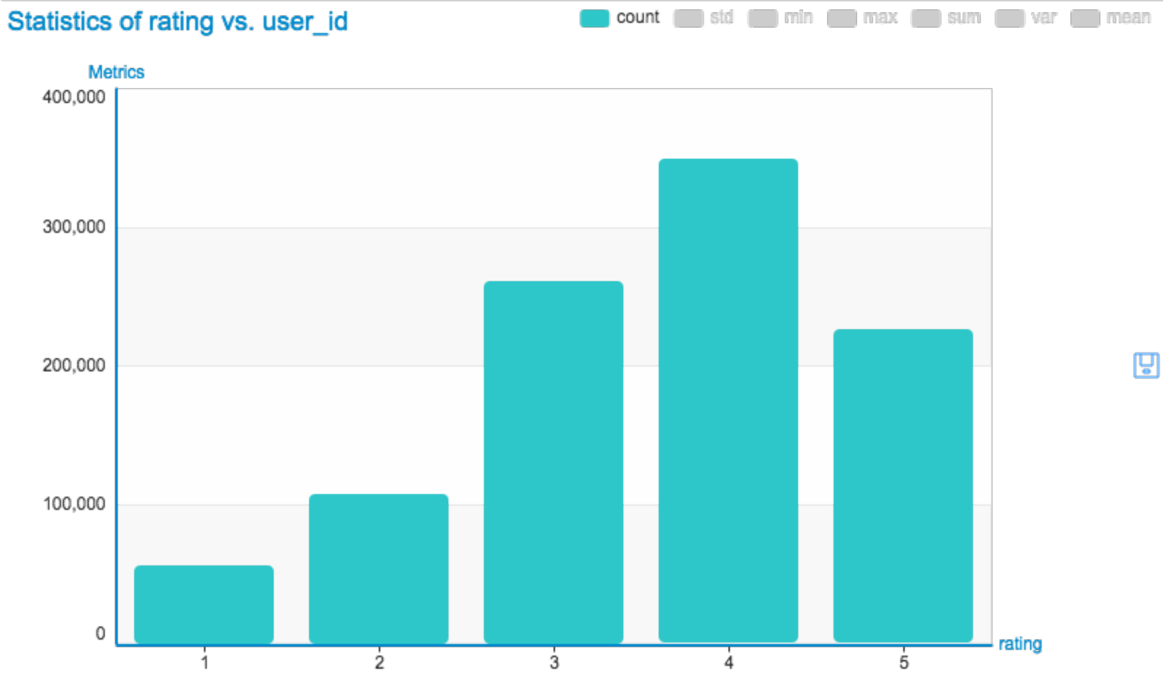
Importing the merged DataFrame into the GraphLab environment

In [107]:
```
data_gl = gl.SFrame(data)
```

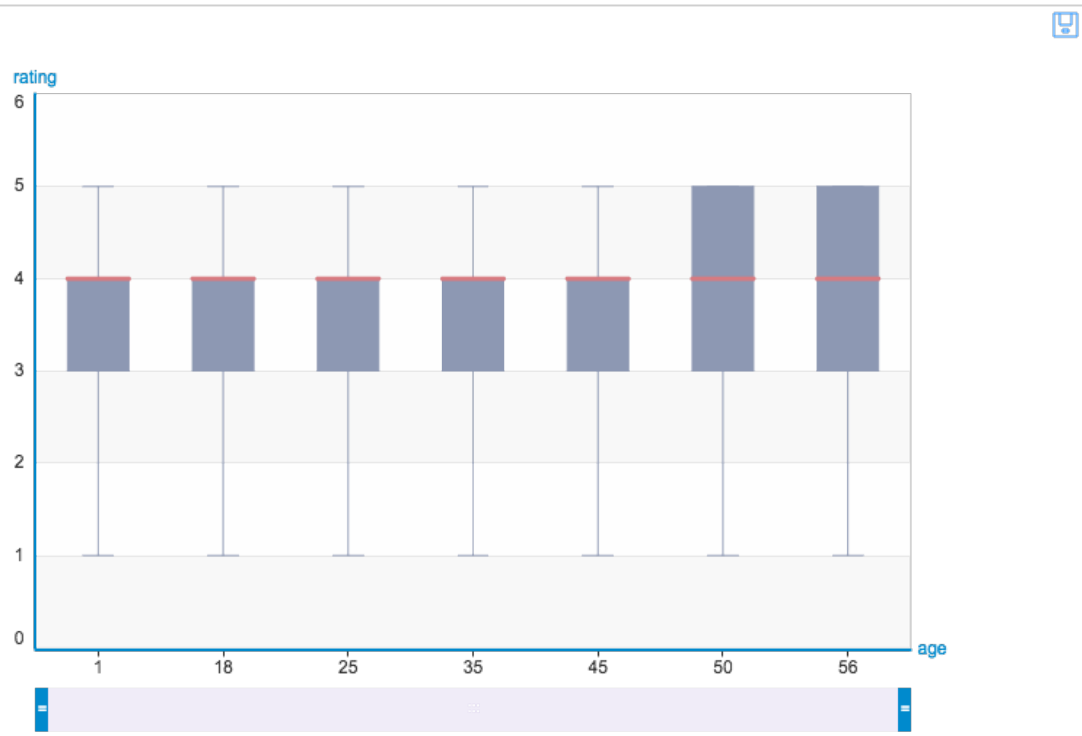
In [108]:
```
gl.canvas.set_target("ipynb")

data_gl.show(view = "Bar Chart", x = "Age", y=None)
```



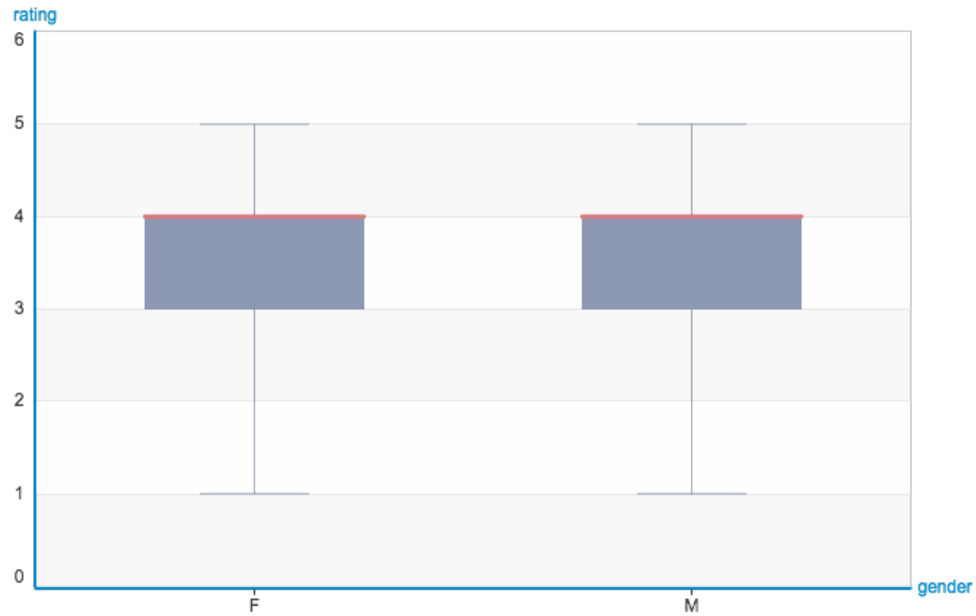
In [109]:
```
data_gl.show(view = "Bar Chart", x = "rating", y=None)
```



In [111]:
```
data_gl[["age", "rating"]].show(view = "BoxWhisker Plot", x = "age", y = "rating")
```



In [113]:
```
data_gl[["gender", "rating"]].show(view = "BoxWhisker Plot", x = "gender", y = "rating")
```



Data preparation: elimination of rare items, e.g. ratings count <= 5

In [11]:
```
rare_items = actions.groupby('movie_id', gl.aggregate.COUNT).sort('Count')
rare_items = rare_items[rare_items['Count'] <= 5]
items = items.filter_by(rare_items['movie_id'], 'movie_id', exclude=True)
actions = actions.filter_by(rare_items['movie_id'], 'movie_id', exclude=True)
actions['timestamp'] = actions['timestamp'].astype(datetime)
```

Extracting year from movie title and parsing genres

In [12]:
```
items['year'] = items['title'].apply(lambda x: x[-5:-1])
items['title'] = items['title'].apply(lambda x: x[:-7])
items['genres'] = items['genres'].apply(lambda x: x.split('|'))
```

