Sistemas Recomendadores en Python

May 11, 2018

Los Sistemas Recomendadores analizan patrones de interés del usuario como artículos o productos para poder proporcionar recomendaciones personalizadas que satisfagan sus preferencias.

Para poder llevar esto adelante se deben realizar diferentes tareas.

Python tiene un gran cantidad de librerías que nos permiten y facilitan esto:

- Pandas: Herramienta de análisis / manipulación de datos muy potente y flexible;
- SciKit-Learn: Librería que provee técnicas de minería de datos y machine learning.
- SciKit-Surprise: Librería para probar y evaluar diferentes algoritmos de recomendación. * Numpy: Librería de computación científica con funciones matemáticas de alto nivel para operar con vectores y matrices.
- Jupyter Notebook: Librería que permite crear y compartir documentos que contengan códigos, ecuaciones, visualizaciones y textos.

```
In [51]: print('Hola PyDay')
```

```
Hola PyDay
```

0.1 Hola

Dataset a utilizar: Películas de MovieLens con información de iMDB

```
  * 45,000 películas. De cada película se conoce el título, género, plot, ganancias...
  * 270,000 usuarios.
  * 26,000,000 ratings (1,10)
  * 750,000 etiquetas sobre las películas
```

0.1.1 Levántando los datos con Pandas

Pandas es la herramienta de análisis / manipulación de datos de código abierto más potente y flexible. Proporciona estructuras de datos rápidas, flexibles y expresivas diseñadas para que trabajar con datos relacionales o etiquetados.

```
In [1]: import pandas as pd
        import json
        import ast
        import numpy as np
        import matplotlib.pyplot as plt

In [52]: def load_movies_metadata(file_path):
             df = pd.read_csv(file_path, dtype='unicode')

             df['release_date'] = pd.to_datetime(df['release_date'], errors='coerce').apply(lamb
             numeric_columns  = ['budget', 'vote_average','revenue','vote_count']
             for c in numeric_columns:
                 df[c] = pd.to_numeric(df[c], errors='coerce')

             # columnas en json
             json_columns = ['belongs_to_collection', 'genres', 'production_companies', 'product
             for column in json_columns:
                 # Se usa ast porque los datos json tienen comillas simples en el csv, y no "
                 df[column] = df[column].apply(lambda x: np.nan if pd.isnull(x) else ast.literal


             return df

         movies = load_movies_metadata('movies/movies_metadata.csv')

In [53]: movies.head(3)

Out[53]:    adult                              belongs_to_collection      budget  \
         0  False  {u'backdrop_path': u'/9FBwqcd9IRruEDUrTdcaafOM...  30000000.0
         1  False                                                NaN  65000000.0
         2  False  {u'backdrop_path': u'/hypTnLot2z8wpFS7qwsQHW1u...         0.0

                                                 genres  \
         0  [{u'id': 16, u'name': u'Animation'}, {u'id': 3...
         1  [{u'id': 12, u'name': u'Adventure'}, {u'id': 1...
         2  [{u'id': 10749, u'name': u'Romance'}, {u'id': ...

                                    homepage     id    imdb_id original_language  \
         0  http://toystory.disney.com/toy-story    862  tt0114709                en
         1                                   NaN   8844  tt0113497                en
         2                                   NaN  15602  tt0113228                en

              original_title                                           overview  \
         0         Toy Story  Led by Woody, Andy's toys live happily in his ...
         1           Jumanji  When siblings Judy and Peter discover an encha...
         2  Grumpier Old Men  A family wedding reignites the ancient feud be...

              ...     release_date      revenue runtime  \
```

```
0    ...       1995-10-30  373554033.0    81.0
1    ...       1995-12-15  262797249.0   104.0
2    ...       1995-12-22          0.0   101.0

                                      spoken_languages    status  \
0       [{u'iso_639_1': u'en', u'name': u'English'}]  Released
