The Role of Semantic Similarity for Intelligent Question Routing

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***Abstract*—Intelligent Question Routing Systems (IQRS) serve as a knowledge exchange medium in an arbitrary field of expertise, where intensive communication between users is required (e.g., large enterprises, e-government agencies, technical support, health care system, army). Other applications can involve a support in educational and collaboration processes, where IQRS facilitates an efficient and effective knowledge exchange between scholars. The benefit coming from deployment of such systems includes: (a) reducing unnecessary "pinging" of experts, which are a valuable resource and (b) increasing the system owners' (enterprise, government, university) quality of service, since users are more satisfied with answers, because their questions are answered by the right persons. In this paper we investigate the role of semantic similarity for each stage of IQRS process. For question and answer analysis we use semantic enrichment, more precisely semantic query expansion with ConceptNet, WordNet (Antelope), and SemNet, string weighting and IQRS system features. Also, for question routing stage we used techniques developed for semantic similarity between two paragraphs sentences. Finally, for evaluation we used representative subsets of Yahoo! L6 Answers dataset from which we extracted three different types of users: (1) Top questioneers, (2) Top answerers, and (3) Top combination of previous user types to model interest and expertise. Over these users we build special semantic profiles and match them to questions, answers or the whole question threads, according to the specific IQRS stage.**

I. Introduction

The key functionality of Intelligent Question Routing Systems (IQRS) is that for a question addressed by a user, to provide a good answer by searching the list of all (other) available users. The answer is provided by selecting a certain number of competent users (experts) and forwarding them the question. Selected users can provide an answer, which is then returned to the user that posed the question. The survey of state of the art in IQRS is given in [1] which introduced an original presentation paradigm that generalizes the essence of approaches found in the open literature. The presentation paradigm includes three basic processing stages related to the three major problems of system implementation: question analysis, question forwarding, and users' knowledge profiling. All approaches presented in the survey are analyzed regarding these three basic processing stages. The outcome of the analysis was a proposal for new approaches that tackle identified problems and the work presented in this paper is a consequence of this research.

Questions are usually short in length and even may be ambiguous. Therefore, as a format for acquisition, storing and representation of information related to questions or user profiles, we have chosen an approach in which the detected concepts are presented in the form of concepts cloud (similar to TagCloud visualization) [2], [3]. One advantage of this approach is that "a significant concept has assigned a higher weight," which provides an intuitive idea of specific relationships between concepts and their importance in the question. Therefore, the generated concept cloud represents a set of information that describes the question. Concepts together with their weights in this set make the specific context in a broader sense which represents a fingerprint of processed text. This fingerprint is specific to each question and it is similar for questions with the same subject and the same meaning. Finally, this fingerprint reveals specific relationships between questions, and the relationship between the question and the topics which the question touches. On the other hand, for each user IQRS system is maintaining profile which is represented in the same way, describing user's interests based on his/her questions and answers. Therefore, identified concepts from questions and user profiles are represented as pairs (keyword, weight) which are further referred as *evidences*.

The task of finding a competent user is done by comparing the information extracted from the question with all available user profiles, giving a ranked list of users or "candidates to answer". Based on this ranked list one or more users can be selected, which then should be contacted for an answer. Since the information extracted from the question as well

as those maintained in the user profiles are presented in the same way, as lists of evidences, comparison of these two lists is reduced to the calculation of their similarity. Determining the similarity can be carried out by exact comparison, i.e. determining exact matching between words, or by calculating the semantic similarity. Since the question can be semantically very similar to the profile, but still lexically very different, the better results can be achieved by using the semantic similarity. As an example that illustrates this point we can use the appearance of synonyms, words with the identical or very similar meaning, but very different in its form (e.g. words intelligent and smart). Therefore, the main focus of the work presented in this paper is calculation of semantic similarity between the question and the user profile, as well as semantic information extraction from questions and answers in order to calculate this similarity.

