MSDS 7331: Project 3

Recommendation System

Team Member Names:

Name 1: Araya Messa
Name 2: Manjula Kottegoda
Name 3: Rajeev Kumar

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1. Object and Background-Business Understanding

As e-commerce websites entice consumers into an age of discovery leaving behind the era of search, online shoppers are beginning to see products and services they did not know existed but were 'handpicked' to fit their individual tastes. Often these handpicked selections are presented to consumers as non-obtrusive recommendations with the goal of enhancing the shopping experience all while increasing the retailer's cross-selling potential. Highly successful retailers like Amazon make such recommendations dressed more like a value-added service and presented using language like "Customers who bought this item also bought…" coupled with an easily scrollable list of cross-sell merchandise to browse. As the CEO of Amazon revealed in 2015, 35% of sales at Amazon were a direct result of successful cross-selling [1] highlighting the enormous commercial potential of accurate recommendations.

Recommendations made by on-line retailers are not made at random, but are based on other similar consumers' preferences or purchases. Increasingly this phenomenon is becoming a powerful must-have marketing tool that retailers deploy to meet consumer expectations and generate sales through up-selling or cross-selling. Getting an understanding on a consumer's preferences and inclinations is a complex art and a science. And the engine behind customized 'handpicking' is powered by algorithm based Recommendation Systems using an array of techniques such as Collaborative Filtering and Markov Chains.

The goal of this project is to build a Recommendation System for book buyers through Collaborative Filtering. We chose the book buyers data from the Book-Crossing Dataset [2] collected in 4 weeks spanning August to September of 2004 to build our recommendation system. The dataset consists of data from 278,858 individual users providing both implicit and explicit ratings on 271,379 books [3]. Once the model is built we will validate its quality and performance and explore methods of enhancing the model to fit a commercial deployment scenario.

2. Data Descriptions (Data Understanding)

The Book-Crossing dataset [3] used in the study comprised of three delimited files and the delimiter was ";".

BX-Users:
This file contained sanitized user data primarily consisting of unique user identifications, user's location and the Age.

BX-Books: Books data consisted of the details on each particular book. Starting with the International Standard Book Number (ISBN) code, Author of the Book, Year of publication, Publisher name, and Book cover image URLs. In case of several authors only the first is listed. We had three URLs for each book cover (small image,medium image,large image).

BX-Book-Ratings: This data file contains the book rating information. The user ID that did the rating along with the ISBN identifier of the book and the rating (1-10) given are the three data elements. Rating of 10 will indicate the highest rating, a rating of 1 is the lowest rating and a rating of 0 is an implicit rating.

3. Data Preparation

Data preparation for this study followed the high-level steps below

- Import three Data files in to three dataframes
- Removing implicit elements from the dataset
- Removing missing values from the dataset
- Remove bad records from the dataset
- Merge Book details and Book ratings datasets by ISBN
- Clean up the merged Book_details_Book_ratings dataset
- Visualize Data using Graph Lab

Importing Data using Pandas Dataframe

In [1]:

```
#Importing data into Pandas DataFrame from the datasets and dropping “NA”
import pandas as pd
df_Users = pd.read_csv("BX-CSV-Dump/BX-Users.csv", sep=";",error_bad_lines=False).dr
df_Books = pd.read_csv("BX-CSV-Dump/BX-Books.csv",sep=";", error_bad_lines=False).dr
df_Book_Ratings=pd.read_csv("BX-CSV-Dump/BX-Book-Ratings.csv",sep=";",error_bad_line
```

```
Skipping line 6452: expected 8 fields, saw 9
Skipping line 43667: expected 8 fields, saw 10
Skipping line 51751: expected 8 fields, saw 9

Skipping line 92038: expected 8 fields, saw 9
Skipping line 104319: expected 8 fields, saw 9
Skipping line 121768: expected 8 fields, saw 9

Skipping line 144058: expected 8 fields, saw 9
Skipping line 150789: expected 8 fields, saw 9
Skipping line 157128: expected 8 fields, saw 9
Skipping line 180189: expected 8 fields, saw 9
Skipping line 185738: expected 8 fields, saw 9

Skipping line 209388: expected 8 fields, saw 9
Skipping line 220626: expected 8 fields, saw 9
Skipping line 227933: expected 8 fields, saw 11
Skipping line 228957: expected 8 fields, saw 10
Skipping line 245933: expected 8 fields, saw 9
Skipping line 251296: expected 8 fields, saw 9
Skipping line 259941: expected 8 fields, saw 9
Skipping line 261529: expected 8 fields, saw 9

//anaconda/envs/gl-env/lib/python2.7/site-packages/IPython/core/intera
ctiveshell.py:2723: DtypeWarning: Columns (3) have mixed types. Specif
y dtype option on import or set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

In [2]:

```
## printing first 5 rows for df_Users
df_Users.head()
```

Out[2]:

	User-ID	Location	Age
1	2	stockton, california, usa	18.0
3	4	porto, v.n.gaia, portugal	17.0
5	6	santa monica, california, usa	61.0
9	10	albacete, wisconsin, spain	26.0
10	11	melbourne, victoria, australia	14.0

In [3]:

```
#Print Data Types of the Users Dataframe
df_Users.dtypes
```

Out[3]:

```
User-ID       int64
Location     object
Age         float64
dtype: object
```

In [4]:

```
## printing first 5 rows for df_Books
df_Books.head()
```

Out[4]:

	ISBN	Book-Title	Book-Author	Year-Of-Publication	Publisher	Image-URL-S
0	0195153448	Classical Mythology	Mark P. O. Morford	2002	Oxford University Press	http://images.amazon.co
1	0002005018	Clara Callan	Richard Bruce Wright	2001	HarperFlamingo Canada	http://images.amazon.co
2	0060973129	Decision in Normandy	Carlo D'Este	1991	HarperPerennial	http://images.amazon.co
3	0374157065	Flu: The Story of the Great Influenza Pandemic...	Gina Bari Kolata	1999	Farrar Straus Giroux	http://images.amazon.co
4	0393045218	The Mummies of Urumchi	E. J. W. Barber	1999	W. W. Norton & Company	http://images.amazon.co

In [5]:

```
## printing first 5 rows for df_Ratings
df_Book_Ratings.head()
```

Out[5]:

	User-ID	ISBN	Book-Rating
0	276725	034545104X	0
1	276726	0155061224	5
2	276727	0446520802	0
3	276729	052165615X	3
4	276729	0521795028	6

Removing Implicit Ratings (all zero values)

There are situations where ratings are not **explicitly** provided for products. In our case, not all users rate all the books they encounter. Never-the-less interactions between users and books are captured as they either look at a book or show interest in a book by clicking through it. Such interactions are compiled as **implicit** ratings. The Book Crossing Dataset contains both implicit and explicit ratings. Implicit ratings are indicated by a rating value of 0 in the Book ratings dataset.

Here we are removing the implicit data from the dataset to reduce the noise and get a better idea on the preferences of users as we create an item-to-user model based on explicit ratings.

In [6]:

```
#Dropping Implicit Ratings and their associated elemnts from the dataset
df_Book_Ratings=df_Book_Ratings[~(df_Book_Ratings['Book-Rating'] ==0 )]
```

In [7]:

```
## Quick view of the dataset after removing all zeroes
df_Book_Ratings.head()
```

Out[7]:

	User-ID	ISBN	Book-Rating
1	276726	0155061224	5
3	276729	052165615X	3
4	276729	0521795028	6
6	276736	3257224281	8
7	276737	0600570967	6

Merging Books and Book Ratings using ISBN as a key

Let us merge the books and book-Ratings data, that contain the list of **identifiers**, **titles of the books** and the **ratings** gave by the **users** respectively.

In [8]:

```
 # Merge Book rating dataset with book dataset on ISBN
dfBooks_BookRatings = df_Book_Ratings.merge(df_Books, on="ISBN", how="outer").dropna
dfBooks_BookRatings.head()
```

Out[8]:

	User-ID	ISBN	Book-Rating	Book-Title	Book-Author	Year-Of-Publication	Publisher	Image-U
0	276726.0	0155061224	5.0	Rites of Passage	Judith Rae	2001	Heinle	http://im
1	276729.0	052165615X	3.0	Help!: Level 1	Philip Prowse	1999	Cambridge University Press	http://im
2	276729.0	0521795028	6.0	The Amsterdam Connection : Level 4 (Cambridge ...	Sue Leather	2001	Cambridge University Press	http://im
8	276744.0	038550120X	7.0	A Painted House	JOHN GRISHAM	2001	Doubleday	http://im
9	11676.0	038550120X	10.0	A Painted House	JOHN GRISHAM	2001	Doubleday	http://im

In [9]:

```
# Print Data Types of the Combined book-user-rating Dataframe
dfBooks_BookRatings.dtypes
```

Out[9]:

```
User-ID                float64
ISBN                    object
Book-Rating            float64
Book-Title              object
Book-Author             object
Year-Of-Publication     object
Publisher               object
Image-URL-S             object
Image-URL-M             object
Image-URL-L             object
dtype: object
```

converting datatypes into integer

In [10]:

```
import numpy as np
## converting age and year of publication to int for df_Users and df_Books
df_Users['Age'] = df_Users['Age'].apply(np.int64, errors=False)
df_Books["Year-Of-Publication"]=df_Books["Year-Of-Publication"].apply(np.int64, erro

## converting Book-Rating, User-ID, and Year-Of-Publication  to int for df_Books_Ra
dfBooks_BookRatings["Book-Rating"] = dfBooks_BookRatings["Book-Rating"].apply(np. in
dfBooks_BookRatings["User-ID"] = dfBooks_BookRatings["User-ID"].apply(np. int64, err
dfBooks_BookRatings["Year-Of-Publication"] = dfBooks_BookRatings["Year-Of-Publicatio
```

In [11]:

```
# Print Data Types of the Combined book-user-rating Dataframe after conversion
dfBooks_BookRatings.dtypes
```

Out[11]:

```
User-ID                  int64
ISBN                    object
Book-Rating              int64
Book-Title              object
Book-Author             object
Year-Of-Publication      int64
Publisher               object
Image-URL-S             object
Image-URL-M             object
Image-URL-L             object
dtype: object
```

Converting Dataframe to SFrame

In [12]:

```
import graphlab as gl

#users info
sf_Users = gl.SFrame(data=df_Users)

#book info
sf_Books = gl.SFrame(data=df_Books)

#combined(book and book rating info)
sfBooks_BookRatings=gl.SFrame(data=dfBooks_BookRatings)
```

```
[INFO] graphlab.cython.cy_server: GraphLab Create v2.1 started. Loggin
g: /tmp/graphlab_server_1493589179.log
```

```
This non-commercial license of GraphLab Create for academic use is ass
igned to rajeevk@smu.edu and will expire on April 12, 2018.
```

Preparing SFrame for data visualization

In [13]:

```
## Slicing User-ID and Book-Rating to merge with users info sothat we use
## it to visualize data
sfUserRatings=sfBooks_BookRatings[['User-ID','Book-Rating']]

## converting 'sfUserRatings' to dataframe
dfUserRatings=sfUserRatings.to_dataframe()

## Merging 'df_Users' and 'dfUserRatings' i.e User-Id,Location, Age to
## User-Id, and Book-Ratings
dfUsers_UserRatings=df_Users.merge(dfUserRatings, on="User-ID", how="outer").dropna(

## Converting User-ID, Age, and Book-Rating to int
dfUsers_UserRatings["User-ID"] = dfUsers_UserRatings["User-ID"].apply(np. int64, err
dfUsers_UserRatings["Age"] = dfUsers_UserRatings["Age"].apply(np. int64, errors=Fals
dfUsers_UserRatings["Book-Rating"] = dfUsers_UserRatings["Book-Rating"].apply(np. in

## Converting dfUsers_UserRatings to SFrame
sfUsers_UserRatings=gl.SFrame(data=dfUsers_UserRatings)
```

In [14]:

```
# Print top 10 records from the SFrame dataset.
sfUsers_UserRatings.head()
```

Out[14]:

User-ID	Location	Age	Book-Rating
19	weston, ,	14	7
42	appleton, wisconsin, usa	17	7
44	black mountain, north carolina, usa ...	51	8
51	renton, washington, usa	34	9
56	cheyenne, wyoming, usa	24	7
56	cheyenne, wyoming, usa	24	9
64	lyon, rhone, france	32	7
67	framingham, massachusetts, usa ...	43	7
70	rochester, new york, usa	44	10
75	long beach, california, usa ...	37	5

[10 rows x 4 columns]

In [15]:

```
# Print Data Types of the user-rating SFrame
sfUsers_UserRatings.dtype()
```

Out[15]:

```
[int, str, int, int]
```

4. Data Exploration

Summary and Visualization

Let us see some insights about the data using Graphlab. We can visualize data using *SFrame.show()* by a built-in API called Canvas. The output can be shown as a separate browser or just inline with the Note. The Graphlab data visualization information is found at https://turi.com/products/create/docs/generated/graphlab.SFrame.show.html (https://turi.com/products/create/docs/generated/graphlab.SFrame.show.html)

In [16]:

```
# Print Column Names of the user-rating SFrame
sfUsers_UserRatings.column_names()
```

Out[16]:

```
['User-ID', 'Location', 'Age', 'Book-Rating']
```

Breaking Age into intervals

In [17]:

```
# Function to define Age group
def combine_age(Age):

    if Age<15:
        return '15-'
    elif Age>=15 and Age<20:
        return'15-20'
    elif Age>=20 and Age<25:
        return'20-25'
    elif Age>=25 and Age<30:
        return'25-30'
    elif Age>=30 and Age<35:
        return'30-35'
    elif Age>=35 and Age<40:
        return'35-40'
    elif Age>=40 and Age<50:
        return'40-50'
    elif Age>=50 and Age<60:
        return'50-60'
    elif Age>=60 and Age<70:
        return '60-70'
    elif Age>=70:
        return '70+'
```

In [18]:

```
# Combine Age group to the user-rating SFrame.
sfUsers_UserRatings['Age']=sfUsers_UserRatings['Age'].apply(combine_age)
sfUsers_UserRatings.head()
```

Out[18]:

User-ID	Location	Age	Book-Rating
19	weston, ,	15-	7
42	appleton, wisconsin, usa	15-20	7
44	black mountain, north carolina, usa ...	50-60	8
51	renton, washington, usa	30-35	9
56	cheyenne, wyoming, usa	20-25	7
56	cheyenne, wyoming, usa	20-25	9
64	lyon, rhone, france	30-35	7
67	framingham, massachusetts, usa ...	40-50	7
70	rochester, new york, usa	40-50	10
75	long beach, california, usa ...	35-40	5

[10 rows x 4 columns]

Age vs. Age count

In [19]:

```
# Plot of Age vs User Count
gl.canvas.set_target("ipynb")
sfUsers_UserRatings.show(view="Bar Chart",x="Age", y=None)
```

From the above plot, it can be observed that most participants are aged between 20 and 60. It is also evident f that users aged 50 and above have less of a presence on the Amazon website. It could possibly be because online shopping is not popular among the 50+ demography.

Book Rating vs. Book Rating count

In [20]:

```
# Histogram of Ratings
gl.canvas.set_target("ipynb")
sfUsers_UserRatings.show(view="Bar Chart",x="Book-Rating", y=None)
```

From the above plot, after removing all the implicit (zero ratings), it is clear that majority of books are rated high and only small fraction of books are rated low by customers.

Age vs. Book Rating

In [21]:

```
# Distribution of Rating by Age Groups
gl.canvas.set_target("ipynb")
sfUsers_UserRatings[["Age", "Book-Rating"]].show(view="BoxWhisker Plot",x="Age", y='
```

1st percentile: 2
25th percentile: 7
50th percentile: 8
75th percentile: 9
99th percentile: 10

The figure above show that most of the low ratings came from Book-crossing teen age users(aged between 15 and 20) and old users (older than 70). Where as, age 30s-50s are good raters. This is in line with the common understanding [11] that users who rate books are disproportionately ones that are happy with the product.

Preparing target columns

In [22]:

