AUTOMATIC CREATION OF LISTS FROM WIKIPEDIA ARTICLES

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ABSTRACT

In the paper, we will introduce an approach to automatic list completion based on few keywords specified by the user, using knowledge base constructed previously from English Wikipedia articles. Our approach is similar to Google Sets experiment which does not exist nowadays but its part was integrated in Google Drive (formerly Google Docs) for some time. After writing few words the system recommends additional words to create the list. Our solution is based on offline processing of the English Wikipedia corpus where it searches for tables and lists (as a special case of one column table). These tables/lists are indexed by the system and this index is used to extend user defined keywords by relevant items.

KEYWORDS

Wikipedia, Information Extraction, Automatic Extraction, Completion of Text Lists

1. INTRODUCTION

Auto list completion for numbered items, dates, times, and other range-oriented lists is not a special task today. On the other hand, supplementing the lists based on unstructured text is much more difficult and in many cases not fully functioning. One of the first solutions in this area was Google's Google Sets¹ experiment. This product, after entering few words (the minimum number was 3) supplemented the list with "relevant" items. Unfortunately, Google does not provide API to this product today, but its parts have been integrated into Google Drive^{2,3}.

Our work was partly inspired by Google's product. Google Sets has analysed downloaded pages and searched for structured information such as lists. Concept in our paper seeks to broaden the presented contribution by not only searching the lists but also tables, which in many cases are also useful sources of lists. There are more solutions inspired by Google Sets experiment. Unlike the other ones, our solution does not use the internet to build the lists but one of the largest free downloads - Wikipedia⁴. Other solutions presented on the web mostly work as online tools, searching the web in the time of query, which is really slow.

The paper consists five chapters. In chapter 2, we present existing solutions similar to our framework. Chapter 3 presents the concept of our framework. Chapter 4 contains the evaluation of the results obtained by our solution. In the last chapter we present pros/cons of our approach and possible further research directions.

¹ <http://labs.google.com/sets> - not accessible today

² <http://googlesystem.blogspot.sk/2012/11/google-sets-still-available.html> - didn't work from June 2014

³ <https://drive.google.com>

⁴ <http://www.wikipedia.org/>

2. EXISTING SOLUTIONS

As mentioned above, most solutions for auto list completion use the internet to extract lists and look for structured information. When designing our solution, we have reviewed existing solutions that can be divided into four groups:

- Creating lists based on page structure
 - **Google Sets**: While Google Sets had never been presented at any conference, the patent filed by Google clearly describes the algorithm used for retrieving the lists. Specifically, Google Sets automatically generates lists of items based on their frequency in lists on the internet. Google Sets automatically extracts information from HTML tags: `<UL>`, `<OL>`, `<DL>`, and `<H1> ... <H6>`.
 - **WebTables** [5]: WebTables authors worked or are still working at Google, so their solution is similar to Google Sets. But unlike Google Sets, they extract lists from specific tables (HTML tag `<TABLE>`) while trying to understand the scheme and integrate all data from these tables in one list.
 - **Mining Data Records** [6]: The Mining Data Records framework seeks to get lists by analysing the DOM⁵ structure of each website. This solution is based on two observations:
 1. A list of data records (item list) is in a coherent web page area and are similarly formatted (using similar HTML tags and patterns)
 2. Records in the data area are assigned to one parent node. Consequently, the probability that HTML `<UL>` and `<DIV>` tags will separate lists is approximately the same.
- Creating online wrappers to get lists
 - **RoadRunner** [7]: The RoadRunner algorithm is able to understand the structure of a website and create an online wrapper for this site. The resulting wrapper is very effective in extracting structured repeating objects, but cannot be modified to extract lists from the web in general.
 - **Set Expander for Any Language** [8]: The algorithm used in this solution is similar to the RoadRunner algorithm – it creates a wrapper for any web page. However, unlike the RoadRunner solution, this wrapper is created at the time of search query, but needs multiple keywords to complete the set. In addition, since the wrapper is formed at the time of demand, it is extremely slow⁶.
- Extracting lists based on visual object layout
 - **Visual List Extraction** [1]: The Visual List Extraction algorithm represents the generated web page as an array of areas and therefore attaches great importance to the visual appearance of the page. The area has a given position and size. The area may include: text, images, or other areas. Each area is actually represented by a DOM object. So all objects that are defined within a region (siblings) are considered part of the list.
- Using Wikipedia articles to extract lists
 - **Word Grab Bag**⁷: Only few useful information about Word Grab Bag solution can be found. One of them says that the solution is mainly based on word2vec⁸ framework developed by Google [9]. It processes Wikipedia articles and searches for similar words based on the relative distance between them.