[Back to Top](#)

3. Model Building

Train Recommender Model

In [14]:
```
training_data, validation_data = gl.recommender.util.random_split_by_user(actions, 'user_id',
'movie_id')
model = gl.recommender.create(training_data, 'user_id', 'movie_id')
```

```
Recsys training: model = item_similarity

Warning: Ignoring columns rating, timestamp;

    To use one of these as a target column, set target =

    and use a method that allows the use of a target.

Preparing data set.

    Data has 964251 observations with 6040 users and 3377 items.

    Data prepared in: 0.441962s

Training model from provided data.

Gathering per-item and per-user statistics.

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

| Elapsed Time (Item Statistics) | % Complete |

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

| 4.401ms                        | 16.5       |

| 27.212ms                       | 100        |

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

Setting up lookup tables.

Processing data in one pass using dense lookup tables.

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

| Elapsed Time (Constructing Lookups) | Total % Complete | Items Processed |

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

| 148.246ms                           | 0                | 0               |

| 886.549ms                           | 100              | 3377            |

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

Finalizing lookup tables.

Generating candidate set for working with new users.

Finished training in 1.94232s
```

Interactively explore & evaluate model

In [17]:
```
view = model.views.overview(validation_set = validation_data,
                            user_data = users,
                            item_data = items,
                            item_name_column = 'title')
view.show()
```

Back to Top

3.1 User-Item

"5-lines recommendation model" All code from here is based on Data Mining Notebook # 13 Collaborative Filtering in Turi (formerly Dato, Formerly GraphLab) by Eric Larsson

In [114]:
```
model = gl.recommender.create(data_gl, user_id = "user_id", item_id = "title", target = "rati
ng")
results = model.recommend(users = None, k = 15)
model.save("user_item")
```

```
Recsys training: model = ranking_factorization_recommender
Preparing data set.
    Data has 1000209 observations with 6040 users and 3706 items.
    Data prepared in: 1.55031s
Training ranking_factorization_recommender for recommendations.
+--------------------------------+--------------------------------------------------+--------
--+
| Parameter                      | Description                                      | Value
|
+--------------------------------+--------------------------------------------------+--------
--+
| num_factors                    | Factor Dimension                                 | 32
|
| regularization                 | L2 Regularization on Factors                     | 1e-09
|
| solver                         | Solver used for training                         | adagrad
|
| linear_regularization          | L2 Regularization on Linear Coefficients         | 1e-09
|
| ranking_regularization         | Rank-based Regularization Weight                 | 0.25
|
| max_iterations                 | Maximum Number of Iterations                     | 25
|
+--------------------------------+--------------------------------------------------+--------
--+
  Optimizing model using SGD; tuning step size.
  Using 125026 / 1000209 points for tuning the step size.
+---------+-------------------+------------------------------------------+
| Attempt | Initial Step Size | Estimated Objective Value                |
+---------+-------------------+------------------------------------------+
| 0       | 5.55556           | Not Viable                               |
| 1       | 1.38889           | Not Viable                               |
| 2       | 0.347222          | 0.824167                                 |
| 3       | 0.173611          | 1.20798                                  |
| 4       | 0.0868056         | 0.646125                                 |
| 5       | 0.0434028         | 0.717895                                 |
| 6       | 0.0217014         | 1.085                                    |
| 7       | 0.0108507         | 1.72713                                  |
+---------+-------------------+------------------------------------------+
| Final   | 0.0868056         | 0.646125                                 |
+---------+-------------------+------------------------------------------+
Starting Optimization.
+---------+--------------+-------------------+-----------------------+-------------+
| Iter.   | Elapsed Time | Approx. Objective | Approx. Training RMSE | Step Size   |
```

```
+---------+--------------+-------------------+----------------------+-------------+
| Initial | 103us        | 2.44693           | 1.11708              |             |
+---------+--------------+-------------------+----------------------+-------------+
| 1       | 2.67s        | DIVERGED          | DIVERGED             | 0.0868056   |
| RESET   | 3.64s        | 2.44701           | 1.11712              |             |
| 1       | 5.87s        | 3.90663           | 1.68493              | 0.0434028   |
| 2       | 7.86s        | 3.30251           | 1.6027               | 0.0434028   |
| 3       | 9.94s        | 1.87893           | 1.24141              | 0.0434028   |
| 4       | 11.80s       | 1.45959           | 1.0962               | 0.0434028   |
| 5       | 13.55s       | 1.30216           | 1.02512              | 0.0434028   |
| 6       | 15.28s       | 1.21993           | 0.994315             | 0.0434028   |
| 7       | 16.98s       | 1.15485           | 0.970963             | 0.0434028   |
| 8       | 18.68s       | 1.10102           | 0.95379              | 0.0434028   |
| 9       | 20.48s       | 1.06195           | 0.939376             | 0.0434028   |
| 10      | 22.32s       | 1.03362           | 0.929486             | 0.0434028   |
| 11      | 24.05s       | 1.01308           | 0.922706             | 0.0434028   |
| 12      | 25.71s       | 0.998079          | 0.917837             | 0.0434028   |
| 13      | 27.30s       | 0.982852          | 0.911275             | 0.0434028   |
| 14      | 28.98s       | 0.977212          | 0.911079             | 0.0434028   |
| 15      | 30.81s       | 0.96693           | 0.907214             | 0.0434028   |
| 16      | 32.58s       | 0.957616          | 0.903775             | 0.0434028   |
| 17      | 34.13s       | 0.954678          | 0.903094             | 0.0434028   |
| 18      | 35.67s       | 0.947747          | 0.900412             | 0.0434028   |
| 19      | 37.20s       | 0.944789          | 0.900455             | 0.0434028   |
| 20      | 38.73s       | 0.941145          | 0.898532             | 0.0434028   |
| 21      | 40.26s       | 0.939263          | 0.897955             | 0.0434028   |
| 22      | 41.78s       | 0.935198          | 0.896202             | 0.0434028   |
| 23      | 43.29s       | 0.931502          | 0.894985             | 0.0434028   |
| 24      | 44.80s       | 0.929998          | 0.894606             | 0.0434028   |
| 25      | 46.30s       | 0.926617          | 0.892427             | 0.0434028   |
+---------+--------------+-------------------+----------------------+-------------+
Optimization Complete: Maximum number of passes through the data reached.
Computing final objective value and training RMSE.
       Final objective value: 0.914895
       Final training RMSE: 0.885341
recommendations finished on 1000/6040 queries. users per second: 6362.29
recommendations finished on 2000/6040 queries. users per second: 6377.51
recommendations finished on 3000/6040 queries. users per second: 6360.39
recommendations finished on 4000/6040 queries. users per second: 6339.52
recommendations finished on 5000/6040 queries. users per second: 6337.4
```

```
recommendations finished on 6000/6040 queries. users per second: 6240.98
```

In [27]:
```
results
```

Out[27]:

user_id	title	score	rank
1	Stand by Me (1986)	4.80613530853	1
1	Fifth Element, The (1997)	4.65117407271	2
1	Go (1999)	4.64907295682	3
1	Star Wars: Episode VI - Return of the Jedi (1 ...	4.58215263911	4
1	Matrix, The (1999)	4.53050312453	5
2	Batman (1989)	4.35598371603	1
2	Rock, The (1996)	4.23964182713	2
2	Top Gun (1986)	4.21831451037	3
2	Nutty Professor, The (1996) ...	4.21780065873	4
2	Bug's Life, A (1998)	4.20996509173	5

[30200 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.

