Entity Type Recognition using an Ensemble of Distributional Semantic Models to Enhance Query Understanding

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Abstract—We present an ensemble approach for categorizing search query entities in the recruitment domain. Understanding the types of entities expressed in a search query (Company, Skill, Job Title, etc.) enables more intelligent information retrieval based upon those entities compared to a traditional keyword-based search. Because search queries are typically very short, leveraging a traditional bag-of-words model to identify entity types would be inappropriate due to the lack of contextual information. Our approach instead combines clues from different sources of varying complexity in order to collect real-world knowledge about query entities. We employ distributional semantic representations of query entities through two models: 1) contextual vectors generated from encyclopedic corpora like Wikipedia, and 2) high dimensional word embedding vectors generated from millions of job postings using word2vec. Additionally, our approach utilizes both entity linguistic properties obtained from WordNet and ontological properties extracted from DBpedia. We evaluate our approach on a data set created at CareerBuilder; the largest job board in the US. The data set contains entities extracted from millions of job seekers/recruiters search queries, job postings, and resume documents. After constructing the distributional vectors of search entities, we use supervised machine learning to infer search entity types. Empirical results show that our approach outperforms the state-of-the-art word2vec distributional semantics model trained on Wikipedia. Moreover, we achieve micro-averaged \textit{F1} score of 97% using the proposed distributional representations ensemble.

I. INTRODUCTION

Entity Recognition (\textit{ER}) is an information extraction task which refers to identifying regions of text corresponding to entities. A sub-task related to \textit{ER} is the Entity Type Recognition (\textit{ETR}) which refers to categorizing these entities into a predefined set of types \cite{1}. The focus of the majority of \textit{ETR} research has been on Named Entity Recognition (\textit{NER}), which typically limits entity types to \textit{Person}, \textit{Location}, and \textit{Organization} \cite{2–5}. Most techniques used in \textit{ETR} rely on a mix of local information about the context of the entity and external knowledge usually gained through learning on training data. \textit{ETR} in search queries is considered extremely important; a Microsoft’s study reported that 71% of queries submitted to their Bing search engine contain named entities somewhere, while 20 – 30% are purely named entities \cite{6}. Recognizing the type of named entities in queries enables a search engine to understand the intent of users, which subsequently leads to more accurate results being returned. \textit{ETR} in search queries is very challenging, however, due to the lack of textual context surrounding the query. Search queries are usually made of just a few words, which is typically not enough context to independently and accurately recognize the types of the entities within a search query. Our research is specifically targeted at the problem of \textit{ETR} within the job search and recruitment domain. Unfortunately, none of the published \textit{ETR} datasets fully resemble the entity categories within the job search and recruitment domain. Some of the specific entity categories within this domain include \textit{Company}, \textit{Job Title}, \textit{School}, and \textit{Skill}, which all aren’t found explicitly within existing \textit{ETR} datasets. As a result, we can’t leverage any existing gazetteers for these entity types.

In this paper we introduce a novel system for \textit{ETR} in search queries which has been applied successfully within the job search and recruitment domain. The proposed system utilizes features collected from Wikipedia, DBpedia, WordNet, and a corpus of more than 60 million job postings provided by Careerbuilder. We integrated this model within CareerBuilder’s semantic search engine \cite{7–9}, which improved the quality of search results for tens of millions of job seekers every month.

The system is used within the search engine in two ways: 1) offline, to classify a list of pre-recognized entities extracted from popular queries found in CareerBuilder’s search logs, and 2) online, to dynamically classify the search entities within new, previously unseen queries as part of CareerBuilder’s semantic query parser.

To the best of our knowledge we are the first group targeting \textit{ETR} of queries within the job search and recruitment domain. We evaluated this system using a data set provided by CareerBuilder which contains more than 177K labeled entities. The results demonstrate that our system achieves a 97% micro-averaged \textit{F1} score over all the categories.

The main contributions of this paper are:

1) We introduce a novel approach for generating distributional semantic vectors of named entities in search queries
using Wikipedia as an intermediate corpus.

2) Our approach is simple and efficient. It outperforms state-of-the-art techniques for distributional representations like word2vec.

3) We evaluate our method on the largest labeled entity type data set within the recruitment domain achieving a 97% micro-averaged F1 score.

4) We demonstrate increases in overall system accuracy through an ensemble of features leveraging distributional semantic representations, entity ontologies, and entity linguistic properties.

