Relation Discovery from Web Data for Competency Management

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Abstract

In current organizations, valuable enterprise knowledge is often buried under rapidly expanding huge amount of unstructured information in the form of web pages, blogs, and other forms of human text communications. We present a novel unsupervised machine learning method called CORDER (COmmunity Relation Discovery by named Entity Recognition) to turn these unstructured data into structured information for knowledge management in these organizations. CORDER exploits named entity recognition and co-occurrence data to associate individuals in an organization with their expertise and associates. We discuss the problems associated with evaluating unsupervised learners and report our initial evaluation experiments in an expert evaluation, a quantitative benchmarking, and an application of CORDER in a social networking tool called BuddyFinder.

Keywords: relation discovery, clustering, named entity recognition

1. Introduction

At a time in which organizations increasingly regard the knowledge and skills of their employees as their most valuable resource, competency management, knowing who knows what, has become a critical activity. Equally important is knowing who knows whom, both outside and inside the organization, so

that project teams with the right mix of skills, contacts and experience of working together can be assembled.

We argue that documents are a primary resource for discovering information about people's skills and associations. Text based approaches have already been used in some specialist domains, for example to create a database about the competencies of expert witnesses [8]. We propose to use text documents in a more general scenario and to concentrate on finding the relations between entities of several kinds rather than classifying experts against a taxonomy of skills. The documents used may be intended to summarize competency information, such as the large collection of Brazilian researchers' curricula vitae held on the Lattes Platform (http://lattes.cnpq.br/historico.jsp), but they might equally be ordinary documents, such as web pages and reports which reflect day to day activity within the organization.

We propose tackling competency discovery from documentary resources using an unsupervised machine learning method which we call CORDER (COmmunity Relation Discovery by named Entity Recognition). Named Entity Recognition (NER) is used as a preliminary step to identify named entities (NEs) of interest, such as people's names, organization names and knowledge areas, thus partially tackling the problem of unstructured web data identified by some of the earliest writers on web mining [10]. The output of the CORDER method is a matrix of entities. In a competency management scenario the target dimensions of this matrix is people, for example employees or researchers. The other dimension is the parameters against which competency is being assessed, which might be subject domains, contacts, organizations with which a person has collaborated or projects they have worked on. The values in the matrix are the relation strength calculated by CORDER of the relation between a person and a given parameter. The output of CORDER can also be seen as an association network, where nodes are named entities, links between these nodes are relations discovered by CORDER, and weights on these links are relation strength.

CORDER builds on work such as DIPRE [4], Snowball [1] and KNOWITALL [11], but, because it uses co-occurrence rather than relatively rare patterns for discovering relations, it can discover relations in collections smaller than the whole Web, making it suitable for corporate intranets. CORDER has similarities to the relation discovery method by Hasegawa *et al.* [15] which clusters pairs of NEs according to the similarity of context words between them. Their method works well on newspaper text, which usually consists of well-formed sentences. The advantage of the co-occurrence method we use is that it is general enough to detect relations in inhomogeneous text where relations may not be explicitly specified by context words. Their method also does not address ranking relations in terms of relevance.

CORDER can serve as the basis for building knowledge management and entity based semantic search applications, since CORDER can effectively and efficiently turn unstructured information, such as text documents and web pages, into structured information efficient for querying, search, and knowledge management. Structured information in the form of relations between named entities can be used to satisfy users' information needs that are difficult to be met using unstructured information, e.g., finding who is an expert on X? If a user enters X in the system, he/she will get a list of experts based on the relations discovered by CORDER. However, traditional document based search applications return documents instead of entities inside them to a search query. In knowledge management applications, the discovered relations in a network can be visualized and presented to the user. Various social network analysis methods such as clustering algorithms can be applied to the network to group entities that are closely related to each other. In semantic search based applications, the user can search in concept instead of keywords to locate entities embedded in documents directly, thus users' cognitive overload as the result of a large amount of unstructured information can be alleviated.

This paper is organized as follows. In Section 2 we describe the CORDER method. In Section 3 we discuss issues concerning the evaluation of unsupervised machine learning algorithms in general. The experimental setup for expert and quantitative benchmark based evaluations is described in details in

Sections 4. Section 5 and 6 present three evaluation studies, first, expert evaluation of CORDER's results and a comparison of CORDER, experts' opinions, and two quantitative benchmarks, and second, an user evaluation of an integrated system of CORDER and an online matchmaking tool called BuddyFinder. Work related to our relation discovery approach is discussed in Section 7. Finally in Section 8 we conclude and describe some of our on-going work applying and refining the CORDER method.

2. CORDER

CORDER discovers relations by identifying lexical co-occurrences of NEs in text. This approach is based on the intuition that if an individual has expertise in an area, his/her name will be often associated with key terms about that area in text in many documents. Similarly, if two individuals often work together we expect to see their names associated. In general, we assume that NEs that are closely related to each other tend to appear together more often and closer.

The process of the CORDER method comprises the steps of:

1. *data selection*, in which the documents that will represent the organization are identified,
2. *named entity recognition*, in which the pages are preprocessed for named entities, and
3. *relation strength and ranking*, in which we propose a novel way to calculate the relation strength of NEs related to the target by integrating entity co-occurrences, entity distances, entity frequencies, and document relevance.

We describe these steps below, concentrating on relation strength.

2.1 Data Selection

We find documents from an organization's web site using a web spider. Documents, which contain noisy data, e.g., out-dated information and irrelevant information, may be removed. Documents which are linked from the web site may be taken into account if they contain relevant information.

