Learn Query Similarity Through Link Analysis of a Web-scale Click Graph with an Entity Ontology

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Abstract

The search for relevant information in websites can be very frustrating for users who, unintentionally, use too general or inappropriate keywords to express their requests. To overcome this situation, researchers and scientists focus on various potential query understanding techniques. And Query similarity is one of the most important part and is the key to do the tasks like Query Rewriting, Query Expansion, Similarity Search, Recommendation, Query Alteration and so on. Those queries with similar search intents but in different forms or words can also help Information Retrieval (IR) task for better retrieving proper documents. However, current existing approaches and algorithms are very hard to scale to real industrial environment and large dataset, and many issues like entity mismatch, ambiguity are not fully solved.

Here I want to model query similarity issue through link analysis of Click-through Bipartite Graph in real web search environment with an Entity Ontology (solving entity mismatch issue and disambiguation issue), and aim at experimenting a way for modelling query similarity based on click graph, which can be directly applied in a real web-scale industrial environment.

1 Introduction

Learning similarity between pairs of objects is an important generic problem in machine learning. Query similarity here is, definitely, a problem about short text similarity in search environment. The challenges include how to model the query similarity functions based on click graph data, and how to accurately and efficiently learn the query similarity functions. The existing work mostly employ various approaches based on user search logs, and I will follow this resource, and consider a weighted bipartite graph based on click-through data and an entity ontology for further reasoning.

In this section, we examine several papers dealing with query similarity, from state-of-the-art approaches in academia to current modern industrial methods applied today, to understand the problem and the methods used to tackle it. I have divided this section into several broad parts based on their main content; for investigation part, I present a summary, and then the main contribution and key techniques of the relevant papers in first two parts. Then, I will summarize existing similarity scores to model query similarity and related tasks. After this, I will summarize what is our goal to achieve.

1.1 State-of-the-art approaches in academia

Traditional methods to model query similarity are mostly feature based, including vector space model, BM25, and Language Model. These models are more focusing on query-query's phrase/word/char level matching. These methods are very straightforward with low recall. Ming query similarity from a click graph have been proposed in several papers([2],[3]). The click-through bipartite graph, which represents users' implicit judgements on query-query relevance relations, have been proved to be a very valuable source for measuring the similarities. This graph-based link analysis will be also applied in my project.

Wu et al. [1] consider leveraging information from both a click-through bipartite graph and features to measure query-document and query-query similarity, as they called it an enriched click graph data. And they proposed a method based

on M-PLS(Multi-View Partial Least Squares) for modeling the similarity in a principled way. From this work, click count as a link weight and linear mapping function can be considered in my project.

Craswell et al. [4] build an Anchor-2-Url bipartite graph and use Url intersection and Jaccard Similarity to mining similar queries. The limitation here is for those queries that don't appear in anchors, they cannot give a principled solution.

1.2 Industrial approaches in modern web search

In industry, as far as I know, for query similarity modeling, it is separated into several very detailed sub-problem from different views. From query view, typically, according query complexity, it's divided into easy query and hard query, or head query and tail query, or different segmented query depending on various areas. From similarity view, the first level issue is stemming and spelling correction, and the second layer issue is alteration among synonyms and antonyms in query text words. Then, the hardest one is generally real rewritten on queries with some proper query relaxation to better understand search intents.

From a view of used resources, the most common used resource is user session log. In general, for example, when a user search something in web search engine without getting necessary relevant information, he/she possibly tries to express his/her search intents by some other words. So, this kind of resource is initial widely used in modeling query similarity related task through memorization. For other resources, such as Wikipedia Graph and some private-owned knowledge based, are also popular to solve the problem.

For methodology, typically, empirical rules, parser and language model are combined. Furthermore, based on existing contents and properties, a binary classifier is commonly used to identify a pair of two queries have similar intents or not. As far as I know, in Google search engine and Microsoft search engine, there are huge amount of query classifiers and learned pattern matching in production.

