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Article

A Purely Entity-Based Semantic Search Approach for Document Retrieval

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Abstract: Over the past decade, Knowledge bases (KB) have been increasingly utilized to complete and enrich the representation of queries and documents in order to improve the document retrieval task. Although many approaches have used KB for such purpose, understanding how effectively leverage entity-based representation still needs to be resolved. This paper proposes a Purely Entity-based Semantic Search Approach for Information Retrieval (PESS4IR) as a novel solution. The approach includes (i) its own entity linking method, (ii) an inverted indexing method, and for document retrieval and ranking, (iii) an appropriate ranking method is designed to take advantage of all the strengths of the approach. We report the findings on the performance of our approach tested by queries annotated by two known entity linking tools, REL and DBpedia-Spotlight. The experiments are performed on the standard TREC 2004 Robust and MSMARCO collections. By using the REL method, for queries whose all terms are annotated and whose average annotation scores are greater than or equal to 0.75, our approach achieves the maximum nDCG@5 score (1.000). Thus, using our approach with any other document retrieval method would be an added value, unless that method achieves the maximum nDCG@5 score for those highly annotated queries.

Keywords: information retrieval; document retrieval; knowledge graphs; entity-based search; entity linking

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1. Introduction

B Because of their semi-structured rich, and strong semantics, knowledge bases are exponentially used in the different information retrieval tasks. Furthermore, the quality and quantity of the knowledge bases such as DBpedia [1] are continuously increasing, which gives us an idea of the knowledge bases' usefulness now and in the future [2]. Moreover, knowledge bases such as DBpedia and Freebase [3] are among the widely used ones.

Based on knowledge bases, a given text could be represented by a suitable set of entities. This representation of text by entities would be called entity-based representation. Moreover, there are several ways to utilize knowledge bases to improve the representation of queries and documents for better ad hoc document retrieval tasks. When entity-based representation is used alongside term-based representation for query representation, in this case, knowledge bases are used for query expansion [4,5]. Furthermore, it is used for both query and document representation completing and enriching the term representation for better document retrieval [6–8].

Although many entity-based representation approaches have been proposed for semantic document retrieval, understanding how effectively to leverage entity-based representation still needs to be resolved [9,10] (see Section 2, for more details). To answer the question "How to know when an approach (a retrieval method) does its best, and for what type of queries?" it is essential to explore the strengths and weaknesses of the approach and, on the other side, analyze its performance towards different queries. On the other hand, because of the complexity and dynamic nature of queries, no document retrieval approach achieves the same performance for every query. Although a better approach has a higher performance score regarding the whole query set, a lower-quality approach may have better performance for some of those queries. Once these questions are effectively addressed, a document retrieval system, such as a search engine, could leverage many approaches alongside each other regarding the different kinds of queries for better information retrieval.

We propose a novel semantic search approach, named Purely Entity-based Semantic Search for Information Retrieval (PESS4IR), purely based on entity representation, and explore its strengths and weaknesses for better document retrieval. In other words, in our approach, the "Purely entity-based representation" concept means that documents and queries are only represented by entities. The approach is mainly composed of three components. The first one is its own entity linking method, which is more appropriate for document text, named Entity Linking for Document Text (EL4DT). We note that, for the entity linking task, there are many tools available online, such as DBpedia Spotlight [11], TagMe [12], and REL [13]. However, the main reason for designing EL4DT is that these tools do not provide certain information and statistics necessary for our document retrieving and ranking method. The second component is an inverted indexing method to achieve the indexing task. Finally, the third one is an appropriate document retrieval and ranking method, as it is designed to leverage the strengths of the approach.

Our approach introduces the concept of "**strong entity**" to describe entities annotated by EL4DT with high scores. The concept plays an important role in our retrieval and ranking methods. Furthermore, alongside the strong entity concept, our retrieving and ranking method leverages many other aspects, of our approach, such as document title weighting, and all information and statistics stored in the index such as number of semantically related entities in the same paragraph, and so on (see the Inverted Index, Section 3.2).

Before discussing the evaluation of our approach, it is vital to understand the nature of the purely entity-based representation. In fact, queries are ambiguous [6] due to the nature of their text, which is usually short and suffers from a lack of context, contrary to document text, which could be well represented by entities because of its textual richness. Annotating the query set of the TREC 2004 Robust collection (250 queries) by DBpedia Spotlight and REL entity linking tools highlights the "**completely annotated query"** concept; we consider a query as completely annotated when all its terms are annotated, stopwords are not obligatory. DBpedia Spotlight and REL annotate 72% and 6.8% of queries, respectively, as completely annotated queries (see appendices A.1 and A.2). Thus, in our experiments, only completely annotated queries are considered. Since our approach is designed to handle only completely annotated queries, the evaluation will be on the corresponding partial results. Therefore, in the evaluation, it is necessary to consider the partial nature of the results. Moreover, we use the well-known baseline Galago tool [14], a search engine extended by the Lemur and Indri projects for research purposes [15], to get the corresponding results performed by Galago (Dirichlet method) and LongP (Longformer) [16] model for all our experiments to demonstrate the added value achieved by our approach. For our experiments, we use TREC 2004 Robust and MSMARCO collections. We use REL and DBpedia Spotlight entity linking tools for the query annotation process as arbitrary entity linking methods instead of our entity linking method. In other words, our approach is tested with the queries annotated by other methods. Also, in the evaluation, we use standard evaluation metrics such as nDCG@k, MAP, and P@k.

In this work, we explore the strengths and weaknesses of our approach by taking advantage of its strengths and avoiding its weaknesses. The exploration study allowed us to effectively address the main question "for which query a purely entity-based approach would be recommended?". Furthermore, for queries with an average annotation score (average annotation score of query entities) higher than or equal to 0.75, annotated by the REL method, our approach achieves the maximum nDCG@5 score (1.000), which would be an added value for any ad-hoc document retrieval method which does not reach the maximum nDCG@5 score for those highly annotated queries.

The remainder of the paper is organized as follows: Section 2 discusses the related work and background. Section 3 introduces the proposed approach, PESS4IR, by explaining all its components in details. Section 4 provides the results of the performed experiments. Then the Section 5 provides the discussion of the results. Finally, the conclusion is given in Section 6.

2. Related Works

Semantic search significantly improves information retrieval (IR) tasks, including ad hoc document retrieval tasks [6–8,10,17–21,23], which is our concern in this paper. On the other hand, recently, knowledge bases have been used increasingly to improve semantic search [6–8,19,23]. Knowledge bases allow an entity-based representation of text instead of the lexical representation used in traditional models such as the BM25 model [22]. Below, we provide the non-entity-based document retrieval and entity-based document retrieval, our primary concern in this paper, and the entity linking task as a secondary concern.

2.1. Non-Entity-Based Document Retrieval

The approaches based on pre-trained Transformer language models such as BERT [24] are the current state-of-the-art for text re-ranking [25]. In this section, we present some state-of-the-art document retrieval models which are not based on knowledge bases. Li et al. (2020) [26] proposed an approach named PARADE, which is a re-ranking model. They claimed an improvement achieved by the model on TREC Robust04 and GOV2 collections; where the model achieves its most effective performance when it is adopted as a re-ranker namely PARADE-Transformer. The Longformer model [27] is also a transformer-based model. Its performance on Robust04 and MSMARCO collections is provided in [16]. We use the LongP Longformer model [16] in our comparisons against state-of-the-art methods. Moreover, Gao & Callan (2022) [25] proposed the MORES+ model, which is a re-ranking method, and tested it on two classical IR collections Robust04 and ClueWeb09. Wang et al. (2023) [28] proposed a ranking method named ColBERT-PRF. They evaluated it on MSMARCO document ranking and TREC Robust04 for document ranking tasks. The approach could be exploited for both end-to-end ranking and reranking scenarios.

2.2. Entity-Based Document Retrieval

In the literature, over the last decade, many document retrieval approaches have explored different types of using entity-based representation for improving the representation of documents and queries. Xiong et al. (2017) [6] proposed a neural information retrieval approach using both term-based and entity-based representations for queries and documents. The approach performs the four-way interactions allowing four matching possibilities between query and document. The four possible representations of document and query are: query terms (words) to document terms, query entities to document entities, query entities to document terms, and query terms to document entities. Thus, they achieve their document retrieval and ranking by integrating those combinations into neural models. Liu et al. (2018) [7] also introduced a neural ranking model that combines entity-based and term-based representations of documents and queries. They used a translation layer in their neural architecture, matching queries and documents without using handcrafted features. Bagheri et al. (2018) [19] proposed a document retrieval approach that uses neural embeddings considering both word embeddings and entity embeddings. Also, they compared both word and entity embedding performances. Lashkari et al. (2019) [8] proposed a neural embeddings-based representation for documents by considering the term, entity, and semantic type within the same embedding space. Gerritse et al. (2022) [23] proposed EM-BERT model, which incorporates entity embeddings into a point-wise document ranking approach. The model combines words and entities into an embedding representation to represent both query and document using BERT [24] model. Although many entity-based document retrieval approaches have been proposed, understanding how effectively to leverage entity-based representation still needs to be resolved. Guo et al. [10] presented a survey on existing neural ranking models, highlighting models that learn with external knowledge, such as knowledge bases. They indicated that more research is needed to improve the effectiveness of neural ranking models with external knowledge and understand external knowledge's role in ranking tasks.

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Moreover, Reinanda et al. [9] describe that understanding how effectively leverage entity-based representation in conjunction with term-based representation still needs to be solved. On the other hand, these approaches and models use knowledge graphs as embedding-based representations, where entity embeddings are learned from knowledge graphs in many ways in the literature [29–31].

To understand how effectively leverage knowledge graph alongside any other model, we introduced PESS4IR, a novel solution, to empirically study the impact of purely entity-based representation for document retrieval. With PESS4IR, queries and documents are represented only by an entity-based representation without using a neural network and embedding-based representation. Below, we discuss the background related to the entity-based document retrieval task.

2.3. Entity Linking

Entity linking is the task concerned with linking terms of a given text to appropriate entities extracted from Knowledge bases; in other words, it gives an entity-based representation which suits the given text. There are many entity linking tools, among which DBpedia Spotlight [11], TagMe [12], REL [13], WAT [32], and FEL [33] are the most widely used. Most of these entity-linking tools are designed for general text annotation purposes. Moreover, some of them would perform better for short text than others, such as TagMe, which is known for its performance for short text [34]. However, to get a more appropriate entity linker for document text, we developed a novel entity linking method, which gives specific information and statistics our approach needs. In the literature, an effective entity linking method is generally designed based on the general pipeline, which is composed of three steps: mention detection, candidate selection, and disambiguation. Moreover, disambiguation is the most challenging step [35]. According to Balog [35], modern disambiguation should consider three important types of evidence: prior importance, contextual similarity, and coherence. Many researchers deal with disambiguation via a graph-based approach. Kwon et al. [36] recently dealt with the disambiguation issue by proposing a graph-based solution. Our entity linking method (EL4DT) uses a graph-based method for the disambiguation task, and the three types of evidence described in [35] are considered.

