# Assignment 5

CS834-F16: Introduction to Information Retrieval Fall 2016 Erika Siregar

## Question 10.3

Compute five iterations of HITS (see Algorithm 3) and PageRank (see Figure 4.11) on the graph in Figure 10.3. Discuss how the PageRank scores compare to the hub and authority scores produced by HITS.

#### Answer

Figure 1 shows the directed graph from the textbook [1] on which we will calculate the scores of HITS and PageRank. Computing HITS (authorities and hubs) and PageRank scores are pretty easy since we can just utilize the Link Analysis procedure that is provided by python library 'networkx' [2].

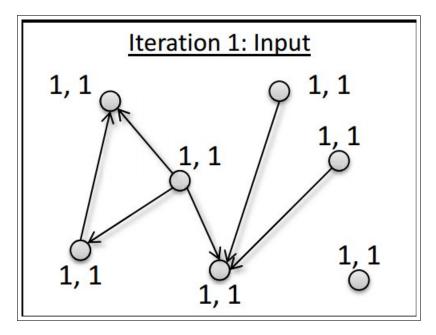


Figure 1: Figure 10.3 from the textbook [1]

Figure 2 shows the scores of HITS (authorities and hubs) and PageRank, which are obtained by running the code in listing 1. We only need to set the number of iterations.

```
🕽 📵 erikaris@erikaris-Inspiron: /media/erikaris/DATA/ODU/Semester_3/intro_to_info_retrieval/assi
erikaris@erikaris-Inspiron:/media/erikaris/DATA/ODU/Semester_3/intro_to_info_retrieva
l/assignments/a5/code_report$ PS1='\u:\W\$
erikaris:code_report$ PS1='\u@\h: '
erikaris@erikaris-Inspiron: python 10 3.py
HITS Algorithm (5 iterations)
Hubs values = {1: 0.19870751068593528, 2: 0.19870751068593528, 3: 0.258854060655404,
4: 0.1789639731325056, 5: 0.0823834724201099, 6: 0.0823834724201099, 7: 0.0}
Authorities values = {1: 0.20153417015341699, 2: 0.20153417015341699, 3: 0.2523245002
3245, 4: 0.18816829381682937, 5: 0.07821943282194328, 6: 0.07821943282194328, 7: 0.0}
Pagerank Algorithm (5 iterations)
----------
Pagerank values = {1: 0.15415210590313183, 2: 0.15415210590313183, 3: 0.2151836555953
412, 4: 0.2730700543561289, 5: 0.08952435340504106, 6: 0.08952435340504106, 7: 0.0243
93371432183873}
erikaris@erikaris-Inspiron:
```

Figure 2: HITS and Pagerank for Figure 10.3 with 5 Iterations

To make the analysis and comparison easier, I transformed the output int figure 2 into a neat table format as can be seen on table 1. From table 1, we can see that, generally, the authorities values are linearly proportional to those of PageRank. After 5 iterations, node 3 gets the highest score for 'authorities' and the second highest score for 'PageRank'. Nodes 1 and 2 get lower 'authorities' score than that of node 3, but higher 'authorities' score compare to nodes 5 and 6. The same thing can also be concluded by comparing the PageRank scores for those five nodes (1, 2, 3, 5, and 6). The strange thing happens on node 4, where its 'authorities' score is lower than node 3, but its 'PageRank' score is higher than node 3. This anomaly takes place probably because we only do 5 iterations. Maybe, if we continue iterating until the values converge into certain number, this anomaly will not happen.