1  [{u'iso_639_1': u'en', u'name': u'English'}, {...  Released
2       [{u'iso_639_1': u'en', u'name': u'English'}]  Released

                                             tagline             title  video  \
0                                                NaN         Toy Story  False
1          Roll the dice and unleash the excitement!           Jumanji  False
2  Still Yelling. Still Fighting. Still Ready for...  Grumpier Old Men  False

  vote_average vote_count
0          7.7     5415.0
1          6.9     2413.0
2          6.5       92.0

[3 rows x 24 columns]
```

```
In [56]: #movies['original_language'].unique()
         #movies[movies['original_language']=='es']
         movies.groupby('original_language').size()
```

```
Out[56]: original_language
         104.0        1
         68.0         1
         82.0         1
         ab          10
         af           2
         am           2
         ar          39
         ay           1
         bg          10
         bm           3
         bn          29
         bo           2
         bs          14
         ca          12
         cn         313
         cs         130
         cy           1
         da         225
         de        1080
         el         113
         en       32269
         eo           1
```

```
es         994
et          24
eu           3
fa         101
fi         297
fr        2438
fy           1
gl           1
          ...
pa           2
pl         219
ps           2
pt         316
qu           1
ro          57
ru         826
rw           1
sh           5
si           1
sk           9
sl          17
sm           1
sq           5
sr          63
sv         384
ta          78
te          45
tg           1
th          76
tl          23
tr         150
uk          16
ur           8
uz           1
vi          10
wo           5
xx          33
zh         409
zu           1
Length: 92, dtype: int64
```

```
In [57]: movies.columns
```

```
Out[57]: Index([u'adult', u'belongs_to_collection', u'budget', u'genres', u'homepage',
       u'id', u'imdb_id', u'original_language', u'original_title', u'overview',
       u'popularity', u'poster_path', u'production_companies',
       u'production_countries', u'release_date', u'revenue', u'runtime',
       u'spoken_languages', u'status', u'tagline', u'title', u'video',
```

```
       u'vote_average', u'vote_count'],
      dtype='object')
```

```
In [58]: movies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45466 entries, 0 to 45465
Data columns (total 24 columns):
adult                     45466 non-null object
belongs_to_collection     4494 non-null object
budget                    45463 non-null float64
genres                    45466 non-null object
homepage                  7782 non-null object
id                        45466 non-null object
imdb_id                   45449 non-null object
original_language         45455 non-null object
original_title            45466 non-null object
overview                  44512 non-null object
popularity                45461 non-null object
poster_path               45080 non-null object
production_companies      45463 non-null object
production_countries      45463 non-null object
release_date              45376 non-null object
revenue                   45460 non-null float64
runtime                   45203 non-null object
spoken_languages          45460 non-null object
status                    45379 non-null object
tagline                   20412 non-null object
title                     45460 non-null object
video                     45460 non-null object
vote_average              45460 non-null float64
vote_count                45460 non-null float64
dtypes: float64(4), object(20)
memory usage: 8.3+ MB
```

```
In [59]: genres = []
         for i,row in movies.iterrows():
             if row['genres'] is not np.nan:
                 a = row['genres']
                 for item in a:
                     if item['name'] not in genres:
                         genres.append(item['name'])
         print(genres)
```