In [28]:
```
data_gl.head()
```

Out[28]:

user_id	movie_id	rating	timestamp	gender	age	occupation	zip	title	genres
1	1193	5	978300760	F	1	10	48067	One Flew Over the Cuckoo's Nest (1975) ...	Drama
2	1193	5	978298413	M	56	16	70072	One Flew Over the Cuckoo's Nest (1975) ...	Drama
12	1193	4	978220179	M	25	12	32793	One Flew Over the Cuckoo's Nest (1975) ...	Drama
15	1193	4	978199279	M	25	7	22903	One Flew Over the Cuckoo's Nest (1975) ...	Drama
17	1193	5	978158471	M	50	1	95350	One Flew Over the Cuckoo's Nest (1975) ...	Drama
18	1193	4	978156168	F	18	3	95825	One Flew Over the Cuckoo's Nest (1975) ...	Drama
19	1193	5	982730936	M	1	10	48073	One Flew Over the Cuckoo's Nest (1975) ...	Drama
24	1193	5	978136709	F	25	7	10023	One Flew Over the Cuckoo's Nest (1975) ...	Drama
28	1193	3	978125194	F	25	1	14607	One Flew Over the Cuckoo's Nest (1975)	Drama

Back to Top

3.2 Item-Item

In [116]:
```
density= float(data_gl.shape[0])/float(len(pd.unique(data_gl['user_id'])) *
                                       len(pd.unique(data_gl['movie_id'])) *
                                       len(pd.unique(data_gl['rating'])))
sparsity = 1 - density

print(sparsity)
```

```
0.991063274876
```

Based on the high (0.991) sparsity, cosine distance is more appropriate

In [117]:
```
item_item = gl.recommender.item_similarity_recommender.create(data_gl,
                                  user_id = "user_id",
                                  item_id = "title",
                                  target = "rating",
                                  only_top_k = 15,
                                  similarity_type = "cosine")

results = item_item.get_similar_items(k = 15)
results.head()
```

```
Recsys training: model = item_similarity

Warning: Ignoring columns movie_id, timestamp, gender, age, occupation, zip, genres;

    To use these columns in scoring predictions, use a model that allows the use of additiona
l features.

Preparing data set.

    Data has 1000209 observations with 6040 users and 3706 items.

    Data prepared in: 0.647663s

Training model from provided data.

Gathering per-item and per-user statistics.

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

| Elapsed Time (Item Statistics) | % Complete |

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

| 16.189ms                       | 16.5       |

| 37.315ms                       | 100        |

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

Setting up lookup tables.

Processing data in one pass using dense lookup tables.

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

| Elapsed Time (Constructing Lookups) | Total % Complete | Items Processed |

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

| 66.285ms                            | 0                | 0               |

| 952.509ms                           | 100              | 3706            |

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

Finalizing lookup tables.

Generating candidate set for working with new users.

Finished training in 1.04101s
```

Out[117]:

title	similar	score	rank
One Flew Over the Cuckoo's Nest (1975) ...	Godfather, The (1972)	0.538922727108	1
One Flew Over the Cuckoo's Nest (1975) ...	Fargo (1996)	0.529114544392	2
One Flew Over the Cuckoo's Nest (1975) ...	Shawshank Redemption, The (1994) ...	0.514273047447	3
One Flew Over the Cuckoo's Nest (1975) ...	Taxi Driver (1976)	0.512597680092	4
One Flew Over the Cuckoo's Nest (1975) ...	Graduate, The (1967)	0.512318372726	5
One Flew Over the Cuckoo's Nest (1975) ...	Amadeus (1984)	0.511262476444	6
One Flew Over the Cuckoo's Nest (1975) ...	Apocalypse Now (1979)	0.507278621197	7
One Flew Over the Cuckoo's Nest (1975) ...	Godfather: Part II, The (1974) ...	0.498695671558	8
One Flew Over the Cuckoo's Nest (1975) ...	Schindler's List (1993)	0.49817097187	9
One Flew Over the Cuckoo's Nest (1975) ...	Pulp Fiction (1994)	0.497593343258	10

[10 rows x 4 columns]

Back to Top

4. Evaluation

Data breakup into training and test

In [123]:
```
train, test = gl.recommender.util.random_split_by_user(data_gl,
                                                       user_id = "user_id", item_id = "title"
,
                                                       max_num_users = 10000, item_test_propo
rtion = 0.2)
```

In [124]:
```
len(train)
```

Out[124]: 800177

In [125]:
```
len(test)
```

Out[125]: 200032

Back to Top

4.1 Item-Item

In [126]:
```
from IPython.display import display
from IPython.display import Image

gl.canvas.set_target('ipynb')


item_item = gl.recommender.item_similarity_recommender.create(train,
                                  user_id = "user_id",
                                  item_id = "title",
                                  target = "rating",
                                  only_top_k = 25,
                                  similarity_type = "cosine")

rmse_results = item_item.evaluate(test)
```

```
Recsys training: model = item_similarity

Warning: Ignoring columns movie_id, timestamp, gender, age, occupation, zip, genres;

    To use these columns in scoring predictions, use a model that allows the use of additiona
l features.

Preparing data set.

    Data has 800177 observations with 6040 users and 3677 items.

    Data prepared in: 0.548545s

Training model from provided data.

Gathering per-item and per-user statistics.

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

| Elapsed Time (Item Statistics) | % Complete |

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

| 10.612ms                       | 16.5       |

| 30.9ms                         | 100        |

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

Setting up lookup tables.

Processing data in one pass using dense lookup tables.

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

| Elapsed Time (Constructing Lookups) | Total % Complete | Items Processed |

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

| 59.729ms                            | 0                | 0               |

| 702.274ms                           | 100              | 3677            |

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

Finalizing lookup tables.

Generating candidate set for working with new users.

Finished training in 0.762399s

recommendations finished on 1000/6037 queries. users per second: 20988.1

recommendations finished on 2000/6037 queries. users per second: 25562

recommendations finished on 3000/6037 queries. users per second: 27920.7

recommendations finished on 4000/6037 queries. users per second: 29280.4

recommendations finished on 5000/6037 queries. users per second: 29932.2

recommendations finished on 6000/6037 queries. users per second: 28824.3
```

```
Precision and recall summary statistics by cutoff
+--------+-----------------+------------------+
| cutoff | mean_precision  |   mean_recall    |
+--------+-----------------+------------------+
|   1    | 0.432002650323  | 0.0210899733997  |
|   2    | 0.405747888024  | 0.0384558886512  |
|   3    | 0.386505438684  | 0.0538605096694  |
|   4    | 0.367069736624  | 0.0664353018696  |
|   5    | 0.352426702004  | 0.0788688855294  |
|   6    | 0.338413119099  | 0.0893152404291  |
|   7    | 0.32693627393   | 0.0992976216165  |
|   8    | 0.317044889846  |  0.10872502924   |
|   9    | 0.308873060571  |  0.118185556364  |
|   10   | 0.299569322511  |  0.126349246049  |
+--------+-----------------+------------------+
[10 rows x 3 columns]

('\nOverall RMSE: ', 3.6773714442306926)

Per User RMSE (best)
+---------+-------+----------------+
| user_id | count |      rmse      |
+---------+-------+----------------+
|    4    |   1   | 0.371690618992 |
+---------+-------+----------------+
[1 rows x 3 columns]


Per User RMSE (worst)
+---------+-------+------+
| user_id | count | rmse |
+---------+-------+------+
|   4338  |   1   | 5.0  |
+---------+-------+------+
[1 rows x 3 columns]


Per Item RMSE (best)
+----------------+-------+----------------+
|     title      | count |      rmse      |
+----------------+-------+----------------+
| Century (1993) |   1   | 0.972215128251 |
+----------------+-------+----------------+
[1 rows x 3 columns]


Per Item RMSE (worst)
+-------------------------------+-------+------+
|             title             | count | rmse |
+-------------------------------+-------+------+
| Two or Three Things I Know... |   1   | 5.0  |
+-------------------------------+-------+------+
[1 rows x 3 columns]
```

In [127]:
```
print rmse_results.viewkeys()
```

```
dict_keys(['rmse_by_user', 'precision_recall_overall', 'rmse_by_item', 'precision_recall_by_u
ser', 'rmse_overall'])
```

In [128]:
```
rmse_results['rmse_by_item']
```

Out[128]:

title	count	rmse
Parent Trap, The (1998)	54	3.41011320465
Sneakers (1992)	220	3.76372074301
Man from Laramie, The (1955) ...	5	3.99325838832
Much Ado About Nothing (1993) ...	132	4.09793328035
X-Men (2000)	306	3.91439764803
Psycho (1998)	53	2.98915362295
Black Sabbath (Tre Volti Della Paura, I) (1963) ...	2	3.53453524366
Boondock Saints, The (1999) ...	19	3.45649655302
Drop Dead Fred (1991)	60	2.64513308129
Phantasm III: Lord of the Dead (1994) ...	14	3.0261447089

[3463 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.