```
## Slicing User-ID, Book-Title, and Book-Rating to use for recommendations
sf_TargetCols=sfBooks_BookRatings[["User-ID","Book-Title","Book-Rating"]]
## printing top 1000 records for target columns
sf_TargetCols.print_rows(10000)
```

```
+---------+--------------------------------+-------------+
| User-ID |           Book-Title           | Book-Rating |
+---------+--------------------------------+-------------+
|  276726 |        Rites of Passage        |      5      |
|  276729 |         Help!: Level 1         |      3      |
|  276729 | The Amsterdam Connection :...  |      6      |
|  276744 |        A Painted House         |      7      |
|  11676  |        A Painted House         |      10     |
|  16877  |        A Painted House         |      9      |
|  17975  |        A Painted House         |      6      |
|  20806  |        A Painted House         |      6      |
|  21340  |        A Painted House         |      9      |
|  21356  |        A Painted House         |      7      |
|  22625  |        A Painted House         |      10     |
|  23243  |        A Painted House         |      7      |
|  29168  |        A Painted House         |      7      |
|  31315  |        A Painted House         |      6      |
|  32188  |        A Painted House         |      8      |
|  33974  |        A Painted House         |      8      |
```

In [23]:

```
# Print Data Types of the Target SFrame
sf_TargetCols.dtype()
```

Out[23]:

```
[int, str, int]
```

5. Modeling-Book Recommendation

We now begin the modeling phase. Here we will be looking at building relationships between Books and users and well amongst books themselves. We will also look at parameters that could be calibrated to optimize models. The ultimate goal of the model is to recommend products to a given user that they would show interest in there by enhancing their shopping experience.

We have two goals here. One is to recommend similar items (item_item), other is to predict rating of the book that user has not read/rated(user_item) based on his/her past preference.

5.1. User-Item Recommendation System

The GraphLab Create recommender toolkit provides a unified interface to train a variety of recommender models and use them to make recommendations.

Let's use graphlab.recommender.create to recommend top 15 items for each users.

In [24]:

```
# User-Item Similarity model to recommend top 15 items to each user
model = gl.recommender.create(sf_TargetCols, user_id="User-ID", item_id="Book-Title'
results = model.recommend(users=None, k=15)
model.save("Recommender_model_1")

results.print_rows(15) # the recommendation output
```

```
Recsys training: model = ranking_factorization_recommender

Preparing data set.

    Data has 383839 observations with 68091 users and 135565 items.

    Data prepared in: 0.625921s

Training ranking_factorization_recommender for recommendations.

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

| Parameter                      | Description
| Value    |

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

| num_factors                    | Factor Dimension
```

As shown above, our model recommended top 15 highest rated items for a user with user id "276726". We would evaluate these results in the validation phase.

5.2. Item-Item Recommendation System

Now let's look at creating the item-item similarity matrix. That is, for each item, what are the top closest items based upon user ratings.

Measure of Similarity

There are three choices of similarity metrics to use: 'jaccard', 'cosine' and 'pearson'.

Jaccard similarity is used to measure the similarity between two set of elements. Jaccard is a good choice when one only has implicit feedbacks of items (e.g., people rated them or not), or when one does not care about how many stars items received.

If one needs to compare the ratings of items, Cosine and Pearson similarity are recommended. Cosine similarity is recommended to use when there is a sparse data. A problem with Cosine similarity is that it does not consider the differences in the mean and variance of the ratings made to items i and j. On the other hand Pearson Correlation similarity is used where the effects of means and variance have been removed.

Predictions of items depend on whether target is specified(when item is rated) or not(when item is not rated). In our case as we have a book dataset with high sparsity *so We are going to use *cosine similarity* for our item-item similarity recommender.[4]

Sparsity of the Dataset

In [25]:

```
density= float(dfBooks_BookRatings.shape[0])/float(len(pd.unique(dfBooks_BookRatings
sparsity = 1 - density
```

In [26]:

```
print sparsity
```

```
0.999995841738
```

Sparsity of the dataset is 0.99999584, which is very high. Therefore, cosine distance should be used for item similarity.

In [27]:

```
# Item-Item Similarity model to recommend top 15 items
from graphlab import item_similarity_recommender
item_item = gl.recommender.item_similarity_recommender.create(sf_TargetCols,
                                  user_id="User-ID",
                                  item_id="Book-Title",
                                  target="Book-Rating",
                                  only_top_k=15,
                                  similarity_type="cosine")

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

```
Recsys training: model = item_similarity

Preparing data set
```

```
Preparing data set.

    Data has 383839 observations with 68091 users and 135565 items.

    Data prepared in: 0.819454s

Training model from provided data.

Gathering per-item and per-user statistics.

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

| Elapsed Time (Item Statistics) | % Complete |

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

| 6.975ms                        | 1.25       |

| 49.007ms                       | 100        |

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

Setting up lookup tables.

Processing data in one pass using sparse lookup tables.

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

| Elapsed Time (Constructing Lookups) | Total % Complete | Items Proce
ssed |

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

| 1.05s                               | 0                | 0
|

| 2.06s                               | 63.5             | 86156
|

| 3.09s                               | 66.25            | 90001
|

| 4.49s                               | 69               | 93557
|

| 5.07s                               | 71               | 96353
|

| 6.20s                               | 71.75            | 97478
|

| 7.08s                               | 72.25            | 98068
|

| 8.08s                               | 75               | 101784
```

```
| 8.08s                              | 75              | 101784
|

| 9.09s                              | 87.25           | 118590
|

| 10.19s                             | 94              | 127477
|

| 12.66s                             | 99.25           | 134566
|

| 15.37s                             | 100             | 135565
|

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

Finalizing lookup tables.

Generating candidate set for working with new users.

Finished training in 15.4696s

+-------------------+-------------------------------+-----------------+
------+
|    Book-Title     |            similar            |      score      |
rank |
+-------------------+-------------------------------+-----------------+
------+
| Rites of Passage | Hamlet (Arden Edition of t... |  0.691094756126 |
1   |
| Rites of Passage |   The Christy Moore Songbook  |  0.345547378063 |
2   |
| Rites of Passage | Cuantas Veces En Un Siglo ... |  0.345547378063 |
3   |
| Rites of Passage | Frida Kahlo: Mujer, ideolo... |  0.345547378063 |
4   |
| Rites of Passage |            Skerrett           |  0.345547378063 |
5   |
| Rites of Passage | O sexo dos anjos (Argumentos) |  0.345547378063 |
6   |
| Rites of Passage |     50 Poemas Del Milenio     |  0.244338870049 |
7   |
| Rites of Passage |           Sandcastle          |  0.244338870049 |
8   |
| Rites of Passage |       An Accidental Man       |  0.227544546127 |
9   |
| Rites of Passage |          Oscar Wilde          |  0.192131876945 |
10  |
| Rites of Passage | Death in Dublin: A Novel o... |  0.191675186157 |
11  |
| Rites of Passage |          Small World          |  0.180374264717 |
12  |
| Rites of Passage | The Cinderella Complex: Wo... |  0.177782654762 |
```

```
13  |
| Rites of Passage |        The Family Tree        | 0.0851475596428 |
14  |
| Rites of Passage |          Wild Animus          | 0.0172265768051 |
15  |
+------------------+-------------------------------+-----------------+
------+
[1703026 rows x 4 columns]
```

Item-item model recommended the top 15 similar items to each item.

The item-item matrix is typically a good baseline. However, we can do better with a more personalized model that takes into account the various preferences of specific users, rather than all users rating specific items.

5.3. Cross Validation

Once the models are built we need to validate its performance, quality as well as its versatility, as in how well it generalizes to other data. Hence, we need targeted evaluations performed on certain criteria of the model. The chosen criteria to perform the evaluation are RMSE, Precision and Recall.

We start off with the standard approach of splitting the data into two parts, a training dataset and a testing dataset using an 80:20 split. The model is built using the larger training dataset whilst the model evaluation is performed using the testing dataset ensuring that model validation is not performed on the same data that the model was trained on. In other words, model validation is done using data that it has not come across. For all practical purposes this could be considered a simulated ‘live’ test.

The most widely used evaluation measurement is the RMSE or Root Mean Squared Error. It is a straightforward difference measurement on predicted vs expected rating value. In other words RMSE measures how good the model’s prediction is. The lower the RMSE the closer the prediction is to the actual rating.

Another evaluation measurement is ***Precision*** which in short is a measure of exactness given as a fraction of the books the model showed from what the user actually liked. Or a proportion of recommended books that are actually good.

Recall on the other hand is a measure of completeness that shows the fraction of relevant items retrieved by the model out of all relevant items. In our context, Recall is the fraction of the liked books that the model found.

Of the three evaluation metrics, we chose RMSE as the key criteria to make a judgement on the quality of the model. This is primarily based on the context of the problem where the accuracy was important so as to generate models that would blend better with other models keeping in mind that that our goal is to formulate a blended model approach for final deployment.

Splitting data into Train and Test data for model training and validation

We used a recommender-friendly train-test split provided on the Graghlab Create API. This can be found at this (https://turi.com/products/create/docs/generated/graphlab.recommender.util.random_split_by_user.html).

To accurately evaluate the precision-recall of a model trained on explicit rating data, it's important to only include highly rated items in our test set as these are the items a user would likely choose. So we split our dataset into two, one with high rated books and other with low rated books. The test dataset is generated by first choosing max_num_users out of the total number of users in the highly rated dataset. Then, for each of the chosen test users, a portion of the user's items (determined by item_test_proportion) is randomly chosen to be included in the test set. This split allows the training data to retain enough information about the users in the testset, so that adequate recommendations can be made. The total number of users in the test set may be fewer than max_num_users if a user was chosen for the test set but none of their items are selected. We also use an 80/20 ratio splitting in our dataset that many articles have been using it.
The GraphLab Create recommender toolkit provides several ways of working with rating data while ensuring good precision-recall. To accurately evaluate the precision-recall of a model trained on explicit rating data, it's important to only include highly rated items in your test set as these are the items a user would likely choose.

In [28]:

```
## Number of records on target SFrame
len(sf_TargetCols)
```

Out[28]:

383839

In [29]:

```
## Train/Test split
high_rated_data = sf_TargetCols[sf_TargetCols["Book-Rating"] >= 6]
low_rated_data = sf_TargetCols[sf_TargetCols["Book-Rating"] < 6]
train_1, test = gl.recommender.util.random_split_by_user(
                                    high_rated_data, user_id='User-ID', item_id='Boo
train = train_1.append(low_rated_data)
```

5.3.1. Evaluating Item-Item Similarity Recommender

In [30]:

```
## item-item model evaluation
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="Book-Title",
                                  target="Book-Rating",
```

```
                                    only_top_k=25,
                                    similarity_type="cosine")
rmse_results = item_item.evaluate(test)
```

```
Recsys training: model = item_similarity

Preparing data set.

    Data has 383031 observations with 67978 users and 135383 items.

    Data prepared in: 0.606475s

Training model from provided data.

Gathering per-item and per-user statistics.

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

| Elapsed Time (Item Statistics) | % Complete |

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

| 7.731ms                        | 8.75       |

| 44.691ms                       | 100        |

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

Setting up lookup tables.

Processing data in one pass using sparse lookup tables.

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

| Elapsed Time (Constructing Lookups) | Total % Complete | Items Proce
ssed |

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

| 904.043ms                           | 0                | 2
|

| 1.94s                               | 43               | 58522
|

| 3.69s                               | 50.5             | 68654
|

| 3.91s                               | 51.5             | 69852
|

| 5.08s                               | 60               | 81520
|
```

```
| 5.92s                                | 68.75             | 93260
|

| 7.86s                                | 95.5              | 129494
|

| 7.95s                                | 95.75             | 129859
|

| 8.93s                                | 98.75             | 133935
|

| 10.92s                               | 100               | 135383
|

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

Finalizing lookup tables.

Generating candidate set for working with new users.

Finished training in 11.0103s

Precision and recall summary statistics by cutoff
+--------+------------------+-------------------+
| cutoff |  mean_precision  |    mean_recall    |
+--------+------------------+-------------------+
|   1    | 0.00274725274725 | 0.000392464678179 |
|   2    | 0.00412087912088 |  0.00124280481423 |
|   3    | 0.00457875457875 |  0.00438252223967 |
|   4    | 0.00343406593407 |  0.00438252223967 |
|   5    | 0.0032967032967  |  0.00575614861329 |
|   6    | 0.00320512820513 |  0.00606139891854 |
|   7    | 0.00313971742543 |  0.00743502529217 |
|   8    | 0.00274725274725 |  0.00743502529217 |
|   9    | 0.00274725274725 |  0.0101822780394  |
|   10   | 0.00247252747253 |  0.0101822780394  |
+--------+------------------+-------------------+
[10 rows x 3 columns]

('\nOverall RMSE: ', 8.131246243103114)

Per User RMSE (best)
+---------+-------+---------------+
| User-ID | count |      rmse     |
+---------+-------+---------------+
|  201353 |   9   | 5.85125497185 |
+---------+-------+---------------+
[1 rows x 3 columns]


Per User RMSE (worst)
+---------+-------+------+
```

User-ID	count	rmse
75096	1	10.0

[1 rows x 3 columns]

Per Item RMSE (best)

Book-Title	count	rmse
The Green Mile: The Mouse ...	1	4.48197603226

[1 rows x 3 columns]

Per Item RMSE (worst)

Book-Title	count	rmse
Ophelia Speaks : Adolescen...	1	10.0

[1 rows x 3 columns]

Overall RMSE of Item_Item model is worst (8.1311) in recommending rating of book.

RMSE Results by Item for Item-Item Similarity

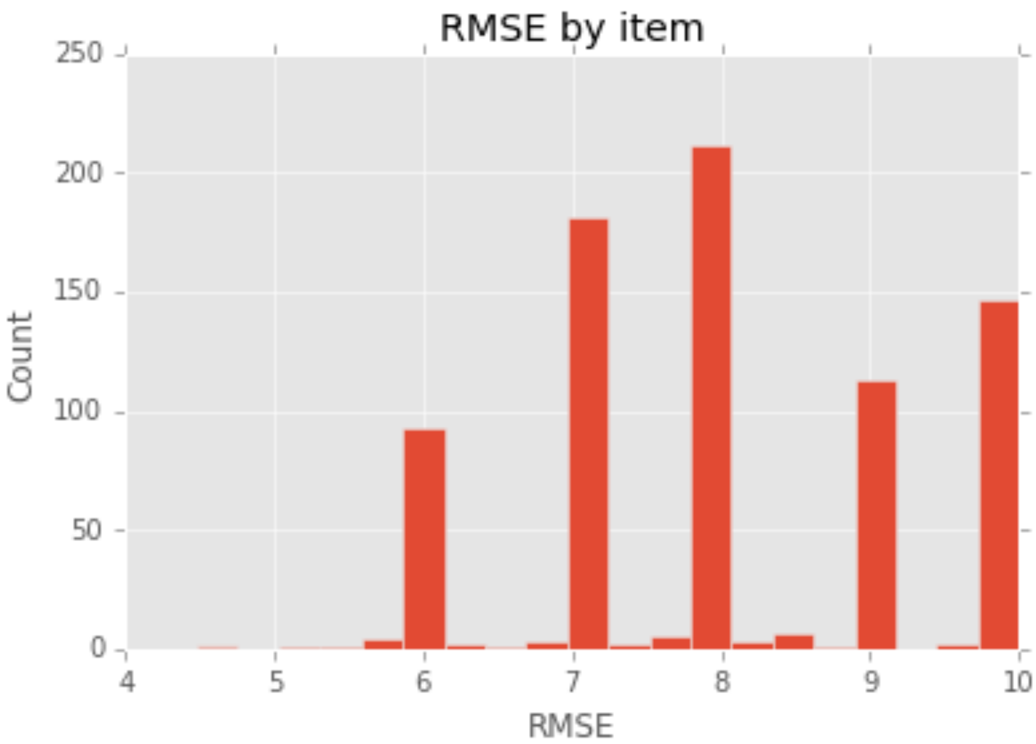
In [31]:

```
# printing RMSE by item
print rmse_results.viewkeys()
print rmse_results['rmse_by_item']
```

```
dict_keys(['rmse_by_user', 'precision_recall_overall', 'rmse_by_item',
'precision_recall_by_user', 'rmse_overall'])
+--------------------------------+-------+------+
|           Book-Title           | count | rmse |
+--------------------------------+-------+------+
|        House of Echoes         |   1   | 9.0  |
| Small Gods (Discworld Nove...  |   1   | 9.0  |
| Crowner'S Quest : A Crowne...  |   1   | 8.0  |
| The Adventures of Hucklebe...  |   1   | 8.0  |
| Ophelia Speaks : Adolescen...  |   1   | 10.0 |
| My Land: A Homesteader's Tale  |   1   | 7.0  |
| The Adventures Pete and Ma...  |   1   | 8.0  |
| The Bear and the Dragon (J...  |   1   | 8.0  |
|       A Southern Family        |   1   | 6.0  |
| Jenny Dale's Puppy Patrol ...  |   1   | 8.0  |
+--------------------------------+-------+------+
[777 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 a
nd columns.
```

In [32]:

```
# Plotting RMSE by item
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()
```



RMSE by item of Item_Item model is also worst in recommending rating of book.