The rest of the paper is organized as follows. In Section II we give a brief overview of related work and available technologies for calculating the semantic similarity of short texts. Next, we introduce our proposed SemSim algorithm for determining the numerical similarity score between the question and the user profile. In Section IV we explain different evidence extraction types and sources that we use. Lastly, we evaluate SemSim on a Yahoo! Answers question and answers dataset and show the results of executions using various settings and in Section VI.

II. Related Work & Available Technologies

Based on the analysis of existing approaches for semantic similarity of short texts (or short text semantic similarity - STSS) it was concluded that none of the available solutions can be directly applied for determining the similarity between questions and user profiles. Therefore, determining the similarity is done by using a bag-of-words approach based on a modification of LinSTSS approach [4], in which for all evidences in the question Q we find the most similar matching evidences in the profile P. We decided to base our approach on LinSTSS for the following reasons:

1) This approach includes weights assigned to each compared word, i.e. can naturally deal with evidences.
2) It does not rely on any external knowledge base (e.g. WordNet), manually created inference rules or specific linguistic tools, which would be an obstacle in working with languages that lack these resources. Furthermore, the LinSTSS approach does not use the semantic similarity measure alone, but includes string similarity measure as well, so it gives better results for different forms of infrequent proper nouns, which is one of the major shortcomings of the knowledge-based approaches [5].
3) Finally, LinSTSS is inspired by the method proposed in [6] that relies on a similar bag-of-words approach, but uses word specificity as in [7] to weight the word similarity. However it overcomes the problem of method [7], which has a tendency to overestimate text similarity because it allows multiple words from one text to be paired up with a single word in the other text.

The last item is significant in determining the semantic similarity of two short texts, since it is important to determine which pairs of sentences are semantically similar, but also which are different. However, we wanted to explore if this stands also for the task of finding competent users, i.e. calculating similarity between the question and the user profile, because in this case it is necessary to determine just which profile is the most similar to the question, while it is not necessary to determine those that are different. To some extent this relates to one-class-classification problem, since we only have positive examples, e.g. we are aware of the user that provided the best answer to the question, but negative examples are unknown, i.e. we don't know which users are not able to provide the best answer. Therefore, we introduced modification named SemSim to determine the highest (maximum) similarity between evidences from the question to evidences from the profile, but not vice versa.

The rest of the section gives a brief description of algorithms and tools that are used for user profiling, i.e. analyzing questions and answers. To be able to measure similarity between questions and user profiles, we had to extract as many semantic evidences about users as possible, their behaviour as possible. In this study we used the following techniques and sources:

- **ConceptNet** [8] is a semantic knowledge base that describes general human knowledge. It includes words and common phrases from many written texts. They are related through open domain predicates and through common knowledge. The database was created manually and partially automatically from Wiktionary and ReVerb system, which is an open information extraction tool that extracts binary relationships of type *phrase-relation-phrase* in an unsupervised manner. The whole database contains 414 thousand English concepts and 903 thousand relationships between them.
- **Antelope** (Advanced Natural Language Object-oriented Processing Environement) [9] is a natural language processing framework (NLP) that can handle large corpora and consists of many extensible modular components. It uses an extended lexicon version of WordNet lexicon with improved conceptualization and integrates a higher level formal ontology. The main components offer syntactic and semantic analysis of texts, anaphora extraction, word sense disambiguation and paraphrase extraction. It also includes access to other opensource NLP libraries such as Stanford Parser, WordNet and VerbNet.
- **SemNet** (Semantic Network of Terms) [10] is a large-scale network of technical terminology which allows querying terms and retrieving ranked lists of their semantically related terms. The network was automatically constructed based on the noun terms from English Google Books Ngram Dataset using word co-occurrence analysis. The network consists of 2.8 million distinct single and multi-word terms and 37.5 million weighted edges between them. SemNet includes a large part of the same concepts and relationships from similar semantic knowledge bases such as WordNet [11] and ConceptNet [8].

- **TF-IDF** (term frequency-inverse document frequency) is a general numerical statistic that defines the importance of each word in a document collection. It is often used in information retrieval and text mining as it gives good string-based performance.

III. Semantic Similarity

This section describes phase-by-phase the algorithm of determining the numerical similarity score between the question and the user profile. The source code is accessible in publicly available repository[1].