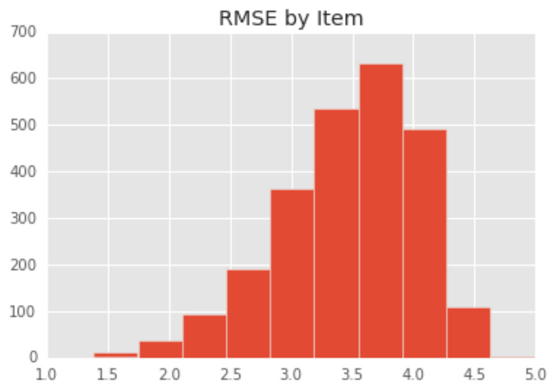
In [129]:
```
rmse_results['rmse_by_user']
```

Out[129]:

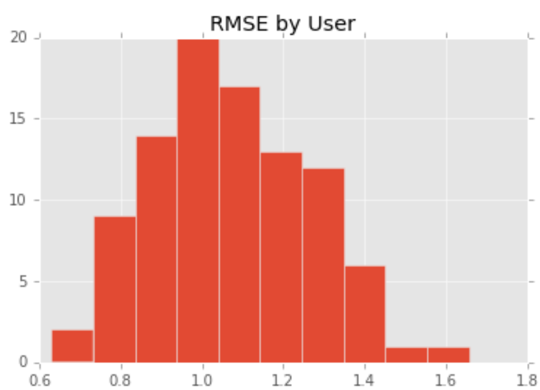
user_id	count	rmse
5288	8	3.70416139188
3143	36	3.50597692124
5684	95	3.77688126409
2779	33	3.80149631736
118	56	3.9018353489
3988	37	3.84118681622
5783	8	3.65595993975
2847	75	2.80578451918
5499	12	4.44373112793
5531	24	3.90787945931

[6037 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 [134]:
```
from matplotlib import pyplot as plt
%matplotlib inline
plt.style.use('ggplot')

rmsevals = rmse_results['rmse_by_item']['rmse']
rmsevals = rmsevals[rmse_results['rmse_by_item']['count'] > 10]

plt.hist(rmsevals, bins = 10)
plt.title('RMSE by Item')
plt.show()
```



In [69]:
```
from matplotlib import pyplot as plt
%matplotlib inline
plt.style.use('ggplot')

rmsevals = rmse_results['rmse_by_user']['rmse']
rmsevals = rmsevals[rmse_results['rmse_by_user']['count'] > 5]

plt.hist(rmsevals, bins = 10)
plt.title('RMSE by User')
plt.show()
```



Precision & Recall

In [37]:
```
rmse_results['precision_recall_by_user']
```

Out[37]:

user_id	cutoff	precision	recall	count
11	1	0.0	0.0	30
11	2	0.5	0.0333333333333	30
11	3	0.333333333333	0.0333333333333	30
11	4	0.25	0.0333333333333	30
11	5	0.4	0.0666666666667	30
11	6	0.333333333333	0.0666666666667	30
11	7	0.285714285714	0.0666666666667	30
11	8	0.25	0.0666666666667	30
11	9	0.222222222222	0.0666666666667	30
11	10	0.2	0.0666666666667	30

[1800 rows x 5 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 [38]:
```
import graphlab.aggregate as agg

agg_list = [agg.AVG('precision'),agg.STD('precision'),agg.AVG('recall'),agg.STD('recall')]

rmse_results['precision_recall_by_user'].groupby('cutoff',agg_list)
```

Out[38]:

cutoff	Avg of precision	Stdv of precision	Avg of recall	Stdv of recall
36	0.200277777778	0.166216753846	0.27624805404	0.124967878935
2	0.38	0.36823905279	0.0365450061209	0.0533931217992
46	0.18	0.151896641806	0.316741228943	0.132507160652
31	0.211935483871	0.175577240341	0.254322648222	0.125537656118
26	0.226538461538	0.183239665869	0.233224851885	0.117834923208
8	0.29	0.246779253585	0.10114753941	0.0825916547687
5	0.326	0.270784046797	0.0769256156073	0.076594010678
16	0.25625	0.203004772111	0.173224036516	0.100463877923
41	0.191463414634	0.159131155242	0.300390439691	0.128063510805
4	0.34	0.292660212533	0.0652058637624	0.0734827094785

[18 rows x 5 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.

Back to Top

4.2 User-Item

In [136]:
```
user_item = gl.recommender.ranking_factorization_recommender.create(train,
                                    user_id = "user_id",
                                    item_id = "title",
                                    target = "rating")

rmse_results = user_item.evaluate(test)
```

```
Recsys training: model = ranking_factorization_recommender
Preparing data set.
    Data has 800177 observations with 6040 users and 3677 items.
    Data prepared in: 1.27397s
Training ranking_factorization_recommender for recommendations.
+--------------------------------+--------------------------------------------------+--------
--+
| Parameter                      | Description                                      | Value
|
+--------------------------------+--------------------------------------------------+--------
--+
| num_factors                    | Factor Dimension                                 | 32
|
| regularization                 | L2 Regularization on Factors                     | 1e-09
|
| solver                         | Solver used for training                         | adagrad
|
| linear_regularization          | L2 Regularization on Linear Coefficients         | 1e-09
|
| ranking_regularization         | Rank-based Regularization Weight                 | 0.25
|
| max_iterations                 | Maximum Number of Iterations                     | 25
|
+--------------------------------+--------------------------------------------------+--------
--+
  Optimizing model using SGD; tuning step size.
  Using 100022 / 800177 points for tuning the step size.
+---------+-------------------+------------------------------------------+
| Attempt | Initial Step Size | Estimated Objective Value                |
+---------+-------------------+------------------------------------------+
| 0       | 5.55556           | Not Viable                               |
| 1       | 1.38889           | Not Viable                               |
| 2       | 0.347222          | Not Viable                               |
| 3       | 0.0868056         | 0.92645                                  |
| 4       | 0.0434028         | 0.723878                                 |
| 5       | 0.0217014         | 1.46887                                  |
+---------+-------------------+------------------------------------------+
| Final   | 0.0434028         | 0.723878                                 |
+---------+-------------------+------------------------------------------+
Starting Optimization.
+---------+--------------+-------------------+-----------------------+-------------+
| Iter.   | Elapsed Time | Approx. Objective | Approx. Training RMSE | Step Size   |
+---------+--------------+-------------------+-----------------------+-------------+
| Initial | 95us         | 2.44595           | 1.11696               |             |
```

```
+---------+--------------+-------------------+----------------------+-------------+
| 1       | 2.40s        | DIVERGED          | DIVERGED             | 0.0434028   |
| RESET   | 3.16s        | 2.4463            | 1.117                |             |
| 1       | 5.01s        | 1.75216           | 1.08099              | 0.0217014   |
| 2       | 6.80s        | 1.35801           | 0.976769             | 0.0217014   |
| 3       | 8.60s        | 1.33836           | 0.996168             | 0.0217014   |
| 4       | 10.22s       | 1.39974           | 1.0326               | 0.0217014   |
| 5       | 11.80s       | 1.35495           | 1.02325              | 0.0217014   |
| 6       | 13.36s       | 1.32318           | 1.01731              | 0.0217014   |
| 7       | 14.89s       | 1.28717           | 1.00637              | 0.0217014   |
| 8       | 16.36s       | 1.26941           | 1.00217              | 0.0217014   |
| 9       | 17.85s       | 1.24433           | 0.993703             | 0.0217014   |
| 10      | 19.23s       | 1.25311           | 0.99852              | 0.0217014   |
| 11      | 20.59s       | 1.22235           | 0.986533             | 0.0217014   |
| 12      | 22.09s       | 1.21701           | 0.984777             | 0.0217014   |
| 13      | 23.63s       | 1.20351           | 0.980044             | 0.0217014   |
| 14      | 25.18s       | 1.19516           | 0.977334             | 0.0217014   |
| 15      | 26.65s       | 1.18604           | 0.974102             | 0.0217014   |
| 16      | 28.13s       | 1.18885           | 0.976827             | 0.0217014   |
| 17      | 29.53s       | 1.16565           | 0.965818             | 0.0217014   |
| 18      | 30.92s       | 1.16858           | 0.966914             | 0.0217014   |
| 19      | 32.40s       | 1.15199           | 0.960259             | 0.0217014   |
| 20      | 33.78s       | 1.15421           | 0.962962             | 0.0217014   |
| 21      | 35.10s       | 1.1423            | 0.957522             | 0.0217014   |
| 22      | 36.76s       | 1.13213           | 0.953483             | 0.0217014   |
| 23      | 38.21s       | 1.13219           | 0.954238             | 0.0217014   |
| 24      | 39.57s       | 1.11879           | 0.948584             | 0.0217014   |
| 25      | 40.98s       | 1.1134            | 0.946701             | 0.0217014   |
+---------+--------------+-------------------+----------------------+-------------+
Optimization Complete: Maximum number of passes through the data reached.
Computing final objective value and training RMSE.
       Final objective value: 1.09663
       Final training RMSE: 0.937989
recommendations finished on 1000/6037 queries. users per second: 5686.86
recommendations finished on 2000/6037 queries. users per second: 5807.2
recommendations finished on 3000/6037 queries. users per second: 5903.63
recommendations finished on 4000/6037 queries. users per second: 5955.05
recommendations finished on 5000/6037 queries. users per second: 5990.03
recommendations finished on 6000/6037 queries. users per second: 5912.77
```

```
Precision and recall summary statistics by cutoff
+--------+-----------------+------------------+
| cutoff |  mean_precision |   mean_recall    |
+--------+-----------------+------------------+
|   1    |  0.115620341229 | 0.00395175487979 |
|   2    |  0.109325824085 | 0.00720194420416 |
|   3    |  0.103307382254 | 0.00993475861744 |
|   4    |  0.100588040417 |  0.012766008109  |
|   5    | 0.0973662415107 | 0.0153614683872  |
|   6    | 0.0951355529789 | 0.0180561728147  |
|   7    | 0.0928322960789 | 0.0205809938671  |
|   8    |  0.090359450058 | 0.0229492957761  |
|   9    | 0.0885097454586 | 0.0255601591297  |
|   10   | 0.0864667881398 | 0.0277278560888  |
+--------+-----------------+------------------+
[10 rows x 3 columns]

('\nOverall RMSE: ', 1.0600954257239266)

Per User RMSE (best)
+---------+-------+----------------+
| user_id | count |      rmse      |
+---------+-------+----------------+
|   373   |   1   | 0.127437317788 |
+---------+-------+----------------+
[1 rows x 3 columns]


Per User RMSE (worst)
+---------+-------+---------------+
| user_id | count |      rmse     |
+---------+-------+---------------+
|   3113  |   5   | 4.57797478083 |
+---------+-------+---------------+
[1 rows x 3 columns]


Per Item RMSE (best)
+----------------------------+-------+------------------+
|           title            | count |       rmse       |
+----------------------------+-------+------------------+
| Uninvited Guest, An (2000) |   1   | 0.00635918320534 |
+----------------------------+-------+------------------+
[1 rows x 3 columns]


Per Item RMSE (worst)
+------------------------+-------+---------------+
|         title          | count |      rmse     |
+------------------------+-------+---------------+
| Billy's Holiday (1995) |   1   | 6.66371960458 |
+------------------------+-------+---------------+
[1 rows x 3 columns]
```