RMSE Results by User for Item-Item Similarity

In [33]:

```
# Printing RMSE by user
rmse_results['rmse_by_user']
```

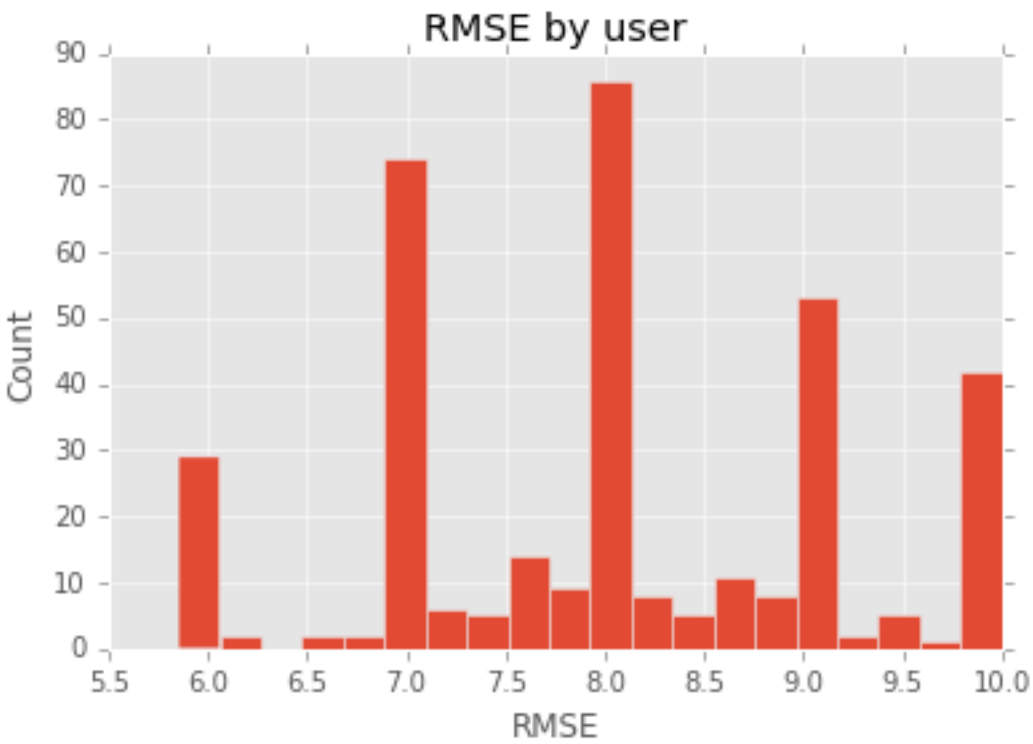
Out[33]:

User-ID	count	rmse
21045	1	7.0
163409	1	8.0
234288	1	8.0
32516	4	9.53939201417
75096	1	10.0
31820	1	6.0
128782	3	7.72442015084
94445	1	6.0
127244	1	9.99719079614
179922	1	6.0

[364 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 [34]:

```
#Plotting RMSE by user
from matplotlib import pyplot as plt
%matplotlib inline
plt.style.use('ggplot')
rmsevals=rmse_results['rmse_by_user']['rmse']
plt.hist(rmsevals, bins=20)
plt.xlabel('RMSE')
plt.ylabel('Count')
plt.title('RMSE by user')
plt.show()
```



RMSE by user of Item_Item model is worst in recommending rating of book.

Recall and Precision

Another evaluation criterion is the per-user-recall or the per-user-precision. Precision (also called positive predictive value) is the fraction of retrieved instances that are recommended by our model that are relevant to user, while recall (also known as sensitivity) is the fraction of relevant instances that are retrieved by our model.

In [35]:

```
## printing precision and recall by cutoff
precision_recall_by_user=rmse_results['precision_recall_by_user']
precision_recall_by_user.print_rows(num_rows=1000, num_columns=5, max_column_width=3
```

User-ID	cutoff	precision	recall	count
99	1	0.0	0.0	1
99	2	0.0	0.0	1
99	3	0.0	0.0	1
99	4	0.0	0.0	1
99	5	0.0	0.0	1
99	6	0.0	0.0	1
99	7	0.0	0.0	1
99	8	0.0	0.0	1
99	9	0.0	0.0	1
99	10	0.0	0.0	1
99	11	0.0	0.0	1
99	16	0.0	0.0	1
99	21	0.0	0.0	1
99	26	0.0	0.0	1
99	31	0.0	0.0	1
99	36	0.0	0.0	1

Aggregate values of precision, recall, and Standard deviation by Cutoff

In [36]:

```
import graphlab.aggregate as agg

# we will be using these aggregations for comparison
agg_list = [agg.AVG('precision'),agg.STD('precision'),agg.AVG('recall'),agg.STD('rec

# apply these functions to each group (we will group the results by 'k' which is the
# the cutoff is the number of top items to look for.
rmse_results['precision_recall_by_user'].groupby('cutoff',agg_list)

# the groups are not sorted
```

Out[36]:

cutoff	Avg of precision	Stdv of precision	Avg of recall	Stdv of
36	0.00114468864469	0.00657307823036	0.0234606663178	0.137526
2	0.00412087912088	0.0584558319532	0.00124280481423	0.0172925
46	0.00107501194458	0.00547760128418	0.0298709227281	0.156113
31	0.00115207373272	0.00727934457445	0.0179661608233	0.116819
26	0.00137362637363	0.00867921853108	0.0179661608233	0.116819
8	0.00274725274725	0.0243600932019	0.00743502529217	0.0684136
5	0.0032967032967	0.03616369818	0.00575614861329	0.0631018
16	0.00171703296703	0.0129905771424	0.011555904413	0.0896450
41	0.00120611096221	0.00614560144079	0.0298709227281	0.156113
4	0.00343406593407	0.0433237054613	0.00438252223967	0.0575235

[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.

Item-Item model's Avg Precision and Recall are not good and we should try to improve our model by using user-item model

5.3.2. Evaluating User-Item Similarity Recommender

5.3.2.1. User-Item Similarity Recommender with Default Parameters

In [37]:

```
# Create a base User-item recommendation model
m1 = gl.recommender.ranking_factorization_recommender.create(train,
                                  user_id="User-ID",
                                  item_id="Book-Title",
                                  target="Book-Rating")

rmse_results =m1.evaluate(test)
```

```
Recsys training: model = ranking_factorization_recommender

Preparing data set.

    Data has 383031 observations with 67978 users and 135383 items.

    Data prepared in: 0.554497s

Training ranking_factorization_recommender for recommendations.

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

| Parameter                      | Description
| Value    |

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

| num_factors                    | Factor Dimension
```

RMSE Results by Item for User-Item Similarity with Default Parameters

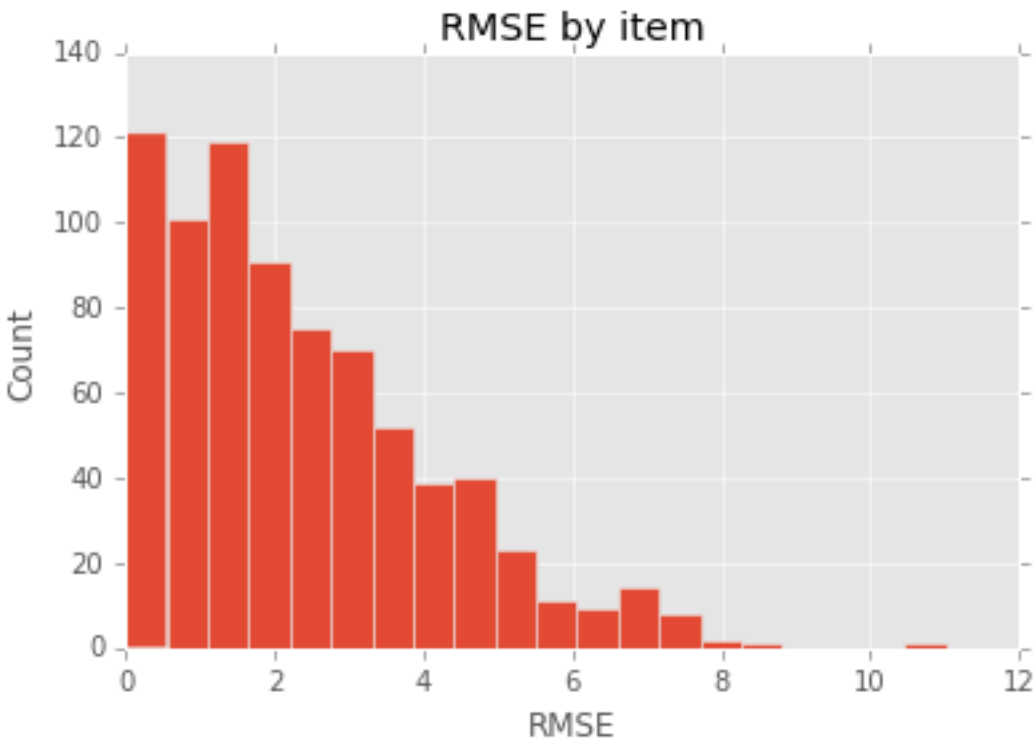
In [38]:

```
print rmse_results.viewkeys()
print rmse_results['rmse_by_item']
```

```
dict_keys(['rmse_by_user', 'precision_recall_overall', 'rmse_by_item',
'precision_recall_by_user', 'rmse_overall'])
+-------------------------------+-------+----------------+
|           Book-Title          | count |      rmse      |
+-------------------------------+-------+----------------+
|        House of Echoes        |   1   | 4.02309819771  |
|  Small Gods (Discworld Nove... |   1   | 4.54861357523  |
|  Crowner'S Quest : A Crowne... |   1   |  4.4940809281  |
|  The Adventures of Hucklebe... |   1   | 0.277145511525 |
|  Ophelia Speaks : Adolescen... |   1   | 7.48605259968  |
|  My Land: A Homesteader's Tale |   1   | 0.625813576447 |
|  The Adventures Pete and Ma... |   1   | 0.107231828438 |
|  The Bear and the Dragon (J... |   1   | 0.304125580059 |
|       A Southern Family        |   1   | 0.464159761501 |
|  Jenny Dale's Puppy Patrol ... |   1   | 0.107231828438 |
+-------------------------------+-------+----------------+
[777 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 a
nd columns.
```

In [39]:

```
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()
```



As per the above plot, RMSE by item has improved substantially with user-item recommendation model.

RMSE Results by User for User-Item Similarity with Default Parameters

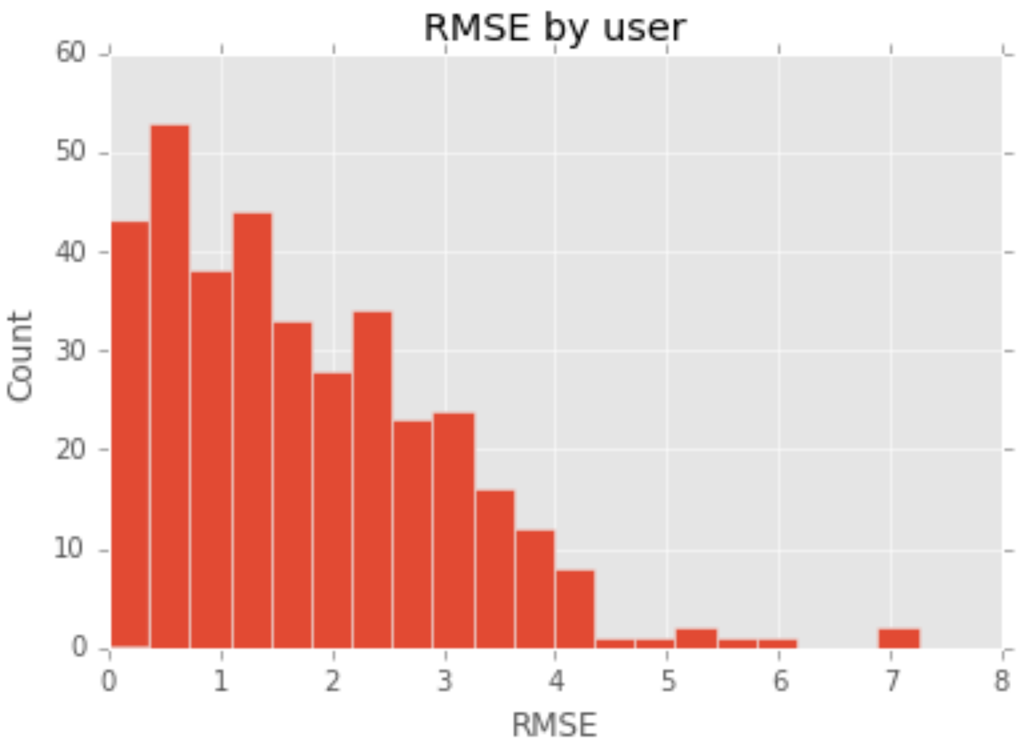
In [40]:

```
print rmse_results.viewkeys()
print rmse_results['rmse_by_user']
```

```
dict_keys(['rmse_by_user', 'precision_recall_overall', 'rmse_by_item',
'precision_recall_by_user', 'rmse_overall'])
+---------+-------+-----------------+
| User-ID | count |       rmse      |
+---------+-------+-----------------+
|  21045  |   1   |  1.01427557232  |
|  163409 |   1   |  0.277145511525 |
|  234288 |   1   |  1.70193555666  |
|  32516  |   4   |  2.07997636268  |
|  75096  |   1   |  1.19704270078  |
|  31820  |   1   |  1.29127104865  |
|  128782 |   3   |  2.73475033299  |
|  94445  |   1   | 0.0157295195926 |
|  127244 |   1   | 0.0335496394504 |
|  179922 |   1   |  0.87520650314  |
+---------+-------+-----------------+
[364 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 a
nd columns.
```

In [41]:

```
from matplotlib import pyplot as plt
%matplotlib inline
plt.style.use('ggplot')
rmsevals=rmse_results['rmse_by_user']['rmse']
plt.hist(rmsevals, bins=20)
plt.xlabel('RMSE')
plt.ylabel('Count')
plt.title('RMSE by user')
plt.show()
```



As per the above plot, RMSE by user has improved substantially with user-item recommendation model.

