Entity Linking Based on the Co-occurrence Graph and Entity Probability

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ABSTRACT

This paper describes our system for the Entity Recognition and Disambiguation Challenge 2014. There are two tasks: one to find entities in queries (Short Track), the other to find entities in texts from web pages (Long Track).

We have participated in both tracks with the same system tuned to each of the tasks. On the final test set, we reached the f-measure of 71.9% on the Long Track and of 66.9% on the Short Track. We describe our system and its components in depth, together with their influence on performance. The specifics of each of the tasks are also discussed.

Categories and Subject Descriptors

I.2.7 [**Computing methodologies**]: Natural language processing—*Information extraction*; I.2.6 [**Computing Methodologies**]: Artificial Intelligence—*Learning*

General Terms

Algorithms, Performance

Keywords

entity recognition and disambiguation, entity linking, sense disambiguation

1. INTRODUCTION

One of the peculiar tasks in the area of language understanding is to describe the meaning of a word or a group of words used in some context. This task differs across the word categories from connectives through verbs to substantives. Substantives form a special category alone. If we think about the types of meaning they could bear, we could separate them into two classes. The first one—common nouns—involves expressions which are used to describe some ideals or classes of objects. The second one—proper nouns—are used as pointers to some concrete or abstract entities. Nouns could be considered as the most important objects when building a knowledge base, which is a storage of complex information about our world and is accessible by a computer program.

Identifying the proper nouns in the text, as well as their correct meaning (disambiguation), is the key issue which we try to handle in this work. While the problem with disambiguation of common nouns is heavily dependent on a given ontology, it could present a hard problem for a computer as well as for a human. In case some pre-given ontology is used, it could be useful mostly for people or domains that accept it. The problem with ambiguity is a problem of definition of the meaning.

- Is 'game of chess' a type of 'sport'?
- Can we describe '1992 Los Angeles riots' as a 'war'?

These questions show us the type of ambiguity we can observe while handling common nouns. Do we describe 'sport' as a "competitive physical activity" (Wikipedia[13]) or as "an activity that you do for pleasure and that needs physical effort or skill" (Oxford Advanced American Dictionary)? Is war "an act of violence to compel our opponent to fulfil our will" (Carl von Clausewitz [12]) or a " state-based conflict or dyad ... [with] [a]t least 1000 battle-related deaths in one calendar year." (UCDP [10])?

The proper nouns disambiguation offers a more attainable goal. It could be more or less described as matching one particular (concrete or abstract) object in our world with a part of analysed text. The problem of ontology is a bit less harsh because there is a simple linkage between the name and the object and a well defined domain of objects. The problem with ambiguity is caused by similarity or equality of expressions describing different entities.

- "George Bush faints, then falls after choking on pretzel." (January 2002)
- "George Bush fainted at a banquet hosted by the Prime Minister of Japan." (January 1992)

In the two sentences above, we can observe the reference "George Bush" pointing to two different entities—George W. Bush and George H. W. Bush, respectively. But without the context we could only guess if the reference is related to one of the Presidents of the USA, American biblical scholar, young politician (son of Jeb Bush) or former NASCAR driver.

A successful solution of entity recognition can be used for a more sophisticated form of data indexing. Its applications

ERDC '2014 Gold Coast, Australia
ACM 978-1-4503-3023-7/14/07 ...$15.00.
http://dx.doi.org/10.1145/2633211.2634349 .

might cover improved relevance signals or snippet generation due to the matching of entities from the query with those in the documents, or dividing the search results into groups or tagging them according to the contained entities. Likewise, users could help the search engine identify the right meaning of a query by selecting or refining the set of desired entities associated with it.

In this paper, we describe our system for entity detection and disambiguation, which is being developed within the Seznam.cz company. The system is appropriately modified so as to follow the rules of the Entity Recognition and Disambiguation Challenge 2014 (ERDC). The objective is, as ERDC organizers put it, " to recognize mentions of entities in a given text, disambiguate them, and map them to the entities in a given entity collection or knowledge base."

The ERD Challenge consists of two different parts, the Short Track and the Long Track. Short Track systems are intended to search for all possible entities in texts of search queries. Long Track systems' goal is to identify particular entities occurring in short excerpts of web documents.

