CMSC5733 Social Computing

Tutorial 4: Link Analysis & Memory-based Collaborative Filtering

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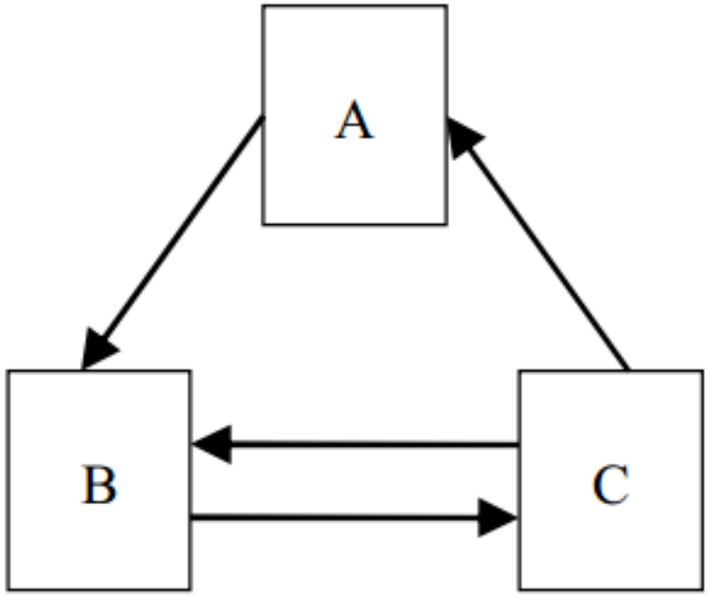
Outline

- NetworkX
  - PageRank
  - HITS
- Crab
  - Introduction
  - Installing
  - Running a first recommender engine
  - Building a Recommender System

PageRank in NetworkX

$$PR(A) = \frac{1-d}{N} + d\left(\frac{PR(B)}{L(B)} + \frac{PR(C)}{L(C)} + \frac{PR(D)}{L(D)} + \cdots\right).$$



The number of web pages $N = 3$
The damping parameter $d = 0.7$

$PR(A) = (1 - d) \times (1 / N) + d \times (PR(C) / 2)$
$PR(B) = (1 - d) \times (1 / N) + d \times (PR(A) / 1 + PR(C) / 2)$
$PR(C) = (1 - d) \times (1 / N) + d \times (PR(B) / 1)$

So

$PR(A) = 0.1 + 0.35 \times PR(C)$
$PR(B) = 0.1 + 0.70 \times PR(A) + 0.35 \times PR(C)$
$PR(C) = 0.1 + 0.70 \times PR(B)$

By solving the above system of linear equations, we get

$PR(A) = 0.2314$
$PR(B) = 0.3933$
$PR(C) = 0.3753$

PageRank in NetworkX (cont.)

PageRank

PageRank analysis of graph structure.

pagerank(G[, alpha, personalization, ...])	Return the PageRank of the nodes in the graph.
pagerank_numpy(G[, alpha, personalization, ...])	Return the PageRank of the nodes in the graph.
pagerank_scipy(G[, alpha, personalization, ...])	Return the PageRank of the nodes in the graph.
google_matrix(G[, alpha, personalization, ...])	Return the Google matrix of the graph.

PageRank in NetworkX (cont.)

pagerank(*G*, *alpha=0.85*, *personalization=None*, *max_iter=100*, *tol=1e-08*, *nstart=None*, *weight='weight'*)

Return the PageRank of the nodes in the graph.

PageRank computes a ranking of the nodes in the graph G based on the structure of the incoming links. It was originally designed as an algorithm to rank web pages.

Parameters : **G** : graph

A NetworkX graph

alpha : float, optional

Damping parameter for PageRank, default=0.85

personalization: **dict, optional** :

The "personalization vector" consisting of a dictionary with a key for every graph node and nonzero personalization value for each node.

max_iter : integer, optional

Maximum number of iterations in power method eigenvalue solver.

tol : float, optional

Error tolerance used to check convergence in power method solver.

nstart : dictionary, optional

Starting value of PageRank iteration for each node.

weight : key, optional

Edge data key to use as weight. If None weights are set to 1.