⁵ <http://www.w3.org/DOM/>

⁶ <http://www.boowa.com/> - not accessible anymore, redirected to the original author webpage

⁷ <http://wordgrabbag.com/>

⁸ <https://code.google.com/archive/p/word2vec/>

3. WIKIPEDIA SETS EXTRACTOR

In our solution, we focused on extracting tables and lists from Wikipedia pages, so we focused on offline processing of Wikipedia articles. Our solution does not depend on the amount of information downloaded from the web, but on the free download of Wikipedia. There were 5,871,771⁹ articles (without redirects, talks, users and any other special pages) in English Wikipedia at the time of writing. This version has packed size 15GB (67GB extracted). Since this is a relatively large amount of data, we decided to process it on clusters with 14 computers, each with 24 cores (HTT enabled). Wikipedia can be downloaded in XML, or as an SQL database export. For our distributed processing, the XML version is much more practical. We used the Apache Hadoop¹⁰ framework (especially Apache Spark¹¹) for distributed processing. Since Hadoop can only work with two types of data by default, a sequential file (native format) and a text file, we had to implement support for parsing XML¹² MediaWiki¹³ format over which Wikipedia is built. Another problem was the extraction of tables and lists because the parser¹⁴ used in MediaWiki is quite robust and allows tables and lists that do not fully meet the specification. We tested several solutions in Scala or Java^{15,16}, but none of them suited us. After these experiences we switched to Python and used the WikiTextParser¹⁷ combined with our own parser, based on regular expressions. The following figure shows the table in MediaWiki format.

```
{| class="wikitable"
|+
! Port name
! Location
! Connected to
|-
| Port of [[Florence, Alabama|Florence]] ||'[[Florence, Alabama|Florence]]/[[Muscle
Shoals, Alabama|Muscle Shoals]]', on '[[Pickwick Lake]]' || [[Tennessee River]]
```

Figure 1. Snippet of the table raw data in MediaWiki format

After processing the raw data and removing the line editing formatting, we get the final table as shown below.

```
{| class="wikitable"
|+
! Port name
! Location
! Connected to
|-
| Port of Florence ||Florence/Muscle Shoals, on Pickwick Lake||Tennessee River
```

Figure 2. Table processed by our system

⁹ https://en.wikipedia.org/wiki/Wikipedia:Database_reports/Page_count_by_namespace

¹⁰ <http://hadoop.apache.org/>

¹¹ <https://spark.apache.org/>

¹² <https://github.com/databricks/spark-xml>

¹³ <http://www.mediawiki.org/wiki/MediaWiki>

¹⁴ <https://github.com/wikimedia/parsoid>

¹⁵ <http://wiki.eclipse.org/Mylyn/Incubator/WikiText>

¹⁶ <http://wikipedia-miner.cms.waikato.ac.nz/>

¹⁷ <https://github.com/5j9/wikitextparser#wikitextparser>

It is similar with the lists that have a relatively simpler structure than tables:

Table 1. Different list types used in MediaWiki format

Item	Type
*	bulleted list
#	numbered list
;; :	term and definition

```
*[[Category:American male film actors|List of American film actors]]
*[[Category:American film actresses|List of American film actresses]]
*[[Category:American male television actors|List of American television actors]]
*[[Category:American television actresses|List of American television actresses]]
```