1.3 Similarity Functions

For Graph-based similarity functions, typically, what I learnt from our lecture are 1) common neighbors (CN), 2) Jaccard Index(JI, it's also called Jaccard Similarity in some papers like [4]), 3) SimRank. They are very common and classical.

In [3], they found SimRank is failed on their task with a query-2-Ads, so they revise SimRank into SimRank++ considering sampled weighted click graph and introducing evidences scores to make an increasing function of the common neighbors between two queries. In other words, they introduced two extensions on SimRank: one that takes into account the weights of the edges in the click graph, and another that takes into account the "evidence" supporting the similarity between queries. I will also borrow the idea: the evidence score here for entity matching to support the similarity between queries.

Another proposed similarity function is P-Rank(Penetrating Rank) from [5], they present P-Rank is not only a new similarity measure, but also it towards effectively computing the structural similairties of entities in real information networks. And P-Rank is proven to be a unified structural similarity framework, under which all state-of-the-art similarity measures, including CoCitation, Coupling, Amsler and SimRank are just its special cases. The intuition is taking into account both in- and out-link relationships of entity pairs and penetrates the structural similarity computation beyond neighborhood of vertices to the entire graph. This idea will also be in my consideration to employ.

1.4 Goals

The project I propose is to first build a weighted bipartite click-through graph(query-url) on a real web-scale search log data, and second project this graph into query space graph by conditional/linear mapping, then model query similarity according to state-of-the-art similarity functions with considering entity matching and Disambiguation through an company-owned Entity Ontology/Graph.

2 Data Collection

Data is always the first important thing to proceed. In this section, I will first deep dive into how I collect the original data from user click logs from a real production web search engine as network data. And then, I will introduce the evaluation data, metrics and methods to be used to evaluate the performances among my method based on structural click graph, current Bing production method and current Google production method.

2.1 Original Data

I collected 7-days (10/01/2018 to 10/07/2018) user click logs from a real production web search engine in English market of United States as original data to be used to build click graph. The log format is Query-Url-ClickCount-MinPositionRank-QueryImpressionCount-UrlImpressionCount-QueryUrlImpressionCount. This original data is very huge since the total number of distinct query-url pairs is 3,375,207,779, the number of distinct queries is 268,621,550 and the number of distinct urls is 689,108,166. The field "ClickCount" will be normalized to weight the graph between edges. And there also reserves some additional fields like MinPositionRank, QueryImpressionCount, QueryUrlImpressionCount, and they are used to do further filtering and pre-processing to simplify the network.

2.2 Evaluation Data

The evaluation data is the ground truth data to measure the performances of query similarity algorithm. Here I have my company owned dataset like the table 1 shows. The number of distinct Queries is 122,634, and the average count of each query's similar queries is 1.56.

Query	Similar Query	Good(1) or Bad(0)
770 area code	what location is area code 770	1
area code 770	what city is 770 area code	1
area code 770	what location is area code 770	1
area code 770	where is phone area code 770	1
lupus symptoms	signs and symptoms of sle	0
lupus symptoms	the signs for lupus	1
the battle of gettysburg	battle of gettysburg how many died	0
the battle of gettysburg	battle of gettysburg how many people died	0
1 acre compared to football field	how many feet are a football field	0
1 acre compared to football field	size of one acre land	0
1 acre contains how many square feet	foot in acre of land	1
1 acre contains how many square feet	how many square footage is in an acreage	1
1 acre contains how many square feet	number sq ft in acre	1
1 acre contains how many square feet	square acre in ft	1
1 acre contains how many square feet	square feet an acre	1
1 acre contains how many square feet	square footage per acre	1
1 acre contains how many square feet	what is the square footage of a house on an acre	0

Table.1 Examples of evaluation data

For evaluation data selection, as for high frequent queries, learning similar queries is easier than low frequent queries. So for this task, I focus more on tail queries (low frequent queries), and also for equality, queries from Bing log and Google log are in a 1:1 ratio. For our internal judgements, we have another side of evaluation on queries, that is easy, moderate or hard, and here I will consider mostly on hard queries. Table.2 shows all the selecting details.