II. RELATED WORK

Both ETR and NER have experienced a surge in the research community in recent years [10–16]. David et al. [2] and Mansouri et al. [17] presented comprehensive reviews about different approaches for NER including several representations that leverage dictionaries, corpora, and various classification methods.

Guo et al. [18] presented a formulation for both NER and ETR in search queries using a probabilistic approach and Latent Dirichlet Allocation (LDA). They represented query terms as words in documents and modeled the entity type classes as topics. They proposed using a weakly supervised learning algorithm to learn the topics, while impressive, their approach was limited to recognizing only one entity per query. Our approach, instead, can accurately identify multiple entities per search query and recognize their types.

Other approaches which utilize knowledge bases to link named entities in text with corresponding entities in the knowledge bases were presented in [1, 19–22]. Wikipedia has been used extensively as a knowledge base for ETR. Many researchers have utilized Wikipedia-based features such as wikilinks, article titles and categories, and graph representations of the inner links between Wikipedia pages.

Han et al. [1] proposed a methodology which relies on having a Wikipedia page whose title is similar to the given entity. After looking up that page, if any, they extracted the category of that entity from the first line in that page. In our case, we couldn’t find a Wikipedia page for most of the popular queries we have, for example, java developer has no corresponding page in Wikipedia. Our methodology can handle such cases by looking in Wikipedia content not titles for the occurrences of that entity and using the context as a representation in order to recognize the entity type.

Richman and Schone proposed a novel system for multi-lingual NER [23]. They utilize wikilinks to identify words and phrases that might be entities within text. Once they recognize the entities, they use category links or interlinks to map those entities with English phrases or categories.

Using Wikipedia concepts as a representation space for query’s intent was introduced in [24]. In this paper each intent domain is represented as a set of Wikipedia articles and categories, then each query intent is predicted by mapping the query into the Wikipedia representation space.

The system introduced in [25] transforms links to Wikipedia articles into named entity annotations by classifying the target articles into the classic named entity types Person, Location, and Organization.

Utilizing Wikipedia infobox for ETR was presented in [26]. The proposed model classifies entities by matching entity attributes extracted from the relevant article infobox with core entity attributes built from Wikipedia infobox templates.

The system introduced in [27] converted Wikipedia into a structured knowledge base (KB). In this work, the authors converted Wikipedia graph structure into a taxonomy. This was done by finding a single main lineage, called the primary lineage, for each concept. This KB is used later to extract, link, and classify entities mentioned in a Twitter stream.

We consider [28] as the most related work to ours. In this work, the authors proposed a system that utilizes Wikipedia as an intermediate corpus to categorize search queries. The system works through two phases; in the first phase, a query is mapped to its relevant Wikipedia pages by searching an index of Wikipedia articles. In the second phase, concepts representing retrieved Wikipedia pages are mapped into categories. Though we also utilize a Wikipedia search index to retrieve articles related to query entities, our approach utilizes totally different features and entity representation to infer entity type.

III. METHODOLOGY

In this section we detail our methodology for recognizing search query entity types. Our approach employs two distributional semantic representations of search entities. Moreover, we utilize ontological properties as well as linguistic properties of search entities to improve overall system performance. The ultimate goal of our system is to categorize a given search entity into one of four categories: Company, Job Title, Skill, and School. We do plan to expand these categories in the future, but these four represent the most important to initially target.

A. System Overview

Prior to performing ETR, it is of course necessary that we first perform ER on incoming search queries so that we know the entities for which we are trying to identify an entity type. Our methodology for recognizing known entities and performing Entity Extraction from queries was previously described in [29]. In essence, we perform data mining on historical search query logs, perform collaborative filtering to determine which queries are used commonly together across many users, and build a semantic knowledge base containing the entities and related entities found from within the mined search logs.

Based upon this semantic knowledge base, we are able to perform entity extraction on future queries for known entities, but we are missing two important components:

1) Identification of entities not found in our semantic knowledge base.

2) Knowledge of the entity type of each identified entity.

To solve the first problem, we implemented a language model of unigrams, bigrams, and trigrams across a corpus of millions of job posting documents. Leveraging Bayes algorithm, we are able to dynamically calculate probabilities as to
whether any combination of keywords entered into a search query constitute a single phrase or multiple phrases. Based upon the combination of our semantic knowledge base, our Bayes-based phrase identifier, and our query parser, we are able to successfully identify the correct query parsing including the constituent named entities with accuracy of greater than 92%.