So, for the user-item similarity model with Default Parameters , the best RMSE per item is 0.001014 and worst is 11.017 . Whereas the best RMSE per user is 0.001014 and worst is 7.2549. The overall RMSE value is 2.92.

Aggregate values of precision, recall, and Standard deviation by Cutoff

In [42]:

```
rmse_results['precision_recall_by_user'].groupby('cutoff',[agg.AVG('precision'),agg
```

Out[42]:

cutoff	Avg of precision	Stdv of precision	Avg of recall	Stdv
36	0.00106837606838	0.00534188034188	0.0245225013082	0.1426
2	0.0	0.0	0.0	0
46	0.0011944577162	0.00495376047619	0.0355115122972	0.1701
31	0.000974831619993	0.00552230790546	0.0216836734694	0.1391
26	0.000739644970414	0.00528212161874	0.0148155416013	0.1172
8	0.0	0.0	0.0	0
5	0.0	0.0	0.0	0
16	0.000171703296703	0.00327138717089	0.000686813186813	0.01308
41	0.00100509246851	0.0048481171171	0.0272697540555	0.1514
4	0.0	0.0	0.0	0

[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.

So, this is getting better, but we might need to tune the model parameters by overriding default parameters.

5.3.2.2. User-Item Similarity Recommender with User-Inputted Parameters

In [43]:

```
# Create a User-item recommendation model by overriding parameters.
m2 = gl.recommender.ranking_factorization_recommender.create(train,
                                  user_id="User-ID",
                                  item_id="Book-Title",
                                  target="Book-Rating",
                                  num_factors=16,                # override the de
                                  regularization=0.01,          # override the defa
                                  linear_regularization = 0.001)   # override the de

rmse_results = m2.evaluate(test)
```

```
Recsys training: model = ranking_factorization_recommender

Preparing data set.

    Data has 383031 observations with 67978 users and 135383 items.

    Data prepared in: 0.715591s

Training ranking_factorization_recommender for recommendations.

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

| Parameter                      | Description
| Value     |

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

| num_factors                    | Factor Dimension
```

With User-Item Model, RMSE has improved and is equal to 1.367

RMSE Results by Item for User-Item Similarity with User-Inputed Parameters

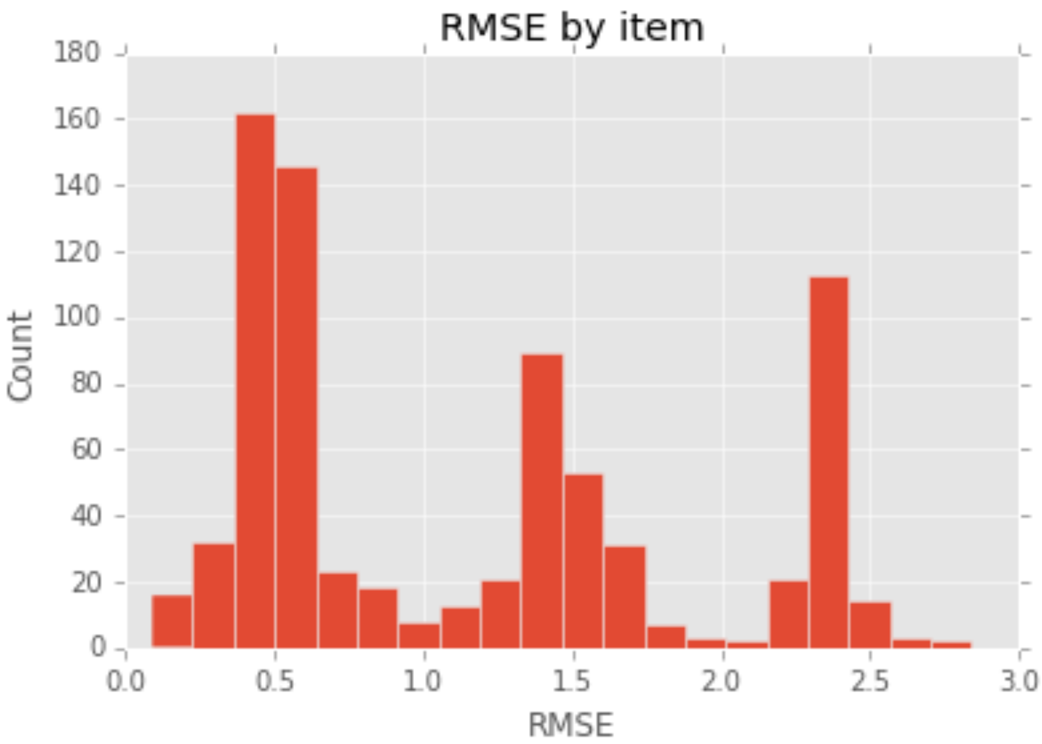
In [44]:

```
print rmse_results.viewkeys()
print rmse_results['rmse_by_item']
```

```
dict_keys(['rmse_by_user', 'precision_recall_overall', 'rmse_by_item',
'precision_recall_by_user', 'rmse_overall'])
+--------------------------------+-------+----------------+
|           Book-Title           | count |      rmse      |
+--------------------------------+-------+----------------+
|        House of Echoes         |   1   |  1.4006896675  |
| Small Gods (Discworld Nove...  |   1   |  1.8094740556  |
| Crowner'S Quest : A Crowne...  |   1   | 0.817484226955 |
| The Adventures of Hucklebe...  |   1   | 0.333601116149 |
| Ophelia Speaks : Adolescen...  |   1   | 2.43164396234  |
| My Land: A Homesteader's Tale  |   1   | 0.625813576447 |
| The Adventures Pete and Ma...  |   1   | 0.37257207913  |
| The Bear and the Dragon (J...  |   1   | 0.377268413028 |
|       A Southern Family        |   1   | 1.57914030837  |
| Jenny Dale's Puppy Patrol ...  |   1   | 0.37257207913  |
+--------------------------------+-------+----------------+
[777 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 a
nd columns.
```

In [45]:

```
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()
```



As per the above plot, RMSE by item has improved further with user-item recommendation model

RMSE Results by User for User-Item Similarity with User-Inputted Parameters

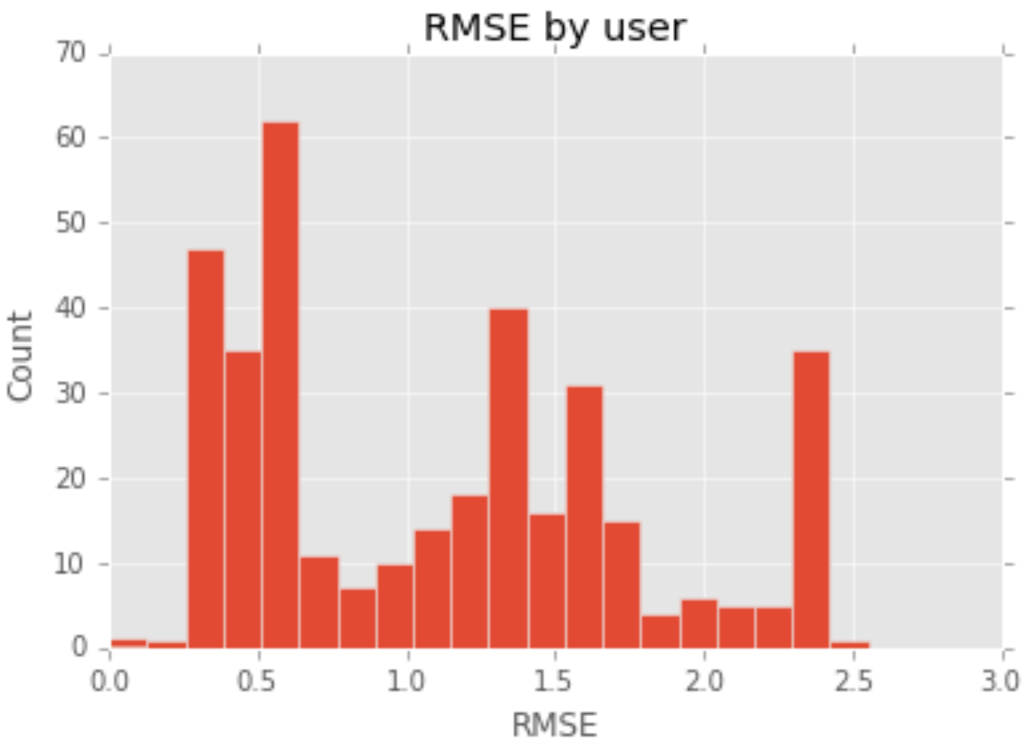
In [46]:

```
print rmse_results.viewkeys()
print rmse_results['rmse_by_user']
```

```
dict_keys(['rmse_by_user', 'precision_recall_overall', 'rmse_by_item',
'precision_recall_by_user', 'rmse_overall'])
+---------+-------+----------------+
| User-ID | count |      rmse      |
+---------+-------+----------------+
|  21045  |   1   | 0.63327360438  |
|  163409 |   1   | 0.333601116149 |
|  234288 |   1   | 0.454876911772 |
|  32516  |   4   | 2.07001779375  |
|  75096  |   1   | 2.33202209877  |
|  31820  |   1   | 1.51344071613  |
|  128782 |   3   | 0.951727807227 |
|  94445  |   1   | 1.60324370028  |
|  127244 |   1   |  2.1543936701  |
|  179922 |   1   | 1.62170893052  |
+---------+-------+----------------+
[364 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 a
nd columns.
```

In [47]:

```
from matplotlib import pyplot as plt
%matplotlib inline
plt.style.use('ggplot')
rmsevals=rmse_results['rmse_by_user']['rmse']
plt.hist(rmsevals, bins=20)
plt.xlabel('RMSE')
plt.ylabel('Count')
plt.title('RMSE by user')
plt.show()
```



As per the above plot, RMSE by user has improved further with user-item recommendation model

So, for the user-item model with user supplied parameters , the best RMSE per item is 0.0869 and worst is 2.83 . Whereas the best RMSE per user is 0.0059 and worst is 2.545. The overall RMSE value is 1.3670.

Models Comparison

Comparison by RMSE

In [48]:

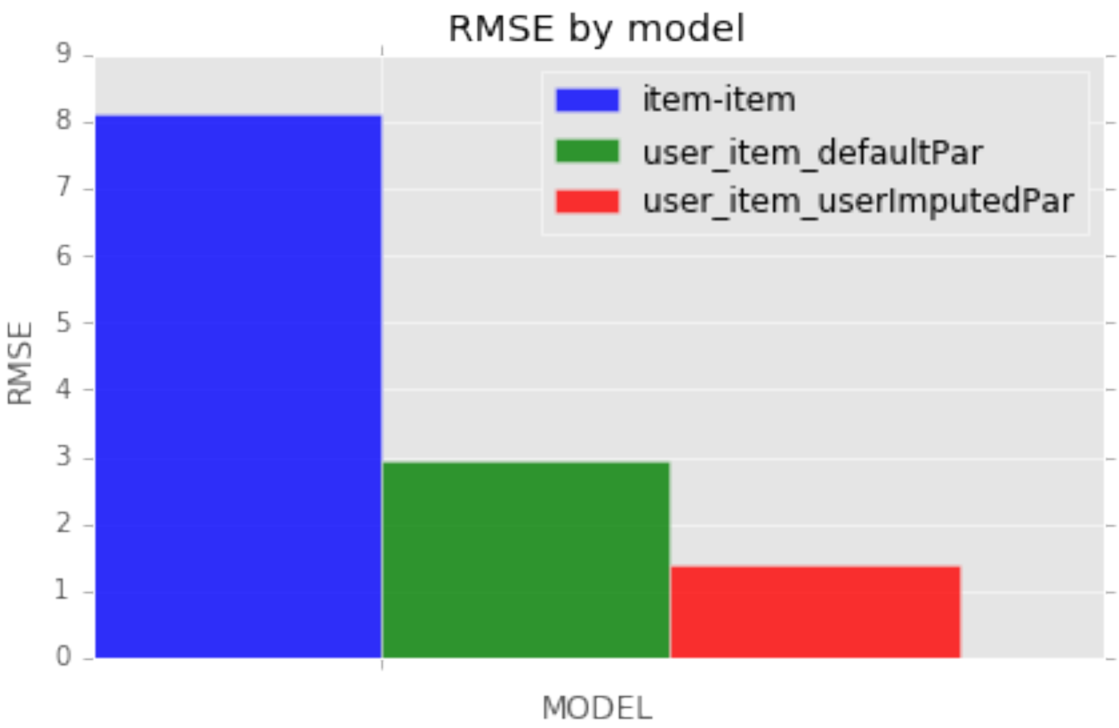
```
comparisons = gl.recommender.util.compare_models(test, [item_item, m1, m2])
```

```
PROGRESS: Evaluate model M0

Precision and recall summary statistics by cutoff
+--------+-----------------+-----------------+
| cutoff |  mean_precision |   mean_recall   |
+--------+-----------------+-----------------+
|   1    | 0.00274725274725 | 0.000392464678179 |
|   2    | 0.00412087912088 |  0.00124280481423 |
|   3    | 0.00457875457875 |  0.00438252223967 |
|   4    | 0.00343406593407 |  0.00438252223967 |
|   5    | 0.0032967032967  |  0.00575614861329 |
|   6    | 0.00320512820513 |  0.00606139891854 |
|   7    | 0.00313971742543 |  0.00743502529217 |
|   8    | 0.00274725274725 |  0.00743502529217 |
|   9    | 0.00274725274725 |  0.0101822780394  |
|   10   | 0.00247252747253 |  0.0101822780394  |
+--------+-----------------+-----------------+
[10 rows x 3 columns]

('\nOverall RMSE: ', 8.13124624310311...)
```

In [82]:

```
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
# Root mean square error(RMSE)
n_groups = 1
ItemItem = (8.1311)
user_item_defaultPar = (2.924)
user_item_userImputedPar = (1.367)


# create plot
fig, ax = plt.subplots()
index = np.arange(n_groups)
bar_width = 0.4
opacity = 0.8

rects1 = plt.bar(index, ItemItem, bar_width,
                 alpha=opacity,
                 color='b',
                 label='item-item')

rects2 = plt.bar(index + bar_width, user_item_defaultPar, bar_width,
                 alpha=opacity,
                 color='g',
                 label='user_item_defaultPar')
rects3 = plt.bar(index + bar_width+bar_width, user_item_userImputedPar, bar_width,
                 alpha=opacity,
                 color='r',
```

```
                 color='r',
                 label='user_item_userImputedPar')

plt.xlabel('MODEL')
plt.ylabel('RMSE')
plt.title('RMSE by model')
plt.xticks(index + bar_width, ('', '', '', ''))
plt.legend()

plt.tight_layout()
plt.show()
```



User-item model with overridden parameters worked the best (RMSE=1.36) among three models based on overall RMSE.