2.2 Named Entity Recognition

A named entity recognizer is used to recognize people, projects, organizations and research areas from the documents. We use ESpotter [30], an NER system which employs standard NER techniques, because it provides methods for rapidly adapting its lexicon and patterns to different domains on the Web. Automated Google searches are used to estimate the number of times a pattern or lexicon occurs on the Web in general and on documents with a URL associated with the domain. These are used to estimate the probability of particular patterns on the domain of interest. Recall and precision can then be

controlled by adjusting a threshold parameter to select which patterns should be used on a given domain. Fine adjustments can be made by the user for individual patterns. This combination of automatic probability estimation and manual refinement allows ESpotter NER to be optimized for a particular organization's documents without a long training process.

Variants of the same NE are prevalent on different documents on a site, e.g., a person's name can be referred to in many ways. The proposed method groups similar NEs together in order to find these variants and align them by taking into account the string similarity of two NEs. String similarity is defined as the length of the longer NE divided by the Levenshtein distance[1] of the two NEs. Two NEs judged similar by their string similarity *StrSim(E1,E2)* are more likely to be variants of the same NE if they appear on the same document or two documents which link to each other (we use the Levenshtein edit distance but other metrics are also suitable). The two NEs may appear on multiple documents, and we define the contextual distance *ConDis(E1, E2)* between two NEs as the minimum number of links, regardless of link direction, between two documents where these two NEs appear. The contextual distance is zero if the two NEs both appear on the same document. We define the similarity between two NEs, *E1* and *E2*, as $Sim(E1,E2)= \frac{StrSim(E1,E2)}{a+b\times ConDis(E1,E2)}$, where *a* and *b* are weights.

2.3 Relation Strength and Ranking

Traditional text window based entity relation discovery methods only count the number of co-occurrences of two entities but do not take into account the distance between them. We argue that the distance between two entities will also affect the relation judgment of them especially when the text window is large. The intuition is that the smaller the distance between two entities, the more likely that they are related. In addition, the frequency of entities in a text segment and the relevance of a document in relation judgments also need to be considered. We propose a novel unified approach for incorporating

four components, i.e., entity co-occurrences, entity distances, entity frequencies, and document relevance, in entity relation discovery.

The process for relation strength and ranking is shown in Figure 1. For each target NE (which may be the person whose competencies we wish to discover), the relation strengths of co-occurring NEs are calculated.

Given:
1. a number of text documents
2. a number of NEs recognized from these documents
3. a target NE

Relation strength approach:
Combining four components, i.e., entity co-occurrences, entity distances, entity frequencies, and page relevance, in a relation strength measure

Output relation strengths of NEs which co-occur with the target NE

Figure 1. The process for relation strength calculation

Our novel relation strength measure between two NEs consists of four components as follows.

1. Co-occurrence: Two entities are considered to co-occur if they appear in the same text fragment, which can be a document or a text window. Generally, if an NE is closely related to a target, they tend to co-occur more often. For two NEs, *E1* and *E2*, we use Resnik's method [22] to compute a relative frequency of co-occurrences of *E1* and *E2* as in Equation 1.

$$\hat{p}(E1, E2) = \frac{Num(E1, E2)}{N} \tag{1}$$

where $Num(E1,E2)$ is the number of documents or text windows in which $E1$ and $E2$ co-occur, and N is the total number of documents or text windows.

2. Distance: Two NEs which are closely related tend to occur close to each other. If two NEs, *E1* and *E2*, both occur only once in a text fragment, the distance between them is the difference between their offsets. If *E1* occurs once and *E2* occurs multiple times in the text fragment, the distance between *E1* and

[1] Levenshtein distance of two strings is the length of the shortest sequence of edit commands that transform one string to the other.

E2 is the difference between the offset of *E1* and the offset of the closest occurrence of *E2*. When both *E1* and *E2* occur multiple times in the text fragment, we average the distance from each occurrence of *E1* to *E2* and define the logarithm distance between *E1* and *E2* in the *i*-th text fragment as in Equation 2.

$$\overline{d_i}(E1,E2) = \frac{\sum_j (1 + \log_2(\min(E1_j, E2)))}{Freq_i(E1)} \quad (2)$$

where $Freq_i(E1)$ is the number of occurrences of *E1* in the *i*-th text fragment and $min(E1_j, E2)$ is the distance between the *j*-th occurrence of *E1*, $E1_j$, and *E2*.

3. Entity Frequency: An NE is considered to be more important if it has more occurrences in a text fragment. Consequently, a numerous NE tends to have strong relations with other NEs which also occur in that text fragment.

4. Document relevance: Given a target, *E1*, the weight of each text fragment is given indicating its relevance in associating other NEs in the text fragment with *E1*, e.g., for a person, a high relevance weight might be set to his/her homepage and a low relevance weight to his/her blog page.

Relation strength: Given a target, *E1*, we calculate the relation strength between *E1* and another NE, *E2*, by taking into account the above four components. The relation strength, $R(E1, E2)$, between *E1* and *E2* is defined in Equation 3.

$$R(E1,E2) = \hat{p}(E1,E2) \times \sum_i \left(\frac{w_i \times f(Freq_i(E1)) \times f(Freq_i(E2))}{\overline{d}_i(E1,E2)} \right) \quad (3)$$

where w_i is the weight showing the relevance of the *i*-th text fragment to *E1*, $f(Freq_i(E1)) = 1 + \log_2(Freq_i(E1))$, $f(Freq_i(E2)) = 1 + \log_2(Freq_i(E2))$, and $Freq_i(E1)$ and $Freq_i(E2)$ are the numbers of occurrences of *E1* and *E2* in the *i*-th text fragment, respectively.

Thus the relation strength between a target and each of its co-occurring NEs is calculated. We rank co-occurring NEs in terms of their relation strengths with the target. Since these NEs are of different types,

we divide the ranked list into a set of ranked lists for each type, e.g., lists of related people and related organizations.

We set a threshold, so that only relations with relation strength above the threshold are selected. For example, we could set the threshold as the value at which two NEs co-occur with only one occurrence each, within a distance *D*, in only one text fragment. Generally, higher thresholds give high precision and low recall, and *vice versa*.