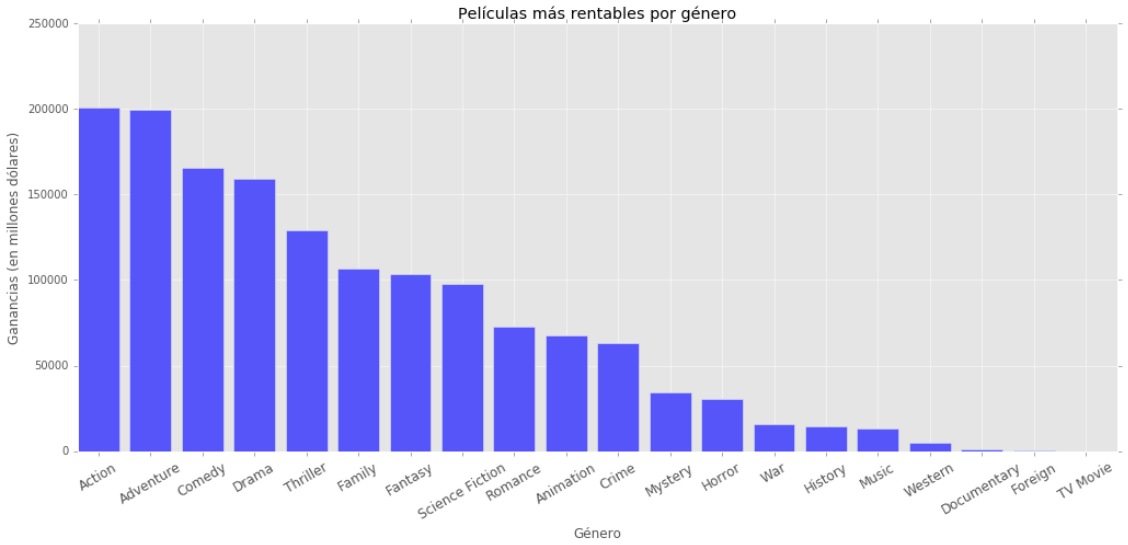
```
['Animation', 'Comedy', 'Family', 'Adventure', 'Fantasy', 'Romance', 'Drama', 'Action', 'Crime',
```

Calcular el género cinematográfico que tuvo más ganancias.

```
In [60]: genre_revenue = {}

         for i in range(movies.shape[0]):
             for item in movies.iloc[i]['genres']:
                 if 'name' in item and movies.iloc[i]['revenue'] >0:
                     genre_name = item['name']
                     b = int(movies.iloc[i]['revenue'])/1000000
                     if genre_name in genre_revenue:
                         genre_revenue[genre_name]['total_revenue'] += b
                     else:
                         genre_revenue[genre_name] = {}
                         genre_revenue[genre_name]['genre'] = genre_name
                         genre_revenue[genre_name]['total_revenue'] = b

         most_profitable_genre = pd.DataFrame(None,None,columns=['genre','revenue'])

         for k,v in genre_revenue.items():
             most_profitable_genre =  most_profitable_genre.append({'genre':v['genre'],'revenue'

In [61]: most_profitable_genre = most_profitable_genre.sort_values(by='revenue',ascending=False)

In [62]: most_profitable_genre.head()

Out[62]:         genre revenue
         13     Action  200726
         11  Adventure  199616
         15     Comedy  165797
         6       Drama  159386
         18   Thriller  129054
```

0.1.2 Visualización de Datos

```
In [63]: plt.style.use('ggplot')
         plt.figure(figsize=(17,7))
         number_of_genres= len(most_profitable_genre['genre'])
         index = np.arange(number_of_genres)
         bar_width = 0.8
         plt.bar(index, most_profitable_genre['revenue'], bar_width, color='#5555FA' )
         plt.gca().set_xlabel(u"Género")
         plt.gca().set_ylabel(u"Ganancias (en millones dólares)")
         plt.xticks(index +bar_width/2, most_profitable_genre['genre'],rotation=30, fontsize=12)
         plt.gca().set_title(u"Películas más rentables por género")
         plt.show()
```