3. Materials and Methods

This section presents our approach (PESS4IR), which mainly includes three methods: entity linking method (EL4DT), indexing method, and retrieval and ranking method. In the following subsections, we explain each method in detail.

3.1. Entity Linking Method

We design and developed an entity-linking method for document annotation, knowing that many available entity-linking methods exist. The main reason is to provide our approach with some required information and statistics, which are not provided by the available entity linking tools. We store the information and statistics in the inverted index to make them available for our retrieval and ranking method. In the following subsections, we provide the details of our entity linking method.

3.1.1. Overview of Our Entity Linking Method

Our entity linking method is designed precisely for the document text, named Entity Linking for Document Text (EL4DT). It is based on two knowledge bases, DBpedia [1] and Facc1 [37], from which the surface forms are constructed. In addition, EL4DT respects the general pipeline of entity linking methods, which supposes that an entity linking method considers three steps: mention detection, candidate selection, and disambiguation. They are explained in more detail in the following three subsections, respectively.

Before going into the details, we briefly describe our Entity Linking method by explaining its three main steps. In the first step, which contains mention detection and candidate selection tasks, the process starts with a given preprocessed text, and by the n-gram method, mentions are generated.

For each generated mention, the candidate entities are extracted from the surface form. During the first step, a pre-disambiguation process is performed by selecting, in the case of many entities proposed by one class of the surface form classes (Table 2), the more probable candidate entity according to the context similarity score. Moreover, for each candidate entity, the score is computed. In the second step, we have the disambiguation method, which performs the disambiguation task using graphs. Figure 3 represents an initialized graph for entities of a given paragraph, where each entity (represented by a node in the graph) could be connected to another if there are some relationships between them. Their relationships (defined by an edge in the graph) are scored according to the nature of those relationships. Besides, the entities which are semantically related will be grouped as a cluster of the graph. Moreover, the relationships between entities are found in article categories (DBpedia), SKOS's relationships, such as broader and related (DBpedia), and document coherence relationships. In the last step, we select the graph's highest score cluster. The selected graph cluster, a set of entities among the paragraph's entities, includes the disambiguated entities. It is important to note that sure entities (entities with a score greater than or equal to 0.5) do not need a disambiguation step. Furthermore, only weak entities (entities with a score less than 0.5) which are not related to the selected cluster are ignored. The EL4DT algorithm (Algorithm 1) introduces the three steps mention detection, candidate selection, and disambiguation. Moreover, the frequently used symbols are listed in Table 1.

Table 1. Frequent symbols.

Symbol	Description
E	All entities.
E_q	Entities in query q.
E_p	Entities in paragraph p.
E_{qp}	Common entities between query q and paragraph p.
E_{qt}	Entities in document title dt.
SE_p	Strong entities in paragraph p.
SE_d	Strong entities in document d.
SE_{qp}	Entities in query q, which are found in paragraph p as strong entities.
T_d	Document text
T_p	Paragraph text

3.1.2. Mention Detection

A mention refers to a contiguous sequence of terms in the text to be annotated, which refers to one or more particular entities in the surface form [35]. The surface form is the structure that includes all possible mentions extracted from knowledge bases. As mentioned earlier, our surface form is based on DBpedia and Facc1 knowledge bases. The surface form of our EL4DT is constructed from the components listed in Table 2.

Table 2. Components of the surface form.

Component (Class)	Description	Knowledge Base
E_db	Entities extracted from Article categories (without stopwords)	DBpedia
cE_db	Entities extracted from Article categories (with stopwords)	DBpedia
ED_db	Entities extracted from Disambiguation (without stopwords)	DBpedia
cED_db	Entities extracted from Disambiguation (with stopwords)	DBpedia
RE_db	Entities extracted from Redirects (without stopwords)	DBpedia
cRE_db	Entities extracted from Redirects (with stopwords)	DBpedia

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E_dbFacc	Common entities extracted from Facc1 and DBpedia's Article categories (without stopwords)	Facc1 and DBpedia
cE_dbFacc	Common entities extracted from Facc1 and DBpedia's Article categories (with stopwords)	Facc1 and DBpedia
E_Similar	Upper- and lower-case modified entities from DBpedia's Article categories	DBpedia

For a given text, which is supposed to be a paragraph, an n-gram method is used to find all possible candidate entities corresponding to each mention. The candidate entities are extracted from the surface form. Therefore, from a given paragraph, all possible mentions, which exist on the surface, would be detected.

3.1.3. Candidate Selection

The main role of the candidate selection method is to select the more probable candidate entity for each mention. There is at least one candidate entity for each mention. Moreover, some candidate entities could be included in others. Also, a mention could be included in another one, in such case the included one would be ignored. For example, if we consider the following sequence of words "The Empire State Building …"; with mention detection step, the three following mentions could be detected from the surface form: "Empire", "Empire State", and "Empire State Building". One can observe that the first two mentions are included in the third one; if there is one or more candidate entities, in the surface form, for the third mention, then the first and second mention will be ignored. In the same way, candidate entities detected for the first and second mentions will be ignored.

The selection score of a candidate entity is computed by considering different factors such as:

- The component weight: It is a defined weight according to each component of the surface form components (Table 2).
- Contextual similarity computations score: It is defined as score of similarity between entity terms and the given paragraph.
- The number of terms in the entity. Thus, these score computations are used in the candidate selection algorithm to select the most appropriate entity for each mention.

3.1.4. Disambiguation

The disambiguation task is achieved using a graph-based algorithm, which is the central part of our EL4DT method. The constructed graph is a weighted graph G = (V, E), where the node set V contains all selected candidate entities from a given paragraph, and each edge represents the semantic relationship between two entities. The main goal of the disambiguation algorithm is to select among ambiguated entities (entities with weak scores) only those related to sure entities (entities with scores higher than or equal to 0.5). Thus, other weak entities are ignored. Furthermore, EL4DT identifies the best cluster, the group of related entities with the higher score among other clusters in the graph. In other words, the best cluster in the graph is supposed to be the paragraph's main idea. In a graph, we note that a cluster is a set of entities connected by edges whose weights are greater than zero.

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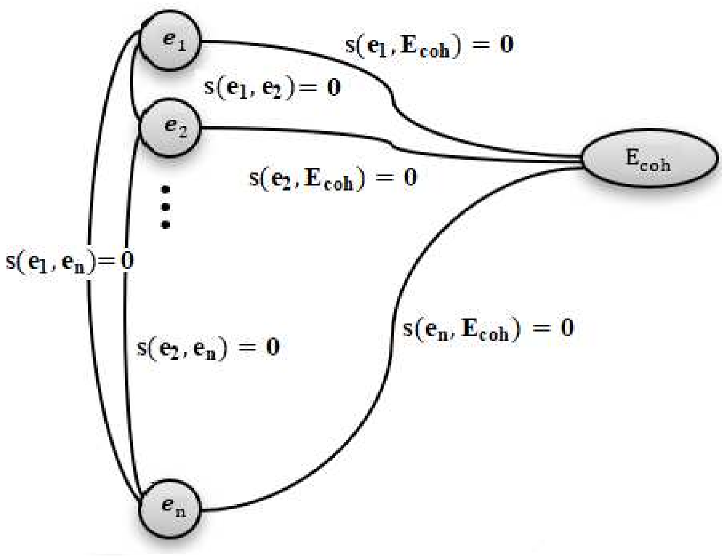

Figure 1. Initialization of a graph built from annotated entities of a paragraph.

The set of entities in a paragraph is expressed below, where n is the number of entities in the paragraph.

$$E_p = \{e_1, e_2, \ldots., e_n\}$$

The $\boldsymbol{E_{coh}}$ symbol stands for coherence entities, which exist in the document title and the document's strong entities. The strong entity concept refers to entities annotated by EL4DT with an annotation score higher than or equal to 0.85. Thus, $\boldsymbol{E_{coh}}$ represents the intersection between the document's strong entities $\boldsymbol{SE_d}$ and document title entities $\boldsymbol{E_{dt}}$, as shown below.

$$E_{coh} = E_{dt} \cap SE_d$$

After the graph initialization step, the graph scoring expression is based on the formula (1), which shows how graph edges are scored:

$$GS(e_i, e_j) = \frac{rScore(e_i,e_j) \times (LScore(e_i) + LScore(e_j))}{|E_p|}, \tag{1}$$

where **rScore**$(\boldsymbol{e_i}, \boldsymbol{e_j})$ is the number of relationships between two entities, computed by (2), where R represents different types of relationships between two entities; moreover, the relationship is either direct or indirect. Direct relationships exist when entities share common article categories of DBpedia. Moreover, from the SKOS of DBpedia, whether there are some relationships between the entities such as <skos:broader> and <skos:related> predicates. However, an indirect relationship means that $\boldsymbol{e_i}$ and $\boldsymbol{e_j}$ have no direct relationships but rather are related by $\boldsymbol{E_{coh}}$ as an indirect relationship. The following formulas (2, 3, 4, and 5) explain formula (1) respectively:

$$rScore(e_i, e_j) = n(e_i, e_j, R) \tag{2}$$

$$\begin{aligned} n(e_i, e_j, R) = & \sum_{c \in ACatg(e_i)} \{exist(c, ACatg(e_j))\} \\ & + exist(e_i, SkosR(e_j)) + exist(e_j, SkosR(e_i)) \\ & + exist(e_i, e_j, E_{coh}) \end{aligned} \tag{3}$$

$$exist(c, ACatg(e_j)) = \begin{cases} 1, c \in ACatg(e_j) \\ 0, \quad otherwise. \end{cases} \tag{4}$$

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$$exist(e_i, e_j, E_{coh})) = \begin{cases} 1, (e_i e_j) \in E_{coh} \\ 0, \quad otherwise. \end{cases} \quad (5)$$

Moreover, $\mathbf{LScore}(\boldsymbol{e_i})$ gives the entity score computed by EL4DT in the candidate selection step. $ACatg(e_i)$ provides the entity category of the entity e_i, which includes all entities of the same category of the DBpedia. $SkosR(e_i)$ provides the Skos relations (<skos:broader> and <skos:related> predicates) of the entity e_i, which are extracted from the DBpedia.