The last stage needed to truly interpret the user’s query correctly is ETR. If a user searches for google software engineer java, it is critical to understand that the user is looking for a job at Google (Company) as a software engineer (Job Title) programming in Java (Skill). Without this knowledge of entity types, we will not be able to fully represent the information need of our users within the search system. The following sections will describe our methodology for performing ETR on our identified entities.

### B. Entity Type Recognition Process

The proposed system combines features from different sources in order to make accurate entity type predictions for a given search entity. This ensemble of features represents our domain-specific knowledge as well as real-world knowledge about the search entity. We call these features clues. Figure 1 shows the system design for how a user’s query is parsed, as well as how the system leverages these feature clues to accurately perform ETR.

The first clue models real-world contextual information about the query entity by searching for that entity inside Wikipedia using a customized search index. The second clue models domain-specific knowledge by building synonym vectors of search entities using the word2vec model [30]. These vectors are generated using millions of job postings from CareerBuilder.

Two other clues, leveraging DBpedia and WordNet, are collected to increase the accuracy and coverage over the Company and Job Title categories specifically. After collecting all the clues for every known query entity, we combine these features and use them to train an entity classifier over labeled entity samples. The classifier can then be used to categorize new search entities, thus improving our understanding of the query intent for future searches.

### C. Constructing Contextual Vectors

The purpose of this phase is to enrich the contextless search entities with contextual information. In order to do so we map each entity into a distributional semantic vector representation. The vector dimensions represent entity contexts in an intermediate corpus. We use Wikipedia as the source for these contextual vectors for all of the search entities which are represented.

As query entities need to be categorized in an online fashion, context vectors are required to be constructed as efficiently as possible. Therefore, we build an inverted index of all Wikipedia articles as a preprocessing step. We build the index using Apache Lucene\(^1\), an open-source indexing and search engine. For each article we index the title, content, length, and categories. We exclude all disambiguation, list of, and redirect pages.

As shown in Equation 1, given an entity \(e_j\), we construct its context vector \(X_{e_j}\) by first searching for that entity in the search index. Then, from the top \(n\) search hits, we retrieve all content words \(W_i\) that occur in the same context of \(e_j\) within a specific window size in each search hit \(i\). We also retrieve category words \(C_i\) of search hits and add them to \(X_{e_j}\).

\[
X_{e_j} = \langle w_1, w_2, \ldots, c_1, c_2, \ldots \rangle : w \in W_i, c \in C_i, i = [1..n] \tag{1}
\]

\(^1\)https://lucene.apache.org/
These context vectors represent available real-world knowledge about the given entity. Table I shows example search entities along with their context vectors. We can notice that contextual words are very representative for the given entity. Moreover, words from search hits categories augment context words and thus enrich the contextual representation of each entity.

D. Constructing Synonymy Vectors

The purpose of this phase is to enrich the search entities with domain-specific knowledge. CareerBuilder has millions of job openings that are posted or modified on daily basis. These postings contain many representative features relevant to the recruitment domain. For example, a typical job posting might contain a job title, job description, required skills, salary information, company information, required experience and education, location...etc.

In order to utilize this information, we use the job postings as an intermediate corpus to train a word2vec model. For a given search entity \( e_j \), we generate its synonyms vector \( S_{ej} \) from words that have closest distributional representations in the trained word2vec model.

Distributional semantic vectors generated in this phase represent domain-specific knowledge about a given entity. Table II shows the same search entities as in Table I along with corresponding synonymy vectors. We can notice that the Company and School entity vectors are somewhat poor and unrepresentative. This is because many job postings are missing company information or sometimes company name is only provided without any context. The same problem arises for school information. On the other hand, synonymy vectors of Job Title and Skill entities are very rich and representative. This observation motivated us to combine features for search entities from both contextual and synonymy vectors in a combined vector space.

E. Entity Ontological Features

Another representative feature is extracted from DBpedia by linking search hits (representing Wikipedia concepts) to their corresponding entries in the DBpedia ontology. We use the type property to determine whether the retrieved concept type is one of our targeted categories, specifically Company.

After searching for a given entity \( e_j \) in the Wikipedia index, we retrieve the top \( n \) search hits (concepts). Then, we check whether the title of any of these concepts is the same as \( e_j \). If any, we check whether the type of this concept in DBpedia ontology is Company and subsequently add a new binary feature indicating that finding.