1. *Preprocessing* begins with the text cleaning procedure which deletes all text characters not belonging to the native script of the language in question, removes numbers and words that contain numbers, eliminates punctuation marks, removes stopwords, shifts all capital letters into lower caseand finally, lemmatizes them. Processing then continues with the removal of stop words from the given texts and the remaining words from both texts are then stemmed. After this stage, if there are evidences where their keyword consists of more than one word, for each word is created new evidence with the same weight as the original one, e.g. from evidence (botanical gardens, 0.5) two evidences are created (botanical, 0.5) and (gardens, 0.5). If there are multiple evidences with the same keyword they are merged into one by calculating resulting weight with the probabilistic T-conorm:

$$\mathrm{sum(a, b)} \;=\; a + b - a \cdot b \tag{1}$$

After the preprocessing input data, the question is represented with a array Q given in (2) and the profile P is given in (3). Q consists of pairs $(q_i, w(q_i))$ representing evidences, where q_i is the keyword and $w(q_i)$ is its assigned weight. Similarly, P is consisted of pairs $(u_i, w(u_i))$. The length of array Q is m and for P is n.

$$Q = \{(q_1, w(q_1)), (q_2, w(q_2)), \ldots (q_m, w(q_m))\} \tag{2}$$

$$U = \{(u_1, w(u_1)), (u_2, w(u_2)), \ldots (u_n, w(u_n))\} \tag{3}$$

2. *Processing of keywords appearing in both question and profile* starts with the identification of those words which are then removed from further processing. Their similarity scores are equal to 1, so their final weight is equal to normalized weight $w(q_i, u_i)$, which is calculated using $w(q_i)$ and $w(u_j)$ as follows:

$$w(q_i, u_j) = 2^{w(q_i) \cdot w(u_j) - 1} \tag{4}$$

After calculating their values, we add them up into a similarity sum S_{same}, and then discard these words from further consideration. For MaxSim this step is omitted since we want to determine the highest (maximum) similarity, as it will be explained in step 7.

3. *String similarity matrix construction* creates a matrix M_1 with dimensions $m \times n$ in which every cell is occupied by a numerical value α, which lies between 0 and 1 representing the string similarity between the column-word and the row-word. The rows of the matrix are used for the remaining words from the question, while the columns represent the remaining words from the profile. A zero value denotes entirely different string contents, while a value of one indicates a perfect string match. The approach which we used to calculate string similarity is the same as in [4].

$$M_1 = \begin{pmatrix} \alpha_{11} & \cdots & \alpha_{1n} \\ \vdots & \ddots & \vdots \\ \alpha_{m1} & \cdots & \alpha_{mn} \end{pmatrix} \tag{5}$$

4. *Semantic similarity matrix construction* creates a matrix M_2 with dimensions $m \times n$ in which every cell is occupied by a numerical value β which lies between 0 and 1 representing the semantic similarity between the column-word and the row-word. The rows of the matrix are used for the words from the question, while the columns represent the words from the profile. Similar to the string similarity measurement, a zero value denotes entirely different semantic contents, while a value of one indicates a perfect semantic match. We gain the semantic similarity of words in a pair by calculating the cosine similarity in the same way as in [4].

$$M_2 = \begin{pmatrix} \beta_{11} & \cdots & \beta_{1n} \\ \vdots & \ddots & \vdots \\ \beta_{m1} & \cdots & \beta_{mn} \end{pmatrix} \tag{6}$$

5. *Similarity matrix unification* combines the string and the semantic similarity matrices into one by multiplying their values by a certain ponderation factor and adding them up as in (7). We used ponderation values of 0.45 and 0.55 for the string and semantic similarity scores, respectively.

$$M_3 \;=\; \psi M_1 + \varphi M_2 \tag{7}$$

$$1 \;=\; \psi + \varphi \tag{8}$$

$$M_3 = \begin{pmatrix} \gamma_{11} & \cdots & \gamma_{1n} \\ \vdots & \ddots & \vdots \\ \gamma_{m1} & \cdots & \gamma_{mn} \end{pmatrix} \tag{9}$$