Figure 3. List raw data in MediaWiki format

However, lists and tables may be arbitrarily combined which may cause confusion in the parsing. Each table column is extracted and creates an individual list. Then, if we want to combine several columns together to create larger lists in the future, we can achieve it easily as the ID of each column is created by the title of a parsed page, hash of the whole table and hash of the column (e. g. 'List of awards and nominations received by Alizée -5206743334941503777 6310303203805118876'). We processed 14,583,057 articles (it is much more than the number in previous paragraph, but the dump consisted of all types of Wikipedia articles) in 17 minutes, but it needed to be executed only once. We extracted 2,482,517 tables (containing 12,903,675 columns/lists) and 18,548,254 lists from the Wikipedia dump (after removing empty and duplicate lists our knowledge base contained 31,141,718 lists). Completely stored datasets are 2.7G ID hashes (the long hash presented before is hashed once again to keep the index smaller) and 8.1G individual lists ([KEY, VALUE] pairs [ID, KEYWORD]). The search function works over these datasets by specifying one or more desired keyword(s). It was executed again on the Apache Spark as we did not want to load whole index into memory. The search took around 40 seconds to return the list extended by keywords suggested by the system. As the keywords entered by the users can be found in several lists, we need to specify ranking function to merge these lists and order them somehow. We found an inspiration in classic *tf-idf* (*term frequency – inverse document frequency*) formula:

$$tfidf(t, d, D) = tf(t, d) * idf(t, D)$$

Equation 1. General *tf-idf* equation

Of course, we can compute *tf* and *idf* using many other formulas. In the paper we present only those needed for our computation:

$$tf(t, d) = \frac{f_{t,d}}{\sum_{t \in d} f_{t,d}}$$

Equation 2. Term frequency adjusted for all keywords in document

Equation 2 presents the classical relative frequency formula, but in our case the numerator is always 1 as we remove duplicate keywords from columns. As every keyword is in the list only once (we have removed the duplicates inside lists) in the denominator we can simply take the length of the list/column.

$$tf(t, d) = \frac{1}{|d|}$$

Equation 3. Term frequency adjusted for list length

We will not present the *idf* formula, because we do not count on *idf*. In *idf* computation, the keyword is penalized if it occurs in many documents (lists). We only use *df* (*document frequency*) formula:

$$df(t, D) = \frac{|d \in D: t \in d|}{|D|}$$

Equation 4. Document frequency adjusted for corpus length

After these partial equations, we can simply compute tfd , which we will use as a ranking algorithm for adding keywords in user pre-defined lists:

$$tfd(t, d, D) = tf(t, d) * df(t, D)$$

Equation 5. Document frequency combined with term frequency

4. RESULTS

In this chapter, we present some of the results we obtained by our system. It is hard to evaluate such results. The only way is to use humans to decide what should be part of the list and what should not. We tried to prepare several queries (ten queries, with some modifications to main query) with human build answers (looking into Wikipedia or other internet sources) and we compared (where applicable) system results to manually built lists.

By using the first query, we wanted to obtain the list of American presidents, using the keywords “Ronald Reagan” and “Jimmy Carter”. The query resulted in the list¹⁸ shown in Table 1.

On the 17th position there is a result “President”¹⁹, with score of 1.49. On the 27th position there is a result “List of Presidents of the United States”, with score of 0.57. If we add additional keyword “Donald Trump” to the list, only the scores changed and “John F. Kennedy” will replace “Gerald Ford” in top ten results. Result “President” moves to the 19th position and the “List of Presidents of the United States” leaves top 30 results.