There are some important distinctions between those two tasks. First, queries are non-formatted pieces of texts with possibly wrong grammar and no capital letters used. Second, the ambiguity of entities in queries could not be resolved sometimes—therefore there can be more than just one solution. Third, the rules specified that for the Long Track it is needed to determine not only the occurrence but the particular position of an entity.

2. RELATED WORK

Let us summarize the existing approaches and techniques recently developed for the task of entity recognition and disambiguation (ERD), also known as entity linking. ERD systems are usually divided into three parts:

- mention identification
- collection of entity candidates for each mention
- candidates disambiguation

Usually all three parts depend on each other and are difficult to separate. The mention identification selects relevant parts of the analysed text. The relevant parts of the text are defined by the purpose why we run ERD. Mentions could be chosen based on token classes from part-of-speech tagging, named entities or entity names from a knowledge base, such as Wikipedia or Freebase, and its morphological variants.

Candidates for each mention are collected by looking up entities in a knowledge base or can be retrieved from a database created by clustering the same mention that occurs in different contexts. The candidates are then ranked or pruned.

Entity disambiguation approaches can be classified into groups depending on disambiguation strategy.

Local level disambiguation

Entities are resolved by exploiting the local context only. In [8], other mention candidates are used to disambiguate their mentions against each other. Relatedness between candidates (Wikipedia articles) and Google Distance inspired measure are computed and averaged at first. The measures take into account article incoming links for relatedness resp. outgoing links for Google Distance inspired measure. Mentions are disambiguated by taking 40% of the most related candidate pairs and the most common pairs from this group are considered entities.

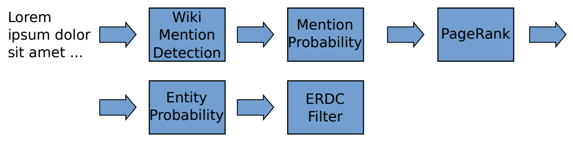


Figure 1: System configuration using several Transformers.

Document or query level disambiguation

To resolve entities, features of all candidates are used. One of the earliest work of entity linking [3] was based on similarity between document and candidate vectors (Wikipedia articles). For each candidate tf-idf vector was generated from its context and its categories. Candidate's score was computed as the similarity between document context vector and candidate vectors.

Corpus level disambiguation

Using features extracted from a corpus after entity linking is applied was proposed in [7]. Context around the same extracted entities can be grouped to global contexts to improve disambiguation in the next iteration. Expected entity count is used as a feature to detect systematic errors. There are several other approaches. One interesting example is in [9], where authors combine word sense disambiguation with entity disambiguation while utilising semantic networks.

3. OUR SYSTEM

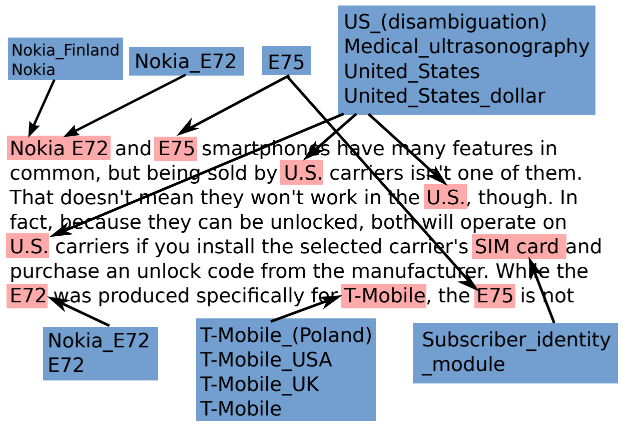
Our system for entity recognition and disambiguation is based on DBpedia entities, while we use the corresponding Wikipedia pages to estimate the entity co-occurrence measure. We then map DBpedia entities to the ERDC-specific subset of entities from Freebase.

We use a modular architecture which permits connecting various methods sequentially. It allows for quick trials using different configurations and combinations. Our basic module called "Transformer" receives a sentence object that contains the text to be annotated, detected mentions, and candidate entities. A Transformer processes the object and returns it back. For example, a Transformer for mention detection finds all mentions in the text and adds them to the object. A disambiguator assigns a score to the candidate entities. There is an example how several Transformers are connected in Figure 1. This configuration is the one we used for final evaluation. The description of its components is in the following section.

In the following subsections, we describe the two main components of the system—the mention detection and the disambiguation—and the final selection of entities to match the pre-selected subset of entities from a knowledge base—the entity snapshot.