Given that companies are already found explicitly in DBpedia, why don’t we just use the DBpedia type feature exclusively for categorizing into the Company entity type? There are five reasons we instead choose to combine multiple feature types:

1) DBpedia ontology suffers from low coverage where many companies in Wikipedia don’t have a type of Company in DBpedia (e.g., Boonton Iron Works\[4\] SalesforceIQ\[5\]).

2) DBpedia provides categories for the canonical form of company name only. If an entity is searched for using a surface form, the DBpedia lookup will fail. In contrast, Wikipedia will generally contain surface forms in the same context as the canonical form (e.g., International Turnkey Systems Group vs. ITS Group\[4\]).

3) As DBpedia covers only Wikipedia concepts, it fails to catch companies that do not have a Wikipedia page. Alternatively, these companies will be correctly categorized using their contextual vectors if mentioned in a representative context within Wikipedia (e.g., Nutonian).

4) Some companies have a type of Organization instead of Company in DBpedia. Unfortunately, entities belonging to one of our other entity types (School) can also be categorized as Organization in DBpedia (e.g., Athens College). This means that we cannot reliably categorize concepts with the type of Organization as Company.

5) Finally, there is a time lag between DBpedia and Wikipedia. So, DBpedia does not contain the most recent snapshot of Wikipedia concepts in its ontology.

F. Entity Linguistic Features

We utilize the lexical properties of search entities to determine whether they belong to one of the target categories, specifically Job Title. The motivation behind this approach is the fact that almost all Job Title entities contain an agent noun (e.g., director, developer, nurse, manager...etc). To determine whether an entity might represent a Job Title, we search its words inside the WordNet lexicon for categorizing Job Title entities inside the WordNet dictionary where all agent nouns are stored at the <noun.person> lexical file. Upon finding any, we add a new binary feature indicating that finding.

While it might be tempting to rely exclusively on the agent noun feature from the WordNet lexicon for categorizing Job Title entities, two challenges prevent this:

1) CareerBuilder operates job boards in many countries and in many different languages. Therefore, we’re biased toward using language independent models where possible. Depending solely on the WordNet lexicon for categorizing Job Title entities would pose limitations on the ETR system for non-English job boards.

2) Not all Job Title entities have an agent noun (e.g., staff, faculty).

G. Building the Prediction Model

To build the ETR model, we use supervised machine learning on a very large labeled set of search entities obtained from CareerBuilder’s search logs. For each discovered search entity \( e_j \), we generate:

1) A Contextual vector \( (X_{ej}) \) using the Wikipedia index.

2) A Synonyms vector \( (S_{ej}) \) using the word2vec model.

3) An Ontological type \( (ont_{ej}) \) if the entity refers to a DBpedia concept. This is a binary feature which is true if DBpedia type is company.

4) A Lexical type \( (lex_{ej}) \). This is a binary feature which is true if one of the entity terms has a <noun.person> type in WordNet, i.e., it is an agent noun.

\[4\] https://en.wikipedia.org/wiki/Boonton_Iron_Works
\[5\] https://en.wikipedia.org/wiki/SalesforceIQ
\[4\] https://en.wikipedia.org/wiki/International_Turnkey_Systems_Group
To combine all those features, we follow a simple yet effective approach. First we utilize the vector space model to generate an entity-word matrix using the distributional semantic vectors (\(X_e, S_e\)). The generated distributional vectors represent semantically-related words to the identified query entities, so it is straightforward to then map each entity as a document of words contained in the entity’s contextual and synonymy vectors. Rows in the entity-word matrix represent entities and columns represent corresponding related words. Secondly, we transform this matrix using term frequency-inverse document frequency (tf-idf) weights. Thirdly, we append \(ont_{e_j}\) and \(lex_{e_j}\) as two additional binary columns to the tf-idf entity-word matrix. Finally, we train an entity type classifier on the produced matrix to generate the ETR model.

IV. EXPERIMENTS AND RESULTS

In this section we present our empirical results. We start by describing the data set used in experiments and then detail different models developed for ETR along with their results.

A. Data set

We build our ETR models using the largest labeled entity data set owned by CareerBuilder. The data set contains more than 177K labeled entities distributed over four categories as shown in Table III. These entities were obtained from CareerBuilder’s search logs, job postings, and resume postings, and were manually reviewed by annotators working at CareerBuilder.