Comparison by Precision and Recall cutoff

In [50]:

```
#Model Comparision
model_comp = gl.compare(test, [item_item, m1, m2])
```

```
PROGRESS: Evaluate model M0

Precision and recall summary statistics by cutoff
+--------+-------------------+-------------------+
| cutoff |   mean_precision  |    mean_recall    |
+--------+-------------------+-------------------+
|   1    | 0.00274725274725  | 0.000392464678179 |
|   2    | 0.00412087912088  |  0.00124280481423 |
|   3    | 0.00457875457875  |  0.00438252223967 |
|   4    | 0.00343406593407  |  0.00438252223967 |
|   5    | 0.0032967032967   |  0.00575614861329 |
|   6    | 0.00320512820513  |  0.00606139891854 |
```

```
|    7    | 0.00313971742543 |  0.00743502529217 |
|    8    | 0.00274725274725 |  0.00743502529217 |
|    9    | 0.00274725274725 |  0.0101822780394  |
|    10   | 0.00247252747253 |  0.0101822780394  |
+--------+------------------+-------------------+
[10 rows x 3 columns]

PROGRESS: Evaluate model M1

Precision and recall summary statistics by cutoff
+--------+----------------+-------------+
| cutoff | mean_precision | mean_recall |
+--------+----------------+-------------+
|    1   |      0.0       |     0.0     |
|    2   |      0.0       |     0.0     |
|    3   |      0.0       |     0.0     |
|    4   |      0.0       |     0.0     |
|    5   |      0.0       |     0.0     |
|    6   |      0.0       |     0.0     |
|    7   |      0.0       |     0.0     |
|    8   |      0.0       |     0.0     |
|    9   |      0.0       |     0.0     |
|    10  |      0.0       |     0.0     |
+--------+----------------+-------------+
[10 rows x 3 columns]

PROGRESS: Evaluate model M2

Precision and recall summary statistics by cutoff
+--------+-------------------+-------------------+
| cutoff |   mean_precision  |    mean_recall    |
+--------+-------------------+-------------------+
|    1   |  0.00274725274725 | 0.000137362637363 |
|    2   |  0.00137362637363 | 0.000137362637363 |
|    3   | 0.000915750915751 | 0.000137362637363 |
|    4   | 0.000686813186813 | 0.000137362637363 |
|    5   |  0.0010989010989  |  0.00151098901099 |
|    6   | 0.000915750915751 |  0.00151098901099 |
|    7   | 0.000784929356358 |  0.00151098901099 |
|    8   |  0.00137362637363 |  0.00700549450549 |
|    9   |   0.001221001221  |  0.00700549450549 |
|    10  |  0.0010989010989  |  0.00700549450549 |
+--------+-------------------+-------------------+
[10 rows x 3 columns]

Model compare metric: precision_recall
```

In [51]:

```
## model comparsion by precision and recall
gl.show_comparison(model_comp,[item_item, m1, m2])
#gl.show_comparison(comparison,[item_item, m1, m2])
```

Item-item model's precision and recall are highest for lower cut off while user-item model's precision and recall are highest for higher cut off.

5.3.2.3. User-Item Similarity Recommender with Grid Search selected parameters

We found out that the user-item model with user overridden parameters values is best for recommendations of book ratings. Now we can finetune the best input parameters using Grid Search Method.

In [52]:

```
## Searching best parameters
params = {'user_id': 'User-ID',
          'item_id': 'Book-Title',
          'target': 'Book-Rating',
          'num_factors': [8, 12, 16, 24, 32],
          'regularization':[0.01] ,
          '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-Param
eter-Search-Apr-30-2017-17-57-2700000' ready for execution
[INFO] graphlab.deploy.map_job: Job: 'Model-Parameter-Search-Apr-30-20
17-17-57-2700000' scheduled.
[INFO] graphlab.deploy.job: Validating job.
[INFO] graphlab.deploy.map_job: A job with name 'Model-Parameter-Searc
h-Apr-30-2017-17-57-2700000' already exists. Renaming the job to 'Mode
l-Parameter-Search-Apr-30-2017-17-57-2700000-5f02c'.
[INFO] graphlab.deploy.map_job: Validation complete. Job: 'Model-Param
eter-Search-Apr-30-2017-17-57-2700000-5f02c' ready for execution
[INFO] graphlab.deploy.map_job: Job: 'Model-Parameter-Search-Apr-30-20
17-17-57-2700000-5f02c' scheduled.
```

In [53]:

```
#Print Job Status
job.get_status()
```

Out[53]:

```
{'Canceled': 0, 'Completed': 0, 'Failed': 0, 'Pending': 5, 'Running':
0}
```

Overall Result

In [54]:

```
# printing the 5 models' parameters
job_result = job.get_results()
job_result.head()
```

Out[54]:

model_id	item_id	linear_regularization	max_iterations	num_factors	n
1	Book-Title	0.001	25	24	
0	Book-Title	0.001	50	16	
3	Book-Title	0.001	50	32	
2	Book-Title	0.001	50	8	
4	Book-Title	0.001	50	16	

regularization	target	user_id	training_precision@5	training_recall@5
0.01	Book-Rating	User-ID	0.00416605372326	0.00361735023214
0.01	Book-Rating	User-ID	0.00416605372326	0.00361735023214
0.01	Book-Rating	User-ID	0.00416605372326	0.00361735023214
0.01	Book-Rating	User-ID	0.00416605372326	0.00361735023214
0.01	Book-Rating	User-ID	0.00416605372326	0.00361735023214

validation_recall@5	validation_rmse
0.00151098901099	1.35053642891
0.00151098901099	1.40062095947
0.00151098901099	1.36711233333
0.00151098901099	1.36701293558
0.00151098901099	1.35081291328

[5 rows x 16 columns]

For each model, it calculated average RMSE, Precision and Recall on the training and test set.

Best Parameters

In [55]:

```
# Printing the best parameters
bst_prms = job.get_best_params()
bst_prms
```

Out[55]:

```
{'item_id': 'Book-Title',
 'linear_regularization': 0.001,
 'max_iterations': 25,
 'num_factors': 24,
 'num_sampled_negative_examples': 4,
 'ranking_regularization': 0.1,
 'regularization': 0.01,
 'target': 'Book-Rating',
 'user_id': 'User-ID'}
```

Printing the five models' information

In [56]:

```
## printing the five model's detail information
models = job.get_models()
models
```

Out[56]:

```
[Class                            : RankingFactorizationRecommender

 Schema
 ------
 User ID                          : User-ID
 Item ID                          : Book-Title
 Target                           : Book-Rating
 Additional observation features  : 0
 User side features               : []
 Item side features               : []

 Statistics
 ----------
 Number of observations           : 383031
 Number of users                  : 67978
 Number of items                  : 135383

 Training summary
```

Model Comparisions

In [57]:

```
## Printing precision and recall to compare the five grid search models
```

```
comparisonstruct = gl.compare(test,models)

## plotting the recall-precision graph to compare the models
gl.show_comparison(comparisonstruct,models)
```

```
PROGRESS: Evaluate model M0

Precision and recall summary statistics by cutoff
+--------+-------------------+-------------------+
| cutoff |   mean_precision  |    mean_recall    |
+--------+-------------------+-------------------+
|   1    |  0.00274725274725 | 0.000137362637363 |
|   2    |  0.00137362637363 | 0.000137362637363 |
|   3    | 0.000915750915751 | 0.000137362637363 |
|   4    | 0.000686813186813 | 0.000137362637363 |
|   5    |  0.0010989010989  |  0.00151098901099 |
|   6    | 0.000915750915751 |  0.00151098901099 |
|   7    |  0.00156985871272 |  0.00700549450549 |
|   8    |  0.00137362637363 |  0.00700549450549 |
|   9    |   0.001221001221  |  0.00700549450549 |
|   10   |  0.00137362637363 |  0.00713036963037 |
+--------+-------------------+-------------------+
[10 rows x 3 columns]

PROGRESS: Evaluate model M1

Precision and recall summary statistics by cutoff
+--------+-------------------+-------------------+
| cutoff |   mean_precision  |    mean_recall    |
+--------+-------------------+-------------------+
|   1    |  0.00274725274725 | 0.000137362637363 |
|   2    |  0.00137362637363 | 0.000137362637363 |
|   3    | 0.000915750915751 | 0.000137362637363 |
|   4    | 0.000686813186813 | 0.000137362637363 |
|   5    |  0.0010989010989  |  0.00151098901099 |
|   6    | 0.000915750915751 |  0.00151098901099 |
|   7    |  0.00156985871272 |  0.00700549450549 |
|   8    |  0.00137362637363 |  0.00700549450549 |
|   9    |   0.001221001221  |  0.00700549450549 |
|   10   |  0.0010989010989  |  0.00700549450549 |
+--------+-------------------+-------------------+
[10 rows x 3 columns]

PROGRESS: Evaluate model M2

Precision and recall summary statistics by cutoff
+--------+-------------------+-------------------+
| cutoff |   mean_precision  |    mean_recall    |
+--------+-------------------+-------------------+
|   1    |  0.00274725274725 | 0.000137362637363 |
|   2    |  0.00137362637363 | 0.000137362637363 |
|   3    | 0.000915750915751 | 0.000137362637363 |
|   4    | 0.000686813186813 | 0.000137362637363 |
|   5    |  0.0010989010989  |  0.00151098901099 |
```

```
|    6    | 0.000915750915751 |  0.00151098901099 |
|    7    |  0.00156985871272 |  0.00700549450549 |
|    8    |  0.00137362637363 |  0.00700549450549 |
|    9    |   0.001221001221  |  0.00700549450549 |
|    10   |  0.0010989010989  |  0.00700549450549 |
+--------+-------------------+-------------------+
[10 rows x 3 columns]

PROGRESS: Evaluate model M3

Precision and recall summary statistics by cutoff
+--------+-------------------+-------------------+
| cutoff |   mean_precision  |    mean_recall    |
+--------+-------------------+-------------------+
|    1   |  0.00274725274725 | 0.000137362637363 |
|    2   |  0.00137362637363 | 0.000137362637363 |
|    3   | 0.000915750915751 | 0.000137362637363 |
|    4   | 0.000686813186813 | 0.000137362637363 |
|    5   |  0.0010989010989  |  0.00151098901099 |
|    6   | 0.000915750915751 |  0.00151098901099 |
|    7   | 0.000784929356358 |  0.00151098901099 |
|    8   |  0.00137362637363 |  0.00700549450549 |
|    9   |   0.001221001221  |  0.00700549450549 |
|   10   |  0.0010989010989  |  0.00700549450549 |
+--------+-------------------+-------------------+
[10 rows x 3 columns]

PROGRESS: Evaluate model M4

Precision and recall summary statistics by cutoff
+--------+-------------------+-------------------+
| cutoff |   mean_precision  |    mean_recall    |
+--------+-------------------+-------------------+
|    1   |  0.00274725274725 | 0.000137362637363 |
|    2   |  0.00137362637363 | 0.000137362637363 |
|    3   | 0.000915750915751 | 0.000137362637363 |
|    4   | 0.000686813186813 | 0.000137362637363 |
|    5   |  0.0010989010989  |  0.00151098901099 |
|    6   | 0.000915750915751 |  0.00151098901099 |
|    7   | 0.000784929356358 |  0.00151098901099 |
|    8   |  0.00137362637363 |  0.00700549450549 |
|    9   |   0.001221001221  |  0.00700549450549 |
|   10   |  0.0010989010989  |  0.00700549450549 |
+--------+-------------------+-------------------+
[10 rows x 3 columns]

Model compare metric: precision_recall
```

From the five models, Model 1 is the best model with respect to RMSE. However, other models are better in terms of precision and recall.

Printing Information for Model 1 (Best out of the 5 Models)

In [84]:

```
models[1]
```

Out[84]:

```
Class                                : RankingFactorizationRecommender

Schema
------
User ID                              : User-ID
Item ID                              : Book-Title
Target                               : Book-Rating
Additional observation features      : 0
User side features                   : []
Item side features                   : []
```

```
Statistics
----------
Number of observations           : 383031
Number of users                  : 67978
Number of items                  : 135383

Training summary
----------------
Training time                    : 11.2977

Model Parameters
----------------
Model class                      : RankingFactorizationRecommender
num_factors                      : 24
binary_target                    : 0
side_data_factorization          : 1
solver                           : auto
nmf                              : 0
max_iterations                   : 25

Regularization Settings
-----------------------
regularization                   : 0.01
regularization_type              : normal
linear_regularization            : 0.001
ranking_regularization           : 0.1
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
```

6. Final Model Evaluation

At this stage in the project we have built a model (or models) that appears to have high quality, from a data analysis perspective. We compared item-item similarity model, user-item with default parameter model, and user-item with user controlled parameters model. We used RMSE, precision, and recall values as our evaluation criteria. Hence, among the models, we found out that the user-item with controlled parameters model works the best. Then we finetuned the best parameters to use as an input for the user-item model.

Now let's evaluate our final model with the best parameters inputted.

In [59]:

```
final_model = gl.recommender.ranking_factorization_recommender.create(train,
                                                                       user_id='User-
                                                                       item_id='Book-
                                                                       target="Book-I
                                                                       num_factors=24
                                                                       regularizatio
                                                                       linear_regula
                                                                       ranking_regula
                                                                       unobserved_rat
                                                                       num_sampled_ne
                                                                       side_data_fact
                                                                       max_iterations
                                                                       sgd_step_size=
                                                                       random_seed=0,
                                                                       binary_target=
                                                                       solver='auto')



rmse_results = final_model.evaluate(test)
```

```
Recsys training: model = ranking_factorization_recommender

Preparing data set.

    Data has 383031 observations with 67978 users and 135383 items.

    Data prepared in: 0.779839s

Training ranking_factorization_recommender for recommendations.

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

| Parameter                      | Description
| Value    |

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

| num_factors                    | Factor Dimension
```

RMSE Results by Item for User-Item Similarity-Final Model

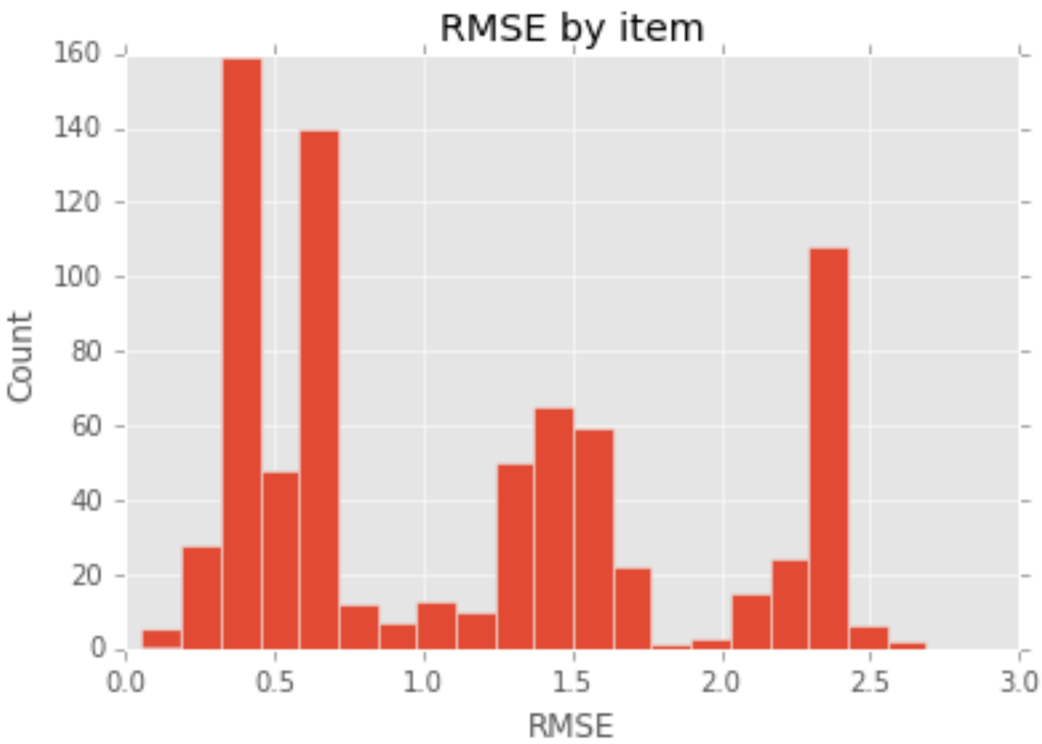
In [60]:

```
# printing RMSE values by item for the final model
print rmse_results.viewkeys()
print rmse_results['rmse_by_item']
```

```
dict_keys(['rmse_by_user', 'precision_recall_overall', 'rmse_by_item',
'precision_recall_by_user', 'rmse_overall'])
+-------------------------------+-------+----------------+
|           Book-Title          | count |      rmse      |
+-------------------------------+-------+----------------+
|        House of Echoes        |   1   | 1.38594008313  |
| Small Gods (Discworld Nove... |   1   | 1.64752795635  |
| Crowner'S Quest : A Crowne... |   1   | 0.66408967687  |
| The Adventures of Hucklebe... |   1   | 0.328969602972 |
| Ophelia Speaks : Adolescen... |   1   | 2.40749126225  |
| My Land: A Homesteader's Tale |   1   | 0.625813576447 |
| The Adventures Pete and Ma... |   1   | 0.371428328047 |
| The Bear and the Dragon (J... |   1   | 0.373958523855 |
|       A Southern Family       |   1   | 1.59500061167  |
| Jenny Dale's Puppy Patrol ... |   1   | 0.371428328047 |
+-------------------------------+-------+----------------+
[777 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 a
nd columns.
```

In [61]:

```
# plotting RMSE values by item for the final model
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()
```



As per the above plot, RMSE by item has improved further with user-item recommendation model with tuned parameters .