Node	Score		
	Hubs	Authorities	PageRank
1	0.198707510685935	0.201534170153416	0.154152105903131
2	0.198707510685935	0.201534170153416	0.154152105903131
3	0.258854060655404	0.252324500232450	0.215183655595341
4	0.178963973132505	0.188168293816829	0.273070054356128
5	0.082383472420110	0.078219432821943	0.089524353405041
6	0.082383472420110	0.078219432821943	0.089524353405041
7	0.00000000000000000	0.00000000000000000	0.024393371432184

Table 1: HITS and Pagerank for Figure 10.3 with 5 Iterations

```
1 #!/usr/bin/python
2 import networkx as nx
```

```
5 def hits (G, iter=100, nstart=None, normalized=True):
if type(G) = nx.MultiGraph or type(G) = nx.MultiDiGraph:
7 raise Exception ("hits() not defined for graphs with multiedges.")
8 \text{ if } len(G) = 0:
9 return {},{}
10 # choose fixed starting vector if not given
if nstart is None:
h=dict. from keys (G, 1.0/G. number of nodes())
13 else:
14 h=nstart
15 # normalize starting vector
s = 1.0 / sum(h.values())
17 for k in h:
18 h[k] *= s
19 i = 0
20 while True: # power iteration: make up to max iter iterations
if i >= iter: break
22
hlast=h
24 h=dict.fromkeys(hlast.keys(),0)
a=dict.fromkeys(hlast.keys(),0)
_{26}\ \#\ this "matrix multiply" looks odd because it is
27 # doing a left multiply a^T=hlast^T*G
28 for n in h:
for nbr in G[n]:
a [nbr] += hlast[n]*G[n][nbr].get('weight',1)
31 # now multiply h=Ga
32 for n in h:
33 for nbr in G[n]:
34 h[n] += a[nbr] *G[n][nbr].get('weight',1)
35 # normalize vector
s = 1.0/\max(h.values())
37 for n in h: h[n]*=s
38 # normalize vector
s=1.0/\max(a.values())
40 for n in a: a[n]*=s
41
42 i += 1
43 if normalized:
44 \text{ s} = 1.0/\text{sum}(\text{a.values}())
45 for n in a:
a[n] *= s
s = 1.0/sum(h.values())
48 for n in h:
49 h[n] *= s
50 return h, a
52 def pagerank (G, alpha=0.85, personalization=None,
iter=100, nstart=None, weight='weight',
54 dangling=None):
if len(G) = 0:
56 return {}
if not G. is directed():
D = G. to directed ()
60 else:
61 D = G
63 # Create a copy in (right) stochastic form
```

```
64 W = nx.stochastic graph (D, weight=weight)
N = W. number of nodes ()
67 # Choose fixed starting vector if not given
68 if nstart is None:
69 \text{ x} = \text{dict} \cdot \text{fromkeys}(W, 1.0 / N)
70 else:
71 # Normalized nstart vector
_{72} s = float(sum(nstart.values()))
73 x = dict((k, v / s) \text{ for } k, v \text{ in } nstart.items())
74
75 if personalization is None:
76 # Assign uniform personalization vector if not given
p = dict.fromkeys(W, 1.0 / N)
78 else:
79 missing = set(G) - set(personalization)
80 if missing:
81 raise nx. Network XError ('Personalization dictionary '
   'must have a value for every node.
   'Missing nodes %s' % missing)
s = float(sum(personalization.values()))
s p = dict((k, v / s) for k, v in personalization.items())
86
87 if dangling is None:
88 # Use personalization vector if dangling vector not specified
89 dangling weights = p
90 else:
missing = set(G) - set(dangling)
92 if missing:
93 raise nx. NetworkXError('Dangling node dictionary'
94 'must have a value for every node.
95 'Missing nodes %s' % missing)
96 \text{ s} = \text{float}(\text{sum}(\text{dangling.values}()))
97 dangling weights = dict((k, v/s) \text{ for } k, v \text{ in dangling.items})
98 dangling_nodes = [n for n in W if W.out_degree(n, weight=weight) == 0.0]
99
100 # power iteration: make up to max iter iterations
for _ in range(iter):
102 \text{ xlast} = x
x = dict.fromkeys(xlast.keys(), 0)
danglesum = alpha * sum(xlast[n] for n in dangling nodes)
105 for n in x:
106 # this matrix multiply looks odd because it is
107 # doing a left multiply x^T=xlast^T*W
108 for nbr in W[n]:
x[nbr] += alpha * xlast[n] * W[n][nbr][weight]
110 \times [n] += danglesum * dangling weights [n] + (1.0 - alpha) * p[n]
111
112 return x
113
114 if __name__ == '__main ':
iter = 5
116 G = nx.Graph()
117
118 # Add 7 nodes
119 G. add nodes from (range(1,8))
120
121 # Add 6 edges
122 G. add edges from ([(1,2), (3,1), (3,2), (3,4), (5,4), (6,4)])
```

```
# Compute hubs and authorities normalized values using hits
h, a = hits(G, iter=iter)

print 'HITS Algorithm ({} iterations)'.format(iter)
print '======='

print 'Hubs values = {}'.format(h)
print 'Authorities values = {}'.format(a)
print ''

# Compute pagerank of each nodes
pr = pagerank(G, iter=iter)

print 'Pagerank Algorithm ({} iterations)'.format(iter)
print '======='

print 'Pagerank values = {}'.format(pr)
```