Returns : **pagerank** : dictionary

Dictionary of nodes with PageRank as value

Example

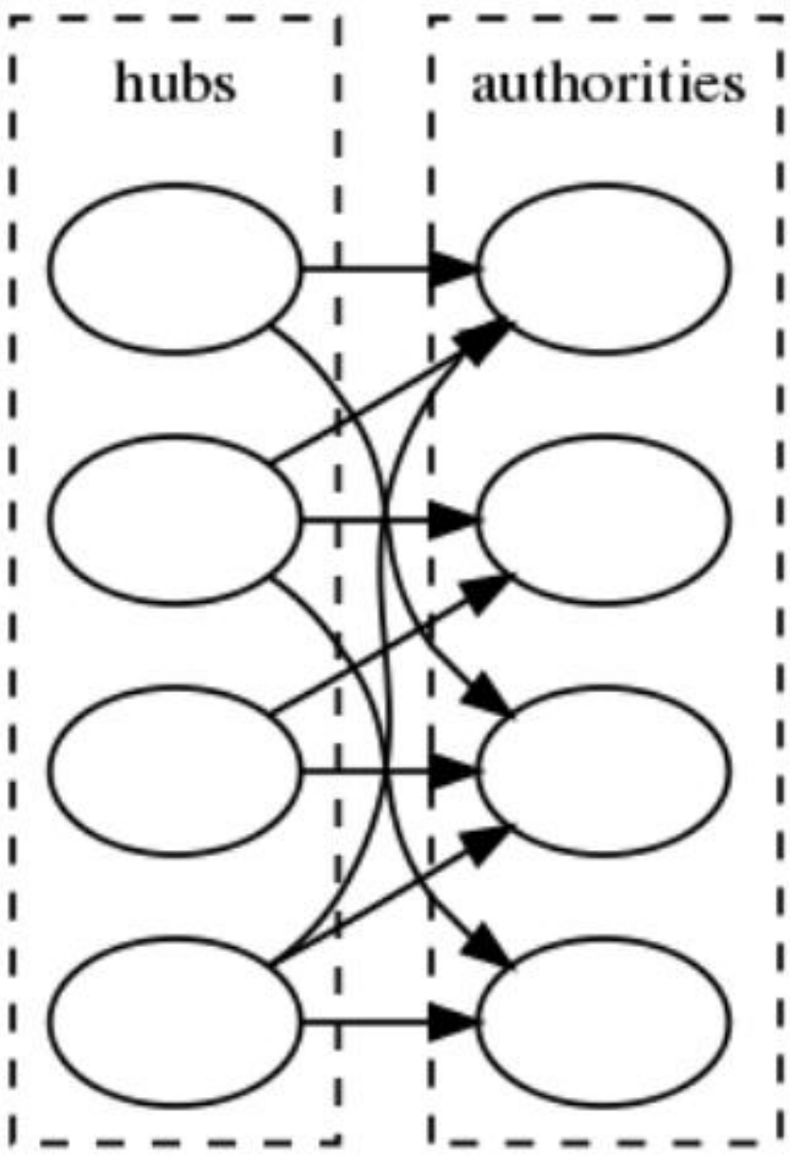
```
import networkx as nx
import matplotlib.pyplot as plt

G=nx.gnp_random_graph(10,0.35)   #ER graph
pr=nx.pagerank(G,alpha=0.9)

nx.draw(G)
plt.savefig("pr.png")
```

HITS

- Hypertext Induced Topics Search (HITS) developed by Jon Kleinberg
- Uses hubs and authorities to define a recursive relationship between web pages
- An authority is a page that many hubs link to
- A hub is a page that links to many authorities



HITS in NetworkX

Hits

Hubs and authorities analysis of graph structure.

hits(G[, max_iter, tol, nstart])	Return HITS hubs and authorities values for nodes.
hits_numpy(G)	Return HITS hubs and authorities values for nodes.
hits_scipy(G[, max_iter, tol])	Return HITS hubs and authorities values for nodes.
hub_matrix(G[, nodelist])	Return the HITS hub matrix.
authority_matrix(G[, nodelist])	Return the HITS authority matrix.