It is worth noting that, since the relation strength part of the method comprises a combination of measures for co-occurrence, frequency, distance and document relevance, the current method has potential for refinement by substituting these components with others that are more sophisticated. Consider the case of judging the strength of the relation between two organizations *E1* and *E2*. If the method were to be deployed in a semantic Web environment where the documents were annotated with reference to an ontology, it would be possible to take account of instances below *E1* and *E2* in the taxonomic structure such as people employed by the organizations or subsidiary companies.

3. Approaches to Evaluation

The evaluation of the CORDER method presents problems typical of unsupervised machine learning methods in general when trying to establish if the method has learnt a model that is fit for purpose. The main approaches to evaluation may be characterized as quantitative, gold standard and task oriented.

Quantitative methods judge whether the model produced is a "good" model based on quantifiable parameters. For example, a classic method for analyzing hierarchical agglomerative clustering is the cophenetic correlation coefficient [23], [14]. Square Error Criterion is commonly used to evaluate the efficiency of numerical data clustering [9]. Another method is Information Gain in which is possible to

assess the quality of the clustering results over categorical data [28]. We are experimenting with this approach to evaluate a CORDER enhanced semantic clustering method (see Section 8).

Gold standard approaches compare the learned model to an "ideal" produced *a priori* by domain experts. These are typical in information retrieval and information extraction, e.g., the MUC (Message Understanding Conference) and TREC (Text REtrieval Conference) series of competitions [7] [21]. Their primary disadvantage is that standard collections are expensive to produce. Moreover, since they are based on expert opinion, they are intrinsically subjective. We have participated in the TREC conference Enterprise Search Track, where a crawl of the W3C (http://www.w3.org) site is used as test collection. CORDER will be further evaluated in terms of its effectiveness in discovering significant associations between entities, e.g., Person-Topic associations, to complete the Expert Search task.

Task oriented evaluations examine algorithms in the context of applications. They are concerned with whether the learning algorithm has produced a model that functions properly in use. Tonella *et al.* [26] discussed some of the problems associated with the task oriented approach including its cost and the need for careful design to minimize subjectivity.

Each approach has deficiencies. Therefore we favor a mixed strategy. Our first evaluation mined competencies using the website of the Knowledge Media Institute (KMi). This meant we had access to experts who could provide subjective data on the validity of the model. In the second evaluation, we compared CORDER's results with two quantitative benchmarks obtained from the whole Web data and a co-occurrence model, respectively. We did our third evaluation on an integrated system of CORDER and an online matchmaking tool called BuddyFinder, where a group of online users' collective opinions are used to evaluate CORDER.

4. Experimental Setup for Expert and Quantitative Benchmark based Evaluations

We applied the CORDER method to our department, the Knowledge Media Institute (KMi), website. We used Verity Ultraseek search engine to get a list of documents which are linked from the KMi homepage and whose URL hostnames are from a list of URLs of sub-sites of the KMi website e.g., URLs for the departmental news, PlanetNews, site[2]. Documents containing noisy data including obsolete web pages were removed using the patterns in their URLs and templates in their content. We got 503 documents, of which 122 are official pages from the KMi website, 202 are from personal homepages, 111 are from the PlanetNews site, and the rest are from other relevant sources.

We used ESpotter to recognize four types of NEs, i.e., people (*PeoNE*), organizations (*OrgNE*), projects (*ProNE*), and research areas (*ResNE*). Built-in lexicon entries and patterns, and lexicon from a domain ontology and research areas from the ACM Computing Classification System[3] are used for recognition.

To align variants of NEs from these documents, we calculated a similarity threshold of 0.833 by setting minimum string similarity of 2.5 and minimum contextual distance of 2 and used the similarity threshold to find clusters of variants. We found 93 clusters for manual alignment. To estimate the precision, P_{NER}, and recall, R_{NER}, of NER, we randomly selected 15 pages from the 503 pages and asked a human evaluator to annotate NEs of the four types respectively. Human annotations were used as a gold standard to compare with the NER results produced by ESpotter, we got P_{NER} and R_{NER}[4] of 91% and 88% respectively. For the 503 documents, the numbers of unique *PeoNE*s, *OrgNE*s, *ProNE*s, and *ResNE*s are 860, 526, 21, and 273, respectively.

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[2] http://news.kmi.open.ac.uk

[3] http://www.acm.org/class/1998/

[4] $P_{NER} = \frac{N_{ESpotter,Correct}}{N_{ESpotter}}$ and $R_{NER} = \frac{N_{ESpotter,Correct}}{N_{User}}$

where $N_{ESpotter,Correct}$ is the number of correct NEs produced by ESpotter for four types on 15 Web pages, $N_{ESpotter}$ is the total number of NEs produced by ESpotter for four types on 15 Web pages, and N_{User} is the number of NEs annotated by the evaluator for four types on 15 Web pages.

The CORDER method was used to discover relations between people working in our department and NEs of the four types. A relevance weight is set as 1 for documents of general relevance to a target NE and 2 for documents of special relevance to the target. There are 3655 relations found by CORDER between the 60 researchers working in KMi and the four types of NEs. Relations found for an expert were evaluated by the expert him/herself in the following Section 5.

5. Expert and Quantitative Benchmark Based Evaluations

We compared CORDER with a co-occurrence based method and a Google hits based method. Given a target NE, the co-occurrence based method ranks other NEs by the number of co-occurrences between the target and each of these NEs in documents or text windows. Given a target NE, the Google hits based method ranks other NEs by the number of co-occurrences between the target and each of these NEs on the whole Web. Thus the ranking that CORDER gets from in depth analysis of a representative subset of pages is compared against a simple analysis of this subset of pages and the whole Web, respectively.

In our expert evaluation, we created a web based form which allowed each expert to access the model that one of the three above three methods had generated for them[5]. Twenty people, representing a range of experience from PhD students to professors, modified their own model to produce rankings and relevance judgments closer to their own view of their interests and associations. These gave us a *post hoc* standard against which to measure the three method's performance.