3.1 Mention detection and candidate selection

The mention detection is based on data provided by Wikipedia. We start by collecting the labels for each entity—the name of the entity and its redirects. We get a set of alter-



Nokia_Finland
Nokia
Nokia_E72
E75
US_(disambiguation)
Medical_ultrasonography
United_States
United_States_dollar
Nokia E72 and E75 smartphones have many features in common, but being sold by U.S. carriers isn't one of them. That doesn't mean they won't work in the U.S., though. In fact, because they can be unlocked, both will operate on U.S. carriers if you install the selected carrier's SIM card and purchase an unlock code from the manufacturer. While the E72 was produced specifically for T-Mobile, the E75 is not
Nokia_E72
E72
T-Mobile_(Poland)
T-Mobile_USA
T-Mobile_UK
T-Mobile
Subscriber_identity_module

Figure 2: Sentence with mentions and entity candidates.

native names for the entity by removing terms in brackets, such as in S60_(software_platform), and tokenizing the remaining text. By reversing the mapping *entity* $\rightarrow$ *names*, we get a set of entities for the text, *mention* $\rightarrow$ *entities*.

The mention detection is restricted to such sequences of tokens that contain at least one capitalized letter, such as "eBay" or "Nokia E72". This restriction decreases recall, but highly increases precision. The mentions that consist only of stopwords are removed as well.

The text is processed sequentially, finding all the possible text mentions about entities. The length of matched text is limited to twenty words. For each mention we have a set of candidate entities that may be its target.

Tracing subsequent mentions of an entity

Besides the candidate selection described above, we also trace subsequent mentions of entities. A subsequent mention may contain only a part of the name of an entity. For example, "Richard Desmond" has a candidate entity Richard_Desmond. Later in the text, the word Desmond probably refers to Richard_Desmond as well, although the word Desmond is not mapped to Richard_Desmond.

For each candidate entity we create a set of alternative names to be recognized as this particular entity. First, we add all words from the name of the entity (except the terms in brackets at the end of the name) and their capitalized version. Then we add all possible abbreviations made from the label. E.g. for "International Olympic Committee" we create a set of labels "International", "Olympic", "Committee", "IOC", "I.O.C" and "I.O.C." If any of these labels are among already found mentions in the text after the first occurrence of the entity, we add the International Olympic Committee as a candidate entity to that mention. For example, in Figure 2, the mention E72 in the last line has two candidate entities—E72 and Nokia_E72. Nokia_E72 has been added after the processing of the mention "Nokia E72" in the first sentence. Note that if there is a word "Nokia" in the remaining text, Nokia_E72 would be listed as a candidate entity as well. It may sound illogical, but in case of a name and surname it makes sense. The score of entity added in this way is boosted even if it is already in the list of candidates.

We limited this approach to one word from the label of the entity, but it may be reasonable to use more than one. In the training texts, there is the following passage:

> *First Citizens BancShares Inc.* of Raleigh, N.C., said it plans to ... *First Citizens* also owns ...

The "First Citizens" in the second sentence clearly points to the same entity as the emphasized full name in the first sentence. To mark all subsets of words from the entity label requires too much processing time, therefore we search for only one word from the label.

After we find a mention and it is followed by a word in brackets, e.g. "Immigration and Refugee Board (IRB)", we use the word as abbreviation of the longest mention before brackets.

Here follows options we have tested, but proved unsuccessful:

- Wikipedia disambiguation pages provide alternative labels as well, but they bring too much noise in the candidate set, making the job too difficult for the disambiguation.
- Using anchor text from Wikipedia links has a similar effect as the previous case.
- When we use the words and abbreviations from the entity label to create new mentions and not only to add the entity to existing mentions, it again brought too much noise even if we filter the added mentions by their idf.
- Not applying the restriction of one capitalized letter to already found mentions, e.g. when we find "Nokia", allow finding "nokia" as well.

3.2 Disambiguation

Disambiguation assigns a score to each candidate entity. We use a threshold to discard the entities with too low a score. Our disambiguation uses three kinds of information—co-occurrence of pairs of entities, the "EntityProbability" that the mention corresponds to the entity ($P(e|a)$, where e is an entity and a is an anchor), and the "MentionProbability" that the mention detection correctly assigns the mention to the entity ($P(e|M)$, where M is mention detection from the previous section). In following sections all three components are described in detail.