In [137]:
```
rmse_results['precision_recall_by_user'].groupby('cutoff',[agg.AVG('precision'),agg.STD('prec
ision'),agg.AVG('recall'),agg.STD('recall')])
```

Out[137]:

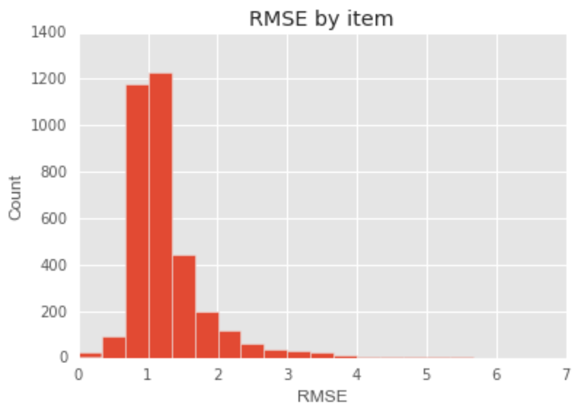
cutoff	Avg of precision	Stdv of precision	Avg of recall	Stdv of recall
36	0.0694375425616	0.0919550600307	0.0813871833527	0.0933468625418
2	0.109325824085	0.240039253355	0.00720194420416	0.0243254379396
46	0.0659771985798	0.0849361371357	0.0990916485079	0.102760837876
31	0.0711953704842	0.0960718199412	0.0714448486586	0.0872754011638
26	0.0739223506326	0.101338904683	0.0626773685444	0.0807455795319
8	0.090359450058	0.148003202062	0.0229492957761	0.0463515463475
5	0.0973662415107	0.174395533468	0.0153614683872	0.0367337795136
16	0.0798823919165	0.116795400432	0.041691649143	0.0648863178078
41	0.0674499125313	0.0880359565851	0.0903135399254	0.0982406321046
4	0.100588040417	0.188377909926	0.012766008109	0.0327284811901

[18 rows x 5 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 [139]:
```
print rmse_results.viewkeys()
print rmse_results['rmse_by_item']
```

```
dict_keys(['rmse_by_user', 'precision_recall_overall', 'rmse_by_item', 'precision_recall_by_u
ser', 'rmse_overall'])
+-------------------------------+-------+-----------------+
|             title             | count |       rmse      |
+-------------------------------+-------+-----------------+
|    Parent Trap, The (1998)    |   54  | 0.921548548681  |
|        Sneakers (1992)        |  220  |  0.8547413354   |
|  Man from Laramie, The (1955) |   5   |  1.56934482819  |
| Much Ado About Nothing (1993) |  132  | 0.955812859708  |
|         X-Men (2000)          |  306  | 0.977373415089  |
|         Psycho (1998)         |   53  |  1.1323777249   |
| Black Sabbath (Tre Volti D... |   2   |  1.61740222095  |
|  Boondock Saints, The (1999)  |   19  |  2.07716212832  |
|     Drop Dead Fred (1991)     |   60  | 0.965476862456  |
| Phantasm III: Lord of the ... |   14  |  1.60811593485  |
+-------------------------------+-------+-----------------+
[3463 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 [140]:
```
from matplotlib import pyplot as plt
%matplotlib inline
plt.style.use('ggplot')
rmsevals=rmse_results['rmse_by_item']['rmse']
plt.hist(rmsevals, bins=20)
plt.xlabel('RMSE')
plt.ylabel('Count')
plt.title('RMSE by item')
plt.show()
```



Tuned Parameters

In [141]:
```
tuned = gl.recommender.ranking_factorization_recommender.create(train,
                                  user_id = "user_id",
                                  item_id = "title",
                                  target = "rating",
                                  num_factors = 16,                 # override the default va
lue
                                  regularization = 0.01,           # override the default val
ue
                                  linear_regularization = 0.001)   # override the default val
ue