RMSE Results by User for User-Item Similarity-Final Model

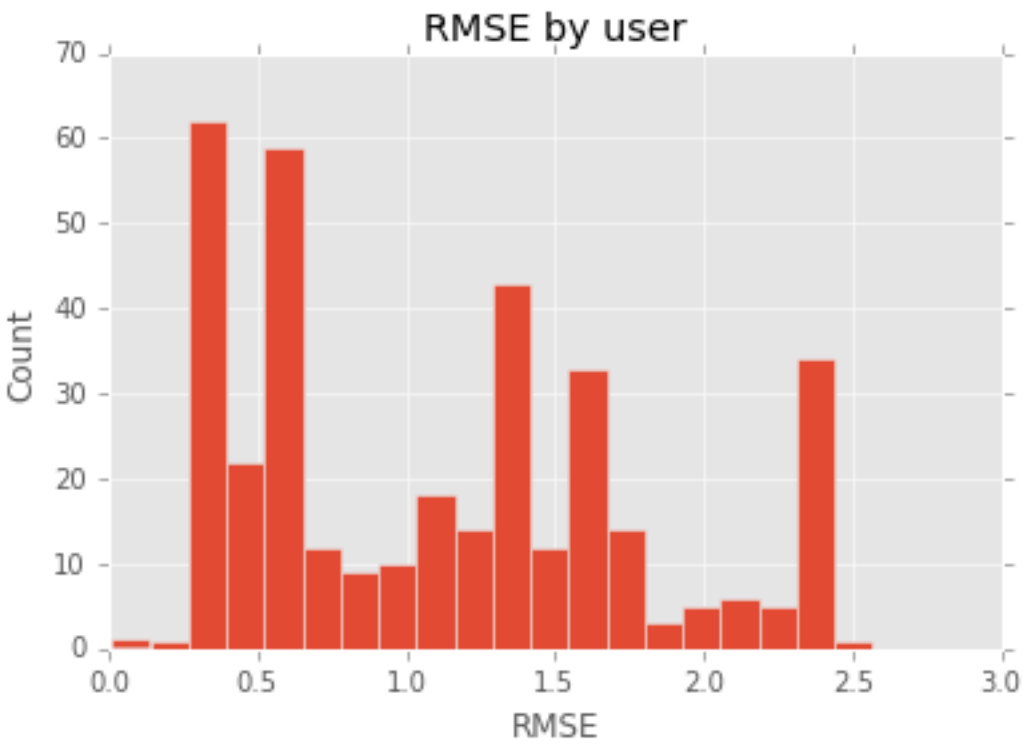
In [62]:

```
# printing RMSE values by user for the final model
print rmse_results.viewkeys()
print rmse_results['rmse_by_user']
```

```
dict_keys(['rmse_by_user', 'precision_recall_overall', 'rmse_by_item',
'precision_recall_by_user', 'rmse_overall'])
+---------+-------+----------------+
| User-ID | count |      rmse      |
+---------+-------+----------------+
|  21045  |   1   | 0.639266308684 |
|  163409 |   1   | 0.328969602972 |
|  234288 |   1   | 0.423742712043 |
|  32516  |   4   | 2.05835162209  |
|  75096  |   1   | 2.31930873282  |
|  31820  |   1   | 1.51455154974  |
|  128782 |   3   | 0.94824014511  |
|  94445  |   1   | 1.61171763815  |
|  127244 |   1   | 2.16777986003  |
|  179922 |   1   | 1.62334517395  |
+---------+-------+----------------+
[364 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 a
nd columns.
```

In [63]:

```
# plotting RMSE values by user for the final model
from matplotlib import pyplot as plt
%matplotlib inline
plt.style.use('ggplot')
rmsevals=rmse_results['rmse_by_user']['rmse']
plt.hist(rmsevals, bins=20)
plt.xlabel('RMSE')
plt.ylabel('Count')
plt.title('RMSE by user')
plt.show()
```



As per the above plot, RMSE by user has improved further with user-item recommendation model with tuned parameters .

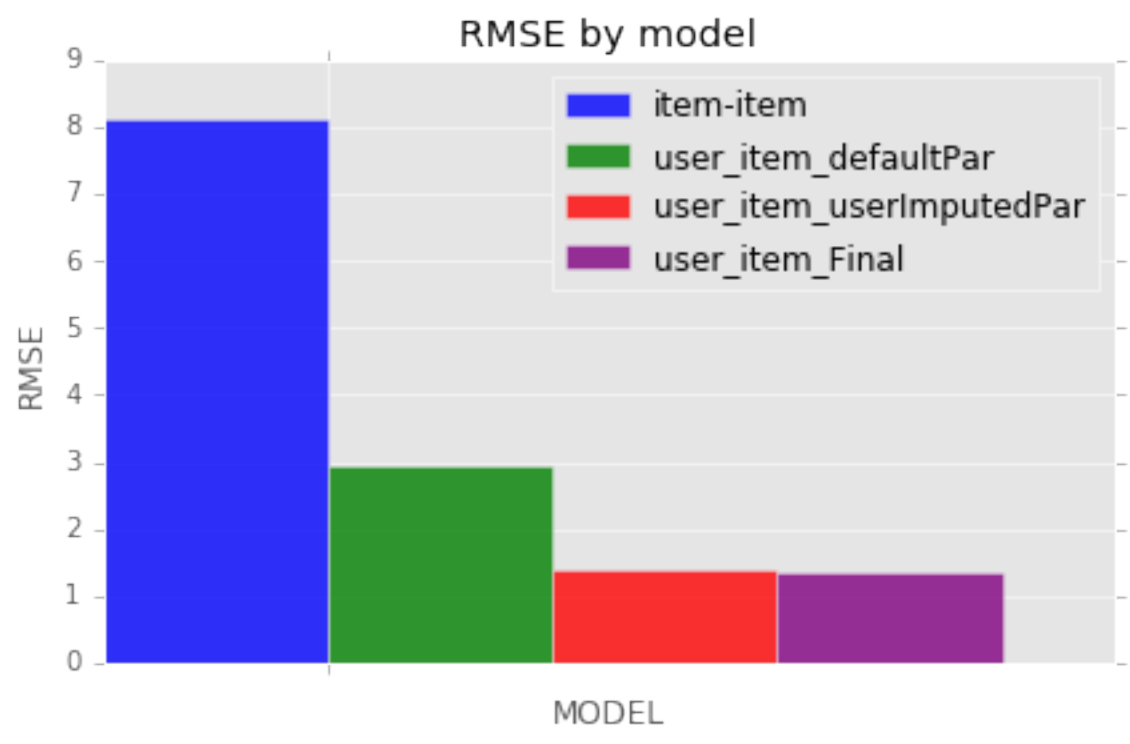
The overall RMSE value for the user-item with best parameters recommendation model is 1.35, which is the smallest value compared to the previous model. This is compared using the following bar graph.

Comparison of Final Model with the Previous Models by RMSE

In [85]:

```
# comparison of final model with previous models
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
# Root mean square error(RMSE)
n_groups = 1
ItemItem = (8.1311)
user_item_defaultPar = (2.924)
user_item_userImputedPar = (1.367)
```

```
user_item_Final = (1.35)


# create plot
fig, ax = plt.subplots()
index = np.arange(n_groups)
bar_width = 0.4
opacity = 0.8

rects1 = plt.bar(index, ItemItem, bar_width,
                 alpha=opacity,
                 color='b',
                 label='item-item')

rects2 = plt.bar(index + bar_width, user_item_defaultPar, bar_width,
                 alpha=opacity,
                 color='g',
                 label='user_item_defaultPar')
rects3 = plt.bar(index + bar_width+bar_width, user_item_userImputedPar, bar_width,
                 alpha=opacity,
                 color='r',
                 label='user_item_userImputedPar')
rects4 = plt.bar(index + bar_width+bar_width+bar_width, user_item_Final, bar_width,
                 alpha=opacity,
                 color='purple',
                 label='user_item_Final')



plt.xlabel('MODEL')
plt.ylabel('RMSE')
plt.title('RMSE by model')
plt.xticks(index + bar_width, ('', '', '', ''))
plt.legend()

plt.tight_layout()
plt.show()
```



Taking RMSE value as a measurer criteria, the user-item-final model has the lowest RMSE.

Comparison of Final Model with the Previous Models by Precision , Recall and Cutoff

In [65]:

```
# printing precision and recall for the all models
comparisonstruct = gl.compare(test, [item_item, m1, m2,final_model])
```

```
PROGRESS: Evaluate model M0

Precision and recall summary statistics by cutoff
+--------+-------------------+-------------------+
| cutoff |   mean_precision  |    mean_recall    |
+--------+-------------------+-------------------+
|   1    | 0.00274725274725  | 0.000392464678179 |
|   2    | 0.00412087912088  |  0.00124280481423 |
|   3    | 0.00457875457875  |  0.00438252223967 |
|   4    | 0.00343406593407  |  0.00438252223967 |
|   5    | 0.0032967032967   |  0.00575614861329 |
|   6    | 0.00320512820513  |  0.00606139891854 |
|   7    | 0.00313971742543  |  0.00743502529217 |
|   8    | 0.00274725274725  |  0.00743502529217 |
|   9    | 0.00274725274725  |  0.0101822780394  |
|   10   | 0.00247252747253  |  0.0101822780394  |
+--------+-------------------+-------------------+
[10 rows x 3 columns]

PROGRESS: Evaluate model M1

Precision and recall summary statistics by cutoff
+--------+----------------+-------------+
| cutoff | mean_precision | mean_recall |
+--------+----------------+-------------+
|   1    |      0.0       |     0.0     |
|   2    |      0.0       |     0.0     |
|   3    |      0.0       |     0.0     |
|   4    |      0.0       |     0.0     |
|   5    |      0.0       |     0.0     |
|   6    |      0.0       |     0.0     |
|   7    |      0.0       |     0.0     |
|   8    |      0.0       |     0.0     |
|   9    |      0.0       |     0.0     |
|   10   |      0.0       |     0.0     |
+--------+----------------+-------------+
[10 rows x 3 columns]

PROGRESS: Evaluate model M2
```

```
Precision and recall summary statistics by cutoff
+--------+------------------+------------------+
| cutoff |  mean_precision  |   mean_recall    |
+--------+------------------+------------------+
|   1    | 0.00274725274725 | 0.000137362637363 |
|   2    | 0.00137362637363 | 0.000137362637363 |
|   3    | 0.000915750915751 | 0.000137362637363 |
|   4    | 0.000686813186813 | 0.000137362637363 |
|   5    | 0.0010989010989  | 0.00151098901099 |
|   6    | 0.000915750915751 | 0.00151098901099 |
|   7    | 0.000784929356358 | 0.00151098901099 |
|   8    | 0.00137362637363 | 0.00700549450549 |
|   9    |  0.001221001221  | 0.00700549450549 |
|   10   | 0.0010989010989  | 0.00700549450549 |
+--------+------------------+------------------+
[10 rows x 3 columns]

PROGRESS: Evaluate model M3

Precision and recall summary statistics by cutoff
+--------+------------------+------------------+
| cutoff |  mean_precision  |   mean_recall    |
+--------+------------------+------------------+
|   1    | 0.00274725274725 | 0.000137362637363 |
|   2    | 0.00137362637363 | 0.000137362637363 |
|   3    | 0.000915750915751 | 0.000137362637363 |
|   4    | 0.000686813186813 | 0.000137362637363 |
|   5    | 0.0010989010989  | 0.00151098901099 |
|   6    | 0.000915750915751 | 0.00151098901099 |
|   7    | 0.00156985871272 | 0.00700549450549 |
|   8    | 0.00137362637363 | 0.00700549450549 |
|   9    |  0.001221001221  | 0.00700549450549 |
|   10   | 0.0010989010989  | 0.00700549450549 |
+--------+------------------+------------------+
[10 rows x 3 columns]

Model compare metric: precision_recall
```

In [66]:

```
## plotting precision and recall values to compare final model with the previous
gl.show_comparison(comparisonstruct,[item_item, m1, m2,final_model])
```

Item-item model's precision and recall are highest for lower cut off while user-item model's precision and recall are highest for higher cut off.

6.1. The Final User-Item Recommendation Model

With the precision and recall criteria, the item-item similarity model came out to be a good model. Which means that it is better in recommending books, however, it cannot predict book ratings as good. For that reason, we consider the RMSE as the best measure to evaluate our models. And with RMSE as a measure criteria, the user-item recommendation model with the tuned parameters came out to be the best. Therefore, we consider user-item model as our final recommendation model.

In [67]:

```
## Model for the user-item with best parameters inputed
final_model = gl.recommender.ranking_factorization_recommender.create(sf_TargetCols,
                                                                       user_id='User-
                                                                       item_id='Book-
                                                                       target="Book-R
                                                                       num_factors=24
                                                                       regularization
                                                                       linear_regular
                                                                       ranking_regula
                                                                       unobserved_rat
                                                                       num_sampled_ne
                                                                       side_data_fact
                                                                       max_iterations
                                                                       sgd_step_size=
                                                                       random_seed=0,
                                                                       binary_target=
                                                                       solver='auto')

# We Recommend books for every user using the final model
Recommendations = final_model.recommend(users=None, k=15)
Recommendations.print_rows(15)
```

```
Recsys training: model = ranking_factorization_recommender

Preparing data set.

    Data has 383839 observations with 68091 users and 135565 items.

    Data prepared in: 0.702912s

Training ranking_factorization_recommender for recommendations.

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

| Parameter                      | Description
| Value    |

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

| num_factors                    | Factor Dimension
```

In [68]:

```
## We recommend books for a specific user(with User-ID '251439' )
## using the final model
rec_books_spUser = final_model.recommend(['251439'],k=15)
rec_books_spUser.print_rows(15)
```

```
+---------+--------------------------------+---------------+------+
| User-ID |           Book-Title           |     score     | rank |
+---------+--------------------------------+---------------+------+
|  251439 | Harry Potter and the Sorce...  | 8.33568544431 |  1   |
|  251439 | Harry Potter and the Priso...  | 8.33046765371 |  2   |
|  251439 | Harry Potter and the Goble...  | 8.31955696388 |  3   |
|  251439 | Harry Potter and the Chamb...  | 8.29538984342 |  4   |
|  251439 |     To Kill a Mockingbird      | 8.28386969609 |  5   |
|  251439 | Harry Potter and the Order...  | 8.22164495034 |  6   |
|  251439 |       The Da Vinci Code        | 8.18007988973 |  7   |
|  251439 | Harry Potter and the Sorce...  | 8.16251654668 |  8   |
|  251439 |     The Secret Life of Bees    | 8.16197176023 |  9   |
|  251439 | The Fellowship of the Ring...  | 8.15596981092 |  10  |
|  251439 | The Two Towers (The Lord o...  |  8.135028017  |  11  |
|  251439 | Tuesdays with Morrie: An O...  | 8.06697912259 |  12  |
|  251439 |   The Lovely Bones: A Novel    | 8.06541265292 |  13  |
|  251439 | Ender's Game (Ender Wiggin...  | 8.05479101582 |  14  |
|  251439 | The Return of the King (Th...  | 8.01828028007 |  15  |
+---------+--------------------------------+---------------+------+
[15 rows x 4 columns]
```

7. Exceptional Work

7.1 Using side features as SFrame in the ranking factorization recommender

In many cases, additional information about the users or items can improve the quality of the recommendations. For example, including information about the age of a user, publisher, and publishing year of a book can be useful information in recommending books. This type of information is called **user side data(user side feature)** or **item side data (item side feature)** depending on whether it goes with the user or the item.