6. The *weighted matrix construction* begins with the creation of a normalized weighted matrix in which every cell is occupied by a weight $w(q_i, u_j)$ calculated using (4). The final similarity matrix M_4, shown in 10, is gained by multiplying each cell of the unified similarity matrix with the corresponding value $\gamma_{i,j}$ from M_3.

$$M_4 = \begin{pmatrix} w(q_1, u_1) \cdot \gamma_{11} & \cdots & w(q_1, u_n) \cdot \gamma_{1n} \\ \vdots & \ddots & \vdots \\ w(q_m, u_1) \cdot \gamma_{m1} & \cdots & w(q_m, u_n) \cdot \gamma_{mn} \end{pmatrix} \tag{10}$$

7. *Best word pair selections* start with the final similarity matrix. The goal is to match words according to their mutual similarity score. Hence, we search for the highest value within the final similarity matrix, and add it to a similarity sum $S_{different}$. We then remove the row and the column of the matrix to which the selected cell belonged, thereby discarding all other word pairs in which words from the chosen pair appeared. We repeat this procedure until there are no more rows and/or columns left in the matrix.

For MaxSim approach this step is executed differently since we wanted to determine the highest (maximum) similarity

[1] https://github.com/szitnik/InterestMining

between evidences from question to profile, but not vice versa. Therefore, only for each row, which represents words from the question, we search for the highest value within the final similarity matrix, and add it to a similarity sum $S_{different}$. Since in the step 2 none of the words is omitted for this approach, $S_{same} = 0$.

8. The *final similarity score calculation* is performed by utilizing the following formula:

$$S(Q,U) = \frac{(S_{same} + S_{different}) \times (m+n)}{2mn} \qquad (11)$$

IV. User Profiling

There are many approaches to extract information from textual documents. The advantages of statistical approaches are mostly higher precision on large corpora, easier implementation and longer history of research. On the other hand, if we need to process a short text, methods from the field of computational linguistics will give the best results. In order to build efficient user profiles, we collect a number of evidences from user's posts. We separate evidences by source, which can origin from question body, answer body, question title, whole post thread or IQRS system. The more detailed description of data set that we used is given in the next section.

Before the evidence extraction we first employ some preprocessing techniques. This step is carried the same way as in step 1 of the proposed algorithm (Section III). From these we further extract evidences of the following types:

Concept extractor (CE): In our implementation of concept extractor we integrated Antelope and ConceptNet (Section II). Since the Antelope tool is based on a much smaller but more precise WordNet lexicon, it is designed to recognize named entities (e.g., names of people, organizations, states and cities) with high precision, but with limited number of concepts. Together with integrated context extraction it can contribute to better identify concepts. On the other hand, ConceptNet contains much richer semantic network, which provides better results in identifying existing and related concepts, but it does not support named entity recognition or context extraction. When we combined these tools (Antelope and ConceptNet) during the query expansion, we got better results than using them individually.

Since both tools, in addition to the identified concepts, determine the weight of the extracted concept within the range $(0, 1]$, we use the following approach to combine both values: If only one of the tools finds some concept, it retains the weight, otherwise we calculate the resulting weight using the probabilistic T-conorm (1).

In order to obtain better results and reduce the number of incorrectly identified concepts we also use the following rules:

1) We empirically defined linear relationship between the minimum weight of a concept (i.e., threshold) and a length of the text:

$$\min(\text{weight}) = 0.875 + \#\text{words\_in\_text} \cdot 0.125$$

If the weight of a concept is less than the minimum weight, it is removed and therefore not used in further calculations.

2) Since it is much harder to detect the topic from the long text rather than from the short text, which consists only of important concepts, the process of context identification is carried as follows: (1) We first detect all the concepts using Antelope and ConceptNet. (2) Then we again use Antelope to find context for all the concepts from the previous step, considering higher precision.

SemNet (SN) allows for searching ranked lists of semantically related terms. For each extracted word in the preprocessing step we select three most semantically related terms as SemNet evidences. For example, the word "car" is within SemNet described with the following evidences: ("front", 0.038), ("side", 0.024) and ("truck", 0.024).