Ratio	Evaluation Data	Notes
Bing Query: Google Query	**1:1**	Bing query means sampling from Bing search log data; Google query means sampling from Google search log data
Easy Query: Hard Query	**2:8**	Easy or Hard query is measured by judgement data based on whole search results.
Head Query: Tail Query	**1:9**	Head or Tail query is measured by query frequency from search logs data.

Table 2. Evaluation data selection

2. 3 Evaluation Metrics

Precision and **Recall** are the most common metrics that are used in query similarity tasks. The general goal is to improve either one of them or both. According to my task here, I define the following formulas to present how the precision and recall calculate with considering query q and algorithm m.

$$\text{Precision} = \frac{1}{number\ of\ queries}\sum_{q}\text{Precision(q, m)}$$
$$= \frac{|\{real\ similar\ queries\ \ to\ q\} \cap \{algorithm\ m\ generated\ similar\ queries\ to\ q\}|}{|algorithm\ m\ generated\ similar\ queries\ to\ q|}$$

$$\text{Recall} = \frac{1}{number\ of\ queries}\sum_{q}\text{Recall(q, m)}$$
$$= \frac{|\{real\ similar\ queries\ to\ q\ \} \cap \{algorithm\ m\ generated\ similar\ queries\ to\ q\}|}{|real\ similar\ queries\ to\ q|}$$

2.4 Evaluation Methods

I conduct the following experiments to compare the performances of weighted(clickCount) Simrank and evidence (introduced entity ontology) based Simrank as techniques for learning query similarities. There are two basslines,

Experiment alias	Experiment type	Method
Bing_Prod	Baseline 1	There is an offline pipeline from Bing production for extracting query-to-similarquery pairs.
Google_Prod	Baseline 2	I did a crawl tool to scrape Google's related queries pairs from its search result pages.
Click-Graph-w-SimRank	Treatment 1	It's my first method with bi-partite click graph with weighted edges based on click-through data.
Click-Graph-e-SimRank	Treatment 2	It's my second method with bi-partite click graph with weighted edges based on click-through data and introduce evidences based on entity ontology.

Table. 3 Experiment Set-ups

3 Network Construction

3.1 Data pre-processing

As I mentioned in Section 2.1, the original data is very huge. Here I do a pre-processing step to clean-up non-clicked query-url pairs and filter out potential low-quality query-url pairs as the Figure. 1 showing.