3.1.5. ED4DT Algorithm

The following algorithm (Algorithm 1) represents an overview of our entity linking method. It gives the main processes of entity linking for a given document, starting with the document text as input and the corresponding annotations as output.

Algorithm 1: ED4DT algorithm (Mention Detection, Candidate Selection, Disambiguation)

Input: T_d ← document_text
Output: *document_annotations*
for $T_p \in T_d$ **do**
    ms ← find_allPossible_candidate_entities (T_p)
    E_p ← select_candidate_entity(ms, T_p)
end for
$E_{coh} \leftarrow E_{dt} \cap SE_d$
for $E_p \in E_d$ **do**
    G (V, E) ← graph_initialization(E_p)
    for v, e ∈ G **do**
        $e \leftarrow \frac{\text{rScore}(e_i,e_j)\times(\text{LScore}(e_i)+\text{LScore}(e_j))}{|E_p|}$
    end for
    E_p ← select_disambiguited_entity_set(G)
    $document_{annotations} = adding(E_p)$
end for

3.2. Indexing

Our approach needs an appropriate indexing method that considers all required information and statistics given by our entity linking method (EL4DT). In fact, there are many indexing techniques, inverted index technique is among the most popular ones, known by its efficiency and simplicity [38]. Our inverted index method performs the indexing task. It considers all needed information for our retrieval and ranking method. Figure 2 illustrates the index structure performed by our inverted index method.

$$\begin{array}{l} \mathrm{e}_1 +> docNo \rightarrow EOccNbD/pargNo/NbEp/isStrong/NbSEp/NbRE.. \\ \mathrm{e}_2 +> docNo \rightarrow EOccNbD/pargNo/NbEp/isStrong/NbSEp/NbRE.. \\ \vdots \\ \mathrm{e}_i +> docNo \rightarrow EOccNbD/pargNo/NbEp/isStrong/NbSEp/NbRE.. \\ \vdots \\ \mathrm{e}_n +> docNo \rightarrow EOccNbD/pargNo/NbEp/isStrong/NbSEp/NbRE.. \end{array}$$

Figure 2. Structure of the inverted index.

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In the Figure, each line corresponds to an entity $\mathbf{e_i}$ with all documents in which it occurs and all other important details. **docNo** represents the document's identifier, **EOccNbD** represents the entity occurrence number in the document, **pargNo** is the paragraph's identifier, **NbEp** represents the number of entities in the paragraph, and **isStrong** takes values (0 or 1), which stand for a non-strong and strong entity, respectively. **NbSEp** represents the number of strong entities in the paragraph, and **NbRE** is the number of semantically related entities identified in entity our linking method.

3.3. Retrieval and Ranking Method

This section introduces the retrieving and ranking method we designed for our approach as one of its key elements. The retrieval process of the method is an end-to-end process that retrieves all relevant documents for a given query. In this section, we first provide the ranking function and its key elements, then the algorithm of the retrieval and ranking method (Algorithm 2).

3.3.1. Document Scoring

Computing document scores for a given query (completely annotated query) according to our approach needs an appropriate and relevant solution. To achieve this goal, we design and develop the following ranking method, which is mainly based on the following formula (6). The formula allows to compute the document relevance score, by summing the relevance score of each paragraph in the document against query entities.

$$S(q,d) = \sum_{p \in d} \frac{\sum_{e \in E_q} [nb\_rE(e) \times nbT(e)] \times |E_{qp}|^2 \times e^{[|SE_{qp}|]}}{|E_p| + e^{[|SE_p| - |SE_{qp}|]}} \tag{6}$$

where, $\boldsymbol{nb\_rE(e)}$, gives the number of a related entities, (from the index); $\boldsymbol{nbT(e)}$, gives the number of terms in entity $\boldsymbol{e}$. Moreover, $|\boldsymbol{E_{qp}}|$, represents the number of query entities found in the paragraph $\boldsymbol{p}$. Furthermore, the exponential function in $\boldsymbol{e^{[|SE_{qp}|]}}$, is used to weight the number of query entities located in paragraph $\boldsymbol{p}$ as strong entities according to the index information.

3.3.2. Title Weighting

The document title plays an important role in document retrieval task. In our approach we also consider document titles, and compute their weights in our retrieval and ranking method. The document title weight is computed according to equation (7):

$$TW(q, E_t) = |E_{qt}| \times S(q,d) \times w, \tag{7}$$

where $|\boldsymbol{E_{qt}}|$ is the number of query entities present in the document title, and $\boldsymbol{w}$ is a parameter used to balance the influence of title weight in the document scoring process. Its value is an arbitrary value established after many tests ($\boldsymbol{w = 0.01}$). Finally, the document title weight is added to the document score.

3.3.3. Algorithm

In this session, we provide the algorithm of our document retrieval and ranking method (Algorithm 2) highlighting all main details. The algorithm represents how to compute the ranking score for retrieved documents corresponding to a given query, where only completely annotated queries are considered.

The inputs are E_p which represents the entities of the given query; subIndexAsRaws represents the loaded lines from the index corresponding to each entity of the query. In line three (3) of the algorithm, getStatisctics() function extracts all statistics and information from the raw lines of the subIndexAsRaws. In line (4) getAllFoundDocsIDs() function retrieves all documents that contain at least one entity of the given query entities, which are the concerned documents. The rest of the algorithm shows how the ranking score is computed for each pair document query. Finally, the

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algorithm returns $ScoreQ\_docs$, which represents the document ranked list with a ranking score for each retrieved document.

Algorithm 2: Retrieval and Ranking Method

Input: q, E_p, subIndexAsRaws
Output: $ScoreQ\_docs$
entity_index_info ← getStatisctics(subIndexAsRaws)
retrievedDocs ← getAllFoundDocsIDs(entity_index_info)
for d ∈ retrievedDocs **do**
    $\text{ScoreQ\_docs}(q,d) \leftarrow \sum_{p \in d} \frac{\sum_{e \in E_q}[nb\_rE(e) \times nbT(e)] \times |E_{qp}|^2 \times e^{[|SE_{qp}|]}}{|E_p| + e^{[|SE_p| - |SE_{qp}|]}}$
    $TW(q, E_t) \leftarrow |E_{qt}| \times \text{ScoreQ\_docs}(q,d) \times w$
    $\text{ScoreQ\_docs}(q,d) \leftarrow \text{ScoreQ\_docs}(q,d) + TW(q, E_t)$
end for

4. Results

In the results section, we provide the data collection used in the experiments, evaluation metrics, and the implementation details used for conducting experiments.

4.1. Data

In our experiments, we use the standard TREC 2004 Robust collection, which was used in TREC 2004 Robust Track. Also, we use the MS MACRO collection [39], which is a large-scale dataset focused on machine reading comprehension, question answering, and passage/document ranking. Table 3 shows information about our use of these collections.

Table 3. Usage of MSMARCO and Robust04 collections.

Collection	Queries (Title Only)	#docs	Qrels
TREC Disks 4 & 5 minus CR	TREC 2004 Robust Track, topics 301-450 & 601-700	528k	Complete qrels [1]
MSMARCO v1	TREC-DL-2019 and TREC-DL-2020	3.2M	ir_datasets (Python API) [2]

[1] https://trec.nist.gov/data/robust/qrels.robust2004.txt; [2] https://ir-datasets.com/msmarco-document.html.

4.2. Evaluation Metrics

Three standard evaluation metrics are used to evaluate the results. NDCG@20, the official TREC Web Track ad-hoc task evaluation metric, is the first one. The second metric is the mean average precision (MAP) of the top-ranked 1000 documents. The third metric is P@20 which provides the precision of the top 20 retrieved documents. Moreover, regarding the importance of the 5-top ranked document, NDCG@5 is also used as an evaluation metric for ad-hoc document retrieval tasks. It is important to note that the nDCG@5 evaluation metric is used to compare performances in many different ranking models and ad-hoc document retrieval tasks [40–42].

4.3. Results of Experiments on Robust04

4.3.1. Query Annotation

Our approach is purely based on entity representation for documents and queries. Assuming that we have the best-designed purely entity-based retrieval system, including the best representation of the document and the best ranking method, if the given query is not completely annotated, the system will not work well because of the ignored term(s) from that query (not-annotated term(s)). Therefore, query annotation is the critical factor in a purely entity-based retrieval system, which is why we consider only completely annotated queries in our experiments. We test our retrieval approach by using two arbitrary entity linking methods for query annotation, including DBpedia Spotlight [11] and REL [13]. Moreover, the two Python APIs provided in Table 4 are the used implementations corresponding to each of these two entity linking methods. Then, to check whether a query was completely annotated, we compare the found mentions with the original query text. Also, the stopwords are not considered if they are not in mentions. Furthermore, the relevance of query annotations could be checked by the average score of query entities' annotation scores. Table 4 presents the number of completely annotated queries by each entity linking method.

Table 4. Completely annotated queries by DBpedia Spotlight and REL for Robust collection queries.

Entity Linking Method	#completely Annotated Queries	% of Completely Annotated Queries	Usage
DBpedia Spotlight	180	72%	Spotlight Python Library (v0.7) [1]
REL	17	6.8%	Python API [2]

[1] https://pypi.org/project/spotlight/; [2] https://github.com/informagi/REL.

Table 4 contains only the queries completely annotated by both DBpedia Spotlight and REL entity linkers. Hence, the process is applied to all Robust04 queries (250 queries). Also, we note that no changes were made to REL's results or DBpedia Spotlight query annotations. Later in our tests, we classify queries according to the average scores of their annotation scores to show the corresponding performances and to understand how to effectively leverage a purely entity-based approach.

Before explaining the results of the experiment achieved on Robust collection, it is crucial to clarify some information about annotation scores achieved by both DBpedia Spotlight and REL entity linkers, where both methods offer scores between 0 and 1). However, the scoring systems and the meaning of the scores are different. Like the probability logic, the general interpretation is the same for both methods, which states that the closer the annotation score is to 1, the more accurate the annotation is. And vice versa when the annotation score is closer to zero.