Including side data is easy with the user_data or item_data parameters to the *recommender.create()* function. These arguments are SFrames and must have a user or item column that corresponds to the user_id and item_id columns in the observation data. Internally, the data is joined to the particular user or item when training the model, the data is saved with the model and also used to make recommendations.

In particular, the *FactorizationRecommender* and the **RankingFactorizationRecommender** both incorporate the side data into the prediction through additional interaction terms between the user, the item, and the side feature. Both of these models also allow us to obtain the parameters that have been learned for each of the side features via the *m['coefficients']* argument.

We may also check the number of columns used as side information by querying *m['observation_column_names']*, *m['user_side_data_column_names']*, and *m['item_side_data_column_names']*. Moreover, by printing the model, we can see this information as well.

Now, we are going to use **user's age** and **location** as side features for a user and **book publisher**, **year of book published**, **book author**, and **url** as side features for an item (book). [5][6]

Side Features

In [69]:

```
## SFrames for side features for the user and item
user_side_info = sf_Users
item_side_info = sf_Books
```

In [70]:

```
# Printing top 10 records for user side features
#user side features
sf_Users.head()
```

Out[70]:

User-ID	Location	Age
2	stockton, california, usa	18
4	porto, v.n.gaia, portugal	17
6	santa monica, california, usa ...	61
10	albacete, wisconsin, spain ...	26
11	melbourne, victoria, australia ...	14
13	barcelona, barcelona, spain ...	26
18	rio de janeiro, rio de janeiro, brazil ...	25
19	weston, ,	14
20	langhorne, pennsylvania, usa ...	19
21	ferrol / spain, alabama, spain ...	46

[10 rows x 3 columns]

In [71]:

```
# Printing top 10 records for item side features
sf_Books.head()#
```

Out[71]:

ISBN	Book-Title	Book-Author	Year-Of-Publication	Publisher
0195153448	Classical Mythology	Mark P. O. Morford	2002	Oxford University Press
0002005018	Clara Callan	Richard Bruce Wright	2001	HarperFlamingo Canada

0060973129	Decision in Normandy	Carlo D'Este	1991	HarperPerennial
0374157065	Flu: The Story of the Great Influenza Pandemic ...	Gina Bari Kolata	1999	Farrar Straus Giroux
0393045218	The Mummies of Urumchi	E. J. W. Barber	1999	W. W. Norton & Company ...
0399135782	The Kitchen God's Wife	Amy Tan	1991	Putnam Pub Group
0425176428	What If?: The World's Foremost Military ...	Robert Cowley	2000	Berkley Publishing Group
0671870432	PLEADING GUILTY	Scott Turow	1993	Audioworks
0679425608	Under the Black Flag: The Romance and the Reality ...	David Cordingly	1996	Random House
074322678X	Where You'll Find Me: And Other Stories ...	Ann Beattie	2002	Scribner

Image-URL-S	Image-URL-M	Image-URL-L
http://images.amazon.com/images/P/0195153448.0 ...	http://images.amazon.com/images/P/0195153448.0 ...	http://images.amazon.com/images/P/0195153448.0 ...
http://images.amazon.com/images/P/0002005018.0 ...	http://images.amazon.com/images/P/0002005018.0 ...	http://images.amazon.com/images/P/0002005018.0 ...
http://images.amazon.com/images/P/0060973129.0 ...	http://images.amazon.com/images/P/0060973129.0 ...	http://images.amazon.com/images/P/0060973129.0 ...
http://images.amazon.com/images/P/0374157065.0 ...	http://images.amazon.com/images/P/0374157065.0 ...	http://images.amazon.com/images/P/0374157065.0 ...
http://images.amazon.com/images/P/0393045218.0 ...	http://images.amazon.com/images/P/0393045218.0 ...	http://images.amazon.com/images/P/0393045218.0 ...

Target Columns

In [72]:

```
# Printing top 10 records for target SFrame
sf_TargetCols.head()
```

Out[72]:

User-ID	Book-Title	Book-Rating
276726	Rites of Passage	5
276729	Help!: Level 1	3
276729	The Amsterdam Connection : Level 4 (Cambridge ...	6
276744	A Painted House	7
11676	A Painted House	10
16877	A Painted House	9
17975	A Painted House	6
20806	A Painted House	6
21340	A Painted House	9
21356	A Painted House	7

[10 rows x 3 columns]

Building a model for side features

In [73]:

```
# model for side features
m_side_info = gl.ranking_factorization_recommender.create(sf_TargetCols,
                                                          user_id="User-ID",
                                                          item_id="Book-Title",
                                                          target="Book-Rating",
                                                          user_data=user_side_info,
                                                          item_data=item_side_info,
                                                          num_factors=24,
                                                          regularization=0.01,
                                                          linear_regularization=0.0
                                                          ranking_regularization=0.
                                                          num_sampled_negative_exam
                                                          side_data_factorization=1
                                                          max_iterations=25,
                                                          sgd_step_size=0,
                                                          random_seed=0,
                                                          binary_target=False,
                                                          solver='auto')
```

```
Recsys training: model = ranking_factorization_recommender

Preparing data set.

    Data has 383839 observations with 195644 users and 242131 items.

    Data prepared in: 1.67138s

Training ranking_factorization_recommender for recommendations.

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

| Parameter                      | Description
| Value    |

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

| num_factors                    | Factor Dimension
| 24       |

| regularization                 | L2 Regularization on Factors
| 0.01     |

| solver                         | Solver used for training
| adagrad  |

| linear_regularization          | L2 Regularization on Linear Coeffic
ients          | 0.001    |

| ranking_regularization         | Rank-based Regularization Weight
| 0.1      |

| side_data_factorization        | Assign Factors for Side Data
| True     |

| max_iterations                 | Maximum Number of Iterations
| 25       |

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

  Optimizing model using SGD; tuning step size.

  Using 47979 / 383839 points for tuning the step size.

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

| Attempt | Initial Step Size | Estimated Objective Value
|

+---------+-------------------+--------------------------------------
```

```
---+

| 0        | 0.0191944          | 4.36315
|

| 1        | 0.00959721         | 4.34855
|

| 2        | 0.0047986          | 4.41615
|

| 3        | 0.0023993          | 4.51841
|

| 4        | 0.00119965         | 4.59402
|

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

| Final    | 0.00959721         | 4.34855
|

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

Starting Optimization.

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

| Iter.    | Elapsed Time | Approx. Objective | Approx. Training RMSE |
Step Size    |

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

| Initial | 1.202ms       | 4.69382            | 1.84134                |
|

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

| 1        | 2.86s         | 4.77861            | 1.79088                |
0.00959721  |

| 2        | 5.73s         | 4.5794             | 1.80139                |
0.00959721  |

| 3        | 10.78s        | 4.52954            | 1.78413                |
0.00959721  |

| 4        | 13.55s        | 4.50825            | 1.77579                |
```

				0.00959721
5	16.36s	4.49567	1.76957	0.00959721
6	19.17s	4.4841	1.76556	0.00959721
7	21.95s	4.47443	1.76129	0.00959721
8	24.73s	4.46968	1.75968	0.00959721
9	27.53s	4.46513	1.75652	0.00959721
10	30.34s	4.46235	1.75576	0.00959721
11	33.10s	4.45557	1.75343	0.00959721
12	35.94s	4.4525	1.75226	0.00959721
13	38.69s	4.45064	1.75109	0.00959721
14	41.47s	4.44707	1.74925	0.00959721
15	44.27s	4.44361	1.74808	0.00959721
16	47.16s	4.44015	1.74685	0.00959721
17	49.90s	4.43741	1.74557	0.00959721
18	52.67s	4.43601	1.74473	0.00959721
19	55.47s	4.43333	1.74351	0.00959721
20	58.25s	4.43187	1.74283	0.00959721
21	1m 1s	4.43102	1.74223	0.00959721
22	1m 3s	4.426	1.74028	

```
0.00959721  |

| 23      | 1m 7s          | 4.42558            | 1.74006                |
0.00959721  |

| 24      | 1m 10s         | 4.42297            | 1.73856                |
0.00959721  |

| 25      | 1m 14s         | 4.42177            | 1.7385                 |
0.00959721  |

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

Optimization Complete: Maximum number of passes through the data reach
ed.

Computing final objective value and training RMSE.

       Final objective value: 4.45747

       Final training RMSE: 1.74674
```

Printing Side Information

In [74]:

```
#### Printing Side Information
a=m_side_info['coefficients']
b=m_side_info['user_side_data_column_names']
c=m_side_info['item_side_data_column_names']
d=m_side_info
print 'coefficients:\n',a
print 'user_side_data_column_names:\n',b
print 'item_side_data_column_names:\n',c
print 'm_side_info:\n',d
```

```
coefficients:
{'Book-Title': Columns:
        Book-Title      str
        linear_terms    float
        factors array

Rows: 242131

Data:
+-------------------------------+--------------------+
|           Book-Title          |    linear_terms    |
+-------------------------------+--------------------+
|      Classical Mythology      | -0.00371379172429  |
```

```
|         Clara Callan         | -0.000477368448628 |
|     Decision in Normandy     | -0.00713179586455  |
| Flu: The Story of the Grea... |  0.00176635594107  |
|    The Mummies of Urumchi    | -0.00345291011035  |
|    The Kitchen God's Wife    |  0.0369068160653   |
| What If?: The World's Fore... | -0.00906210020185  |
|        PLEADING GUILTY       |  0.00190678308718  |
| Under the Black Flag: The ... | -0.00258321803994  |
| Where You'll Find Me: And ... |  -0.0131572689861  |
+------------------------------+--------------------+
+-------------------------------+
|            factors            |
+-------------------------------+
| [0.0, 0.0, 0.0, 0.0, 0.0, ... |
| [0.0, 0.0, 0.0, 0.0, 0.0, ... |
| [0.0, 0.0, 0.0, 0.0, 0.0, ... |
| [0.0, 0.0, 0.0, 0.0, 0.0, ... |
| [0.0, 0.0, 0.0, 0.0, 0.0, ... |
| [0.0, 0.0, 0.0, 0.0, 0.0, ... |
| [0.0, 0.0, 0.0, 0.0, 0.0, ... |
| [0.0, 0.0, 0.0, 0.0, 0.0, ... |
| [0.0, 0.0, 0.0, 0.0, 0.0, ... |
| [0.0, 0.0, 0.0, 0.0, 0.0, ... |
+-------------------------------+
[242131 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 a
nd columns., 'User-ID': Columns:
        User-ID int
        linear_terms    float
        factors array

Rows: 195644

Data:
+---------+--------------------+-------------------------------+
| User-ID |    linear_terms    |            factors            |
+---------+--------------------+-------------------------------+
|    2    | 1.07532371896e-09  | [0.0, 0.0, 0.0, 0.0, 0.0, ... |
|    4    | 4.54733068977e-08  | [0.0, 0.0, 0.0, 0.0, 0.0, ... |
|    6    | 1.28483765849e-08  | [0.0, 0.0, 0.0, 0.0, 0.0, ... |
|    10   | 3.35180239119e-08  | [0.0, 0.0, 0.0, 0.0, 0.0, ... |
|    11   | -4.09923543998e-08 | [0.0, 0.0, 0.0, 0.0, 0.0, ... |
|    13   | 1.74412466691e-08  | [0.0, 0.0, 0.0, 0.0, 0.0, ... |
|    18   | -2.61870383156e-08 | [0.0, 0.0, 0.0, 0.0, 0.0, ... |
|    19   | -0.00521881459281  | [0.0, 0.0, 0.0, 0.0, 0.0, ... |
|    20   | -4.00007564849e-08 | [0.0, 0.0, 0.0, 0.0, 0.0, ... |
|    21   | -4.14812140193e-09 | [0.0, 0.0, 0.0, 0.0, 0.0, ... |
+---------+--------------------+-------------------------------+
[195644 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 a
nd columns., 'intercept': 7.6266950466211085, 'side_data': Columns:
```

```
        feature str
        index   str
        linear_terms    float
        factors array

Rows: 1244552

Data:
+----------+-------------------------------+--------------------+
| feature  |             index             |    linear_terms    |
+----------+-------------------------------+--------------------+
| Location | newquay, england, united k... | -4.71113246192e-08 |
| Location |   oyster bay, new york, usa   | -0.00438971770927  |
| Location |     chester, virginia, usa    |  -0.0136792967096  |
| Location |    marquette, michigan, usa   |  -0.0429210141301  |
| Location |      el paso, texas, usa      |  -0.0101373353973  |
| Location |     aptos, california, usa    |  -0.0244930572808  |
| Location | greenville, south carolina... |  -0.0512146726251  |
| Location |   cheltenham, maryland, usa   | 4.23123864834e-08  |
| Location |      mckinney, texas, usa     |  -0.0160006210208  |
| Location |    seattle, washington, usa   |  -0.0698046833277  |
+----------+-------------------------------+--------------------+
+-------------------------------+
|            factors            |
+-------------------------------+
| [0.0, 0.0, 0.0, 0.0, 0.0, ... |
| [0.0, 0.0, 0.0, 0.0, 0.0, ... |
| [0.0, 0.0, 0.0, 0.0, 0.0, ... |
| [0.0, 0.0, 0.0, 0.0, 0.0, ... |
| [0.0, 0.0, 0.0, 0.0, 0.0, ... |
| [0.0, 0.0, 0.0, 0.0, 0.0, ... |
| [0.0, 0.0, 0.0, 0.0, 0.0, ... |
| [0.0, 0.0, 0.0, 0.0, 0.0, ... |
| [0.0, 0.0, 0.0, 0.0, 0.0, ... |
| [0.0, 0.0, 0.0, 0.0, 0.0, ... |
+-------------------------------+
[1244552 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 a
nd columns.}
user_side_data_column_names:
['User-ID', 'Location', 'Age']
item_side_data_column_names:
['ISBN', 'Book-Title', 'Book-Author', 'Year-Of-Publication', 'Publishe
r', 'Image-URL-S', 'Image-URL-M', 'Image-URL-L']
m_side_info:
RankingFactorizationRecommender
```

Making Recommendation Based on the Learned Side Information

Given a User's **age**, and **Location** categories, the model can incorporate what it knows about the importance of age, and location categories for item recommendations. We illustrate this by inputing a fictional user ID and his/her location in the model. And, the model predicts the top 5 books for the user based on his/her side features.
We will use the **RankingFactorizationRecommender** model to incorporate our side features data. Since we already evaluated this model, so there is no need re-eavaluate it again.

In [75]:

```
# Making recommendation for a new user
new_user_info = gl.SFrame({'User-ID' : ['99999'],
                          'Age' : ['18'], 'Location':['Dallas, Tx']})
recommendations = m_side_info.recommend(['99999'],
                                     new_user_data = new_user_info,k=15)
recommendations.print_rows(15)
```

```
+---------+-------------------------------+---------------+------+
| User-ID |           Book-Title          |     score     | rank |
+---------+-------------------------------+---------------+------+
|  99999  | Harry Potter and the Goble... | 8.46848492449 |  1   |
|  99999  | Harry Potter and the Sorce... | 8.45281967341 |  2   |
|  99999  | Harry Potter and the Priso... | 8.44784317957 |  3   |
|  99999  | Harry Potter and the Order... | 8.39907710085 |  4   |
|  99999  | The Two Towers (The Lord o... | 8.38189973041 |  5   |
|  99999  |     To Kill a Mockingbird     | 8.37286890549 |  6   |
|  99999  | Harry Potter and the Sorce... | 8.34476189734 |  7   |
|  99999  | Harry Potter and the Chamb... | 8.34026091671 |  8   |
|  99999  | The Return of the King (Th... | 8.25676294518 |  9   |
|  99999  | The Fellowship of the Ring... | 8.23525992137 |  10  |
|  99999  |       The Little Prince       | 8.15826402688 |  11  |
|  99999  | Ender's Game (Ender Wiggin... | 8.15302461627 |  12  |
|  99999  |              1984             | 8.14872903535 |  13  |
|  99999  | Harry Potter and the Chamb... | 8.14736236757 |  14  |
|  99999  |       Calvin and Hobbes       | 8.13590301109 |  15  |
+---------+-------------------------------+---------------+------+
[15 rows x 4 columns]
```

Based on new user's Age and Location, our model recommends the top 15 books that he/she may like.