Listing 1: Computing HITS and PageRank

## Question 10.5

Find a community-based question answering site on the Web and ask two questions, one that is low-quality and one that is high-quality. Describe the answer quality of each question.

#### Answer:

For this assignment, I asked 2 questions on 2 different comunity-based question answering site. For the low-quality question, I asked about 'What is the purpose of our life?'¹ on Yahoo Answers https://answers.yahoo.com/ as can be seen on figure 3. For the high-quality question, I asked the question 'BUILD-MAX-HEAP running time for array sorted in decreasing order' on Stackoverflow ² as can be seen on figure 5.



Figure 3: Low Quality Question I asked on Yahoo Answers

<sup>&</sup>lt;sup>1</sup>https://answers.yahoo.com/question/index?qid=20161216122515AAPvTIw&page=4

<sup>&</sup>lt;sup>2</sup>http://stackoverflow.com/questions/39691923/build-max-heap-running-time-for-array-sorted-in-decreasing-order

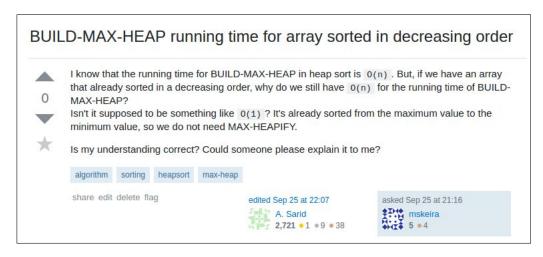


Figure 4: High Quality Question I asked on Stackoverflow

By the time I write this report, I got 37 answers for the low-quality question on Yahoo Answers. Some of the answers can be seen on figure 5. For the high-quality question on Stackoverflow, I only got 2 answers as can be seen on figure 6.

However, for the low-quality question, I also got low-quality answers. This is understandable because for a low-quality question, people tend to post anything that they have in their minds without being afraid of any risks. For example, when I asked 'What is the purpose of our life', I got answers like 'Who says that there's one?', 'To study the paintings of the great Masters, and understand that UFOs are real', and 'Drink beer and have a good time'.

Accordingly, despite the low number of answers, I got high-quality answers for the high-quality question. This is understandable because for this type of question, people will think twice (or maybe more) before submitting the answers. They should be able to provide not only answer, but also the explanation why the answer is correct. People will not take the risk of embarassing themselves by saying something irrelevant. For a high-quality answer, not everyone has the ability to provide a justifiable answer and explanation. Hence, we got a lower number of answers for the high-quality question compare to the low-quality question.