Table 1. List of American presidents

Keyword	Score
Ronald Reagan	26.39
Jimmy Carter	26.39
Bill Clinton	17.87
George W. Bush	17.04
Barack Obama	16.68
George H. W. Bush	13.32
Richard Nixon	11.05
Lyndon B. Johnson	7.75
Donald Trump	7.47
Gerald Ford	6.05

Table 2. List of humans walked on the Moon

Keyword	Score
Alan Shepard	0.12
Ed Mitchell	0.12
Neil Armstrong	0.12
Gene Cernan	0.12
Jim Irwin	0.12
Alan Bean	0.12
Astronaut	0.12
John Young	0.12
Pete Conrad	0.12
Janice Voss	0.01

The next list we want to complete is the list of astronauts who walked on the Moon, by adding two initial keywords “Neil Armstrong” and “Gene Cernan”. The results are shown in Table 2. Now we can see that the 10th result is completely wrong and that there are few astronauts missing. Looking at the score, we can see that the result “Astronaut” is probably from the header, “Janice Voss” comes from another table/list. Other nine results are probably all from one table/list (regarding the scores). Following results are the names of Russian cosmonauts, with the same score as the 10th result (which is completely wrong). Looking into Wikipedia webpage, we can actually find that there is an article “List of people who have walked on the Moon”²⁰, which contains all 12 astronaut names walking on the Moon and our system should found the results. Closer look into the article reveals that Wikipedia templates²¹ are used inside the table and our system can’t process templates yet, because of many different templates and parsing difficulties.

Other query to the system was about returning car manufacturers with specifying keywords “Kia”, “BMW”, “Honda”. The results are shown in Table 3. The results are promising in this case, too, with problems only on the 17th and the 26th position, with “Manufacturer” and “Constructor” results respectively. These results are probably headers from the tables used in this list. If we add keywords “Volvo”, “Citroën”, “Audi” to the query, the results are meshed a little bit (“Volvo”, “Citroën”, “Audi” are inside top 10) and scores are lowered little bit (top result has score of 0.13). But there is no incorrect answer in top 30 results.

¹⁸ All lists will be limited at 10 keywords

¹⁹ We are not removing first row from the table as lot of tables do not have headers

²⁰ https://en.wikipedia.org/wiki/List_of_people_who_have_walked_on_the_Moon

²¹ <https://en.wikipedia.org/wiki/Wikipedia:Templates>

Now let us say we want to fill the list of France regions, specifying four of them: “Burgundy”, “Aquitaine”, “Limousin”, “Alsace” (Table 4.). This is a kind of tricky question as France changed the names of regions in 2015-2016, grouping some of them together under new names. However, all the keywords used in the query were old names so the answers were correct. When we use a query with two new region names “Nouvelle-Aquitaine” and “Grand Est”, the results (shown in Table 5) contain new names and all of them are correct, except the result on the 13th position, where a header keyword (“Region”) is again. The results below the 13th position contain also overseas territories of France.

Table 3. Car manufacturers

Keyword	Score
Honda	1.26
BMW	1.26
Kia	1.06
Mazda	0.75
Ford	0.59
Toyota	0.51
Nissan	0.48
Volkswagen	0.45
Hyundai	0.35
Chevrolet	0.33

Table 4. France political regions

Keyword	Score
Alsace	0.75
Aquitaine	0.75
Auvergne	0.75
Burgundy	0.75
Limousin	0.75
Lorraine	0.75
Picardy	0.75
Franche-Comté	0.67
Poitou-Charentes	0.64
Champagne-Ardenne	0.64

The next query is on (active) German football players, specifying three of them “Toni Kroos”, “Sami Khedira” and “Thomas Müller”. Looking at the results in Table 6, we can see that the 5th result is obviously an error, as “Joachim Löw” is a former football player but today he is a coach of German national team. Also the results “Manager:” and “Substitutions:” are wrong. However, results from the 10th to the 30th position are correct as each listed player comes from Germany.