We used precision (*P*) and recall (*R*) to measure a ranking method's ability to discover relevant NEs (Equation 4).

[5] The identity of the chosen method (CORDER, Google hits, or co-occurrence method) is hidden away from the user in order to avoid bias.

$$P_{T,User} = \frac{N_{User,RM,\mathrm{Relevant}}}{N_{RM,\mathrm{Relevant}}}, \qquad R_{T,User} = \frac{N_{User,RM,\mathrm{Relevant}}}{N_{User,\mathrm{Relevant}}} \tag{4}$$

where T is the type of NE, the number of NEs judged as relevant by a ranking method is $N_{RM,Relevant}$, the number of NEs judged as relevant by the user is $N_{User,Relevant}$[6], and the number of NEs judged as relevant by both the user and the ranking method is $N_{User\ RM,Relevant}$.

A ranking method and the user provide two sets of rankings to the list of $N_{User\ ,RM,Relevant}$ NEs judged as relevant by both. To measure how well a method's ranking match the user's ranking, we used Spearman's coefficient of rank correlation *RA* [12] to measure the ranking method's ability to rank NEs (Equation 5).

$$RA_{T,User} = 1 - \frac{6\sum_{i}(r_{i,User} - r_{i,RM})^2}{N_{User,RM,\mathrm{Relevant}}{}^3 - N_{User,RM,\mathrm{Relevant}}} \tag{5}$$

where $r_{i,User}$ and $r_{i,RM}$ ($1 \le i, r_{i,User}, r_{i,RM} \le N_{User\ ,RM,Relevant}$) are the two rankings provided by the user and the method respectively for the i-th NE in the list. There are no ties in a set of rankings, i.e., for any two NEs, E_i and E_j ($i \neq j$), $r_{i,User} \neq r_{j,User}$ and $r_{i,RM} \neq r_{j,RM}$. *RA*=1 when the two sets of rankings are in perfect agreement and *RA* = -1 when they are in perfect disagreement.

The results in Table 1 show that precision for all the rankings produced by CORDER is above 71%, indicating that most of the relations found by CORDER are correct. Recall is all above 73%, showing that CORDER can find most of the relations of a user. *RA* ranges between -0.086 and 1.0, and the *RA* values for 61 out of 80 lists of NEs for users are above 0.60, suggesting a very high degree of agreement between the rankings produced by CORDER and those by the users themselves.

[6] The users can add NEs that they think are relevant to themselves but are missing from the recommendation list.

Table 1. Precision, recall, and ranking accuracy of three ranking methods evaluated by 20 users.