rmse_results = tuned.evaluate(test)
```

```
Recsys training: model = ranking_factorization_recommender
Preparing data set.
    Data has 800177 observations with 6040 users and 3677 items.
    Data prepared in: 1.22614s
Training ranking_factorization_recommender for recommendations.
+--------------------------------+--------------------------------------------------+--------
--+
| Parameter                      | Description                                      | Value
|
+--------------------------------+--------------------------------------------------+--------
--+
| num_factors                    | Factor Dimension                                 | 16
|
| regularization                 | L2 Regularization on Factors                     | 0.01
|
| solver                         | Solver used for training                         | adagrad
|
| linear_regularization          | L2 Regularization on Linear Coefficients         | 0.001
|
| ranking_regularization         | Rank-based Regularization Weight                 | 0.25
|
| max_iterations                 | Maximum Number of Iterations                     | 25
|
+--------------------------------+--------------------------------------------------+--------
--+
  Optimizing model using SGD; tuning step size.
  Using 100022 / 800177 points for tuning the step size.
+---------+-------------------+------------------------------------------+
| Attempt | Initial Step Size | Estimated Objective Value                |
+---------+-------------------+------------------------------------------+
| 0       | 0.00920788        | 2.04109                                  |
| 1       | 0.00460394        | 2.08087                                  |
| 2       | 0.00230197        | 2.12445                                  |
| 3       | 0.00115098        | 2.16827                                  |
+---------+-------------------+------------------------------------------+
| Final   | 0.00920788        | 2.04109                                  |
+---------+-------------------+------------------------------------------+
Starting Optimization.
+---------+--------------+-------------------+-----------------------+-------------+
| Iter.   | Elapsed Time | Approx. Objective | Approx. Training RMSE | Step Size   |
+---------+--------------+-------------------+-----------------------+-------------+
| Initial | 76us         | 2.446             | 1.11695               |             |
+---------+--------------+-------------------+-----------------------+-------------+
| 1       | 1.50s        | 2.14202           | 1.10985               | 0.00920788  |
```

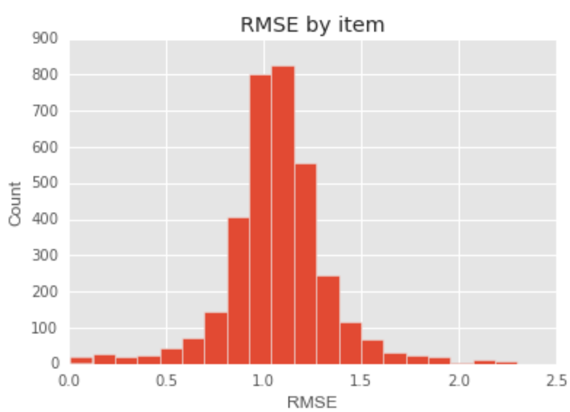
```
| 2       | 2.94s        | 2.1083           | 1.13488              | 0.00920788  |
| 3       | 4.34s        | 2.04254          | 1.11514              | 0.00920788  |
| 4       | 5.77s        | 2.0179           | 1.09882              | 0.00920788  |
| 5       | 7.23s        | 2.00611          | 1.08928              | 0.00920788  |
| 6       | 11.62s       | 1.99985          | 1.08422              | 0.00920788  |
| 7       | 12.96s       | 1.99639          | 1.07819              | 0.00920788  |
| 8       | 14.36s       | 1.99457          | 1.0759               | 0.00920788  |
| 9       | 15.77s       | 1.99324          | 1.07303              | 0.00920788  |
| 10      | 17.22s       | 1.99252          | 1.0707               | 0.00920788  |
| 11      | 18.72s       | 1.99238          | 1.06849              | 0.00920788  |
| 12      | 20.20s       | 1.99249          | 1.0678               | 0.00920788  |
| 13      | 21.52s       | 1.99212          | 1.06644              | 0.00920788  |
| 14      | 22.81s       | 1.99245          | 1.06517              | 0.00920788  |
| 15      | 24.14s       | 1.99268          | 1.06443              | 0.00920788  |
| 16      | 25.52s       | 1.99288          | 1.06367              | 0.00920788  |
| 17      | 26.85s       | 1.99287          | 1.06261              | 0.00920788  |
| 18      | 28.17s       | 1.99325          | 1.06242              | 0.00920788  |
| 19      | 29.53s       | 1.99327          | 1.06156              | 0.00920788  |
| 20      | 30.90s       | 1.99332          | 1.06218              | 0.00920788  |
| 21      | 32.25s       | 1.99398          | 1.06026              | 0.00920788  |
| 22      | 33.58s       | 1.99397          | 1.06093              | 0.00920788  |
| 23      | 34.89s       | 1.99407          | 1.06011              | 0.00920788  |
| 24      | 36.20s       | 1.9942           | 1.05987              | 0.00920788  |
| 25      | 37.52s       | 1.99424          | 1.05992              | 0.00920788  |
+---------+--------------+------------------+----------------------+-------------+
Optimization Complete: Maximum number of passes through the data reached.
Computing final objective value and training RMSE.
       Final objective value: 2.01029
       Final training RMSE: 1.05687
recommendations finished on 1000/6037 queries. users per second: 7507.51
recommendations finished on 2000/6037 queries. users per second: 7573
recommendations finished on 3000/6037 queries. users per second: 7590.57
recommendations finished on 4000/6037 queries. users per second: 7600.18
recommendations finished on 5000/6037 queries. users per second: 7595.48
recommendations finished on 6000/6037 queries. users per second: 7546.14
```

```
Precision and recall summary statistics by cutoff
+--------+-----------------+------------------+
| cutoff | mean_precision  |   mean_recall    |
+--------+-----------------+------------------+
|   1    | 0.234719231406  | 0.00918385175136 |
|   2    | 0.205068742753  | 0.0147712382536  |
|   3    | 0.196676053227  |  0.020587220923  |
|   4    | 0.191692893821  | 0.0272190362335  |
|   5    | 0.188570482027  | 0.0338368097455  |
|   6    | 0.18762078295   | 0.0418914951166  |
|   7    | 0.184031803876  | 0.0479747915908  |
|   8    | 0.178234222296  |  0.053165050724  |
|   9    | 0.173044006405  | 0.0577342925973  |
|   10   | 0.169239688587  | 0.0629528662764  |
+--------+-----------------+------------------+
[10 rows x 3 columns]

('\nOverall RMSE: ', 1.062040776320665)

Per User RMSE (best)
+---------+-------+-----------------+
| user_id | count |       rmse      |
+---------+-------+-----------------+
|   1190  |   1   | 0.0262226963412 |
+---------+-------+-----------------+
[1 rows x 3 columns]


Per User RMSE (worst)
+---------+-------+---------------+
| user_id | count |      rmse     |
+---------+-------+---------------+
|   1102  |   5   | 2.34008470395 |
+---------+-------+---------------+
[1 rows x 3 columns]


Per Item RMSE (best)
+---------------------------+-------+------------------+
|           title           | count |       rmse       |
+---------------------------+-------+------------------+
| Mummy's Ghost, The (1944) |   1   | 0.00793184316609 |
+---------------------------+-------+------------------+
[1 rows x 3 columns]


Per Item RMSE (worst)
+-------------------------------+-------+---------------+
|             title             | count |      rmse     |
+-------------------------------+-------+---------------+
| Across the Sea of Time (1995) |   1   | 2.29944664052 |
+-------------------------------+-------+---------------+
[1 rows x 3 columns]
```

In [144]:
```
print rmse_results.viewkeys()
print rmse_results['rmse_by_item']
```

```
dict_keys(['rmse_by_user', 'precision_recall_overall', 'rmse_by_item', 'precision_recall_by_u
ser', 'rmse_overall'])
+-------------------------------+-------+----------------+
|             title             | count |      rmse      |
+-------------------------------+-------+----------------+
|    Parent Trap, The (1998)    |   54  | 0.975727386839 |
|        Sneakers (1992)        |  220  | 0.942227855552 |
|  Man from Laramie, The (1955) |   5   | 0.702016846559 |
| Much Ado About Nothing (1993) |  132  | 1.15290278113  |
|         X-Men (2000)          |  306  | 1.02087179202  |
|         Psycho (1998)         |   53  | 1.10291216465  |
| Black Sabbath (Tre Volti D... |   2   | 0.902213868132 |
|  Boondock Saints, The (1999)  |   19  | 1.40181830033  |
|     Drop Dead Fred (1991)     |   60  | 1.00999418636  |
| Phantasm III: Lord of the ... |   14  | 1.04484528439  |
+-------------------------------+-------+----------------+
[3463 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 [145]:
```
from matplotlib import pyplot as plt
%matplotlib inline
plt.style.use('ggplot')
rmsevals=rmse_results['rmse_by_item']['rmse']
plt.hist(rmsevals, bins=20)
plt.xlabel('RMSE')
plt.ylabel('Count')
plt.title('RMSE by item')
plt.show()
```