We classified the completely annotated queries into four classes according to their annotation average scores regarding each entity linking method. The reason for this classification is to observe the performance of the PESS4IR method while the annotation score increases. Moreover, four classes (four is an arbitrary number) are suitable for the results' readability. So, the four average score classes are (min = 0.65, 0.85, 0.95, 1.00) and (min = 0.50, 0.65, 0.70, 0.75) for DBpedia Spotlight and REL, respectively. Moreover, for each of these average scores, the corresponding query numbers are (154,132,109, and 3) and (12, 9, 4, and 2), respectively, for each method. We note that DBpedia Spotlight tends to assign higher scores than the REL tool; thus, we assigned the average score classes' values of DBpedia Spotlight higher than those of REL entity linker. Finally, for both entity linkers, the completely annotated queries are separately classified into these different classes. Figure 3 shows the performance of PESS4IR and the Galago (Dirichlet model), according to each class of queries, where for PESS4IR queries are annotated by DBpedia Spotlight and REL entity linkers (respectively in (a) and (b)). In the figure the performance is presented by NDCG@20 scores.

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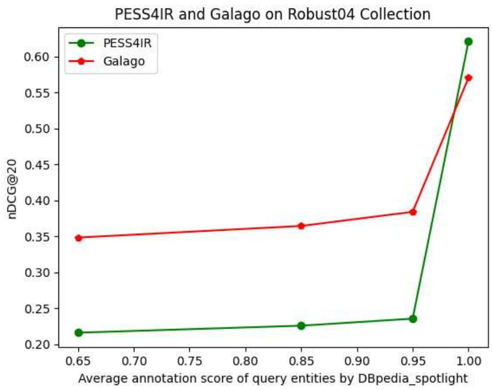
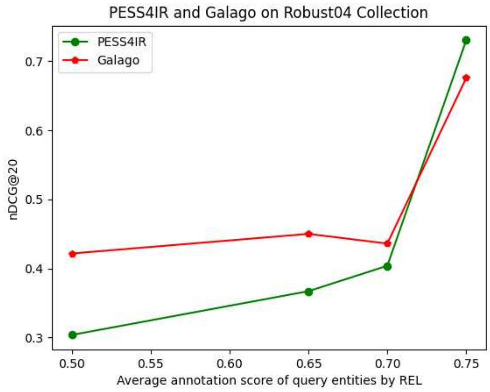


(**a**) nDCG@20 scores for groups of queries annotated by DBpedia spotlight.



(**b**) nDCG@20 scores for groups of queries annotated by REL.

Figure 3. nDCG@20 retrieval scores for queries annotated by DBpedia spotlight and REL (a and b respectively).

In Figure 3a, Galago (Dirichlet model) outperforms our approach for the first three classes of queries, where queries are annotated by DBpedia Spotlight entity linker. However, for the last query class, PESS4IR outperforms Galago, where the average annotation score of that class is equal to (1.0). The corresponding nDCG@20 scores are provided in Table 4, with more details.

Table 4. nDCG@20 scores for queries' classes given by DBpedia spotlight.

Method	nDCG@20			
	AVGs >= Min (154 Queries)	**AVGs >=0.85 (132 Queries)**	**AVGs >=0.95 (109 Queries)**	**AVGs =1.0 (3 Queries)**
Galago (Dirichlet)	0.3498	0.3643	0.3839	0.5702
PESS4IR	0.2160	0.2257	0.2355	**0.6207**

In the Figure 3b, for the last queries class, which corresponds to average annotation scores larger than or equal to (0.75), PESS4IR outperforms Galago method. Moreover, the corresponding nDCG@20 scores are listed in Table 5.

Table 5. nDCG@20 scores for queries' classes given by REL.

Method	nDCG@20			
	AVGs >=Min (12 Queries)	**AVGs >=0.65 (9 Queries)**	**AVGs >=0.7 (4 Queries)**	**AVGs >=0.75 (2 Queries)**
Galago (Dirichlet)	0.4216	0.4500	0.4360	0.6759
PESS4IR	0.3036	0.3670	0.4038	**0.7306**

From the perspective of a retrieval system based on multi-method, which leverages different approaches (retrieval method) for better document information retrieval, PESS4IR could be leveraged for the well-represented queries (queries with high annotation scores, such as the class of highest average annotation score, in (Tables 4 and 5)), and other methods for the rest of queries. In fact, due to its autonomy, the PESS4IR approach could be used alongside any other document retrieval method. Table 6 illustrates the added value of PESS4IR when it is used alongside Galago. Moreover, for Galago, the added value is expressed by all used metrics. Furthermore, PESS4IR provides an added value for any state-of-the-art method on the TREC 2004 Robust collection and its query set. When one uses PESS4IR for the highest represented queries set (AVG_score >= 0.75, annotated by REL), and any other state-of-the-art method for the rest of the queries. In this case, an added value is achieved by PESS4IR unless that SOTA method reaches the maximum nDCG@5 score for those highly annotated queries. In the discussion session (see Section 5.1), we give more details about the added value achieved by PESS4IR.

Table 6. PESS4IR's added value upon Galago.

Method	nDCG@5	nDCG@20	MAP	P@20
Galago (Dirichlet)	0.3729	0.3300	0.1534	0.2795
Galago+PESS4IR	**0.3758**	**0.3311**	**0.1540**	**0.2803**

4.3.2. PESS4IR with LongP (Longformer) Model

We compare PESS4IR against LongP (Longformer) model and combine them to have better performance for ad hoc document retrieval task. Moreover, in this experiment, PESS4IR is used for the highest represented queries set (AVG_score >= 0.75, annotated by REL), and LongP (Longformer) is used for the rest of the queries. The added value achieved by PESS4IR appears when it is used alongside with LongP model. The results are illustrated in the following table (Table 7).

Table 7. PESS4IR and Long (Longformer) on Robust Collection.

Method	nDCG@5	MAP	P@5
LongP (Longformer)	0.6542	**0.3505**	0.6723
LongP (Longformer)+PESS4IR	**0.6551**	0.3492	**0.6731**

In Table 7, the evaluation is given by nDCG@5 metric, where it shows better ranking performance, which is due to the outperforming of PESS4IR upon Long (Longformer) model for the highest annotated queries. In Section 5.1, we provide the details of the added value, achieved by PESS4IR.

4.4. Results of the Experiment on MSMARCO

We would test PESS4IR by queries annotated by both REL and DBpedia Spotlight entity linking methods, however, we test it only by the DBpedia Spotlight tool (see Appendixes B.3 and B.4). The reason for not testing PESS4IR with queries annotated by the REL tool is that among the completely annotated queries, of both query sets of TREC-DL-2019 and TREC-DL-2020, there is no query whose annotation avg score is greater than 0.75 (for TREC-DL-2020 query set, see Appendix B.1); and for the query set of TREC-DL-2019 there is only one query, but it has a scoring issue (see Appendix B.2). In the Discussion (see Section 5.2), we provide the details related to that scoring issue.

In the following table (Table 8), we provide the performance and results of our approach (PESS4IR) and LongP (Longformer) model on MSMARCO collection. Moreover, the nDCG@10 metric is used. It is important to note that the Python API of MSMARCO collection does not provide judgment values (qrels) of some queries for TREC DL 2019 and TREC DL 2020 query subsets. Among them, the highest annotated queries exist (annotated by DBpedia Spotlight tool, whose annotation avg score is equal to 1). And with these highest annotated queries PESS4IR supposed to do its best performance. However, the corresponding judgment values are provided by the MSMARCO collection.

Table 8. nDCG@10 scores for PESS4IR and LongP (Longformer) on MSMARCO.

Method	nDCG@10					
	TREC DL 2019			TREC DL 2019		
	avg>=Min (24 Queries)	avg>=0.95 (16 Queries)	avg=1.0 (1 Query)	avg>=Min (24 Queries)	avg>=0.95 (10 Queries)	avg=1.0 (1 Query)
LongP (Longformer)	**0.7179**	**0.7464**	None	**0.6850**	**0.6605**	None
PESS4IR	0.3842	0.4110	None	0.2733	0.2790	None

The LongP (Longformer) model outperforms PESS4IR for the first two class for each sets (TREC DL 2019 and TREC DL 2020). And for the last class, where PESS4IR is supposed to do its best performance with the highest annotated queries, there no corresponding qrels; this why we put "None".

5. Discussion

In the discussion section, we explain and discuss the added value achieved by PESS4IR, when it is tested with queries annotated by REL entity linking method. Moreover, we discuss our experiments presenting the strengths and limitations of our approach (PESS4IR).

5.1. Added Value of PESS4IR

Since a purely entity-based method is appropriate for only completely annotated queries, the results are partial, where only completely annotated queries are considered. Among them, the ones with higher scores are doing better than the rest. Thus, the purely entity-based approach is recommended for highly represented queries (whose entities have high annotation scores). Furthermore, this session shows how our approach achieves the maximum nDCG@5 score. The following experiment shows how our approach offers added value. In the experiment, we use the REL entity linking method for query annotation (see Appendix A.2). Table 9 contains highly represented queries whose entities have an average annotation score greater than or equal to 0.75. The table also contains the query text which is the original text (query title). It shows for each query, in REL annotation column, the detected mentions with the corresponding entities and their annotation scores.

Table 9. REL annotations whose average scores are higher than or equal to 0.75.

qID	Query Text	REL Annotations ("Mention" → Entity → Score)	Annotation Avg Scores
365	El Nino	"El Nino"→El_Niño→0.76	0.76
423	Milosevic, Mirjana Markovic	"Milosevic"→Slobodan_Milošević→0.99 "Mirjana Markovic"→Mirjana_Marković→0.98	0.98

In addition, to analyze the performance achieved by our purely entity-based approach, we present the results of PESS4IR together with the results of LongP (Longformer) and the Galago (Dirichlet) models. Moreover, Figure 4 comparatively shows the results of our approach, against the two models. In the experiment, illustrated in Table 10 and Figure 4, the nDCG@k scores are for the 5-top ranked documents, and the results of the LongP (Longformer) model are provided.

With these results, our approach achieves the maximum nDCG@5 score of 1.000 for the highest represented queries (annotated by the REL entity linking method). This score is an added value for any document retrieval method which does not reach that score. Moreover, in this experiment, the achieved score is the maximum nDCG@5 score, corresponding to only two queries. This low number of queries represents a limitation of our approach. But this limitation is caused by comparison needs, where we get that maximum nDCG@5 score after selecting the highest represented queries (with the highest annotation average score). Thus, this is how we compared our approach to any other document retrieval approach.