			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
OrgNE	Precision (%)	CORDER	89.1	83.3	100	92.7	76.9	83.3	92.9	83.3	88.9	88.9	95.8	100	100	85.7	83.3	100	100	100	100	71.4
		Co-Occ	85.2	77.3	90	87.6	71.3	80.6	87.8	74.3	82.3	85.6	87.8	90.0	90.0	80.3	75.3	100	100	100	100	68.5
		Google	78.3	75.0	80	82.3	68.3	75.6	80.3	65.3	75.1	79.8	81.3	80.0	70.0	74.3	67.1	100	100	100	100	56.5
	Recall (%)	CORDER	83.7	93.8	90	95	83.3	88.2	86.7	83.3	80	94.1	97.9	90	83.3	92.3	83.3	81.8	88.9	83.3	80	83.3
		Co-Occ	82.3	89.2	85	91.2	71.3	75.6	74.5	80.5	76.8	87.8	91.2	85.3	72.3	86.7	74.3	72.3	82.3	83.3	80	76.5
		Google	75.0	77.1	75	87.6	74.6	74.3	65.3	75.4	68.6	86.3	85.6	76.5	64.5	79.8	70.4	64.4	74.4	83.3	80	64.3
	RA (%)	CORDER	92.3	91.0	70.2	77.0	38.2	55.1	100	98.2	15.7	97.7	99.8	87.6	25.5	89.7	100	23.3	80.0	100	100	100
		Co-Occ	85.9	87.6	69.5	74.6	31.5	45.8	87.8	85.6	12.1	94.6	87.6	81.3	21.3	82.4	54.3	12.3	52.3	100	100	53.2
		Google	67.2	79.6	65.8	74.3	36.4	36.2	78.5	75.3	6.3	87.3	75.3	75.3	22.3	79.6	32.1	3.5	42.3	100	100	64.8
PerNE	Precision (%)	CORDER	91.8	89.7	83.3	95.2	83.3	84.2	88.9	90.7	94.2	89.7	94.9	91.7	86.7	75	80	85.7	88	88.9	92.3	100
		Co-Occ	82.3	87.3	75.2	88.6	74.3	81.2	82.3	84.6	89.6	88.3	86.9	85.5	78.5	75	60	71.4	82.3	81.3	85.3	85.0
		Google	76.3	80.1	73.5	80.6	68.9	74.3	68.8	74.2	78.8	82.5	75.3	79.9	68.3	50	60	56.3	75.2	75.3	76.6	75.0
	Recall (%)	CORDER	85.6	96.3	93.8	87.0	86.2	80	84.2	86.7	85.5	92.9	100	100	81.3	90	88.9	75	95.7	100	85.7	86.7
		Co-Occ	82.1	92.2	90.2	84.3	82.3	76.3	80.1	81.3	80.9	87.6	95.0	85.2	74.4	90	77.2	65.2	91.2	82.3	78.6	78.7
		Google	72.3	83.2	85.6	78.6	72.9	72.6	63.2	74.3	74.3	75.3	87.6	74.6	63.2	70	65.3	41.2	87.8	75.3	72.3	69.7
	RA (%)	CORDER	87.7	87.2	86.4	87.2	53.0	63.2	9.2	23.3	93.2	89.0	95.8	91.9	95.5	98.2	83.3	100	23.3	100	100	72.3
		Co-Occ	80.5	81.9	82.6	79.3	45.2	52.3	12.5	14.6	89.5	87.5	91.3	86.6	87.5	98.2	78.3	100	14.6	100	100	67.8
		Google	73.5	82.1	81.6	75.5	35.6	49.8	-15.6	5.6	78.2	84.3	87.3	75.3	75.3	74.3	65.3	93.3	3.5	93.3	100	62.1
ProNE	Precision (%)	CORDER	100	100	80	87.5	100	100	100	80	87.5	81.8	75	80	100	100	100	100	100	100	80	100
		Co-Occ	90.0	90.0	75	84.1	90.0	90.0	92.3	75.6	84.6	75.3	72.6	80	93.3	100	100	100	100	100	80	100
		Google	85.0	83.3	70	80.6	87.6	87.6	68.9	72.3	56.6	72.1	68.1	80	93.3	100	100	100	100	100	80	100
	Recall (%)	CORDER	84.6	83.3	100	100	83.3	87.5	75	80	77.8	90	100	100	100	80	80	100	100	100	80	100
		Co-Occ	81.4	82.4	90	95.0	76.3	84.3	74.6	74.3	74.6	85.5	100	100	100	60	80	100	100	100	80	100
		Google	77.4	78.8	80	84.3	69.8	74.6	76.3	69.8	65.6	81.3	100	100	100	40	80	100	100	100	80	100
	RA (%)	CORDER	87.7	87.2	100	98.3	-8.6	68.0	100	89.2	48.2	68.8	50.0	87.9	100	88.7	18.2	100	100	100	100	100
		Co-Occ	80.8	83.3	92.3	85.3	-13.6	64.5	93.6	86.3	42.6	65.3	40.0	56.3	50.0	75.3	5.3	100	100	100	50	100
		Google	79.4	80.9	84.3	84.6	-12.7	60.3	75.6	78.3	23.5	54.1	30.0	45.2	60.0	64.1	12.4	100	100	100	50	100
ResNE	Precision (%)	CORDER	84.9	86.4	82.4	92.9	91.7	95.8	71.4	75	84.2	94.1	90	83.3	100	92.9	100	100	100	100	88.9	87.5
		Co-Occ	80.2	82.3	80.3	87.3	85.5	89.9	68.3	69.0	78.7	87.6	85.0	75.5	75.0	87.3	100	100	100	100	76.4	81.4
		Google	74.3	74.1	72.5	84.3	84.3	87.5	59.6	58.3	68.5	79.6	70.0	68.3	50.0	74.2	100	100	100	100	72.2	75.3
	Recall (%)	CORDER	91.8	92.7	73.7	81.3	91.7	92	83.3	85.7	69.6	86.5	100	90.9	91.7	86.7	100	80	100	80	80	77.8
		Co-Occ	87.6	85.2	70.9	80.6	87.3	87.8	74.3	76.9	56.5	84.6	100	84.2	75.6	81.3	100	80	100	80	72.3	74.4
		Google	82.6	74.9	71.3	75.1	84.4	84.3	72.0	68.2	57.9	81.2	100	76.8	68.3	74.3	100	80	100	80	65.6	68.2
	RA (%)	CORDER	80.1	82.2	22.7	2.12	51.2	73.0	100	98.2	99.0	54.3	33.3	67.3	71.8	93.4	100	100	68.8	80.0	50.0	90.0
		Co-Occ	79.3	81.0	25.6	1.56	45.3	74.3	91.3	86.3	89.6	45.5	45.6	57.7	68.8	74.1	100	100	85.6	80.0	45.3	85.0
		Google	75.0	78.6	29.6	-5.6	44.9	74.6	68.2	69.9	78.3	41.2	23.1	51.3	57.6	65.3	100	100	52.3	80.0	35.6	76.4

We can see that CORDER consistently outperformed both the co-occurrence and Google hits based methods in terms of precision, recall and ranking accuracy on four types of entities for 20 users. The co-occurrence based method taking into account web pages on the website performed better than the Google hits based method taking into account the whole Web.

The total number of NEs of four types for all 20 users judged as relevant by a ranking method is $Total_{RM,Relevant}$, the total number of NEs judged as relevant by 20 users is $Total_{User,Relevant}$, and the total number of NEs judged by both 20 users and the ranking method as relevant is $Total_{RM,User,Relevant}$. We define the overall precision, P_{Total} and recall, R_{Total} in Equation 6.

$$P_{Total} = \frac{Total_{RM,User,\mathrm{Relevant}}}{Total_{RM,\mathrm{Relevant}}}, \quad R_{Total} = \frac{Total_{RM,User,\mathrm{Relevant}}}{Total_{User,\mathrm{Relevant}}} \tag{6}$$

For the CORDER method, we got P_{Total} and R_{Total}, as 90.5% and 88.2%. For the co-occurrence based method, we got P_{Total} and R_{Total} as 82.4% and 78.5%. For the Google hits based method, we got P_{Total} and R_{Total} as 76.5% and 72.7%. We averaged the ranking accuracies for four ranked lists of the 20 users to get the overall ranking accuracy, RA_{Total}, as 76.9%, for the CORDER method, 65.4% for the co-occurrence based method, and 53.2% for the Google hits based method. We can see that CORDER performed considerably better than both the co-occurrence and Google hits based methods.

However, the *post hoc* standard is imperfect in a number of ways which need to be addressed. The experts could only judge NEs that were found by the ranking methods. Some experts were inclined only to look at the top of ranking methods' rankings, i.e. the most relevant NEs. Some experts reported that it was hard to rank certain types of NEs, such as people, because their personal view of levels of importance was hard to quantify. Presenting experts with a randomized list to rank might give better results, but it would be a harder task. It may be that experts should instead be given a simpler task such as assigning NEs to groups such as "highly relevant", "relevant" and "not relevant".