TF-IDF (TFIDF) is a standard measure for weighting words within text documents. Intuitively the word has different weight depending on the source of occurence. Therefore we calculate TF-IDF measures separately for question titles, question bodies and answers. For example, a word "car" has the following TF-IDF weights[2]: (1) 0.163 in the question title, (2) 0.066 in the question body, (3) and 0.0246 in the best answer.

Categories: Each post also contains associated categories. In our dataset there are three hierarchical category types. Their values are more thoroughly explained within the dataset description (Section V-A).

V. Evaluation

This section contains an overview of available datasets and the one that we created from Yahoo! Answers L6 dataset, and as well results of evaluation and discussion.

A. Dataset

We reviewed many question answering (QA) systems and datasets. Finally, we decided to use Yahoo! Answers Webscope L6 dataset [12] because it contains a broad range of distinct question categories and there are enough active users in each of the categories that we selected. Other datasets could be extracted from sites such as AskVille (http://askville.amazon.com), Mahalo (http://mahalo.com), Quora (http://quora.com) and StackOverflow (http://stackoverflow.com). The latter also includes a lot of users but it does not have specified specific categories and more importantly, the whole dataset is mostly single domain oriented. Furthermore, there are lots of other systems like AllExperts (http://allexperts.com), Ask.com (http://ask.com), Answers.com (http://answers.com) and others that lack of one or more public features to build useful dataset.

Yahoo! Answers is a QA site where people post questions and answers, which are publicly available to any web user. The L6 dataset was collected from this site in 2007 and it includes all the questions (i.e. 4483032) and their corresponding answers. Next to these data some anonymized metadata is included, so that we can can extract evidences related to the each user.

Questions and answers represent instances of post type and a question with all available answers forms a thread. Each post instance consists of text in the body, selection of main

[2]The example was taken calculated on the post 1512658 from the L6 dataset.

category, category and subcategory and the id of the user who wrote the post. Questions additionally contain also a title. For answer posts, a owner user is known only if this post was considered as the best answer for the question, which imposed the limitation that only for the users that provided the best answer we can relate extracted evidences.

Depending of the post type from which evidences are extracted we distinguish Question, Answer, and Thread type of evidences. User instances are completely anonymized, so we modeled them using their id number. Also, for each user we counted how many answers or questions he/she posted in specific category type.

From the full dataset we extracted three database types:

- **Type 1**: This dataset models interest as it contains users that asked at least ten questions and each of these questions must have at least five answers.
- **Type 2**: To model knowledge, we extracted users who best answered at least ten questions. Again, each question thread needed to have at least five answers.
- **Type 3**: To jointly represent interest and knowledge, we extracted users that asked at least five questions and best answered at least five questions. Also, each of these threads needed to have at least five answers.

Each database type contains 100 users which are distinct across the dataset. As there are many different categories in the original dataset, we representatively selected five of them and extracted 100 users for each dataset. Distribution of users per each category is shown in Table I. Also, in all three database types, for each user we also selected one additional question for which he/she provided an answer that was considered as the best answer for that question. This question is then used for evaluation as explained in the following section.

Table I. DISTRIBUTION OF POST CATEGORIES IN EACH DATABASE TYPE

Category	Number of selected users
Society & Culture	35
Food & Drink	35
Computers & Internet	15
Travel	10
Cars & Transportation	5
Total	100

B. Results and Discussion

To evaluate our work we used mean reciprocal rank (MRR) and Precision@N (P@N) which are widely used in the field. They are defined as follows: (1) MRR is a measure to evaluate information retrieval task in which a list of possible responses to a query (question) is ordered by a probability of correctness. The score is defined in (12) as the average of the reciprocal ranks for a set of questions Q, where for each question from the dataset we determine the similarity to all available profiles and accordingly rank users, and then finally calculate the rank of the user that provided the best answer.