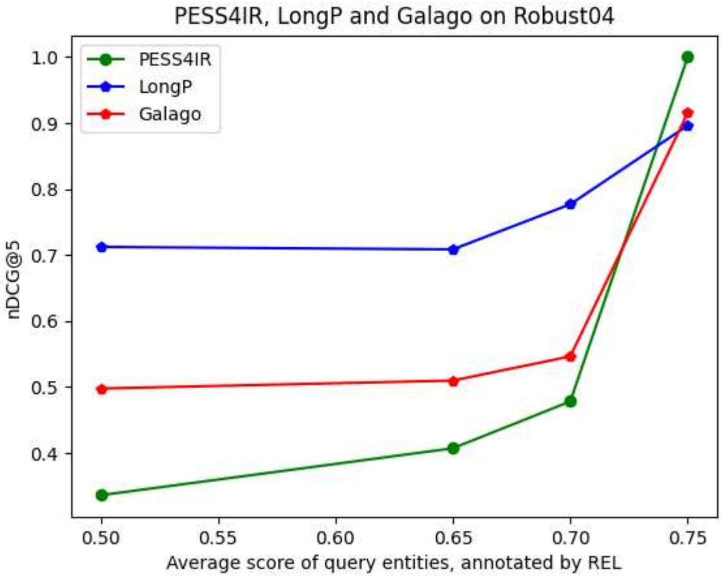


Figure 4. nDCG@5 retrieval scores for the groups of queries, of Robust collection, annotated by REL.

Table 10 shows how LongP (Longformer) model outperforms PESS4IR and Galago method, with big difference, for the first three classes of queries. However, queries of the last class (queries whose entities have an average annotation score greater than or equal to 0.75), LongP (Longformer) model and Galago (Dirichlet) are outperformed by our approach PESS4IR.

Table 10. nDCG@5 scores for queries' classes given by REL on Robust collection.

Method	nDCG@5			
	AVGs >= Min (12 Queries)	**AVGs >=0.65 (9 Queries)**	**AVGs >=0.7 (4 Queries)**	**AVGs =0.75 (2 Queries)**
Galago (Dirichlet)	0.4976	0.5097	0.5463	0.9152
LongP (Longformer)	**0.7122**	**0.7085**	**0.7769**	0.8962
PESS4IR	0.3336	0.4071	0.4781	**1.0000**

5.2. Query Annotation Weaknesses

The weakness of the annotation of a given query could be represented by using DBpedia spotlight, REL, and TagMe tools, for the query sets such as TREC 2019 and TREC 2020 of MSMACO collection. In the following table (Table 11), we show an example of the weakness of a purely-based approach, which could be caused by query entity linking methods.

Table 11. Example of query annotation weakness.

qID	Query Text	REL Annotations (Entity → Score)	DBpedia Spotlight (Entity → Score)	TagMe Annotations (Entity → Score)
1037798	"who is robert gray"	Robert_Gray_(poet) → 0.94	2015_Mississippi_gubernatorial_election → 0.69	Robert_Gray_(sea_captain) → 0.3

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We note that REL gives its annotations of this query as the highest annotated query with an annotation score of 0.94. Such annotation would surely negatively affect any purely entity-based approach. Generally, entity linking methods use a disambiguation process to select an entity among many candidate entities, as we explain in session (3.2.4). In this case, for the given query "who is robert gray", among many entities (known people, with the same name) REL method selects "Robert_Gray_(poet)" to be the entity. However, the issue is the computed annotation score, which means that the selected entity is sure. In other words, the 0.94 score means that there is no way it could be another "robert gray". However, with TagMe tool the selected entity was "Robert_Gray_(sea_captain)", with 0.3 as the annotation score. Thus, such a case could negatively affect our approach and let it perform poor when it is supposed to have better performance.

6. Conclusion

We introduce a purely entity-based semantic search approach for ad-hoc information retrieval (PESS4IR) as a novel solution. The main goal of this paper is to analyze the impact of purely entity-based semantic search on the effectiveness of ad hoc document retrieval by giving clear answers about when such an approach does its best and when it does not, showing its strengths and weaknesses. Our proposed approach represents queries and documents only by entity-based representation. It includes mainly its own entity linking method appropriate for document text (EL4DT), an inverted indexing method, and a method for document retrieving and ranking designed to leverage all strengths of the approach. To evaluate the approach, we used TREC 2004 Robust and MSMARCO collections, and linking query by two different entity linking methods, DBpedia Spotlight and REL. Since our approach uses a purely entity-based representation for queries and documents, only completely annotated queries are considered. Galago (Dirichlet) and LongP (Longformer) models are used to compare the performance on the corresponding group of queries of the two collections, and to show how PESS4IR could be compared to any other retrieval method.

In the experiments, we used the average annotation score of each query's entities as only completely annotated queries are considered. The results indicate that as the average annotation score increases, the ranking score gets higher, as well. Indeed, with the highest-scored queries annotated by DBpedia Spotlight and REL, our approach outperforms the Galago method based on the nDCG@20 evaluation metric. Thus, our approach offers an added value when used with the Galago (Dirichlet method) or LongP (Longformer) model. For the queries with the highest annotation average score (avg_score $\geq$ 0.75) among the queries annotated by the REL entity linking method, our approach achieved the maximum nDCG@5 score (1.000), which would be an added value for any ad-hoc document retrieval method that does not reach the same score for the same queries. LongP (Longformer) model is the confirmation of this added value reached by PESS4IR, where it is among the current state-of-the-art models.

For further research, how to increase the quality and number of completely annotated queries can be investigated. It would also be interesting to investigate how to do automatic query reformulation and query recommendation tasks based on knowledge bases, with purely entity representation as output of these techniques.

Appendix A

Appendix A provides the query annotations, of TREC 2004 Robust collection, used to test our approach. The annotations of query sets are achieved by two entity linking tools DBpedia Spotlight and REL.

Appendix A.1. DBpedia Spotlight Annotations for Robust04

In the Appendix Section, we have a query set of the TREC 2004 Robust collection, annotated by the DBpedia Spotlight entity linker. For each query, the average score is provided. The information is: (qID: query ID; Y: Yes, query completely annotated; AVG_score: computed average score; Query_Annotations: annotations of a query).

qID<++> Y<++>AVG_score<++>Annotations
301<++>Y<++>0.9422930034709613<++>International_law->Organized_crime
303<++>Y<++>0.9916617532774215<++>Hubble_Space_Telescope->Xbox_Live
305<++>Y<++>0.8233757355772809<++>Bridge_of_Independent_Lists->Dangerous_(Michael_Jackson_album)->Vehicle
308<++>Y<++>0.999981850897192<++>Dental_implant->Dentistry
309<++>Y<++>0.8381166338949552<++>Rapping->Crime
310<++>Y<++>0.9636187527358652<++>Radio_Waves_(Roger_Waters_song)->Brain->Cancer
311<++>Y<++>0.9999999998394102<++>Industrial_espionage
312<++>Y<++>0.9999998935852566<++>Hydroponics
314<++>Y<++>0.9637588769999175<++>United_States_Marine_Corps->Vegetation
316<++>Y<++>0.9823531973603806<++>Polygamy->Polyandry->Polygyny
321<++>Y<++>0.8304033796129933<++>Woman->Parliament_of_England
322<++>Y<++>0.9761505135024882<++>International_law->Art->Crime
323<++>Y<++>0.9989506398073358<++>Literature->Journalism->Plagiarism
324<++>Y<++>0.843523719434736<++>Argentina->United_Kingdom->International_relations
325<++>Y<++>0.9957677409995997<++>Cult->Lifestyle_(sociology)
327<++>Y<++>0.6741173791837178<++>Modern_architecture->Slavery
329<++>Y<++>0.9026182851898723<++>Mexico->Air_pollution
331<++>Y<++>0.9392907092908471<++>World_Bank->Criticism
332<++>Y<++>0.9928067801874498<++>Income_tax->Tax_evasion
333<++>Y<++>0.9998904550378483<++>Antibiotic->Bacteria->Disease
334<++>Y<++>0.9953981065544416<++>Export->Control_system->Cryptography
336<++>Y<++>0.8170574260324551<++>Race_and_ethnicity_in_the_United_States_Census->Bear->Weather_Underground
337<++>Y<++>0.9999999999997335<++>Viral_hepatitis
338<++>Y<++>0.9999863000468299<++>Risk->Aspirin
340<++>Y<++>0.7146518568004271<++>Land->Mining->Ban_of_Croatia
341<++>Y<++>0.9999999992114041<++>Airport_security
342<++>Y<++>0.6708548569598859<++>Diplomacy->Expulsion_of_the_Acadians
343<++>Y<++>0.9932852359003905<++>Police->Death
346<++>Y<++>0.984505597445497<++>Education->Technical_standard
347<++>Y<++>0.9994111465790465<++>Wildlife->Extinction
348<++>Y<++>0.99999987750514<++>Agoraphobia
349<++>Y<++>0.9992382152114924<++>Metabolism
350<++>Y<++>0.9953751424684443<++>Health->Computer->Airport_terminal
351<++>Y<++>0.9527758884363138<++>Falkland_Islands->Petroleum->Hydrocarbon_exploration
352<++>Y<++>0.8502584285986691<++>United_Kingdom->Channel_Tunnel->Impact_event
353<++>Y<++>0.9723341881170074<++>Antarctica->Exploration
354<++>Y<++>0.9620560629515208<++>Journalist->Risk
356<++>Y<++>0.896155611833978<++>Menopause->Estrogen->United_Kingdom
357<++>Y<++>0.8588779634116539<++>Territorial_waters->Sea_of_Japan_naming_dispute