6. Application of CORDER in BuddyFinder and User Evaluation

The first competence discovery application we are building is the search service for the BuddySpace jabber environment (http://buddyspace.sourceforge.net/), called BuddyFinder. Finding useful contacts on instant messaging services is commonly based on registration information provided by the users. This has a number of weaknesses. In particular, users tend not to be motivated to provide more than a few keywords and the information can quickly go out of date. The BuddyFinder system asks them to supply the URL of their homepage; users are more motivated to keep their homepage comprehensive and current than a profile on their instant messaging system. A user typically uses a keyword based search query describing a topic to find his/her buddies. The CORDER method uses the keywords in the query as the target NEs and calculates the strength of the relations between the topic and users within the groups that the searcher belongs to based on data mined from their homepages and closely associated pages (for example blog pages). The results are presented as a ranked list of users (see Figure 2).

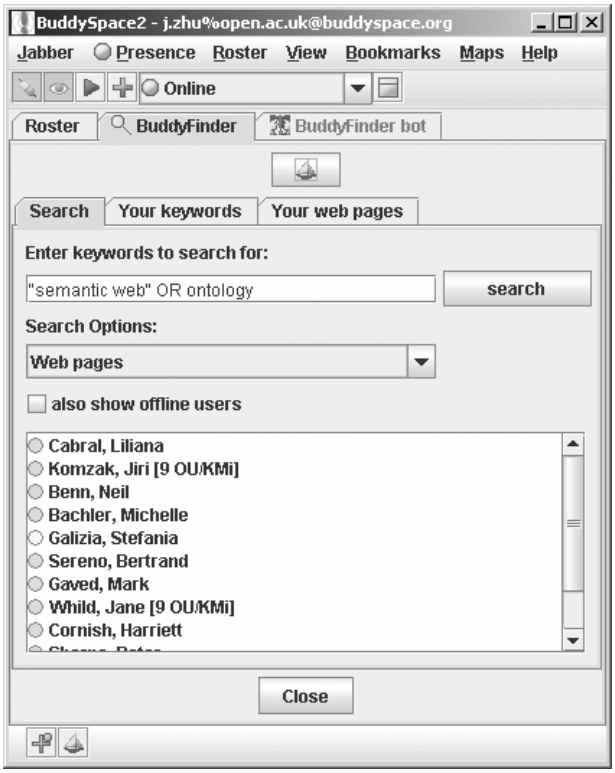


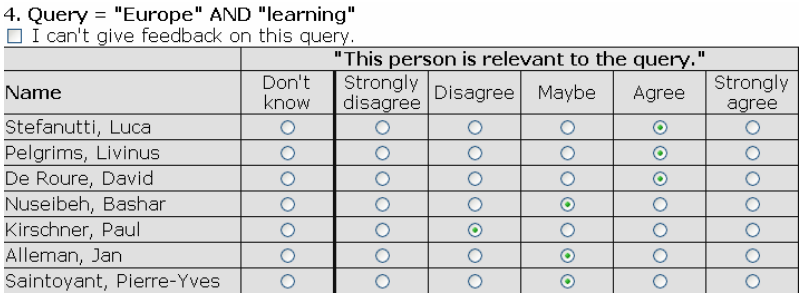
Figure 2. BuddyFinder output for a search on "semantic web" OR ontology

In our user evaluation, we designed a strategy to get a group of users' collective opinions on who were most relevant to a given topic within their group. In a large organization, everybody knows about the expertise and associations of some of his/her colleagues, and is not sure of, or does not know about, the others. Given a topic, e.g., "semantic web", a group of people may have various opinions about who is strongly associated with the topic in their organization. We assume that, just like a democratic voting or referendum system, we can identify the 'experts' from the collective opinions expressed by the ratings given by a group of people. Therefore, we use their collective opinions as a *standard* to evaluate the CORDER method.

We have evaluated BuddyFinder-CORDER on two groups of users, namely, 70 people in the Knowledge Media Institute (http://kmi.open.ac.uk), and 142 people in the ELeGI project (http://www.elegi.org/) [3], a 23-partner European consortium. There are 5 people who are in both

groups, i.e., work in both KMi and the ELeGI project. For the KMi and ELeGI groups, there are in total 1,011 and 1,978 documents from people's profiles, respectively.

Two members of the KMi and ELeGI groups have selected 17 and 19 queries for user evaluation on the two groups, respectively, as listed in the left most columns of Table 2 and Table 3. For each query, we have applied the CORDER method to the dataset. Since users generally only look at the top ranked buddies to find their answers, we selected up to top 10 ranked buddies (can be less than 10 when there are less than 10 buddies in the list) returned by CORDER for each query as the relevant buddy set.


4. Query = "Europe" AND "learning"
☐ I can't give feedback on this query.

Name	"This person is relevant to the query."					
	Don't know	Strongly disagree	Disagree	Maybe	Agree	Strongly agree
Stefanutti, Luca	○	○	○	○	◉	○
Pelgrims, Livinus	○	○	○	○	◉	○
De Roure, David	○	○	○	○	◉	○
Nuseibeh, Bashar	○	○	○	◉	○	○
Kirschner, Paul	○	○	◉	○	○	○
Alleman, Jan	○	○	○	◉	○	○
Saintoyant, Pierre-Yves	○	○	○	◉	○	○

Figure 3. A query with a relevant buddy list generated by CORDER in randomized order for user evaluation.