B. Experimental Setup

We conducted several experiments in order to evaluate the performance of the ETR system with different models. We started by evaluating models built from a single feature source i.e., contextual vectors or word synonymy vectors. Then we evaluated a model built using an ensemble of both of these distributional vectors. Finally, we evaluated a model which combines both distributional vectors plus the entity’s ontological and lexical features (i.e., \(ont_{e_j}\) and \(lex_{e_j}\) respectively).

To assess the effectiveness of our approach, we built two baseline models. The first one is the bag-of-words (bow) model which depends solely on words that appear in search entities as features without any contextual enrichment. The second model (\(wikim\)) is a distributional semantic model built by training word2vec on Wikipedia. After word2vec produces word distributional vectors, word synonymy vectors of search entities are generated as described in Section III.D. We then generate a tf-idf entity-word matrix from these vectors as described in Section III.G.

We built the Wikipedia search index using the English Wikipedia dump of March 2015. The total uncompressed XML dump size was about 52GB representing about 7 million articles. We extracted the articles using a modified version of the Wikipedia Extractor\(^7\). Our version\(^8\) extracts articles as plain text, discarding images and tables. We discarded the References and External Links sections (if any). We pruned all articles which are not under the main namespace, and excluded all disambiguation, list of, and redirect pages as well. Eventually, our index contained about 4 million documents.

While searching the Wikipedia index, we search both content and title fields. For efficiency, we limit retrieved results to the top 3 hits which have a minimum length of 100 bytes.

To build the word embedding vectors, we trained word2vec on more than 60 million job postings from CareerBuilder. We used Apache Spark’s scalable machine learning library (MLlib\(^9\) which has an implementation of word2vec in Scala.\(^8\) We configured the parameters of the word2vec model as follows: minimum word count = 50, number of iterations (epoch)=1, vector size = 300, and number of partitions = 5000. The model took about 32 hours to fit on one of CareerBuilder’s Hadoop clusters with 69 data nodes, each having a 2.6 GHz

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\(^3\)https://dumps.wikimedia.org/enwiki/20150304/
\(^4\)http://medialab.di.unipi.it/wiki/WikipediaExtractor
\(^5\)https://github.com/walid-shalaby/wikiextractor
\(^6\)https://spark.apache.org/mllib/
\(^7\)http://www.scala-lang.org/

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### Table I. Sample Contextual Vectors

| Company       | ...market, operate, website, acquired, employment, companies, establishments, ceo... |
|---------------|-------------------------------------------------------------------------------------|
| Nurse Assistant| ...journalist, worker, secretary, members, politicians, living, people, youth, office... |
| Skill         | ...editor, graphics, developed, image, title, software, application, version, program... |
| School        | ...university, north, carolina, college, student, organization, professor, school... |

### Table II. Sample Synonymy Vectors

| Company       | ...us, software, recruiter, digital... |
|---------------|-------------------------------------------------------------------------------------|
| Nurse Assistant| ...licensed, registered, nurse, rn, lpn, office, coordinator, lvn, midwife... |
| Skill         | ...dreamweaver, flash, acrobat, macromedia, illustrator, pagemaker... |
| School        | ...raleigh, durham, morrisville, hospital, concord, morrisville, durham... |

### Table III. Distribution of Entities over Categories

| Category      | Number of instances |
|---------------|---------------------|
| Company       | 32,934              |
| Job Title     | 3,608               |
| Skill         | 25,093              |

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\(^3\)https://dumps.wikimedia.org/enwiki/20150304/
\(^4\)http://medialab.di.unipi.it/wiki/WikipediaExtractor
\(^5\)https://github.com/walid-shalaby/wikiextractor
\(^6\)https://spark.apache.org/mllib/
\(^7\)http://www.scala-lang.org/
AMD Opteron Processor with 12 to 32 cores and 32GB to 128GB RAM.

Finally, we evaluate all the ETR models using a Support Vector Machine (SVM) classifier with a linear kernel, leveraging the scikit-learn machine learning library [31]. Because entity instance frequencies over categories is a bit skewed and to avoid overfitting, we configured the classifier to use a different regularization value for each category relative to category frequencies. For each model we report Precision (P), Recall (R), and their harmonic mean (F1) scores. All results are calculated using 10-fold cross-validation over the labeled entities data set. Folds were randomly generated using stratified sampling.