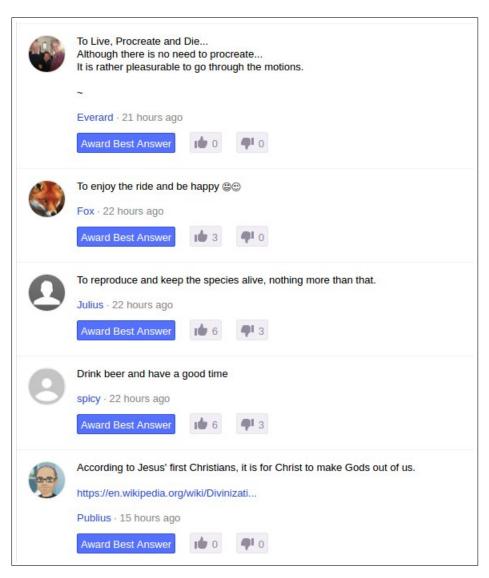


Figure 5: Answers for the low-quality question I asked on Yahoo Answers

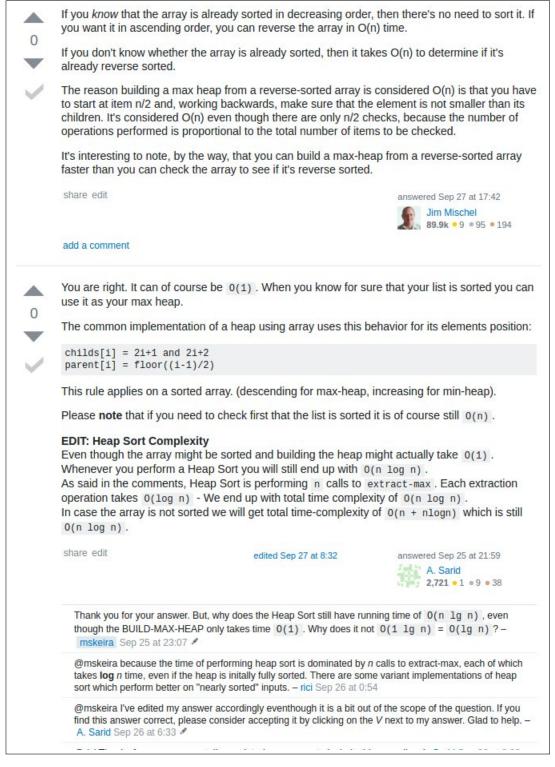


Figure 6: Answers for the high-quality question I asked on Stackoverflow

## Question 10.6

Find two examples of document filtering systems on the Web. How do they build a profile for your information need? Is the system static or adaptive?

#### Answer

I found 2 examples of document filtering systems on the Web, which are:

- 1. Google Alerts (https://www.google.com/alerts). This is a content change detection and notification service, offered by the search engine company Google.
- 2. Twilert (https://www.twilert.com/). This is a tool to get realtime alerts anytime a certain keyword you are interested in are mentioned on Twitter.

Both Google Alerts and Twilert use the same method to build the profile: using input from the user. Figure 7 and 8 shows the creation of profile on Google Alerts and Twilert, respectively. To build a profile on Google Alerts, a user needs to input several information:

- 1. The keyword that the user is interested in. This keyword will be the profile's name.
- 2. Sources: news, blogs, videos, etc
- 3. Language: English, Arabic, etc
- 4. Region: select a country's name
- 5. How many: best results, all results.
- 6. Deliver to: user's email address.

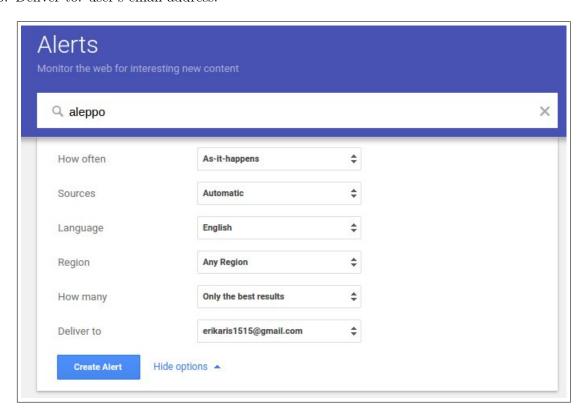


Figure 7: Creating a profile on Google Alerts

Similarly, to build a profile on Twilert, user also needs to input several information such as the keyword, the location of the tweets, and the type of the tweets (positive, negative, or question).