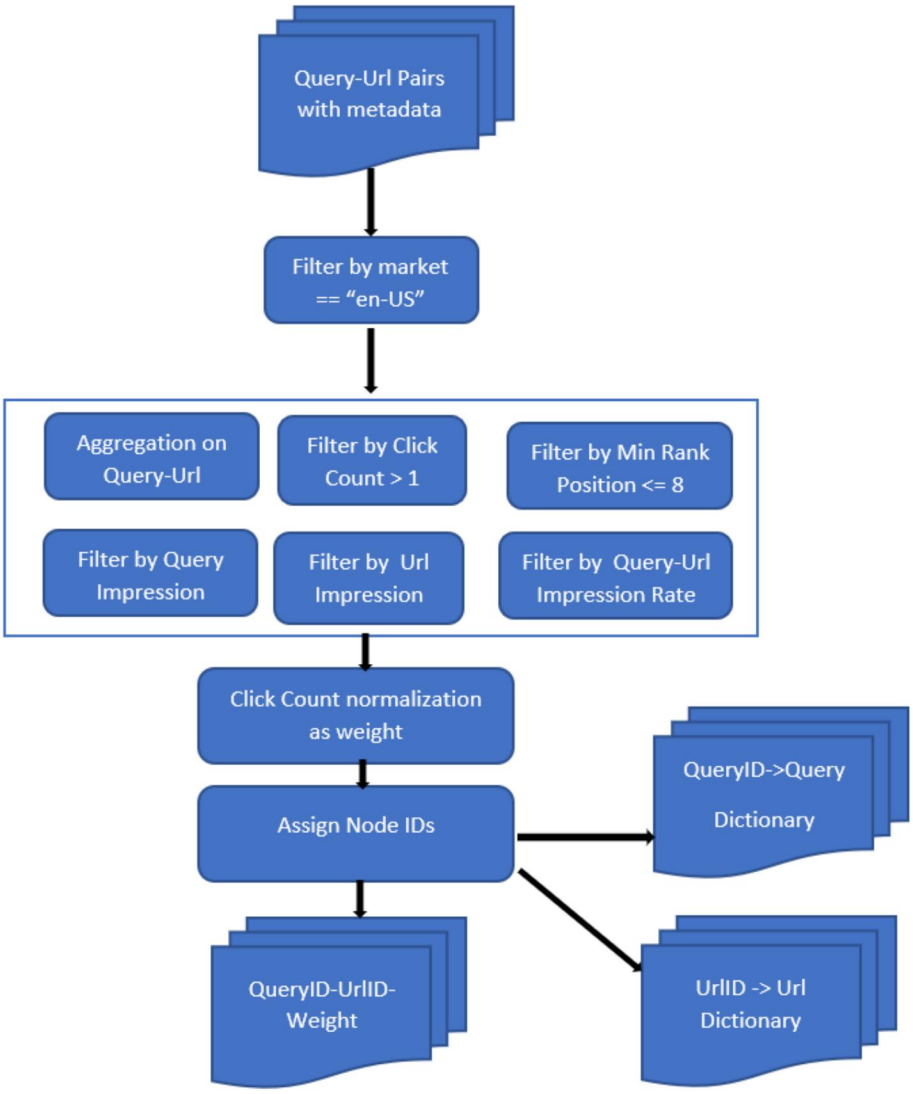


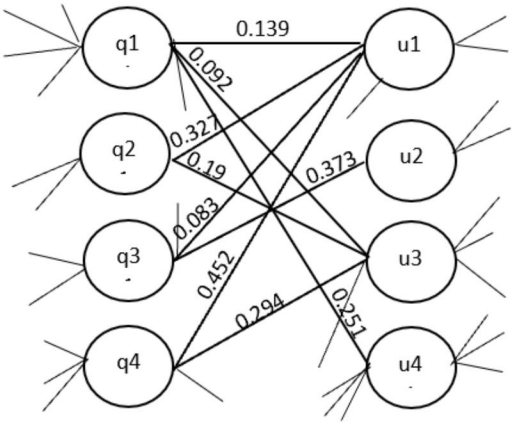
Figure.1 Data Pre-processing flow

3.2 Bipartite Click Graph Construct

Let Q denote a set of n queries and U denote a set of m urls. A click-through graph for a specific period is an undirected, weighted, bipartite graph G = (Q, U, E) where E is a set of edges that connect queries with urls. The graph G has an edge (q, u) if it satisfies 3 conditions. The first condition is at least there are 2 impressions on query q. The second one is at least 2 impressions on url side. The third one is during the time period there are at lease 2 clicks on the url u by the query q. These 3 conditions is used to avoid some bad quality connections between queries and urls.

The bipartite click graph is constructed based on the data from the process of the section 3.1 and the definition and the rules above. The figure.2 shows an example by a very minor part of my bipartite click graph, and also presents some stats of the bipartite click graph.