C. Results

Table IV shows the results obtained from the baseline models compared to the contextual vectors model using 10-fold cross-validation on the labeled entities data set.

The first baseline model is the bow. This model gives relatively lower F1 scores on all categories as shown in Table IV. Due to the absence of contextual information, this model fails to generalize well with unseen entities, as they contain terms that are not in the model’s feature space. This is very clear with categories that have high naming variations (i.e., Company and Skill). bow performs relatively well on Job Title as it has limited naming variations. It also performs very well on School entities as they have common naming conventions (e.g., university, school, institute...etc).

The second baseline model is wikiw which is built by training word2vec on Wikipedia. This model utilizes contextual features inferred from word distributional properties, hence it performs better than bow on all categories. As shown in Table IV, the wikiw F1 score is higher than bow by more than 5% on Company, 2% on Job Title, 1% on School, and 11% on Skill. Those results indicate the viability of distributional semantic representations for ETR of short search entities.

The third model is wikix which is built using contextual vectors generated by searching the Wikipedia index. It retrieves search entity contexts and category information from search hits and then utilizes them as learning features. As shown in Table IV, this novel approach outperforms both bow and wikiw models substantially on Company and Skill. It also performs slightly better on School. These results indicate the effectiveness of the wikix model in recognizing these categories accurately.

It is important to mention that, though both the wikix and wikiw models use Wikipedia as an intermediate corpus to learn distributional representations of words, the wikix representations are more successful for the ETR task. Compared with the wikiw model, the F1 scores of the wikix model increased on the Company class by 5%, on the School class by 1%, and on the Skill class by 5%.

As shown in Table V, we combined both contextual vector (wikix) and synonyms vector (jobw) representations and built an ensemble of the two models (wikix,jobw). The ensemble improved the results over wikix across all categories. The largest improvement was on Job Title, which saw a 3% improvement in F1 score. More importantly, this ensemble outperforms the wikiw and bow models on all categories.

In order to increase overall system performance, we built four ETR models that combine features from different sources as described in Section III.G. We first built jobw which models domain-specific knowledge of search entities. The jobw model is built by training word2vec on the textual content of millions of job postings.

As shown in Table V, we combined both contextual vector (wikix) and synonyms vector (jobw) representations and built an ensemble of the two models (wikix,jobw). The ensemble improved the results over wikix across all categories. The largest improvement was on Job Title, which saw a 3% improvement in F1 score. More importantly, this ensemble outperforms the wikiw and bow models on all categories.
Table V, increased F1 score on Company by −0.4%.

The third ensemble is \((\text{wiki}, \text{job}, \text{lex}, \text{ctx})\). It aims at increasing system accuracy on Job Title class by incorporating entity’s linguistic features \((\text{lex})\) as described in Section III.F. As shown in Table V, the F1 score on Job Title increased by −0.6% when incorporating this feature.

Finally, we combined all features generating an ensemble of contextual vectors, synonymy vectors, ontological features, and linguistics features \((\text{wiki}, \text{job}, \text{lex}, \text{out})\). As shown in Table V, this model produced the best F1 scores on all categories among all the aforementioned models.

V. Conclusion

In this paper we presented an effective approach for ETR of search query entities in the job search and recruitment domain. We proposed a novel ensemble of features which enrich short query entities with real-world and domain-specific knowledge. The ensemble entity representation model contains features representing: 1) contextual information in Wikipedia, 2) embedding information in millions of job postings, 3) class type in DBpedia for Company entities, and 4) linguistic properties in WordNet for Job Title entities.

Our approach is novel and distinct from other ETR approaches. To our knowledge, generating distributional semantic vectors of query entities using contextual information from Wikipedia as a search index was not reported before in the literature.

Evaluation results on a data set of more than 177K search entities were very promising. The results showed that our Wikipedia-based model outperforms the state-of-the-art word2vec model trained on Wikipedia on three out of four target entity categories. Moreover, our ensemble representation could achieve 97% micro-averaged F1 score on the four entity types outperforming the word2vec baseline by 6% on Company, 1% on Job Title, 1% on School, and 5% on Skill.

In terms of performance, our system takes 30ms per entity type request, making it efficient and appropriate for serving online search queries.

Our system has been integrated within CareerBuilder’s semantic search engine, which improved the quality of search results for tens of millions of job seekers every month.

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