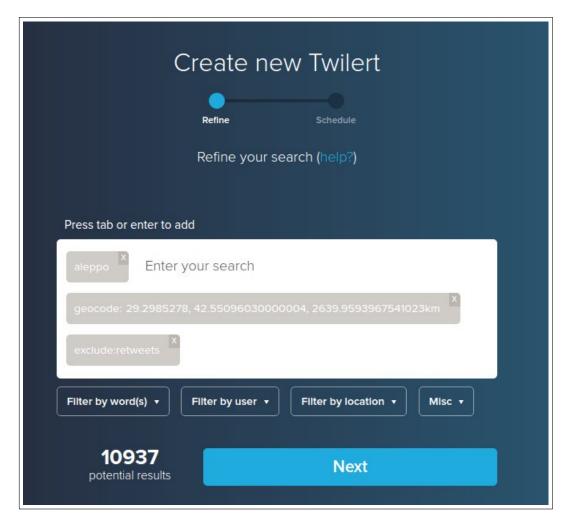


Figure 8: Creating a profile on Twilert

The key to determine if a filtering system is static or adaptive is to check whether the profile is updateable or not. Based on this definition, I can conclude that both Google Alerts and Twilert are using adaptive filtering system since they provide a menu to update/edit profile. Figure 9 and 10 illustrate the profile update for Google Alerts and Twilert, respectively. In this case, I make the keyword more specific by changing 'aleppo' to 'aleppo evacuation'. For Twilert, I also specify the tweet location to 'Syria' (figure 11).

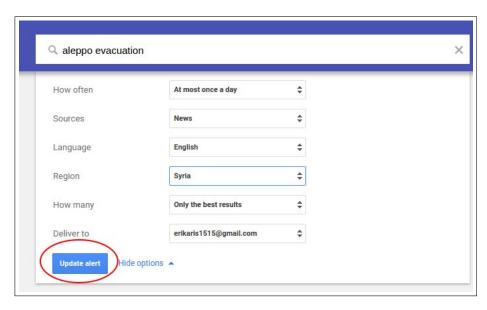


Figure 9: Update a profile on Google Alerts

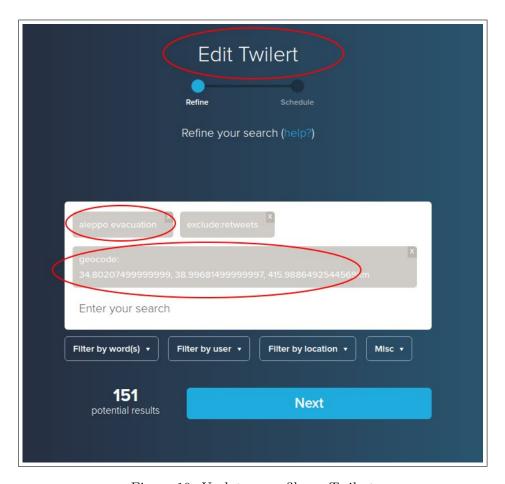


Figure 10: Update a profile on Twilert

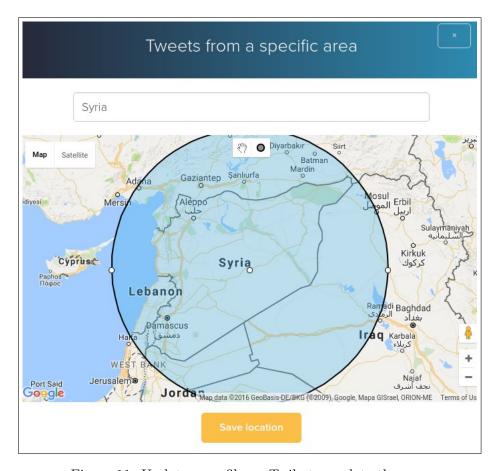


Figure 11: Update a profile on Twilert - update the area

Figure 12 and 13 show the filtering result from Google Alerts and Twilert, respectively.

### Alert preview

There are no recent results for your search query. Below are existing results that match your search query.