Data Statistics	
Query Nodes Count	13,312,354
Url Nodes Count	9,880,213
Edges Count	17,584,456



u1-(ID)873991: http://snap.stanford.edu/

u2-(ID)139490: https://cs.stanford.edu/people/jure/teaching.html

u3-(ID)884023: http://snap.stanford.edu/snappy/index.html

u4-(ID)638232: http://www.snapnetwork.org/

q1-(ID)1939494: snap network

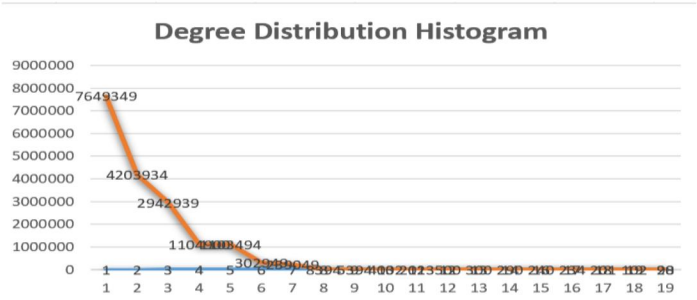
q2-(ID)2003923: snap Stanford

q3-(ID)1537837: jure Stanford

q4-(ID)1938931: snap edu

Figure.2 Bipartite Click Graph example and data statistics

Among construction of the click graph, I did lots of noise filtering works to remove suspicious click data. And, as the data is very huge, I also filtered out some data by clicks thresholds. The degree distribution and other some basic metrics of the bipartite click graph is showed as the following, which represents a long tail line as expected.



3. 3 Project into Query Graph

Based on the above constructed bipartite click graph G, I will project it into query-only graph to reason the query similarities. A query-only graph derived from graph G is an undirected, weighted graph GQ = (Q, E') where E' is a set of edges that connect among related queries. The graph GQ has an edge (q, q') if there is a common url that both q and q' are connected to. The weight of an edge (q, q') is defined as the following formula, and it's based on the idea of page rank.

$$\mathrm{W}(\mathrm{q}, \mathrm{q}') = \text{ Constant} * \sum \frac{weight(q, cu)}{\sum_{u \in U} weight(q, u)} * \sum \frac{weight(q', cu)}{\sum_{u \in U} weight(q', u)}$$

3.4 Similarity Queries Extraction

I can extract similar queries through the whole query graph GQ. Here I set up two empirical thresholds, one is at most top 5 similar queries are extracted since the baselines from Bing production and Google production can only output or scrape 3 to 5 similar queries, and the other one is similarity function score threshold.

As mentioned above, I conducted two similarity functions showed in the following,

$$\mathrm{W} - \mathrm{SimRank}(\mathrm{q}, \mathrm{q}') = \text{ Constant} * \sum_{i \in E(q)} \sum_{j \in (q')} W(q, i) * W(q', j) * S(i, j)$$

$$\mathrm{E} - \mathrm{SimRank}(\mathrm{q}, \mathrm{q}') = \text{ evidence}(\mathrm{q}, \mathrm{q}') * \text{Constant} * \sum_{i \in E(q)} \sum_{j \in (q')} W(q, i) * W(q', j) * S(i, j)$$

For evidence (q, q'), it's depending on an entity ontology, that means I will consider entity match between query q and query q'. This evidence can improve the precision of similar queries and avoid typo/speller errors and noise among similar queries. Some extracted similar queries are showed in the following Figure.3.

Method	Query	Generated Similar Query
Bing Production	Aspirin side effects	Aspirin side effects in men taking aspirin daily side effects aspirin side effects and warnings low dose aspirin side effects Aspirin baby side effects
Google Production	Aspirin side effects	What are the most common side effects of aspirin What are the side effects of taking aspirin daily Who should not take aspirin and why? Is it dangerous to suddenly stop taking aspirin
Click-Graph-W-SimRank	Aspirin side effects	What side effects does aspirin have Bad effects of aspirin Side effects iburophen Aspirin cox 1 stomach bleeding
Click-Graph-E-SimRank	Aspirin side effects	What side effects does aspirin have Bad effects of aspirin Aspirin cox 1 stomach bleeding

Figure.3 Examples of generated similar queries (N_{max}=5)