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358<++>Y<++>0.9882173961307686<++>Blood_alcohol_content->Death
360<++>Y<++>0.8809526917328019<++>Drug_liberalization->Employee_benefits
361<++>Y<++>0.995345089861352<++>Clothing->Sweatshop
362<++>Y<++>0.8963027195944302<++>People_smuggling
363<++>Y<++>0.9956160648827447<++>Transport->Tunnel->Disaster
364<++>Y<++>0.9982317779257299<++>Rabies
365<++>Y<++>0.9716041526723712<++>El_Niño
367<++>Y<++>0.9692354504948936<++>Piracy
369<++>Y<++>0.9999999999999822<++>Anorexia_nervosa->Bulimia_nervosa
370<++>Y<++>0.9988901469768043<++>Food->Prohibition_of_drugs
371<++>Y<++>0.9276354193704037<++>Health_insurance->Holism
372<++>Y<++>0.9983551804874915<++>Native_American_gaming->Casino
374<++>Y<++>0.9685768957420315<++>Nobel_Prize->Fields_Medal
375<++>Y<++>0.9999999999838174<++>Hydrogen_fuel
376<++>Y<++>0.8702255291357396<++>International_Court_of_Justice
377<++>Y<++>0.9713341665095577<++>Cigar->Smoking
379<++>Y<++>0.9852618198777502<++>Mainstreaming_(education)
380<++>Y<++>0.9595951291022093<++>Obesity->Therapy
381<++>Y<++>0.9999912147260778<++>Alternative_medicine
382<++>Y<++>0.9818197972672459<++>Hydrogen->Fuel->Car
383<++>Y<++>0.8474594732725742<++>Mental_disorder->Drug
384<++>Y<++>0.6671967503078107<++>Outer_space->Train_station->Moon
385<++>Y<++>0.8686428839939203<++>Hybrid_electric_vehicle->Fuel->Car
387<++>Y<++>0.9988472933852381<++>Radioactive_waste
388<++>Y<++>0.9999914286894456<++>Soil->Human_enhancement
389<++>Y<++>0.664255919865177<++>Law->Technology_transfer
390<++>Y<++>0.9999999999991616<++>Orphan_drug
391<++>Y<++>0.9999284901225709<++>Research_and_development->Prescription_costs
392<++>Y<++>0.9995912495852758<++>Robotics
393<++>Y<++>0.9999999999130935<++>Euthanasia
395<++>Y<++>0.9997553022202351<++>Tourism
396<++>Y<++>1.0<++>Sick_building_syndrome
397<++>Y<++>0.9990813178361907<++>Car->Product_recall
400<++>Y<++>1.0<++>Amazon_rainforest
402<++>Y<++>0.9999999999781828<++>Behavioural_genetics
403<++>Y<++>0.999999813435991<++>Osteoporosis
404<++>Y<++>0.6941772057336428<++>Ireland->Peace->Camp_David_Accords
405<++>Y<++>0.4238116228174884<++>Cosmic_ray->Event-driven_programming
407<++>Y<++>0.9923802512157526<++>Poaching->Wildlife->Fruit_preserves
408<++>Y<++>0.9988554001947672<++>Tropical_cyclone
410<++>Y<++>0.9999999999999503<++>Schengen_Agreement
411<++>Y<++>0.9947331398435401<++>Marine_salvage->Shipwreck->Treasure

412<++>Y<++>0.9999999992114041<++>Airport_security
413<++>Y<++>0.9638309080048731<++>Steel->Record_producer
414<++>Y<++>0.9965999250683589<++>Cuba->Sugar->Export
415<++>Y<++>0.775328268440912<++>Drug->Golden_Triangle_of_Jakarta
416<++>Y<++>0.9089337936090394<++>Three_Gorges->Project
419<++>Y<++>0.9917482813095554<++>Recycling->Car->Tire
420<++>Y<++>0.9955077748807217<++>Carbon_monoxide_poisoning
421<++>Y<++>0.988845290029708<++>Industrial_waste->Waste_management
423<++>Y<++>0.9893092495209957<++>Slobodan_Milošević->Mirjana_Marković
424<++>Y<++>0.9964270526243968<++>Suicide
425<++>Y<++>0.9999999999996945<++>Counterfeit_money
426<++>Y<++>0.8827453155184075<++>Law_enforcement->Dog
427<++>Y<++>0.7088978447187699<++>Ultraviolet->Damages->Human_eye
428<++>Y<++>0.983580647717166<++>Declension->Birth_rate
429<++>Y<++>1.0<++>Legionnaires'_disease
430<++>Y<++>0.736355241590634<++>Africanized_bee->September_11_attacks
431<++>Y<++>0.9939081414531497<++>Robotics->Technology
432<++>Y<++>0.9928793873474029<++>Racial_profiling->Driving->Police
433<++>Y<++>0.9999999990127844<++>Ancient_Greek_philosophy->Stoicism
434<++>Y<++>0.9914165431145454<++>Estonia->Economy
435<++>Y<++>0.9997750088796703<++>Curb_stomp->Population_growth
436<++>Y<++>0.8336677830661147<++>Classification_of_railway_accidents
437<++>Y<++>0.8809029694466801<++>Deregulation->Natural_gas->Electricity
439<++>Y<++>0.9930600215575294<++>Invention->Science_and_technology_in_the_Philippines
440<++>Y<++>0.9986339435196137<++>Child_labour
441<++>Y<++>0.9999999999999893<++>Lyme_disease
443<++>Y<++>0.9957246203674307<++>United_States->Investment->Africa
444<++>Y<++>0.9999999999999964<++>Supercritical_fluid
447<++>Y<++>0.9999999999975735<++>Stirling_engine
450<++>Y<++>0.9937577543728069<++>Hussein_of_Jordan->Peace
601<++>Y<++>0.9971377057112235<++>Turkey->Iraq->Water
602<++>Y<++>0.9984578739512397<++>0.6696008778483643<++>Czech_language->Slovakia->Sovereignty
603<++>Y<++>0.9999626386064216<++>0.9985629347827838<++>Tobacco->Cigarette->Lawsuit
604<++>Y<++>0.9999235578240981<++>Lyme_disease->Arthritis
605<++>Y<++>0.9263050230611971<++>Great_Britain->Health_care
606<++>Y<++>0.7390800894132427<++>Human_leg->Trapping->Ban_of_Croatia
607<++>Y<++>0.9965927163010586<++>Human->Genetic_code
609<++>Y<++>0.9920468274116302<++>Per_capita->Alcoholic_drink
610<++>Y<++>0.6887291050943438<++>Minimum_wage->Adverse_effect->Impact_event
611<++>Y<++>0.9944237923763072<++>Kurds->Germany->Violence
612<++>Y<++>0.863878896730292<++>Tibet->Protest

613<++>Y<++>0.7739763636616234<++>Berlin->Berlin_Wall->Waste_management
614<++>Y<++>0.9101682857931109<++>Flavr_Savr->Tomato
615<++>Y<++>0.9997069460982296<++>Lumber->Export->Asia
616<++>Y<++>0.9976499909670737<++>Volkswagen->Mexico
617<++>Y<++>0.9915648387755583<++>Russia->Cuba->Economy
619<++>Y<++>0.9901288174962835<++>Winnie_Madikizela-Mandela->Scandal
620<++>Y<++>0.9954808229883216<++>France->Nuclear_weapons_testing
622<++>Y<++>0.9999999999172893<++>Price_fixing
623<++>Y<++>0.9885496976198986<++>Toxicity->Chemical_weapon
624<++>Y<++>0.8927872609865086<++>Strategic_Defense_Initiative->Star_Wars
625<++>Y<++>0.9703964319776107<++>Arrest->Bomb->World_Triathlon_Corporation
626<++>Y<++>0.999999238626556<++>Stampede
628<++>Y<++>0.9156726801921176<++>United_States_invasion_of_Panama->Panama
629<++>Y<++>0.8864125697999727<++>Abortion_clinic->Attack_on_Pearl_Harbor
630<++>Y<++>0.9999999999999929<++>Gulf_War_syndrome
632<++>Y<++>0.7594953405841971<++>Southeast_Asia->Tin
633<++>Y<++>0.9999999999956017<++>Devolution_in_the_United_Kingdom
635<++>Y<++>0.9791804337848896<++>Physician->Assisted_suicide->Suicide
638<++>Y<++>0.9999999999920917<++>Miscarriage_of_justice
640<++>Y<++>0.9772947307709348<++>Parental_leave->Policy
641<++>Y<++>0.7974386442056666<++>Exxon_Valdez->Wildlife->Marine_life
642<++>Y<++>0.9293590486123976<++>Tiananmen_Square->Protest
643<++>Y<++>0.9958501365753133<++>Salmon->Dam->Pacific_Northwest
644<++>Y<++>0.8128402445905525<++>Introduced_species->Import
645<++>Y<++>0.9999999999699298<++>Copyright_infringement
648<++>Y<++>0.994918609349214<++>Parental_leave->Law
649<++>Y<++>0.9999999999584972<++>Computer_virus
650<++>Y<++>0.9960382314988634<++>Tax_evasion->Indictment
651<++>Y<++>0.9949112351673097<++>United_States->Ethnic_group->Population
653<++>Y<++>0.8261480970551885<++>ETA_SA->Basque_language->Terrorism
657<++>Y<++>0.8118982582118629<++>School_prayer->Smoking_ban
658<++>Y<++>0.9980005204988003<++>Teenage_pregnancy
659<++>Y<++>0.9574704050707363<++>Cruise_ship->Health->Safety
660<++>Y<++>0.999429831087146<++>Whale_watching->California
665<++>Y<++>0.9999825174785343<++>Poverty->Africa->Sub-Saharan_Africa
668<++>Y<++>0.998088959251928<++>Poverty->Disease
669<++>Y<++>0.9999828526608379<++>Iranian_Revolution
670<++>Y<++>0.9999998591162672<++>Elections_in_the_United_States->Apathy
675<++>Y<++>0.9023200615457991<++>Olympic_Games->Training->Swimming
676<++>Y<++>0.9024509959024143<++>Poppy->Horticulture
678<++>Y<++>0.8176555408184811<++>Joint_custody->Impact_event
679<++>Y<++>0.7772527227567606<++>Chess_opening->Adoption->Phonograph_record

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680<++>Y<++>0.8252586633730941<++>Immigration->Spanish_language->School
681<++>Y<++>0.8076328345732521<++>Wind_power->Location
682<++>Y<++>0.8430780796585148<++>Adult->Immigration->English_language
685<++>Y<++>0.7973786182622121<++>Academy_Awards->Win–loss_record_(pitching)->Natural_selection
686<++>Y<++>0.9410682082027008<++>Argentina->Fixed_exchange-rate_system->Dollar
687<++>Y<++>0.9920209145313614<++>Northern_Ireland->Industry
689<++>Y<++>0.9962950350527093<++>Family_planning->Aid
691<++>Y<++>0.9991775251948098<++>Clearcutting->Forest
693<++>Y<++>0.9997175525795037<++>Newspaper->Electronic_media
694<++>Y<++>0.9999999999999929<++>Compost
695<++>Y<++>0.7501223260163279<++>White-collar_crime->Sentence_(linguistics)
696<++>Y<++>0.9652985448255742<++>Safety->Plastic_surgery
697<++>Y<++>0.9999999999999822<++>Air_traffic_controller
698<++>Y<++>0.9999767970588322<++>Literacy->Africa
699<++>Y<++>0.9217820925410557<++>Term_limit
700<++>Y<++>0.975172236248435<++>Fuel_tax->United_States

Appendix A.2. REL Annotations for Robust04

In the Appendix Section, we have a query set of the TREC 2004 Robust collection, annotated by the REL entity linker. For each query, the average score is provided. The information is: (qID: query ID; Y: Yes, query completely annotated; AVG_score: computed average score; Query_Annotations: annotations of a query).

qID<++>Y<++>AVG_score<++>Query_Annotations
301<++>Y<++>0.51<++>Transnational_organized_crime
302<++>Y<++>0.515<++>Polio->Post-polio_syndrome
308<++>Y<++>0.74<++>Dental_implant
310<++>Y<++>0.605<++>Radio_wave->Brain_tumor
320<++>Y<++>0.72<++>Submarine_communications_cable
326<++>Y<++>0.59<++>MV_Princess_of_the_Stars
327<++>Y<++>0.56<++>Slavery_in_the_21st_century
341<++>Y<++>0.6<++>Airport_security
348<++>Y<++>0.65<++>Agoraphobia
365<++>Y<++>0.76<++>El_Niño
376<++>Y<++>0.74<++>The_Hague
381<++>Y<++>0.55<++>Alternative_medicine
416<++>Y<++>0.65<++>Three_Gorges_Dam
423<++>Y<++>0.985<++>Slobodan_Milošević->Mirjana_Marković
630<++>Y<++>0.63<++>Gulf_War_syndrome
669<++>Y<++>0.67<++>Iranian_Revolution
677<++>Y<++>0.69<++>Leaning_Tower_of_Pisa

Appendix B

Appendix A provides the query annotations, of MSMARCO collection, used to test our approach. The annotations of query sets are achieved by two entity linking tools DBpedia Spotlight and REL.