NEWS

#### Rebels surrender east Aleppo, evacuations begin

Syria Direct

AMMAN: Rebel forces say they are prepared to leave east **Aleppo** on Thursday, as civilians and the wounded depart for the city's opposition-controlled ...

'Aleppo will remain a mark of shame on the international community': 5 residents say goodbye Syria Direct

The **evacuation** of civilians and fighters from the 3km pocket of land still held by Syrian opposition forces in east **Aleppo** city began on Thursday.

Rebel forces down to final few districts in east **Aleppo** - Syria Direct
Ceasefire in **Aleppo** as eastern half burns, 'bodies lie where they fell' - Syria Direct
Ceasefire falls apart as artillery, airstrikes rock east **Aleppo** - Syria Direct

Civilians increasingly cornered amid ongoing rebel losses in east **Aleppo**, 'stranglehold getting ... Syria Direct

Civilians increasingly cornered amid ongoing rebel losses in east **Aleppo**, ... calls for a mass civilian **evacuation** went unanswered by Russian and Syrian regime ... The regime's ongoing campaign to retake **Aleppo** relies heavily on ...

Figure 12: Filter result by Google Alert

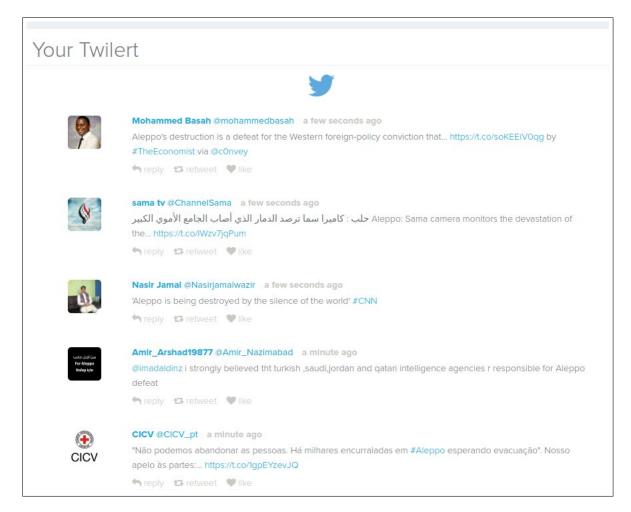


Figure 13: Filter result by Twilert

## Question 7.5

Implement a BM25 module for Galago. Show that it works and document it.

#### Answer

Information about how to impelemnt BM25 on Galago can be found on Lemur Project website [3]. First, we have to make the json query file. The format for the json query is available on [3] and it looks like the example on listing 2.

Listing 2: json query format for BM25

For this assignment, the json query that I use can be found on listing 3.

Listing 3: json query format for BM25

To execute this query, use the command './galago batch-search -index="[path to the index files]" -requested=10 [path to the json query]'. Output of this execution is shown on figure 14.

```
© @ erikaris@erikaris-Inspiron: /media/erikaris/DATA/ODU/Semester_3/intro_to_info_retrieval/assignments
erikaris@erikaris-Inspiron: ./galago batch-search --index="/media/erikaris/DATA/ODU/Semester
__3/intro_to_info_retrieval/assignments/a4/index" --requested=10 /media/erikaris/DATA/ODU/Sem
ester_3/intro_to_info_retrieval/assignments/a3/galago/galago-3.10-bin/query.json
1 Q0 /media/erikaris/DATA/ODU/Semester_3/intro_to_info_retrieval/assignments/a4/code-report/
cacm/CACM-1071.html 1 1.44277471 galago
1 Q0 /media/erikaris/DATA/ODU/Semester_3/intro_to_info_retrieval/assignments/a4/code-report/cacm/CACM-1827.html 2 1.42029563 galago
1 Qoʻ/media/erikaris/DATA/ODU/Semester_3/intro_to_info_retrieval/assignments/a4/code-report/
cacm/CACM-2535.html 3 1.40670063 galago
1 Q0 /media/erikaris/DATA/ODU/Semester_3/intro_to_info_retrieval/assignments/a4/code-report/
cacm/CACM-1410.html 4 1.33970154 galago
1 Q0 /media/erikaris/DATA/ODU/Semester_3/intro_to_info_retrieval/assignments/a4/code-report/
cacm/CACM-1657.html 5 1.32747105 galago
1 Q0 /media/erikaris/DATA/ODU/Semester_3/intro_to_info_retrieval/assignments/a4/code-report/cacm/CACM-1605.html 6 1.32584452 galago
1 Qoʻ/media/erikaris/DATA/ODU/Semester_3/intro_to_info_retrieval/assignments/a4/code-report/
cacm/CACM-1908.html 7 1.24528124 galago
1 Q0 /media/erikaris/DATA/ODU/Semester_3/intro_to_info_retrieval/assignments/a4/code-report/
cacm/CACM-1391.html 8 1.23299466 galago
1 Q0 /media/erikaris/DATA/ODU/Semester_3/intro_to_info_retrieval/assignments/a4/code-report/cacm/CACM-1938.html 9 1.22629823 galago
1 Q0/media/erikaris/DATA/ODU/Semester_3/intro_to_info_retrieval/assignments/a4/code-report/cacm/CACM-2054.html 10 1.20785292 galago
erikaris@erikaris-Inspiron:
```