I randomly sampled some queries to do a deep dive analysis of generated similar queries by my methods and Bing Prod/Google Prod performances. Most of Bing Prod's similar queries and Google Prod's similar queries are very relevant

to the original query, and Bing is good at generating similar queries by narrowing down the query scope to a detailed one while Google is much better at re-descripting queries with some other words or different opposition. And my methods based on click through graph also can retrieve some relevant and similar queries but with some observed noise queries. Specially, for weighted simrank method, it also generates similar queries only on matching some of query terms, which is bad on mismatching the important key entities. For evidence simrank method, it can avoid the entity mismatch situation, but there are still some bad query expansions through url link information.

4 Results and Analysis

According to previous others' work, the common analysis of similar query generation (or query expansion, query rewriting, query suggestion) is based on query path and top N generation. Here, I looked into top 1, top 5, top 10 similar queries by different search engines and my methods, and calculated corresponding precision and recall(for top 1 similar query, I only care about the precision and the recall does not make sense). The results are showed in the following Table.4.

For methodology, no matter top 1, top5, top10, the precision results show Google Production> Bing Production > Click-Graph-E-SimRank > Click-Graph-w-SimRank. My methods have obvious disadvantages comparing with current two biggest search engines' performances, especially, the performances drop fast when the total retrieving number increases to 10. One good point is that Click-Graph-E-SimRank has a better performance than Click-Graph-w-SimRank, which means considering entity matching in raw queries is very helpful and necessary.

This results also reminds us that, structural based methods are very useful to contribute to derive and learn query similarities. I read some technical documents from Bing's and Google's public resources, and I find that, to improve the performances of this task, considering lexicon, text grammar, term alterations and translations (which are missing in my methods) is very promising and necessary.

Results (top 1 similar query)		
Experiment name	**Precision**	**Recall**
Bing Production	89.19%	-
Google Production	90.66%	-
Click-Graph-w-SimRank	70.90%	-
Click-Graph-E-SimRank	77.50%	-
Results (top 5 similar queries)		
Experiment name	**Precision**	**Recall**
Bing Production	73.65%	67.33%
Google Production	88.75%	76.33%
Click-Graph-w-SimRank	65.33%	52.46%
Click-Graph-E-SimRank	69.18%	48.67%
Results (top 10 similar queries)		
Experiment name	**Precision**	**Recall**
Bing Production	66.33%	89.45%
Google Production	70.50%	88.60%
Click-Graph-w-SimRank	49.91%	58.12%
Click-Graph-E-SimRank	43.50%	50.30%

Table.4 Precision-Recall report for learning similar queries.

5 Conclusions

In this task, I studied the issue of learning query similarity from a click-through bipartite graph. The click-through bipartite represents the click relations between queries and documents, and queries that clicking on same or interactive documents can be traced similarities. For this work, I aim to only leverage the click-through bipartite graph and a Microsoft internal entity database to perform the query similarity learning task. I proposed to use two modified SimRank similarity functions to extract similar queries, which are straightforward and easy to do generalization. Although the two methods I tried don't beat present Bing and Google, structural based methods are proven to be very useful on this task and these methods can give more candidates from new perspectives. The issues here I need to mention is that data art is very important, which takes lots of time. And also, since my data is very huge, it makes me have to finally implement by partitioning raw data and sending to cloud services, so scaling is always a big issue.

As future work, I want to further enhance my methods and test its performance with considering more query text attributes, semantic info and some other state-of-art similarity functions. To achieve the goal, I may need to generate text features, and semantic transformers. I also want to study the scale-up of my methods for industrial application, and thus my methods need to be kept straightforward, good generalization and efficiency.

6 Code Submission

GitHub Link: https://github.com/liulijuan/cs224w

Notes: since some data, codes and tools I use are Microsoft internal, please don't clone and share them on any places. And I have to delete the repository later. Sorry for the inconvenience.

Bing public API for Query Rewriting Service: https://api.bing.com/osjson.aspx?query=yourquery

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