Appendix B.1. REL Annotations for TREC DL 2019

In the Appendix Section, we have the query set of the TREC DL 2019 (MSMARCO collection), annotated by the REL entity linker. For each query, the average score is provided. The information is: (qID: query ID; Y: Yes, query completely annotated; AVG_score: computed average score; Query_Annotations: annotations of a query).

qID<++>Y<++>AVG_score<++>Query_Annotations
835929<++>Y<++>0.62<++>United_States_presidential_nominating_convention
1037798<++>Y<++>0.94<++>Robert_Gray_(sea_captain)
1115392<++>Y<++>0.29<++>Phillips_Exeter_Academy_Library

Appendix B.2. REL Annotations for TREC DL 2020

In the Appendix Section, we have the query set of the TREC DL 2019 (MSMARCO collection), annotated by the REL entity linker. For each query, the average score is provided. The information is: (qID: query ID; Y: Yes, query completely annotated; AVG_score: computed average score; Query_Annotations: annotations of a query).

qID<++>Y<++>AVG_score<++>Query_Annotations
985594<++>Y<++>0.54<++>Cambodia
999466<++>Y<++>0.57<++>Velbert
1115392<++>Y<++>0.29<++>Phillips_Exeter_Academy_Library

Appendix B.3. DBpedia Spotlight Annotations for TREC DL 2019

In the Appendix Section, we have the query set of the TREC DL 2019 (MSMARCO collection), annotated by the DBpedia Spotlight entity linker. The information is: (qID: query ID; Y: Yes, query completely annotated; AVG_score: computed average score; Query_Annotations: annotations of a query).

qID<++>Y<++>AVG_score<++>Query_Annotations
1127622<++>Y<++>0.8484174385279352<++>Semantics->Heat_capacity
190044<++>Y<++>0.8865360168634105<++>Food->Detoxification->Liver->Nature
264403<++>Y<++>0.7427101323971266<++>Long_jump->Data_recovery->Rhytidectomy->Neck->Elevator
421756<++>Y<++>0.9887430913683066<++>Pro_rata->Newspaper
1111546<++>Y<++>0.8968400528320386<++>Mediumship->Artisan
156493<++>Y<++>0.7635869346703801<++>Goldfish->Evolution
1124145<++>Y<++>0.8279115042507935<++>Truncation->Semantics
1110199<++>Y<++>0.9999999991887911<++>Wi-Fi->Bluetooth
835929<++>Y<++>0.6801064489366196<++>National_Convention
432930<++>Y<++>0.674476942756101<++>JavaScript->Letter_case->Alphabet->String_instrument
1044797<++>Y<++>1.0<++>Non-communicable_disease

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1124464<++>Y<++>0.5242881180978325<++>Quad_scull->Casting
130510<++>Y<++>0.9984735189751052<++>Definition->Declaratory_judgment
1127893<++>Y<++>0.9984366536772885<++>Ben_Foster->Association_football->Net_worth
646207<++>Y<++>0.8550360631796995<++>Production_designer->Fee_tail
573724<++>Y<++>0.997942323584422<++>Social_determinants_of_health_in_poverty->Health
1055865<++>Y<++>0.952787250107581<++>African_Americans->Win–loss_record_(pitching)->Wimbledon_F.C.
494835<++>Y<++>0.99176134505693<++>Sensibility->Definition
1126814<++>Y<++>0.9993302443272604<++>Noct->Temperature
100983<++>Y<++>0.9977403165673293<++>Cost->Cremation
1119092<++>Y<++>0.9999999990881676<++>Multi-band_device
1133167<++>Y<++>0.9940850423375566<++>Weather->Jamaica
324211<++>Y<++>0.930982239901244<++>Money->United_Airlines->Sea_captain->Aircraft_pilot
11096<++>Y<++>0.9849797749940885<++>Honda_Integra->Toothed_belt->Replacement_value
1134787<++>Y<++>0.8745724110755091<++>Subroutine->Malt
527433<++>Y<++>0.9537101464933078<++>Data_type->Dysarthria->Cerebral_palsy
694342<++>Y<++>0.9330494647762133<++>Geological_period->Calculus
1125225<++>Y<++>0.814538265672667<++>Chemical_bond->Strike_price
1136427<++>Y<++>0.7061718630217163<++>SATB->Video_game_developer
719381<++>Y<++>0.6677662534973824<++>Arabic->Balance_wheel
131651<++>Y<++>0.9335919424902749<++>Definition->Harmonic
1037798<++>Y<++>0.6999974850327338<++>2015_Mississippi_gubernatorial_election
915593<++>Y<++>0.9148964938941618<++>Data_type->Food->Cooking->Sous-vide
264014<++>Y<++>0.8141469569212276<++>Vowel_length->Biological_life_cycle->Flea
1121402<++>Y<++>0.989264712335901<++>Contour_plowing->Redox
1117099<++>Y<++>0.9999999904273409<++>Convergent_boundary
744366<++>Y<++>0.9999997784843903<++>Epicureanism
277780<++>Y<++>0.999845912562023<++>Calorie->Tablespoon->Mayonnaise
1114563<++>Y<++>0.9999999999999787<++>FTL_Games
903469<++>Y<++>0.9868563759225631<++>Health->Dieting
1112341<++>Y<++>0.9740228833162581<++>Newspaper->Life->Thai_people
706080<++>Y<++>0.9999999999775682<++>Domain_name
1120868<++>Y<++>0.8666884704281476<++>Color->Louisiana->Technology
523270<++>Y<++>0.9978601407237909<++>Toyota->Plane_(tool)->Plane_(tool)->Texas
133358<++>Y<++>0.8321951248053688<++>Definition->Counterfeit->Money
67262<++>Y<++>0.9596081186595659<++>Farang->Album->Thailand
805321<++>Y<++>0.8853931908810876<++>Area->Rock_music->Psychological_stress->Breakbeat->Database_trigger->Earthquake
1129828<++>Y<++>0.960301020029886<++>Weighted_arithmetic_mean->Sound_bite
131843<++>Y<++>0.993713148032662<++>Definition->SIGMET
104861<++>Y<++>0.9951204000467133<++>Cost->Interior_design->Concrete->Flooring
833860<++>Y<++>0.9681002268307477<++>Popular_music->Food->Switzerland
207786<++>Y<++>0.9999370910168783<++>Shark->Warm-blooded

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691330<++>Y<++>0.9999992829052942<++>Moderation_(statistics)

1103528<++>Y<++>0.9972950550942021<++>Major_League_(film)

1132213<++>Y<++>0.7489801473531366<++>Length_overall->Professional_wrestling_holds->Bow_and_arrow->Yoga

1134138<++>Y<++>0.7215343120469786<++>Honorary_degree->Semantics

138632<++>Y<++>0.9113521779260643<++>Definition->Tangent

1114819<++>Y<++>0.9999946476896949<++>Durable_medical_equipment->Train

747511<++>Y<++>0.9999998038955745<++>Firewalking

183378<++>Y<++>0.9989397404012138<++>Exon->Definition->Biology

1117387<++>Y<++>0.8663803334217364<++>Chevy_Chase->Semantics

479871<++>Y<++>0.9503704570127932<++>President_of_the_United_States->Synonym

541571<++>Y<++>0.9983833679282048<++>Wat->Dopamine

1106007<++>Y<++>0.8808753545444665<++>Definition->Visceral_leishmaniasis

60235<++>Y<++>0.836409024736343<++>Calorie->Egg_as_food->Frying

490595<++>Y<++>0.7290108662022954<++>RSA_Security->Definition->Key_size

564054<++>Y<++>0.9999999966859434<++>Red_blood_cell_distribution_width->Blood_test

1116052<++>Y<++>0.8321774517493923<++>Synonym->Thorax

443396<++>Y<++>0.9814649278583856<++>Lipopolysaccharide->Law->Definition

972007<++>Y<++>0.9622847968581714<++>Chicago_White_Sox->Play_(theatre)->Chicago

1133249<++>Y<++>0.7394092678658755<++>Adenosine_triphosphate->Record_producer

101169<++>Y<++>0.9949249424089939<++>Cost->Jet_fuel

19335<++>Y<++>0.8545708866482175<++>Anthropology->Definition->Natural_environment

789700<++>Y<++>0.9999999009245122<++>Resource-based_relative_value_scale

47923<++>Y<++>0.8507968217623343<++>Axon->Nerve->Synapse->Control_knob->Definition

301524<++>Y<++>0.9719576176244117<++>Zero_of_a_function->Names_of_large_numbers

952774<++>Y<++>0.7970879064723523<++>Evening

766511<++>Y<++>0.7354697185453023<++>Lewis_Machine_and_Tool_Company->Stock

452431<++>Y<++>0.9935533902835246<++>Melanoma->Skin_cancer->Symptom

1109818<++>Y<++>0.773903290136571<++>Experience_point->Exile

1047902<++>Y<++>0.9396894541136506<++>Play_(theatre)->Gideon_Fell->The_Vampire_Diaries