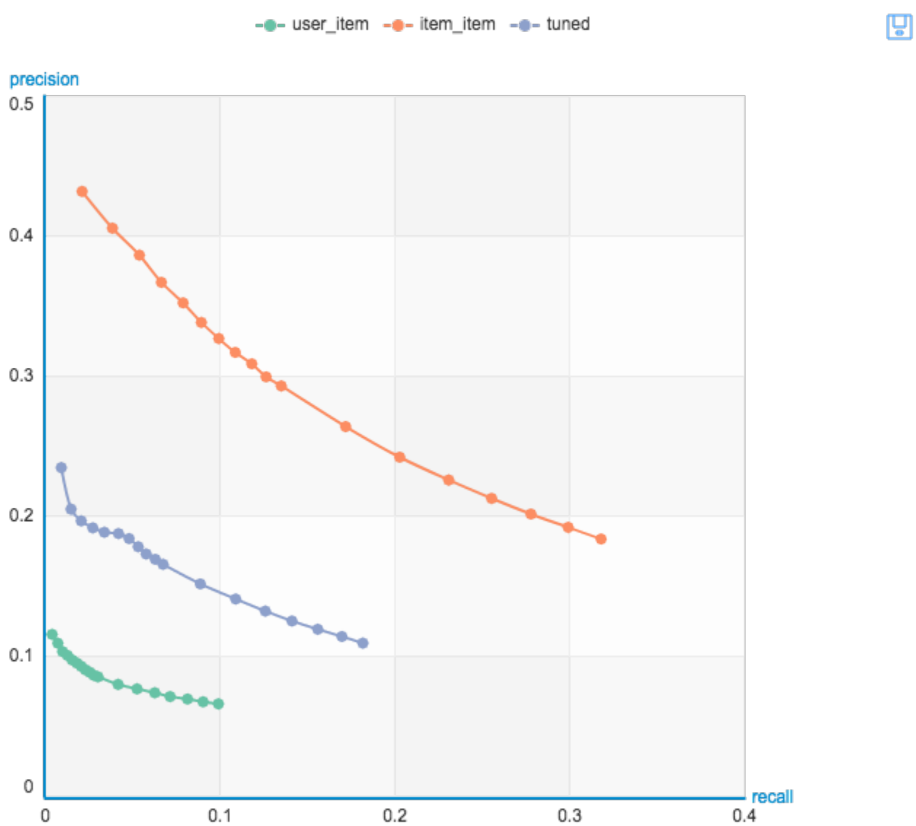


In [142]:
```
comparisonstruct = gl.compare(test,[item_item, user_item, tuned])
```

```
PROGRESS: Evaluate model M0

recommendations finished on 1000/6037 queries. users per second: 19740.6

recommendations finished on 2000/6037 queries. users per second: 23596

recommendations finished on 3000/6037 queries. users per second: 26298.5

recommendations finished on 4000/6037 queries. users per second: 28373.4

recommendations finished on 5000/6037 queries. users per second: 29426.8

recommendations finished on 6000/6037 queries. users per second: 29616.5

Precision and recall summary statistics by cutoff
+--------+----------------+-----------------+
| cutoff | mean_precision |   mean_recall   |
+--------+----------------+-----------------+
|   1    | 0.432002650323 | 0.0210899733997 |
|   2    | 0.405747888024 | 0.0384558886512 |
|   3    | 0.386505438684 | 0.0538605096694 |
|   4    | 0.367069736624 | 0.0664353018696 |
|   5    | 0.352426702004 | 0.0788688855294 |
|   6    | 0.338413119099 | 0.0893152404291 |
|   7    | 0.32693627393  | 0.0992976216165 |
|   8    | 0.317044889846 |  0.10872502924  |
|   9    | 0.308873060571 |  0.118185556364 |
|   10   | 0.299569322511 |  0.126349246049 |
+--------+----------------+-----------------+
[10 rows x 3 columns]

PROGRESS: Evaluate model M1

recommendations finished on 1000/6037 queries. users per second: 5882.42

recommendations finished on 2000/6037 queries. users per second: 5971.59

recommendations finished on 3000/6037 queries. users per second: 5952.36

recommendations finished on 4000/6037 queries. users per second: 5991.64

recommendations finished on 5000/6037 queries. users per second: 6000.17

recommendations finished on 6000/6037 queries. users per second: 5858.88

Precision and recall summary statistics by cutoff
+--------+-----------------+------------------+
| cutoff |  mean_precision |   mean_recall    |
+--------+-----------------+------------------+
|   1    |  0.115620341229 | 0.00395175487979 |
|   2    |  0.109325824085 | 0.00720194420416 |
|   3    |  0.103307382254 | 0.00993475861744 |
|   4    |  0.100588040417 |  0.012766008109  |
|   5    | 0.0973662415107 | 0.0153614683872  |
|   6    | 0.0951355529789 | 0.0180561728147  |
|   7    | 0.0928322960789 | 0.0205809938671  |
|   8    |  0.090359450058 | 0.0229492957761  |
|   9    | 0.0885097454586 | 0.0255601591297  |
|   10   | 0.0864667881398 | 0.0277278560888  |
+--------+-----------------+------------------+
[10 rows x 3 columns]

PROGRESS: Evaluate model M2

recommendations finished on 1000/6037 queries. users per second: 7497.94

recommendations finished on 2000/6037 queries. users per second: 7628.93

recommendations finished on 3000/6037 queries. users per second: 7661.07

recommendations finished on 4000/6037 queries. users per second: 7600.36

recommendations finished on 5000/6037 queries. users per second: 7650.4

recommendations finished on 6000/6037 queries. users per second: 7585.26
```

```
Precision and recall summary statistics by cutoff
+--------+----------------+------------------+
| cutoff | mean_precision |   mean_recall    |
+--------+----------------+------------------+
|   1    | 0.234719231406 | 0.00918385175136 |
|   2    | 0.205068742753 | 0.0147712382536  |
|   3    | 0.196676053227 |  0.020587220923  |
|   4    | 0.191692893821 | 0.0272190362335  |
|   5    | 0.188570482027 | 0.0338368097455  |
|   6    | 0.18762078295  | 0.0418914951166  |
|   7    | 0.184031803876 | 0.0479747915908  |
|   8    | 0.178234222296 |  0.053165050724  |
|   9    | 0.173044006405 | 0.0577342925973  |
|   10   | 0.169239688587 | 0.0629528662764  |
+--------+----------------+------------------+
[10 rows x 3 columns]

Model compare metric: precision_recall
```

In [143]:
```
gl.show_comparison(comparisonstruct,[item_item, user_item, tuned])
```



Back to Top

4.3 Grid Search

In [45]:
```
params = {'user_id': 'user_id',
          'item_id': 'title',
          'target': 'rating',
          'num_factors': [8, 12, 16, 24, 32],
          'regularization':[0.001] ,
          'linear_regularization': [0.001]}

job = gl.model_parameter_search.create( (train,test),
        gl.recommender.ranking_factorization_recommender.create,
        params,
        max_models = 5,
        environment = None)
```

```
[INFO] graphlab.deploy.job: Validating job.
[INFO] graphlab.deploy.job: Creating a LocalAsync environment called 'async'.
[INFO] graphlab.deploy.map_job: Validation complete. Job: 'Model-Parameter-Search-Aug-09-2017
-23-07-1800000' ready for execution
[INFO] graphlab.deploy.map_job: Job: 'Model-Parameter-Search-Aug-09-2017-23-07-1800000' sched
uled.
[INFO] graphlab.deploy.job: Validating job.
[INFO] graphlab.deploy.map_job: A job with name 'Model-Parameter-Search-Aug-09-2017-23-07-180
0000' already exists. Renaming the job to 'Model-Parameter-Search-Aug-09-2017-23-07-1800000-f
1e09'.
[INFO] graphlab.deploy.map_job: Validation complete. Job: 'Model-Parameter-Search-Aug-09-2017
-23-07-1800000-f1e09' ready for execution
[INFO] graphlab.deploy.map_job: Job: 'Model-Parameter-Search-Aug-09-2017-23-07-1800000-f1e09'
scheduled.
```

In [49]:
```
job.get_status()
```

Out[49]:
```
{'Canceled': 0, 'Completed': 5, 'Failed': 0, 'Pending': 0, 'Running': 0}
```

In [48]:
```
job_result = job.get_results()

job_result.head()
```

Out[48]:

model_id	item_id	linear_regularization	max_iterations	num_factors	num_sampled_negative_examples ...
1	title	0.001	50	12	8
0	title	0.001	25	32	4
3	title	0.001	25	8	8
2	title	0.001	50	16	4
4	title	0.001	25	12	4

regularization	target	user_id	training_precision@5	training_recall@5	training_rmse	validation
0.001	rating	user_id	0.451390728477	0.0210706980023	1.03693392809	(
0.001	rating	user_id	0.444834437086	0.0204716712727	1.08117400197	(
0.001	rating	user_id	0.460099337748	0.0215576169584	1.07826416323	(
0.001	rating	user_id	0.450927152318	0.0210438105479	1.06122767649	(
0.001	rating	user_id	0.448344370861	0.0215513867823	1.16327495325	(

validation_recall@5	validation_rmse
0.0188589142706	1.03388054098
0.0292013486135	1.07909429305
0.0224720473503	1.07294212265
0.020050006245	1.05586487914
0.02549362349	1.15627797323

[5 rows x 16 columns]