Figure 14: Output of BM25 implementation using Galago

## Question 7.8

Using the Galago implementation of query likelihood, study the impact of short queries and long queries on effectiveness. Do the parameter settings make a difference?

#### Answer

According to [4], the formula for query likelihood is what can be seen on figure 15.

## Query Likelihood Model

· Unigram query likelihood

$$P(Q \mid \partial D) = \prod_{i=1}^{n} P(q_i \mid D)$$

$$P(q_i \mid D) = \frac{tf_{q_{i,D}}}{\mid D \mid} \iff \text{Maximum liklihood (ML) estimate, defined as:}$$

$$P(Q_i \mid D) = \frac{tf_{q_{i,D}}}{\mid D \mid} \iff \text{Maximum liklihood (ML) estimate, defined as:}$$

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$$P(Q_i \mid D) = \frac{tf_{q_{i,D}}}{\mid D \mid} \iff \text{Maximum liklihood (ML) estimate, defined as:}$$

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$$P(Q_i \mid D) = \frac{tf_{q_{i,D}}}{\mid D \mid} \iff \text{Maximum liklihood (ML) estimate, defined as:}$$

$$P(Q_i \mid D) = \frac{tf_{q_{i,D}}}{\mid D \mid} \iff \text{Maximum liklihood (ML) estimate, defined as:}$$

Figure 15: Query Likelihood Formula

This formula has 2 drawbacks:

Example:

- 1. Results in zero if a term is missing in document (figure 16)
- 2. Document may be relevant to query but the query term is absent from document
  - If a term in a query does not occur in a document, the whole similarity measure becomes zero
  - Example:

```
Q: "gold silver truck"
```

D1: "Shipment of gold damaged in a fire"

D2: "Delivery of silver arrived in a silver truck"

D3: "Shipment of gold arrived in a truck"

- Term Silver does not appear in D<sub>1</sub>. Similarly, silver does not appear in D<sub>3</sub> and gold does not appear in D<sub>2</sub>.
- This would result in Score=0 for all 3 documents.

$$p_{ml}(silver \mid \theta D_i) = \frac{tf(silver, D_i)}{\mid D_i \mid} = 0$$

Figure 16: Problem with missing document. Figure is taken from [4]

To overcome these issues, smoothing is needed. By default, Galago uses DirichletScorer for smoothing [5]. Figure 17 shows the snippet for DirichletScorer code that can be found in file 'DirichletScoringIterator.java' line 56 in Galago Project.

```
public double score(int count, int length) {|
   double numerator = count + (mu * background);
   double denominator = length + mu;
   return Math.log(numerator / denominator);
}
```

Figure 17: Snippet for Dirichlet code in Galago Project

Using short query could impact the effectiveness since short query might contains noises (things that are not really relevant) in the result set. On the other hand, using a very long query could lower the likelihood value, especially if the long query contain a lower proportion of keywords. For example, the query 'search engines' may produce a better result with a web search engine than the query 'what are typical implementation techniques and data structures used in search engines'. Therefore, the best thing to do is to use an average-length query since it has enough keywords to produce a good result, but contain less noise compare to the short query.