We created a web based form (Fig. 3) which allows human evaluators to assess the query results. In order to minimize the influence of the order of the queries and buddies in the relevant buddy set of each query, every time an evaluator visits the form, the order of both the queries and buddies in the relevant buddy set of each query are randomly generated. The order in which CORDER has ranked the list of buddies is hidden from the evaluators. Since each evaluator may not be able to evaluate all the buddies for all the queries, we give them the option to skip a query, or select "don't know" for a buddy to a query. To evaluate the statement that a buddy is relevant to a query, they can choose from "strongly disagree", "disagree", "maybe", "agree", and "strongly agree". 23 people from KMi group, representing a range of experience from PhD students, secretaries, project managers, lecturers, research fellows, and professors, have evaluated the KMi form. 17 people from ELeGI consortium, representing a range of

experience from PhD students, project members, project leaders, lecturers, research fellows, and professors, have evaluated the ELeGI form. Each relevant buddy in each query has been evaluated by at least three people. These gave us a *post hoc* standard against which to measure CORDER's performance.

Evaluators may have different opinions on the association between each buddy in the relevant buddy set of each query and the query. We assign following rating values to their opinions: -2: "strongly disagree", -1: "disagree", 0: "maybe", 1: "agree", 2: "strongly agree", and "don't know" is ignored. We calculate the mean of the opinion values from a group of users as the group's rating value for a buddy. In order to remove dubious user ratings, we calculate the standard deviation of the rating values and remove any user rating value that is two times the standard deviation value away from the mean. After removing dubious ratings, we calculate the mean of a group of users' ratings again as the group's rating value for the buddy.

Given a query, we can use the group of users' rating value for each buddy to rank these buddies. Thus the new ranked list of buddies reflects the group of users' collective opinion in how the list of buddies should be ranked. We use the group's ranked list to evaluate how well CORDER has ranked the buddies to reflect the group's views. We have reused the Spearman coefficient (RA) described in Equation 5 to measure how well CORDER has ranked the buddies to match the group's opinion.

The ranking coefficient for CORDER on each query in the KMi and ELeGI groups is shown in Table 2 and 3, respectively. "AKT", "BuddySpace", "Magpie", and "ScholOnto" are project names. Generally, people would search for people closely related to research areas and projects. We have also experimented with a more variety of types of queries to emulate real users' various needs in their searches, and show that BuddyFinder can give satisfying answers to various types of queries. In Table 3, people's names, e.g., "Marc Eisenstadt", and academic institution's names, "University of Graz", are used. In this case, we are looking for people who are closely related to a given person, e.g., colleagues, collaborators, and closely related to an institution, e.g., employees, collaborators.

Table 2. Spearman's rank correlation for KMi group.

Query/Rank Correlation (RA)	CORDER
1. AKT	0.6842
2. Artificial Intelligence	0.9140
3. Buddyspace AND Messaging	0.3654
4. Hypertext	0.6838
5. Information Extraction	0.7047
6. Knowledge Management	0.9200
7. Knowledge Modelling	0.9596
8. Machine Learning	0.5839
9. Magpie	0.9045
10. Natural Language Processing	-0.1545
11. Ontologies	0.9466
12. Planning AND Scheduling	0.7657
13. Question Answering	0.6171
14. ScholOnto	0.5723
15. Semantic Web	0.9688
16. Web Services	0.6054
17. Social Software	0.7335
RC variance	0.07682
RC average	0.6927

Table 3. Spearman's rank correlation for ELeGI group

Query/Rank Correlation (RA)	CORDER
1. Artificial Intelligence	0.7821
2. BuddySpace	0.6000
3.Europe AND Learning	0.5797
4. Hugh Davis	0.5000
5. Human Learning	0.0909
6. Hypermedia	0.5265
7. Hypertext	0.5385
8. Instant Messaging	0.4643
9. Java and C++	0.5515
10.Knowledge Representation	0.6905
11.Learning AND Grid	0.6835
12. Machine Learning	0.4286

13. Marc Eisenstadt	0.7212
14. Semantic Web	0.2445
15. Social Software	1.0000
16.Software AND Grid	0.2451
17.University of Graz	0.9007
18. University of Southampton	0.8187
19. WSRF	-0.6000
RC variance	0.1246
RC average	0.5140

We can see from Table 2 and 3 that CORDER can find truly relevant buddies and rank them in the correct order in most of the queries. When the ranking correlation of CORDER for a query is low, it is often the result that there are no clear relevant buddies for the query topic. For example, consider the query "natural language processing" (NLP) in Table 2. "NLP" is not a major research area in KMi (hence there are proportionally fewer pages mentioning it) and most evaluators do not have a clear idea about who are associated to it, this is reflected in the standard deviations of users' ratings for each relevant buddy on "NLP", which are all between 0.683 and 1.328, given that for most of the other queries the standard deviations of users' ratings are between 0.0 and 0.7. Associations for "NLP" are also under-represented in documents. We found that there are only two documents matching both "NLP" query and the buddies ranked as No. 1 and 2 in the collective opinion of evaluators, respectively.

7. Related Work

The concept of relation extraction was introduced as part of the information extraction tasks in the Sixth Message Understanding Conference (MUC-6) [7]. Some previous work has adopted a supervised learning approach such as kernel methods [29] and needs richly annotated corpora which are tagged with relation instances. The limitation with this approach is that it takes a great deal of effort to prepare annotated corpora large enough to apply supervised learning. Some other previous work has adopted a

weakly supervised learning approach. This approach has the advantage of not needing large tagged corpora. Brin [4] proposed DIPRE, a bootstrapping method for relation discovery. DIPRE finds patterns for a particular relation between NEs from a small set of training data, and uses these patterns for finding the relation between new NEs on test data. Snowball [1] improved on DIPRE by adopting the constraint of using a named entity tagger. KNOWITALL [11] uses patterns for relation extraction by taking advantage of the scale and redundancy of the Web. DIPRE and Snowball, however, need a small set of training data. It is also unclear how training data should be selected and how much data is needed. DIPRE, Snowball, and KNOWITALL work well on relations embedded in patterns but cannot spot relations shown in the context of text and layout of web pages. The most similar relation discovery method to ours is by Hasegawa *et al.* [15]. They proposed a method which discovers relations among NEs from large corpora by clustering pairs of NEs according to the similarity of context words occurring between the NEs. Their method works well on well-formed text which follows a "house-style", while our co-occurrence based method is general enough to detect relations in inhomogeneous text where relations may not be explicitly specified by context words.