In [50]:
```
bst_prms = job.get_best_params()
bst_prms
```

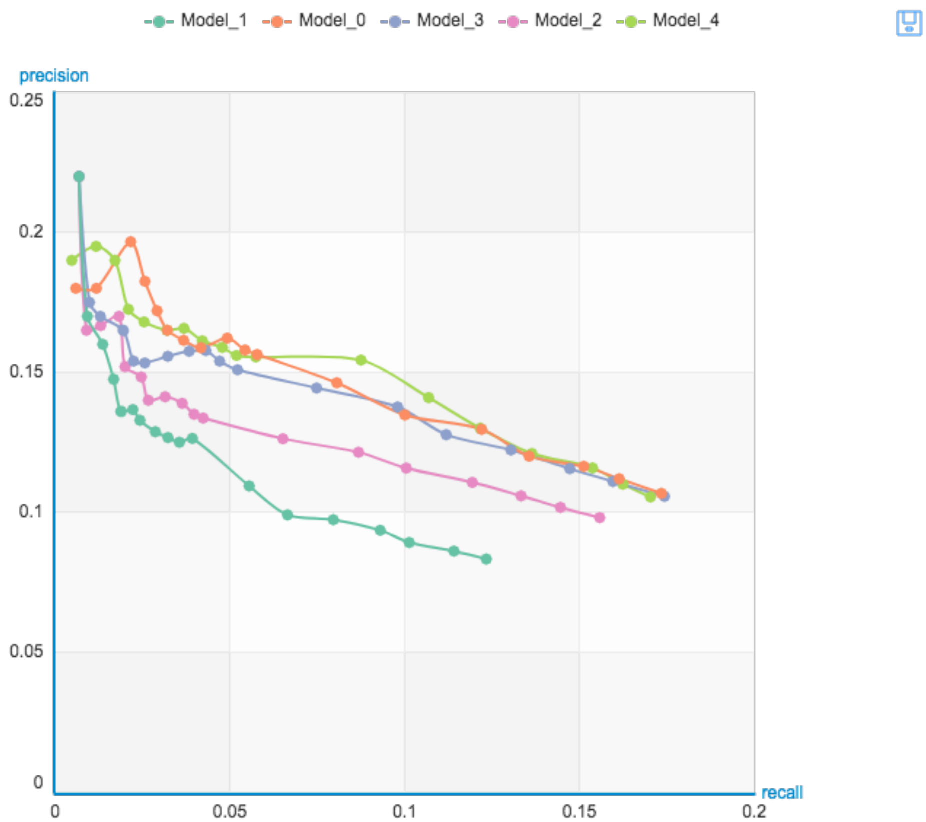
Out[50]:
```
{'item_id': 'title',
 'linear_regularization': 0.001,
 'max_iterations': 50,
 'num_factors': 12,
 'num_sampled_negative_examples': 8,
 'ranking_regularization': 0.5,
 'regularization': 0.001,
 'target': 'rating',
 'user_id': 'user_id'}
```

In [51]:
```
models = job.get_models()
models
```

```
Out[51]: [Class                          : RankingFactorizationRecommender

          Schema
          ------
          User ID                        : user_id
          Item ID                        : title
          Target                         : rating
          Additional observation features  : 7
          User side features             : []
          Item side features             : []

          Statistics
          ----------
          Number of observations         : 997128
          Number of users                : 6040
          Number of items                : 3705

          Training summary
          ----------------
          Training time                  : 62.7761

          Model Parameters
          ----------------
          Model class                    : RankingFactorizationRecommender
          num_factors                    : 32
          binary_target                  : 0
          side_data_factorization        : 1
          solver                         : auto
          nmf                            : 0
          max_iterations                 : 25

          Regularization Settings
          -----------------------
          regularization                 : 0.001
          regularization_type            : normal
          linear_regularization          : 0.001
          ranking_regularization         : 0.25
          unobserved_rating_value        : -1.79769313486e+308
          num_sampled_negative_examples  : 4
          ials_confidence_scaling_type   : auto
          ials_confidence_scaling_factor : 1

          Optimization Settings
          ---------------------
          init_random_sigma              : 0.01
          sgd_convergence_interval       : 4
          sgd_convergence_threshold      : 0.0
          sgd_max_trial_iterations       : 5
          sgd_sampling_block_size        : 131072
          sgd_step_adjustment_interval   : 4
          sgd_step_size                  : 0.0
          sgd_trial_sample_minimum_size  : 10000
          sgd_trial_sample_proportion    : 0.125
          step_size_decrease_rate        : 0.75
          additional_iterations_if_unhealthy : 5
          adagrad_momentum_weighting     : 0.9
          num_tempering_iterations       : 4
          tempering_regularization_start_value : 0.0
          track_exact_loss               : 0,
          Class                          : RankingFactorizationRecommender

          Schema
          ------
          User ID                        : user_id
          Item ID                        : title
          Target                         : rating
          Additional observation features  : 7
          User side features             : []
          Item side features             : []

          Statistics
          ----------
          Number of observations         : 997128
          Number of users                : 6040
```

In [52]:
```
comparisonstruct = gl.compare(test,models)
gl.show_comparison(comparisonstruct,models)
```

```
PROGRESS: Evaluate model M0

Precision and recall summary statistics by cutoff
+--------+-----------------+-------------------+
| cutoff | mean_precision  |    mean_recall    |
+--------+-----------------+-------------------+
|   1    |       0.18      | 0.00595617466299  |
|   2    |       0.18      | 0.0118538111104   |
|   3    | 0.196666666667  | 0.0216574855281   |
|   4    |      0.1825     | 0.0257307618318   |
|   5    |      0.172      | 0.0292013486135   |
|   6    |      0.165      | 0.0321354184941   |
|   7    | 0.161428571429  | 0.0367856109295   |
|   8    |     0.15875     |  0.041730247363   |
|   9    | 0.162222222222  | 0.0492828703296   |
|   10   |      0.158      | 0.0543654122912   |
+--------+-----------------+-------------------+
[10 rows x 3 columns]

PROGRESS: Evaluate model M1

Precision and recall summary statistics by cutoff
+--------+-----------------+-------------------+
| cutoff | mean_precision  |    mean_recall    |
+--------+-----------------+-------------------+
|   1    |       0.22      | 0.00686047280679  |
|   2    |       0.17      | 0.00924504718155  |
|   3    |       0.16      | 0.0136479229208   |
|   4    |      0.1475     | 0.0167700021864   |
|   5    |      0.136      | 0.0188589142706   |
|   6    | 0.136666666667  | 0.0222739168591   |
|   7    | 0.132857142857  | 0.0243012715791   |
|   8    |     0.12875     | 0.0286985007741   |
|   9    | 0.126666666667  | 0.0323092576461   |
|   10   |      0.125      |  0.035582393275   |
+--------+-----------------+-------------------+
[10 rows x 3 columns]

PROGRESS: Evaluate model M2

Precision and recall summary statistics by cutoff
+--------+-----------------+-------------------+
| cutoff | mean_precision  |    mean_recall    |
+--------+-----------------+-------------------+
|   1    |       0.22      | 0.00689446249268  |
|   2    |      0.165      | 0.00900465750424  |
|   3    | 0.166666666667  | 0.0130600887698   |
|   4    |       0.17      | 0.0182960823883   |
|   5    |      0.152      |  0.020050006245   |
|   6    | 0.148333333333  | 0.0246831764154   |
|   7    |       0.14      | 0.0267041325454   |
|   8    |     0.14125     | 0.0315136286224   |
|   9    | 0.138888888889  | 0.0363975232489   |
|   10   |      0.135      | 0.0397686485526   |
+--------+-----------------+-------------------+
[10 rows x 3 columns]

PROGRESS: Evaluate model M3

Precision and recall summary statistics by cutoff
+--------+-----------------+-------------------+
| cutoff | mean_precision  |    mean_recall    |
+--------+-----------------+-------------------+
|   1    |       0.22      | 0.0068842823306   |
|   2    |      0.175      | 0.00986638205553  |
|   3    |       0.17      | 0.0129619831014   |
|   4    |      0.165      |  0.019513770006   |
|   5    |      0.154      | 0.0224720473503   |
|   6    | 0.153333333333  | 0.0256970955614   |
|   7    | 0.155714285714  | 0.0322689146934   |
|   8    |      0.1575     | 0.0383768669241   |
|   9    | 0.157777777778  | 0.0431455679715   |
|   10   |      0.154      | 0.0470924652074   |
+--------+-----------------+-------------------+
```



In [53]:
```
data.dtypes
```

Out[53]:
```
user_id        int64
movie_id       int64
rating         int64
timestamp      int64
gender        object
age            int64
occupation     int64
zip           object
title         object
genres        object
dtype: object
```

Back to Top

5. Deployment

In [ ]:

Back to Top

6. References

Wes McKinney, *Python for Data Analysis: Data Wrangling with Pandas, NumPy, and IPython*, O'Reilly

Eric Larsson, *13. Recommendation Systems: Collaborative Filtering in Turi (formerly Dato, Formerly GraphLab)*, GitHub