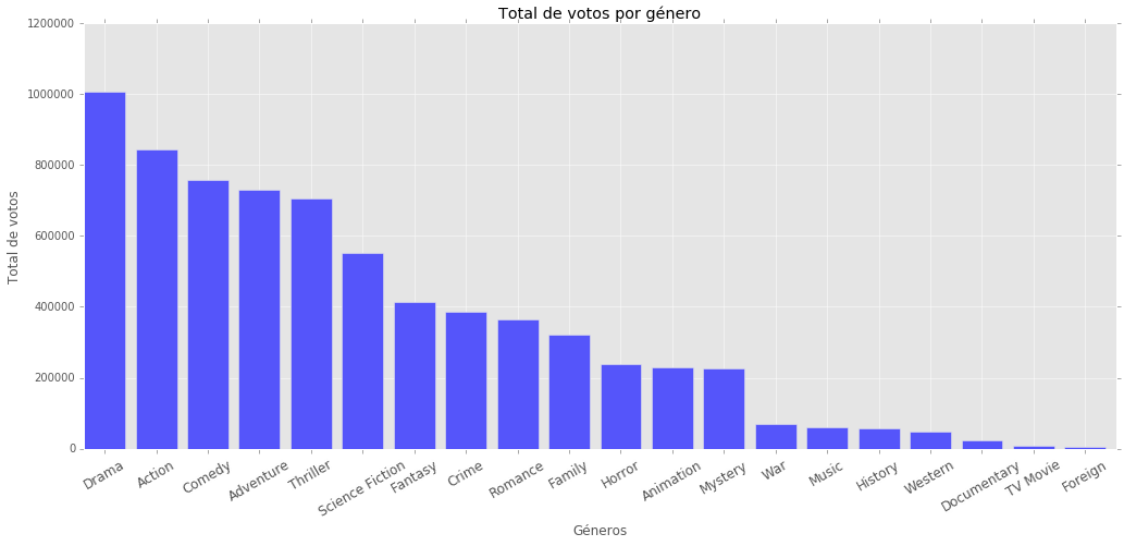
También podemos ver la cantidad máxima de votos para cada género

```
In [64]: genre_vote_count = {}

         for i,_ in movies.iterrows():
             for item in movies.loc[i]['genres']:

                 if 'name' in item and movies.loc[i]['vote_count'] >0:
                     a = item['name']
                     b = movies.loc[i]['vote_count']
                     if a in genre_vote_count:
                         genre_vote_count[a]['total_votes'] += b
                     else:
                         genre_vote_count[a] = {}
                         genre_vote_count[a]['genre'] = a
                         genre_vote_count[a]['total_votes'] = b

         most_votes_genre = pd.DataFrame(None,None,columns=['genre','total_votes'])

         for k,v in genre_vote_count.items():
             most_votes_genre =  most_votes_genre.append({'genre':v['genre'],'total_votes':v['to
```

```
In [66]: most_votes_genre = most_votes_genre.sort_values(by='total_votes',ascending=False)
         most_votes_genre.head()
```

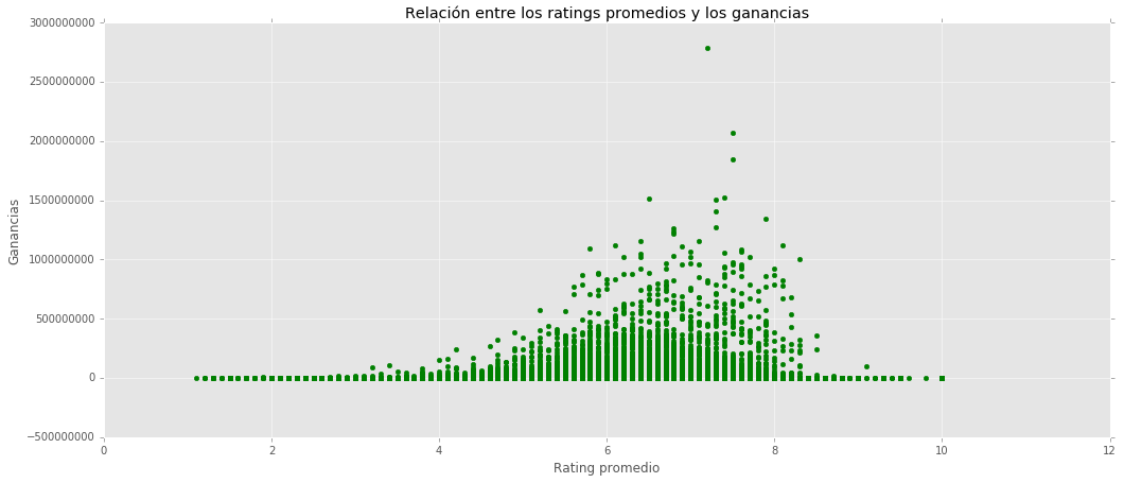
```
Out[66]:         genre  total_votes
         1       Drama    1956070.0
         13     Action    1708508.0
         15     Comedy    1438185.0
         11  Adventure    1434576.0
         18   Thriller    1434045.0
```

```
In [66]: number_of_genres= len(most_votes_genre['genre'])
         index = np.arange(number_of_genres)
         bar_width = 0.8
         plt.figure(figsize=(17,7))
         plt.bar(index, most_votes_genre['total_votes'], bar_width, color='#5555FA' )
         plt.gca().set_xlabel(u"Género")
         plt.gca().set_ylabel(u"Total de votos")
         plt.xticks(index +bar_width/2, most_votes_genre['genre'],rotation=30, fontsize=12)
         plt.gca().set_title(u"Total de votos por género")
         plt.xlabel(u"Géneros")
         plt.ylabel(u"Total de votos")
         plt.show()
```