Our work is closely related to Communities of Practice (CoP). A community of practice refers to a group of professionals formally or informally sharing knowledge and information for performing some common tasks or exploring common problems of their professional activities and interests [19]. Existing research in deriving CoPs has been focused on inferring and visualizing community structure based on explicit linkage patterns, e.g., hyperlinks, contact lists, sender-receiver of emails, and domain-specific ontologies. As an example, Flink [20] visualizes the scientific work and social connectivity of semantic web researchers using semantic data collected from the web through web mining, and existing structured data such as FOAF (Friend Of A Friend) files. Flink presents clusters of related researchers generated by a graph clustering algorithm. ONTOCOPI [2] is an ontology base CoP identification system, which groups similar entities in an ontology network to form CoPs.

Social network discovery has been applied to P2P (Peer to Peer) systems. Peers sharing the same interests, as defined by their document collections, are clustered and can be ranked by their importance to a search query. Jin *et al.* [17] used Latent Semantic Indexing (LSI) to reveal semantic subspaces of feature spaces from documents stored on peers, and support vector machine (SVM) to classify the peers into different categories based on the vectors extracted using LSI.

Term relationships have been used to improve document retrieval. Yoshida et al. [27] discovered semantic relationships between terms based on a thesaurus. Terms relevant to given terms in a search query are organized in a tree structure as suggestions for supporting users to search a domain they are not familiar with. We have applied CORDER for query expansion to enhance the traditional vector space model based information retrieval and our experiments have shown that CORDER based query expansion has improved the performance of the vector space model [13].

Humans encountering a new concept derive the meaning via an accumulation of experience of the contexts in which the concept appears. In the Hyperspace Analogue to Language (HAL) model proposed by Burgess *et al.* [6], the meaning of a word is captured by examining its co-occurrence patterns with other words in the language use, e.g., a corpus of text. HAL represents words as vector spaces of other words, which occur with the target words within a certain distance, e.g., a text window. The associations between concepts can be computed via different means of comparing their underlying vector representations [5] [24] [25]. As HAL model is based on the co-occurrences as well as distances between concepts, the CORDER system can be naturally integrated as one of the association derivation mechanism. We have started integrating HAL model with CORDER, e.g., to tackle users' vague search queries [31]. Since HAL model provides more informative view of NEs in terms of a multi-dimensional vector, we can further improve our relation discovery approach.

8. Conclusions and Continuing Work

8.1 Conclusions

We have shown that the CORDER method can discover competency relationships that are judged to be appropriate by the people they concern. Our user evaluation and quantitative benchmarking suggest that CORDER can discover relations with high precision, recall, and ranking accuracy. CORDER provides better rankings than both a co-occurrence based and Google hits based methods. User evaluation of our first competency application called BuddyFinder has shown that CORDER can recommend people with the right expertise as specified in a term-based query.

Our experiments show that CORDER's running time increases linearly with the size and number of documents it examines. CORDER can incrementally evaluate existing relations and discover new relations by taking into account new documents. Thus CORDER can scale well to a large dataset. When applying CORDER to a large corpus of web documents, the noise in the corpus may affect the performance of CORDER. Thus, we are working on integrating CORDER with information retrieval methods in a language modeling approach, where documents relevant to a query topic are retrieved first and we apply CORDER to the relevant document set.

8.2 Future Work

This work has encouraged us to start deploying the CORDER NE based ranking in more knowledge management scenarios. For example, it could be used on web portals to enhance the presentation of search results by presenting the documents most central for a topic or the best connected authors first. In addition, it could be used to mine text data for RDF triples to automatically input into a triple store.

CORDER's rankings are derived from data mined from a collection of documents. In this way it gives a wider view of the "world" of a domain than data from a single document. We are experimenting with using the closest entities suggested by CORDER to improve the vector descriptions of documents for clustering. Our initial experiments suggest that this approach produces clusters which score as well as

the widely used SOM method [16] on a total information gain measure of cluster quality. The execution time of the CORDER enhanced clustering method however increases linearly with the size and number of documents it examines so that it starts to outperform SOM on collections of more than 700 vectors. We intend to test this clustering approach on the Lattes Platform collection of curricula vitae discussed in Section 1.

Our future work includes but does not confine to:

- integration of CORDER and HAL model based information inferencing approach to further improve our relation discovery approach
- evaluation of CORDER in TREC Enterprise Search Track
- Some refinements to CORDER method are:
    - the introduction of a “timeline” to monitor changes in competencies or a summary of web page contents over time [16]
    - new ways to deal with noise and variants from the named entity recognizer,
    - NLP methods to recognize the kind of relation indicated by co-occurrence,
    - sophisticated distance and relation strength metrics which exploit the power of ontologies (see Section 2 for discussion).

While there is still work to do we are optimistic that the CORDER method is appropriate for use in competency discovery applications and has potential for application in other search scenarios where the ranking of entity data is desirable.

9. Acknowledgements

This research was partially supported by the Designing Adaptive Information Extraction from Text for Knowledge Management (Dot.Kom) project, Framework V, under grant IST-2001-34038 and the

Advanced Knowledge Technologies (AKT) project. AKT is an Interdisciplinary Research Collaboration (IRC), which is sponsored by the UK Engineering and Physical Sciences Research Council under grant number GR/N15764/01. The AKT IRC comprises the Universities of Aberdeen, Edinburgh, Sheffield, Southampton and the Open University. This research was also partially supported by the Brazilian National Research Council (CNPq) with a doctoral scholarship held by Alexandre L. Gonçalves. We are grateful to Chris Denham for the implementation of BuddyFinder.

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