7.2 Popularity Recommendation System

Now let's look at creating the popularity Recommendation System. The Popularity Model ranks an item according to its overall popularity.It is simple and fast and provides a reasonable baseline. It can work well when observation data is sparse. It can be used as the starting point for new users.

In [76]:

```
# Popularity Recommendation model to recommend top 15 items
from graphlab import popularity_recommender
pop_model = gl.recommender.popularity_recommender.create(sf_TargetCols,
                                  user_id="User-ID",
                                  item_id="Book-Title",
                                  target="Book-Rating")
results = pop_model.recommend(k=15)
results.print_rows(15)
```

```
Recsys training: model = popularity

Preparing data set.

    Data has 383839 observations with 68091 users and 135565 items.

    Data prepared in: 0.535878s

383839 observations to process; with 135565 unique items.

recommendations finished on 1000/68091 queries. users per second: 940.
382

recommendations finished on 2000/68091 queries. users per second: 932.
521

recommendations finished on 3000/68091 queries. users per second: 931.
486

recommendations finished on 4000/68091 queries. users per second: 930.
```

Evaluating Popularity Recommender

In [77]:

```
## popularity model evaluation
from IPython.display import display
from IPython.display import Image

gl.canvas.set_target('ipynb')

m0 = gl.recommender.popularity_recommender.create(train,
                                  user_id="User-ID",
                                  item_id="Book-Title",
                                  target="Book-Rating")
rmse_results = m0.evaluate(test)
```

```
Recsys training: model = popularity

Preparing data set.

    Data has 383031 observations with 67978 users and 135383 items.
```

```
    Data prepared in: 0.51561s

383031 observations to process; with 135383 unique items.

Precision and recall summary statistics by cutoff
+--------+----------------+-------------+
| cutoff | mean_precision | mean_recall |
+--------+----------------+-------------+
|   1    |      0.0       |     0.0     |
|   2    |      0.0       |     0.0     |
|   3    |      0.0       |     0.0     |
|   4    |      0.0       |     0.0     |
|   5    |      0.0       |     0.0     |
|   6    |      0.0       |     0.0     |
|   7    |      0.0       |     0.0     |
|   8    |      0.0       |     0.0     |
|   9    |      0.0       |     0.0     |
|   10   |      0.0       |     0.0     |
+--------+----------------+-------------+
[10 rows x 3 columns]

('\nOverall RMSE: ', 1.5922151574930945)

Per User RMSE (best)
+---------+-------+------+
| User-ID | count | rmse |
+---------+-------+------+
|  215542 |   1   | 0.0  |
+---------+-------+------+
[1 rows x 3 columns]


Per User RMSE (worst)
+---------+-------+------+
| User-ID | count | rmse |
+---------+-------+------+
|    99   |   1   | 9.0  |
+---------+-------+------+
[1 rows x 3 columns]


Per Item RMSE (best)
+-------------------------------+-------+------+
|           Book-Title          | count | rmse |
+-------------------------------+-------+------+
| Byzantium (II) : The Apoge... |   1   | 0.0  |
+-------------------------------+-------+------+
[1 rows x 3 columns]


Per Item RMSE (worst)
+-------------------------------+-------+------+
|           Book-Title          | count | rmse |
+-------------------------------+-------+------+
```

```
| Creating Wealth : Retire i... |   1   | 9.0  |
+-------------------------------+-------+------+
[1 rows x 3 columns]
```

Overall RMSE is 1.59, which is not very bad for base model.

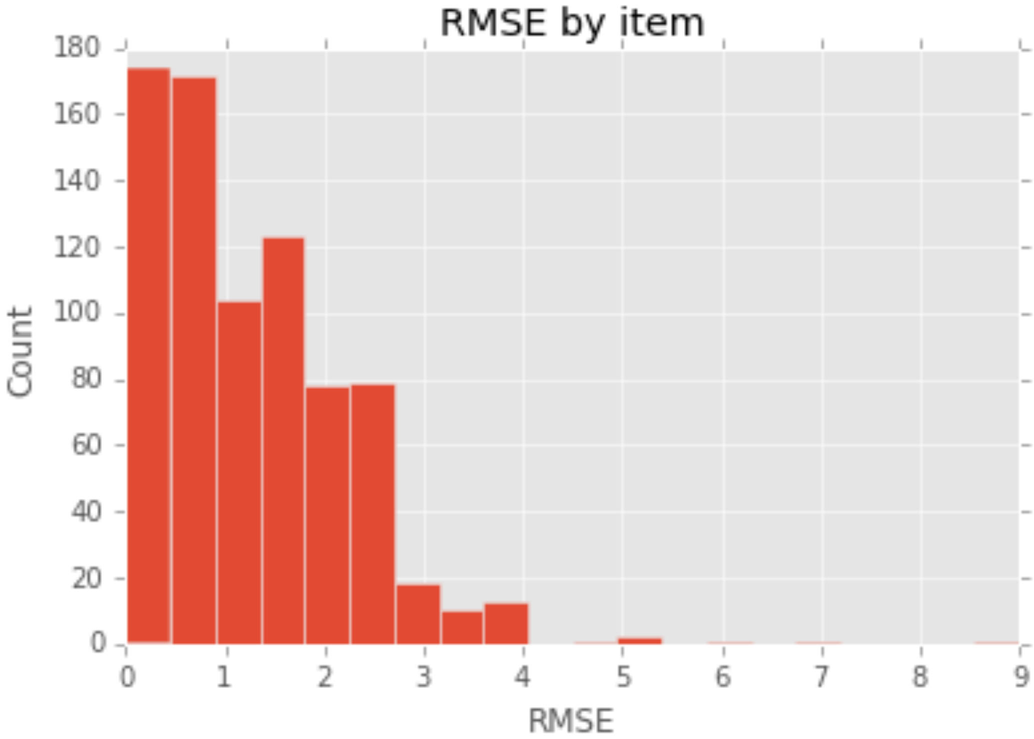
In [78]:

```
# printing RMSE by item
print rmse_results.viewkeys()
print rmse_results['rmse_by_item']
```

```
dict_keys(['rmse_by_user', 'precision_recall_overall', 'rmse_by_item',
'precision_recall_by_user', 'rmse_overall'])
+-------------------------------+-------+----------------+
|           Book-Title          | count |      rmse      |
+-------------------------------+-------+----------------+
|        House of Echoes        |   1   | 0.333333333333 |
| Small Gods (Discworld Nove... |   1   | 0.545454545455 |
| Crowner'S Quest : A Crowne... |   1   | 0.374186423553 |
| The Adventures of Hucklebe... |   1   | 0.310344827586 |
| Ophelia Speaks : Adolescen... |   1   | 2.09090909091  |
| My Land: A Homesteader's Tale |   1   | 0.625813576447 |
| The Adventures Pete and Ma... |   1   | 0.374186423553 |
| The Bear and the Dragon (J... |   1   | 0.36170212766  |
|       A Southern Family       |   1   |      0.5       |
| Jenny Dale's Puppy Patrol ... |   1   | 0.374186423553 |
+-------------------------------+-------+----------------+
[777 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 a
nd columns.
```

In [79]:

```
# Plotting RMSE by item
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()
```



RMSE by item is low, which suggests that book-rating recommendation by item is good.

In [80]:

```
# Printing RMSE by user
rmse_results['rmse_by_user']
```

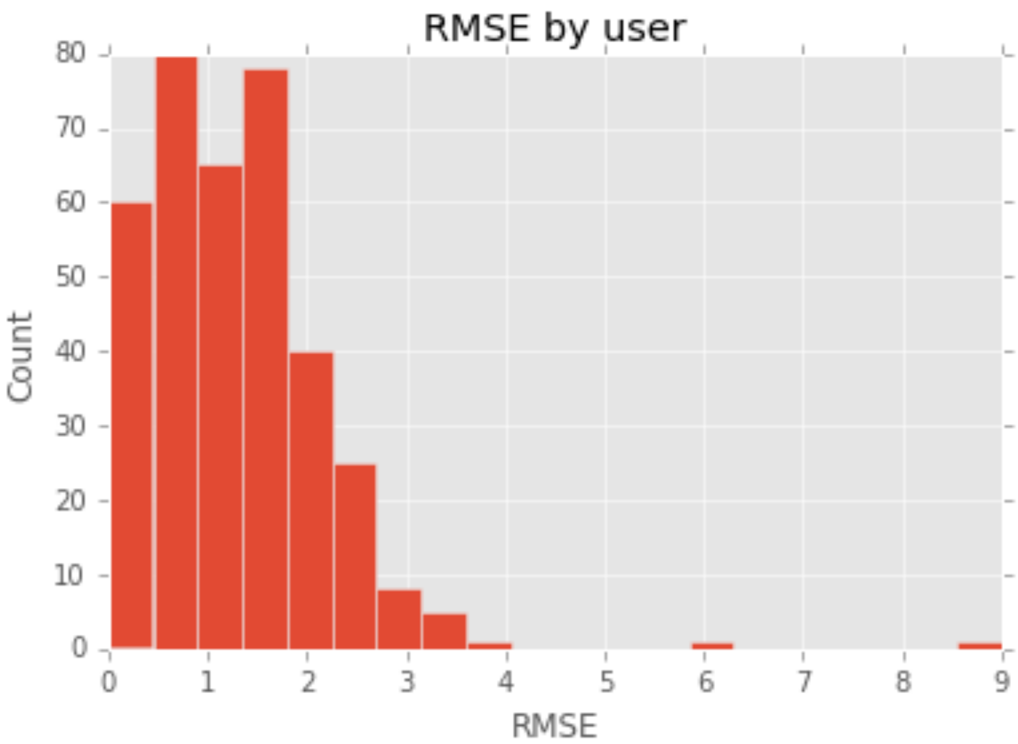
Out[80]:

User-ID	count	rmse
21045	1	0.909090909091
163409	1	0.310344827586
234288	1	2.0
32516	4	2.16039644441
75096	1	1.98333333333
31820	1	0.759259259259
128782	3	0.805763629825
94445	1	1.0
127244	1	1.98371335505
179922	1	1.62581357645

[364 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 [81]:

```
#Plotting RMSE by user
from matplotlib import pyplot as plt
%matplotlib inline
plt.style.use('ggplot')
rmsevals=rmse_results['rmse_by_user']['rmse']
plt.hist(rmsevals, bins=20)
plt.xlabel('RMSE')
plt.ylabel('Count')
plt.title('RMSE by user')
plt.show()
```



RMSE by user is low, which suggests that book-rating recommendation by user is good.

8. Deployment

With the explosive growth in ecommerce where global sales are targeted to top 2.3 Trillion(USD) in 2017 [7], online retailers are deploying a variety of tools to boost traffic and generate sales. As such a key component in boosting online sales is 'getting to know' your consumers and forging a closer relationship with them. Gaining a better understanding of customer needs, preferences and interests are all aspects that are critical in forging this relationship. The go-to technology deployed by retailers to satisfy this need are Recommendation systems.

From a deployment perspective, the best recommendation systems do not always need to generate immediate sales. It needs to enhance the user experience in such a way that the consumer feels 'understood' as the suggestions made by the website starts to align with their own individual tastes. It is at that point that the online shopper would begin to forge a relationship and show genuine interest in suggested merchandise vastly increasing cross-selling potential for the retailer.

Creating a comprehensive commercially viable recommendation system is the ultimate goal of our project. While accurately predicting what the consumer would buy is a key component of a successful recommendation system, we also need to enhance the shopping experience giving the consumers the opportunity to discover novelty items that would interest them. The system also needs to be mindful of user fatigue to repeated recommendations that appear too often or look too obvious. It's also important to not to recommend items that are already in the shopping cart or have already been purchased and/or returned.

Keeping all these factors in mind, our final recommendation system will use a blend of three models coupled with an exclusion list. The three models would be the popularity recommender, the performance tuned item-item recommender and the performance tuned user-item recommender. The exclusion list will contain purchased/returned items, items in the cart and items that might have an expired lifespan. At deployment, the recommendation system would produce a pool of candidate items specifically selected for the user where the depending on the page a set number can be randomly picked by the application layer and shown on screen.

When a first-time user navigates into the site the recommendation item candidate pool, that we randomly pick items from, will consist of candidates from the popularity recommender. As the user begins to click through items in the site candidate pool will get more items from the item-item model and shift to use-item model's items. This blended method will not only keep the recommendations fresh but will also have an element of understanding the user's personality and style. Items shown to returning users will be randomly picked out of a pool of items generated by all three models based on the user's history. Finally, we will diversify the product pool with merchandise that are not books alone.

The integration to the final system will be made available as a web service where the user-id is passed into the service and a recommendation candidate pool is returned back to the application layer. Periodic re-tuning of the models will ensure the longevity of the solution. It's is our belief that this approach would produce a commercially viable recommendation solution that is scalable across different ecommerce web stores.

9. References

1. https://www.forbes.com/sites/chuckcohn/2015/05/15/a-beginners-guide-to-upselling-and-cross-selling/#2f46b14e2912 (https://www.forbes.com/sites/chuckcohn/2015/05/15/a-beginners-guide-to-upselling-and-cross-selling/#2f46b14e2912)
2. http://www2.informatik.uni-freiburg.de/~cziegler/BX/ (http://www2.informatik.uni-freiburg.de/~cziegler/BX/)
3. http://www2.informatik.uni-freiburg.de/~dbis/Publications/05/WWW05.html (http://www2.informatik.uni-freiburg.de/~dbis/Publications/05/WWW05.html)
4. https://turi.com/products/create/docs/generated/graphlab.recommender.item_similarity_recommender.ItemS (https://turi.com/products/create/docs/generated/graphlab.recommender.item_similarity_recommender.Item
5. https://timchen1.gitbooks.io/graphlab/content/recommender/introduction.html (https://timchen1.gitbooks.io/graphlab/content/recommender/introduction.html)
6. https://turi.com/products/create/docs/generated/graphlab.recommender.ranking_factorization_recommende (https://turi.com/products/create/docs/generated/graphlab.recommender.ranking_factorization_recommend
7. https://www.emarketer.com/Article/Worldwide-Retail-Ecommerce-Sales-Will-Reach-1915-Trillion-This-Year/1014369 (https://www.emarketer.com/Article/Worldwide-Retail-Ecommerce-Sales-Will-Reach-1915-Trillion-This-Year/1014369)

8. https://timchen1.gitbooks.io/graphlab/content/recommender/choosing-a-model.html (https://timchen1.gitbooks.io/graphlab/content/recommender/choosing-a-model.html)
9. https://blog.nycdatascience.com/student-works/book-rating-prediction-recommendation-engine/ (https://blog.nycdatascience.com/student-works/book-rating-prediction-recommendation-engine/)
10. https://en.wikipedia.org/wiki/Sparse_matrix (https://en.wikipedia.org/wiki/Sparse_matrix)
11. http://minimaxir.com/2014/06/reviewing-reviews/ (http://minimaxir.com/2014/06/reviewing-reviews/)

In [ ]:

```

```