Relación entre ratings y las ganancias

```
In [74]: revenue_votes=movies[movies['vote_average']>1]
         plt.figure(figsize=(17,7))
         plt.scatter(revenue_votes['vote_average'],revenue_votes['revenue'], c='g', edgecolors='
         plt.ylabel('Ganancias')
         plt.xlabel('Rating promedio')
         ax = plt.gca()
         ax.get_yaxis().get_major_formatter().set_scientific(False)
         plt.title(u'Relación entre los ratings promedios y los ganancias')

         plt.show()
```




```
In [78]: #index=revenue_votes['revenue'].idxmax()
         #print(movies.loc[index]['title'])
```

Distribución de ratings

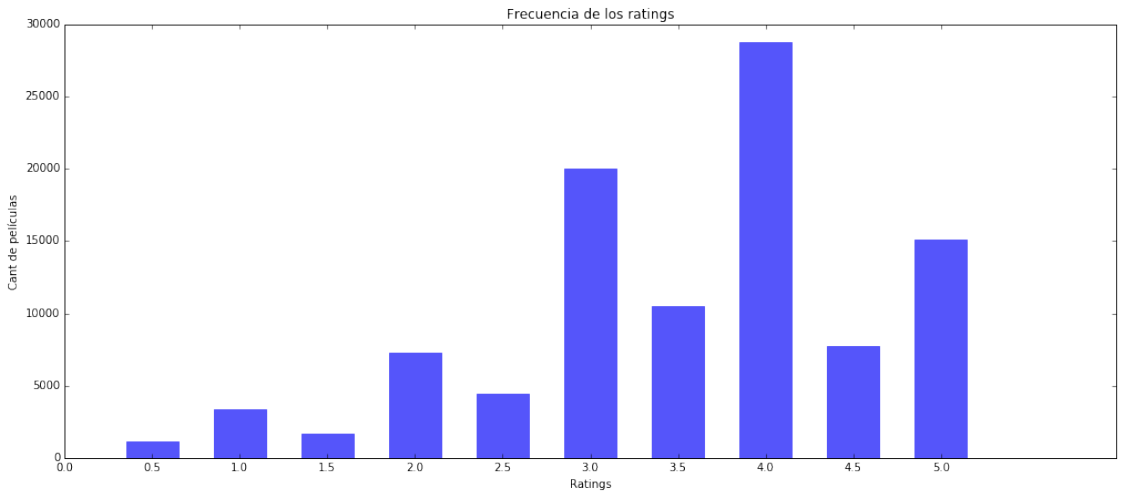
```
In [68]: ratings=pd.read_csv('movies/ratings.csv')
         ratings=ratings.groupby('rating').size().reset_index(name='count')
         ratings.sort_values('count', ascending=False, inplace=True)
         ratings
```