HITS in NetworkX

hits(*G*, *max_iter=100*, *tol=1e-08*, *nstart=None*)

Return HITS hubs and authorities values for nodes.

The HITS algorithm computes two numbers for a node. Authorities estimates the node value based on the incoming links. Hubs estimates the node value based on outgoing links.

Parameters **G** : graph

:

A NetworkX graph

max_iter : interger, optional

Maximum number of iterations in power method.

tol : float, optional

Error tolerance used to check convergence in power method iteration.

nstart : dictionary, optional

Starting value of each node for power method iteration.

Returns : **(hubs,authorities)** : two-tuple of dictionaries

Two dictionaries keyed by node containing the hub and authority values.

Example

```
import networkx as nx
import matplotlib.pyplot as plt

#Return the GNR digraph with n nodes and redirection probability p.
G=nx.gnr_graph(20,0.15)

h,a=nx.hits(G)

nx.draw(G)
plt.savefig("HITS.png")
```

Crab

- Crab is a Python framework for building recommender engines integrated with the world of scientific Python packages (numpy, scipy, matplotlib)
- Features:
  - **Recommender Algorithms**: User-Based Filtering and Item-Based Filtering
  - **Work in progress**: Slope One, SVD, Evaluation of Recommenders
  - **Planed**: Sparse Matrices, REST API's

Installing

- Easy install
  - pip install -U crab
  - easy_install -U crab
- Install from source package
  - Download the package from https://github.com/muricoca/crab/downloads
  - python setup.py install

Running A First Recommender Engine

- Creating the input
  - Consists of an user ID and an item ID
  - Numbers expressing the strength of the user's preference for the items
    - Generally larger values mean stronger positive preferences
      - E.g., if those values are ratings on a scale 1 to 5, the *1* could mean items that the user can't stand, and *5* as favorite items
- Crab includes a few standard datasets

```
>>> from scikits.crab import datasets
>>> movies = datasets.load_sample_movies()
>>> songs = datasets.load_sample_songs()
```

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```

Example

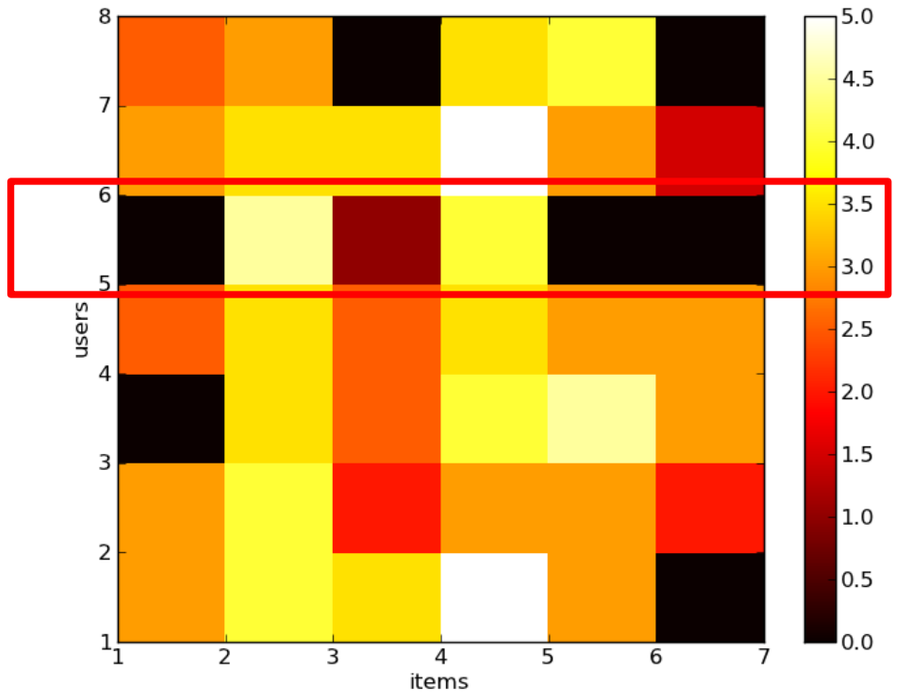
- Format
  - {user_id:{item_id: preference, item_id2: preference, ...}, user_id2: {...}, ...}

```
>>> print movies.data
    {1: {1: 3.0, 2: 4.0, 3: 3.5, 4: 5.0, 5: 3.0},
     2: {1: 3.0, 2: 4.0, 3: 2.0, 4: 3.0, 5: 3.0, 6: 2.0},
     3: {2: 3.5, 3: 2.5, 4: 4.0, 5: 4.5, 6: 3.0},
     4: {1: 2.5, 2: 3.5, 3: 2.5, 4: 3.5, 5: 3.0, 6: 3.0},
     5: {2: 4.5, 3: 1.0, 4: 4.0},
     6: {1: 3.0, 2: 3.5, 3: 3.5, 4: 5.0, 5: 3.0, 6: 1.5},
     7: {1: 2.5, 2: 3.0, 4: 3.5, 5: 4.0}}
```

```
>>> print movies.user_ids
{1: 'Jack Matthews',
 2: 'Mick LaSalle',
 3: 'Claudia Puig',
 4: 'Lisa Rose',
 5: 'Toby',
 6: 'Gene Seymour',
 7: 'Michael Phillips'}
>>>
>>> print movies.item_ids
{1: 'Lady in the Water',
 2: 'Snakes on a Planet',
 3: 'You, Me and Dupree',
 4: 'Superman Returns',
 5: 'The Night Listener',
 6: 'Just My Luck'}
```