Table 5. New France political regions

Keyword	Score
Grand Est	2.11
Hauts-de-France	2.11
Nouvelle-Aquitaine	2.11
Auvergne-Rhône-Alpes	1.94
Occitanie	1.86
Bourgogne-Franche-Comté	1.74
Normandy	1.50
Pays de la Loire	1.41
Centre-Val de Loire	1.29
Provence-Alpes-Côte d'Azur	1.10

Table 6. German football players

Keyword	Score
Toni Kroos	2.12
Sami Khedira	2.12
Thomas Müller	2.12
Mesut Özil	2.06
Joachim Löw	2.01
Jérôme Boateng	1.90
Manager:	1.90
Bastian Schweinsteiger	1.30
Substitutions:	0.98
Benedikt Höwedes	0.93

The query to complete the list of European countries, containing three keywords “Slovakia”, “Italy”, “Germany”, ends with the results shown in Table 7. The first mistake is on the 30th position (“Country”, with score of 5.76), and from the 35th position on there are only few European countries left - 36th “Malta”, 41st “Belarus”, followed by several former republics of Yugoslavia.

Table 7. European countries list

Keyword	Score
Italy	28.91
Germany	28.91
Slovakia	28.84
France	23.17
Spain	20.31
Sweden	16.82
Poland	16.74
Netherlands	15.69
Austria	14.80
Czech Republic	14.76

Table 8. Athletic sports

Keyword	Score
Javelin	17.04
Shot put	12.66
Long jump	12.57
Discus	11.08
High jump	6.70
Event	5.16
Pole vault	4.31
Triple jump	3.83
100 m	3.19
400 m	3.07

If we want to get a list of athletic sports, we can specify a query to our system with keywords “javelin”, “long jump”, “shot put”. The results can be seen in Table 8. Only result “Event” is a mistake (probably again because of a header issue). In top 40 results, all the listed items are correct, except we have again keywords as “Long Jump”, “High Jump” (capital letters issue), etc., which should be merged with the results already added to the list.

When trying to retrieve European capital cities (Table 9.) by initialling the search over six keywords: “Bratislava”, “Prague”, “Vienna”, “Budapest”, “Berlin”, “Paris” (we used so many as an input because we didn’t want to retrieve other major European cities only capital ones), we receive the results with the first error at the 25th position (“Milan”). Below the 25th position, there is a mix of good and bad answers.

The last predefined query is about receiving the list of Himalayan peaks with keywords “Mount Everest”, “K2”, “Nanga Parbat”. The results can be seen in Table 10. These results are correct, missing only on the 15th and 16th positions with results “Mountain” and “Peak” (header issue).

Table 9. European capital cities

Keyword	Score
Bratislava	0.87
Berlin	0.87
Vienna	0.87
Budapest	0.87
Paris	0.87
Prague	0.87
London	0.77
Stockholm	0.77
Copenhagen	0.77
Helsinki	0.67

Table 10. Himalayan peaks

Keyword	Score
Mount Everest	0.34
Dhaulagiri	0.34
Manaslu	0.34
Nanga Parbat	0.34
K2	0.34
Makalu	0.28
Broad Peak	0.28
Lhotse	0.28
Gasherbrum II	0.28
Cho Oyu	0.28

5. CONCLUSION

The first results of our system, described in chapter 4, evaluated manually by viewing the extracted data, show that the selected approach is suitable for extracting and extending user-specified lists. It is not an easy task to evaluate our solution, but our next goal will be to design a semi-automatic method for evaluating our system and comparing it with existing solutions. The problems which arise in the evaluation of our system can be divided into categories:

- technical:
 - build more robust parser (mainly for templates parsing),
 - problems with capital letters (e.g. “Ice hockey” and “Ice Hockey” in Table 8.); it is not such a big problem, but if we do it probably we can combine things, that shouldn’t be merged together,
 - each list created by our system has at least few dozen results; we need to specify the function which will drop rest of the results based on the decreasing score in the list and length of the list,
 - problem with the time used by search; should be lowered to milliseconds and not seconds
- semantical/logical:
 - some items use different names in the tables/lists, e.g. “Edgar Mitchell” is referred also as “Ed Mitchel” (Table 2.),
 - trying to solve the header problems in the tables by some probability function, which will remove common keywords as “Name”, “Manager”, etc.
 - using only subset of input keywords (it will be enough that column contains only part of the input keywords and not all of them) and merging lists together, how-to process sub-lists from Wikipedia articles (e.g. lowering the priority, ...).

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