$$\text{MRR} = \frac{1}{|Q|}\sum_{i=1}^{|Q|}\frac{1}{rank_i}. \tag{12}$$

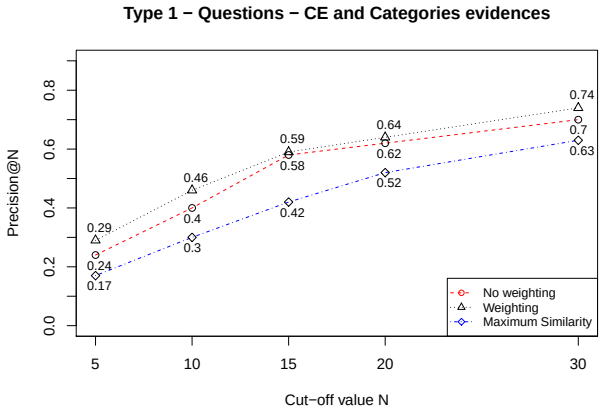

Figure 1. Precision @ N results for database type 1 using questions and evidences from concept extractor and categories.

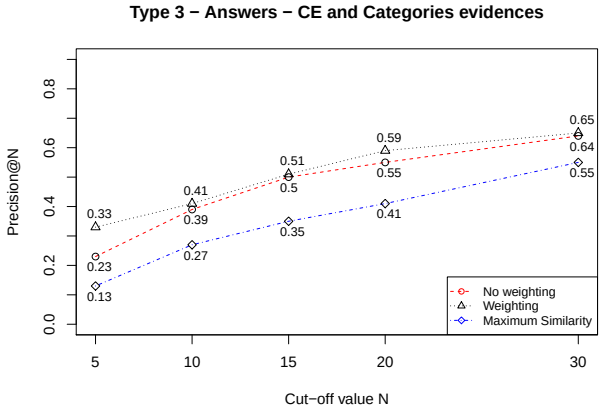

Figure 2. Precision @ N results for database type 3 using answers and evidences from concept extractor and categories.

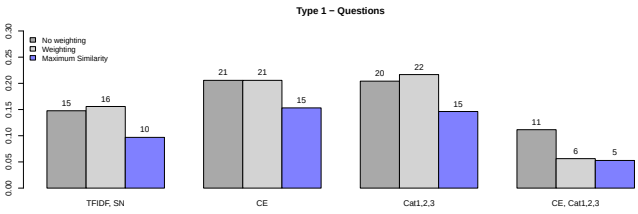

Figure 3. Mean reciprocal rank scores for database of type 1 on question evidences.

(2) Precision is the fraction of the retrieved documents (users) that are relevant to a query (question). Here we count as a relevant user the one that provided the answer to the question that was selected as the best one. P@N is therefore precision which is evaluated at a given cut-off rank N (i.e. considering only top N results). In our domain it measures the proportion of correctly selected users among all users or intuitively a probability of how likely asking among the top N selected users will result in getting a correct answer.

TODO

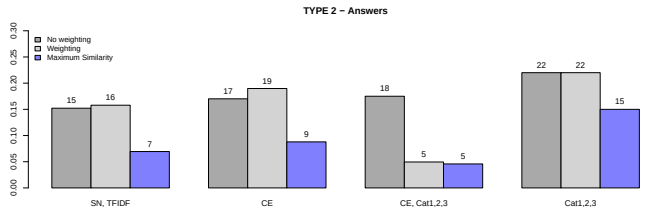

Figure 4. Mean reciprocal rank scores for database of type 2 on answers evidences.

VI. Conclusion

In this paper we investigated the role of semantic similarity for each stage of IQRS process. For question and answer analysis we used semantic enrichment, string weighting and IQRS system features. In the evaluation on subsets of Yahoo! L6 Answers dataset we showed that we can benefit by building three different types of user profiles to independently model interest and expertise.

In the future work we are going to incorporate the techniques from social network analysis for interest and knowledge prediction and together with methods for short text similarity investigate the impact of the new meta model.

Acknowledgment

The work has been supported by the Slovene Research Agency ARRS within the research program P2-0359 and part financed by the European Union, European Social Fund. It was also partially funded by the Ministry of Education and Science of the Republic of Serbia (projects III44009, 44006, 32047).

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