662372<++>Y<++>0.8886998123462867<++>Radio_format->USB_flash_drive->Mackintosh

364142<++>Y<++>0.8255594621305994<++>Wound_healing->Delayed_onset_muscle_soreness

20455<++>Y<++>0.9396229761461882<++>Arabic->Glasses->Definition

1126813<++>Y<++>0.7556818914101636<++>Nuclear_Overhauser_effect->Bone_fracture

240053<++>Y<++>0.7554636687709102<++>Vowel_length->Safety->City_council->Class_action->Goods

1122461<++>Y<++>0.9992610139419709<++>Hydrocarbon->Lipid

1116341<++>Y<++>0.8146863386208845<++>Closed_set->Armistice_of_11_November_1918->Mortgage_loan->Definition

1129237<++>Y<++>0.9981516927084026<++>Hydrogen->Liquid->Temperature

423273<++>Y<++>0.9999999989010391<++>School_meal->Tax_deduction

321441<++>Y<++>0.9990492057816107<++>Postage_stamp->Cost

Appendix B.4. DBpedia Spotlight Annotations for TREC DL 2020

In the Appendix Section, we have the query set of the TREC DL 2019 (MSMARCO collection), annotated by the DBpedia Spotlight entity linker. The information is: (qID: query ID; Y: Yes, query completely annotated; AVG_score: computed average score; Query_Annotations: annotations of a query).

qID<++>Y<++>AVG_score<++>Query_Annotations
1030303<++>Y<++>0.7340946183870847<++>Shaukat_Aziz->Banu_Hashim
1043135<++>Y<++>0.946317312457761<++>Killed_in_action->Nicholas_II_of_Russia->Russia
1045109<++>Y<++>0.7511704665155204<++>Holding_company->John_Hendley_Barnhart->Common_crane
1051399<++>Y<++>0.9831254656185995<++>Singing->Monk->Theme_music
1064670<++>Y<++>0.9970763927894758<++>Hunting->Pattern->Shotgun
1071750<++>Y<++>0.8892464638623135<++>Pete_Rose->Smoking_ban->Hall->Celebrity
1105860<++>Y<++>0.8774266878935226<++>Amazon_rainforest->Location
1106979<++>Y<++>0.9844715509684185<++>Exponentiation->Pareto_chart->Statistics
1108450<++>Y<++>0.8991756241023721<++>Definition->Definition->Gallows
1108466<++>Y<++>0.9749988943992814<++>Connective_tissue->Composer->Subcutaneous_tissue
1108473<++>Y<++>0.8764035354741885<++>Time_zone->Stone_(unit)->Paul_the_Apostle->Minnesota
1108729<++>Y<++>0.9977600686467922<++>Temperature->Humidity->Charcuterie
1109699<++>Y<++>0.99999999999838<++>Mental_disorder
1109707<++>Y<++>0.9340983506154318<++>Transmission_medium->Radio_wave->Travel
1114166<++>Y<++>0.6642622531448081<++>Call_to_the_bar->Blood->Thin_film
1114286<++>Y<++>0.8685393856480332<++>Meat->Group_(mathematics)
1115210<++>Y<++>0.9995145949464947<++>Chaff->Flare
1116380<++>Y<++>0.9239129473029049<++>Unconformity->Earth_science
1119543<++>Y<++>0.7608774457395511<++>Psychology->Cancer_screening->Train->Egg->Organ_donation
1120588<++>Y<++>0.8671935828811231<++>Tooth_decay->Detection->System
1122138<++>Y<++>0.8878011096897418<++>Symptom->Goat
1122767<++>Y<++>0.8876396654279999<++>Amine->Record_producer->Carnitine
1125755<++>Y<++>0.5846332776541447<++>1994_Individual_Speedway_World_Championship->Definition
1127004<++>Y<++>0.9926518244345025<++>Millisecond->Symptom->Millisecond
1127233<++>Y<++>0.8206546286691387<++>Monk->Semantics
1127540<++>Y<++>0.8369614887321695<++>Semantics->Shebang_(Unix)
1128456<++>Y<++>0.9967168751073104<++>Medicine->Ketorolac->Narcotic
1130705<++>Y<++>0.9987446870472948<++>Passport
1130734<++>Y<++>0.9058236234747112<++>Corn_starch->Giraffe->Thickening_agent
1131069<++>Y<++>0.8074044203528561<++>Son->Robert_Kraft
1132044<++>Y<++>0.9849122526400067<++>Brick->Wall
1132247<++>Y<++>0.8942829158806607<++>Vowel_length->Cooking->Potato_wedges->Oven->Frozen_food

1132842<++>Y<++>0.7258539998537346<++>Vowel_length->Stay_of_execution->Infection->Influenza

1132943<++>Y<++>0.8153913684684001<++>Vowel_length->Cooking->Artichoke

1132950<++>Y<++>0.8255429953411267<++>Vowel_length->Hormone->Headache

1133579<++>Y<++>0.9131369795803623<++>Granulation_tissue->Starting_pitcher

1134094<++>Y<++>0.8285001731543475<++>Interagency_hotshot_crew->Member_of_parliament

1134207<++>Y<++>0.9409175836209229<++>Holiday->Definition

1134680<++>Y<++>0.9766952230811329<++>Jenever->Provinces_of_Turkey->Median->Sales->Price

1134939<++>Y<++>0.9912127141822535<++>Overpass->Definition

1135268<++>Y<++>0.9793535412197111<++>Antibiotic->Kindness->Infection

1135413<++>Y<++>0.8892640322015729<++>Differential_(mathematics)->Code->Thoracic_outlet_syndrome

1136769<++>Y<++>0.9991866473974437<++>Lacquer->Brass->Tarnish

118440<++>Y<++>0.7794287084444994<++>Definition->Brooklyn–Manhattan_Transit_Corporation->Medicine

119821<++>Y<++>0.8289089381260273<++>Definition->Curvilinear_coordinates

121171<++>Y<++>0.9236746183603595<++>Definition->Etruscan_civilization

125659<++>Y<++>0.9243819049504125<++>Definition->Preterm_birth

156498<++>Y<++>0.9951922187725896<++>Google_Docs->Autosave

166046<++>Y<++>0.9722765437113997<++>Ethambutol->Therapy->Osteomyelitis

169208<++>Y<++>0.9763904984081142<++>Mississippi->Income_tax

174463<++>Y<++>0.9444240844737418<++>Dog_Day_Afternoon->Dog->Semantics

197312<++>Y<++>0.8524243580136197<++>Group_(mathematics)->Main_Page->Policy

206106<++>Y<++>0.9984726513911077<++>Hotel->St._Louis->Area

227873<++>Y<++>0.9538618238444815<++>Human_body->Redox->Alcohol->Elimination_reaction

246883<++>Y<++>0.7046466212361978<++>Vowel_length->Tick->Survival_skills->Television_presenter

26703<++>Y<++>0.695505587080839<++>United_States_Army->Online_dating_service

273695<++>Y<++>0.7994940831293179<++>Vowel_length->Methadone->Stay_of_execution->System

302846<++>Y<++>0.9999999291388452<++>Caffeine->Twinings->Green_tea

330501<++>Y<++>0.804146658783798<++>Weight->United_States_Postal_Service->Letter_(alphabet)

330975<++>Y<++>0.996579761713109<++>Cost->Installation_(computer_programs)->Wind_turbine

3505<++>Y<++>0.9982497117674316<++>Cardiac_surgery

384356<++>Y<++>0.9944998817120446<++>Uninstaller->Xbox->Windows_10

390360<++>Y<++>0.9763556815701261<++>Ia_(cuneiform)->Suffix->Semantics

405163<++>Y<++>0.9987909780589439<++>Caffeine->Narcotic

42255<++>Y<++>0.8455330333932864<++>Average->Salary->Dental_hygienist->Nebraska

425632<++>Y<++>0.9660983982241111<++>Splitboard->Skiing

426175<++>Y<++>0.9994011991734015<++>Duodenum->Muscle
42752<++>Y<++>0.8009935481520076<++>Average->Salary->Canada->1985
444389<++>Y<++>0.9939103674271949<++>Magnesium->Definition->Chemistry
449367<++>Y<++>0.7916624997735973<++>Semantics->Tattoo->Human_eye
452915<++>Y<++>0.9822391456815329<++>Metabolic_disorder->Medical_sign->Symptom
47210<++>Y<++>0.7671118604971021<++>Weighted_arithmetic_mean->Wedding_dress->Metasomatism->Cost
482726<++>Y<++>0.7674487370523141<++>Projective_variety->Definition
48792<++>Y<++>0.8389210174021245<++>Barclays->Financial_Conduct_Authority->Number
519025<++>Y<++>0.9480360316344636<++>Symptom->Shingles
537060<++>Y<++>0.7097385940332386<++>Village->Frederick_Russell_Burnham
545355<++>Y<++>0.9951076974746371<++>Weather->Novi_Sad
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655526<++>Y<++>0.9330128162719924<++>Ezetimibe->Therapy
655914<++>Y<++>0.678786735195569<++>Drive_theory->Poaching
673670<++>Y<++>0.9999833643179875<++>Alpine_transhumance
701453<++>Y<++>0.9643977768213703<++>Statute->Deed
703782<++>Y<++>0.7785827479942069<++>Anterior_cruciate_ligament_injury->Compact_disc
708979<++>Y<++>0.8104485049064436<++>Riding_aids->HIV
730539<++>Y<++>0.8891690146753408<++>Marine_chronometer->Invention
735922<++>Y<++>0.7026236168739335<++>Wool_classing->Petroleum
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779302<++>Y<++>0.9969106553448834<++>Onboarding->Credit_union
794223<++>Y<++>0.9800531144849391<++>Science->Definition->Cytoplasm
794429<++>Y<++>0.8861366041014064<++>Sculpture->Shape->Space
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804066<++>Y<++>0.9977152604583308<++>Actor->Color
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914916<++>Y<++>0.7560312455207127<++>Type_species->Epithelium->Bronchiole
91576<++>Y<++>0.8914307302033609<++>Chicken->Food->Wikipedia
945835<++>Y<++>0.7647917173318495<++>Ace_Hardware->Open_set
978031<++>Y<++>0.9999876622967928<++>Berlin_Center,_Ohio
985594<++>Y<++>0.9120158209114781<++>Cambodia
99005<++>Y<++>0.8271551120333056<++>Religious_conversion->Quadraphonic_sound->Metre->Quadraphonic_sound->Inch
999466<++>Y<++>0.9999999098099194<++>Velbert

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