Building a Recommender System

- Goal: To recommend a movie to Toby (user 5)
- Toby already watched these movies:
  - Snakes on a Planet (item 2)
  - You, Me and Dupree (item 3)
  - Superman Returns (item 4)
- Recommendation is typically about discovering new things
- Estimate Toby's "ratings" on item 1, 5, and 6



Code

```
>>> from scikits.crab.models import MatrixPreferenceDataModel
>>> #Build the model
>>> model = MatrixPreferenceDataModel(movies.data)
>>>
>>> from scikits.crab.metrics import pearson_correlation
>>> from scikits.crab.similarities import UserSimilarity
>>> #Build the similarity
>>> similarity = UserSimilarity(model, pearson_correlation)
>>>
>>> from crab.recommenders.knn import UserBasedRecommender
>>> #Build the User based recommender
>>> recommender = UserBasedRecommender(model, similarity, with_preference=True)
>>> #Recommend items for the user 5 (Toby)
>>> recommender.recommend(5)
[(5, 3.347789526713101 3), (1, 2.8572508984333034), (6, 2.4473604699719846)]
```

Evaluation

- Training and Testing Data
- Evaluation metrics
  - Root-mean-square error (RMSE): the square root of the average of the squares of the differences between actual and estimated preference values
  - Mean absolute error (MAE): the average absolute value of the differences between actual and estimated preference values
  - The lower, the better!

References

- http://muricoca.github.com/crab/tutorial.html
- http://networkx.lanl.gov/contents.html
- http://www.cis.hut.fi/Opinnot/T-61.6020/2008/pagerank_hits.pdf
- http://www.dcs.bbk.ac.uk/~dell/teaching/ir/examples/pr_example.pdf
- http://en.wikipedia.org/wiki/HITS_algorithm

Betweenness

- The betweenness centrality of a node v is:

$$g(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

- σ_{st} is the total number of shortest paths from node *s* to node *t*
- $\sigma_{st}\,(v)$ is the number of those paths that pass through v

Closeness

- Closeness centrality of a node *u* is the reciprocal of the sum of the shortest path distances from *u* to all *n-1* other nodes
- Normalized by the sum of minimum possible distances *n-1*

$$C(u) = \frac{n-1}{\sum_{v=1}^{n} d(v,u)}$$