Parameter setting (query, query format, input file format, output file format, etc) will have insignificant effect on the query effectiveness. It normally will not affect the top-ranked pages of the search engine result.

## Question 10.8

Implement the nearest neighbor-based collaborative filtering algorithm. Using a publicly available collaborative filtering data set, compare the effectiveness, in terms of mean squared error, of the Euclidean distance and correlation similarity.

#### Answer

For this assignment, I use the movielens dataset which is available at http://grouplens.org/datasets/movielens/100k/. I wrote a python program that utilize python libraries 'scipy' and 'sklearn'. The complete code can be found on listing 4.

Based on the output on figure 18 we can see that the MSE of Euclidean distance is smaller than the MSE of the correlation similarity (Pearson). Therefore, in this case, we can conclude that Euclidean distance is more effective compare to correlation similarity (Pearson).

```
erikaris@erikaris-Inspiron:/media/erikaris/DATA/ODU/Semester_3/intro_to_info_retrievalerikaris@erikaris-Inspiron:/media/erikaris/DATA/ODU/Semester_3/intro_to_info_retrieval/assignments/a5/code_report$ python 10_8.py

Mean Squared Error of Euclidean: 1.427125

Mean Squared Error of Pearson: 2.166100

erikaris@erikaris-Inspiron:/media/erikaris/DATA/ODU/Semester_3/intro_to_info_retrieval/assignments/a5/code_report$
```

Figure 18: Output for question 10 8

```
2 #!/usr/bin/python
3 from numpy import genfromtxt, array, random
4 from sklearn.linear model import LinearRegression
5 from sklearn.metrics import mean squared error
6 from sklearn.neighbors import KNeighborsClassifier
8 \text{ if } name = ' main ':
9 # Read data ratings.csv from movielens
ratings = genfromtxt('ratings.csv', delimiter=',', skip header=1, usecols=range(3))
11
12 # Split data to train and test data, with ratio train:test = 0.9:0.1
13 random. shuffle (ratings)
train, test = ratings [len(ratings)/10:, :], ratings [:len(ratings)/10, :]
16 # Train data using KNN, get 1st top neighbor
neigh = KNeighborsClassifier(n neighbors=1)
18 \# X = 2-dimensional array, y = target = 1st col of X
neigh.fit(train, train[:, 0])
20 # Get neighbors indices (2-dimensional array)
21 distances, neighbors indices = neigh.kneighbors(test)
22 # Get ratings from indices
23 euclidean neighbors = array([train[ns[0]] for ns in neighbors indices])
24
25 # Train data using Pearson
26 lr = LinearRegression()
_{27} \ \# \ X = 2-dimensional \ array, \ y = target = 1st \ col \ of \ X
28 lr. fit (train, train [:, 0])
29 # Get neighbors index (1-dimensional array)
neighbors idx = lr.predict(test)
31 # Get ratings from indices
```

```
pearson_neighbors = array([train[int(idx)] for idx in neighbors_idx])

# Get MSE of predicted ratings, for both euclidean and pearson
y_true = []
for user, movie, rating in test:
y_true.append(rating)

y_pred_euc = []
for user, movie, rating in euclidean_neighbors:
y_pred_euc.append(rating)

y_pred_pear = []
for user, movie, rating in pearson_neighbors:
y_pred_pear.append(rating)

print "Mean Squared Error of Euclidean: %f" % mean_squared_error(y_true, y_pred_euc)
print "Mean Squared Error of Pearson: %f" % mean_squared_error(y_true, y_pred_pear)
```

Listing 4: Code for nearest neighbor-based collaborative filtering algorithm

## References

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