Out[68]:

	rating	count
7	4.0	28750
5	3.0	20064
9	5.0	15095
6	3.5	10538
8	4.5	7723
3	2.0	7271
4	2.5	4449
1	1.0	3326
2	1.5	1687
0	0.5	1101

```
In [50]: ratings.sort_values('rating', inplace=True)
         index= np.arange(0.5,5.5,0.5)
         plt.figure(figsize=(17,7))

         plt.bar(index, ratings['count'], color='#5555FA', edgecolor='#5555FA', align='center',
         plt.xlabel(u'Ratings')
         plt.ylabel(u'Cant de películas')
         plt.title(u'Frecuencia de los ratings')
```

```
plt.xticks(np.arange(0,5.5,0.5))
plt.show()
```



Cantidad de calificaciones por película

```
In [70]: ratings=pd.read_csv('movies/ratings.csv')
         media_rating = ratings['rating'].mean()
         print media_rating

         ratings=ratings.groupby('movieId').size().reset_index(name='count')
         ratings.sort_values('count', ascending=False, inplace=True)
         ratings[ratings['count']>1]
```

```
3.543608255669773
```

```
Out[70]:       movieId  count
         321       356    341
         266       296    324
         284       318    311
         525       593    304
         232       260    291
         427       480    274
         2062     2571    259
         0           1    247
         472       527    244
         522       589    237
         953      1196    234
         100       110    228
         1024     1270    226
         535       608    224
```

2288	2858	220
955	1198	220
644	780	218
966	1210	217
521	588	215
406	457	213
523	590	202
2374	2959	202
45	47	201
48	50	201
328	364	200
695	858	200
129	150	200
3869	4993	200
344	380	198
524	592	196
...	...	...
5164	7541	2
3019	3774	2
3774	4834	2
5414	8482	2
5153	7459	2
3821	4920	2
8221	99764	2
5408	8460	2
3836	4949	2
5146	7449	2
5183	7615	2
3024	3784	2
8329	103539	2
3983	5172	2
5426	8522	2
2883	3613	2
3035	3795	2
5441	8571	2
3802	4885	2
5184	7616	2
3021	3777	2
3840	4956	2
3027	3787	2
3985	5179	2
3838	4952	2
3988	5186	2
8211	99437	2
5187	7624	2
4016	5238	2
5428	8525	2

```
[6003 rows x 2 columns]
```

0.1.3 Sistema Recomendador basado en la información de las películas

Obtener mejores recomendaciones para la peli The Dark Knight, acá conocida como "Batman: el caballero de la noche".

```
In [81]: from sklearn.feature_extraction.text import CountVectorizer
         from sklearn.metrics.pairwise import linear_kernel, cosine_similarity
```

```
In [120]: corpus =['yo programo en python', 'python y yo yo y', 'programo mucho']
          example = tf.fit(corpus)
          data= example.transform(corpus).todense()
          pd.DataFrame(data=data,  index=corpus, columns=example.get_feature_names())
```

Out[120]:

	en	mucho	programo	python	yo
yo programo en python	1	0	1	1	1
python y yo yo y	0	0	0	1	2
programo mucho	0	1	1	0	0

```
In [91]: movies['tagline'] = movies['tagline'].fillna('')
         movies['description'] = movies['overview'] + movies['tagline']
         movies['description'] = movies['description'].fillna('')

         tf = CountVectorizer(analyzer='word', stop_words='english')
         tfidf_matrix = tf.fit_transform(movies['description'])
```

Similitud del coseno

```
In [122]: from sklearn.metrics.pairwise import  cosine_similarity

          film1_index = np.where(movies["title"] =="The Dark Knight")[0]
          tfidf_vector_film_1 =tfidf_matrix[film1_index,:]
          distances = cosine_similarity(tfidf_vector_film_1, tfidf_matrix)[0]
          indices_of_most_simmilar_films = distances.argsort()[-15:-1]
          movies.iloc[indices_of_most_simmilar_films]["title"]
```

Out[122]:

```
585                                                  Batman
40974    LEGO DC Comics Super Heroes: Batman: Be-Leaguered
18009                               This Must Be the Place
41976                                The Lego Batman Movie
18035                                     Batman: Year One
20232             Batman: The Dark Knight Returns, Part 2
21194    Batman Unmasked: The Psychology of the Dark Kn...
26102                                       Going Straight
150                                         Batman Forever
28023                                      The Dead Season
15511                          Batman: Under the Red Hood
1328                                        Batman Returns
```

```
40658                                          Paranoia
18252                                The Dark Knight Rises
Name: title, dtype: object
```

0.1.4 Utilizando Sistemas Recomendadores con Surprise

```
In [10]: from surprise import Reader, Dataset, KNNBasic, evaluate, accuracy
         from surprise.model_selection import KFold

In [128]: ratings=pd.read_csv('movies/ratings.csv')
          #print(ratings.head())

In [130]: # Reader se define para especificar la escala de ratings.
          reader = Reader(rating_scale=(0.5, 5))

          # Las columnas deben ser: user id, item id, ratings, se debe respetar ese orden.
          data = Dataset.load_from_df(ratings[['userId', 'movieId', 'rating']], reader)
```

	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6
User 1	0	3	0	3	0	0
User 2	4	0	0	2	0	0
User 3	0	0	3	0	0	5
User 4	0	0	0	0	3	0
User 5	4	0	0	4	0	0

Filtrado Colaborativo enfoque item-item

```
In [73]: # Se define un iterador para poder hacer cross-validation
         kf = KFold(n_splits=3)

         sim_options = {'name': 'cosine',
                        'user_based': False  # para que compare items
                       }

         algo = KNNBasic(sim_options=sim_options)

         for trainset, testset in kf.split(data):

             # Se entrena y se corre el algoritmo.
             algo.fit(trainset)
```

```
            predictions = algo.test(testset)

            # Se evalua la performance calculando el error RMSE
            accuracy.rmse(predictions, verbose=True)
```

```
Computing the cosine similarity matrix...
Done computing similarity matrix.
RMSE: 0.9970
Computing the cosine similarity matrix...
Done computing similarity matrix.
RMSE: 0.9874
Computing the cosine similarity matrix...
Done computing similarity matrix.
RMSE: 0.9905
```

Filtrado Colaborativo enfoque usuario-usuario

In [20]:
```
# Se define un iterador de cross-validation
kf = KFold(n_splits=3)

sim_options = {'name': 'pearson_baseline'}

algo = KNNBasic(sim_options=sim_options)

for trainset, testset in kf.split(data):

    # Se entrena y se corre el algoritmo.
    algo.fit(trainset)
    predictions = algo.test(testset)

    # Se evalua la performance calculando el error RMSE
    accuracy.rmse(predictions, verbose=True)
    accuracy.fcp(predictions, verbose=True)
```

```
Estimating biases using als...
Computing the pearson_baseline similarity matrix...
Done computing similarity matrix.
RMSE: 1.0061
FCP:  0.6477
Estimating biases using als...
Computing the pearson_baseline similarity matrix...
Done computing similarity matrix.
RMSE: 1.0137
FCP:  0.6428
Estimating biases using als...
Computing the pearson_baseline similarity matrix...
Done computing similarity matrix.
```

```
RMSE: 1.0242
FCP:  0.6398
```

Predecir un rating con mi modelo

```
In [145]: two_ratings = list(algo.trainset.all_ratings())[0:2]

          uid = algo.trainset.to_raw_uid(two_ratings[0][0])  #user id
          iid = algo.trainset.to_raw_iid(two_ratings[1][1])  #item id

          # prediccion de rating para ese usuario y ese item.
          pred = algo.predict(uid, iid,  verbose=True)
```

```
user: 631        item: 1584       r_ui = None   est = 3.79   {u'actual_k': 23, u'was_impossible'
```

0.1.5 Kaggle

https://www.kaggle.com/

Hay muchos datasets disponibles y notebooks con análisis de datos, y recomendaciones.
https://github.com/mcharnelli/PyDayLP2018