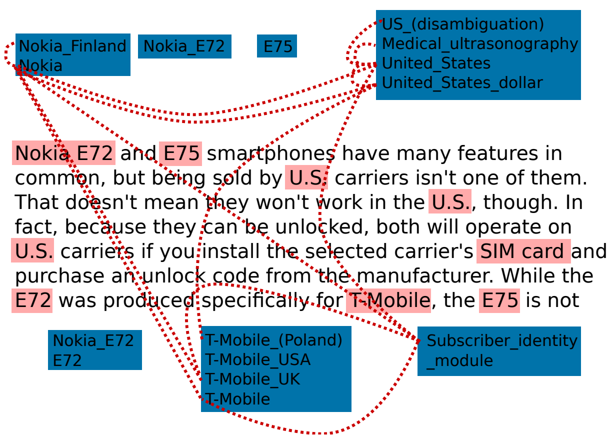
MentionProbability

MentionProbability is computed for each entity to estimate the probability that the mention found by mention detection really leads to the entity.

$$MentionProbability(e) = \frac{\#\text{ mentions found which lead to } e}{\#\text{ mentions found with candidate entity } e}$$

MentionProbability penalizes entities with otherwise commonly used names, e.g. entity 19, which corresponds to year 19 A.D., has $MentionProbability(19) = 0.0002$. On the other hand $MentionProbability(\text{GSM}) = 0.41$.

MentionProbability can be viewed as a probability of mention detection detecting the right entity.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Nokia_E72
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Subscriber_identity _module

Figure 3: Sentence linked entity candidates.

EntityProbability

EntityProbability is an a priori probability that a mention leads to an entity. It is computed from Wikipedia links and their anchors (anchor is the text of the mention).

$$EntityProbability(e|a) = \frac{\#\text{ anchors } a \text{ which lead to entity } e}{\#\text{ anchors } a}$$

For example $EntityProbability(.eu|\text{“eu”}) = 0.01$, which means that if “eu” is an anchor, it leads to entity .eu with probability 0.01. The probability of the anchor is distributed among several entities. Writing EP for $EntityProbability$:

$$EP(\text{GSM}|\text{“gsm network”}) = 0.571$$
$$EP(\text{GSM\_services}|\text{“gsm network”}) = 0.142$$
$$EP(\text{Network\_switching\_subsystem }|\text{“gsm network”}) = 0.285$$

To complete the “eu” example, $EntityProbability(\text{European\_Union}|\text{“eu”}) = 0.95$.

Using entities co-occurrences

Our disambiguation process uses a graph made of entity–mention pairs. Two nodes are linked, if they don't have the same mention and if the their entities are often used in the same context. Links between entities were extracted from Wikipedia articles—two entities are linked in one of the following cases:

1. The page of entity 1 has a link to entity 2.
2. There is a paragraph with a link to entity 1 and to entity 2.
3. The URI of the entities is the same.

These links are used to connect candidate entities in the sentence. We connect two entities if their mentions are close enough and if there is a link found in Wikipedia. In Figure 3 we can see the former example with linked candidate entities. The links to the same entity are omitted. Note that Nokia_E72 or T-Mobile_(USA) have no links other entities than self-links. The figure also illustrates possible imperfections in links structure—there is a links between T-Mobile_(Poland) and United_States_dollar, which we do not expect. Further, Nokia_E72 is not linked with Nokia.

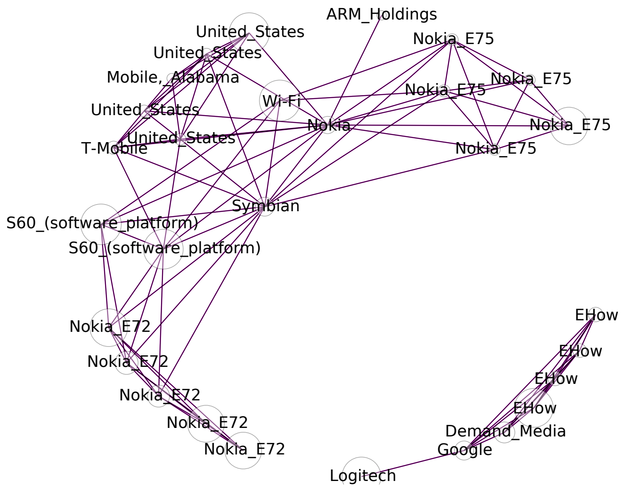

Figure 4: A sample graph of linked entities.

An example of such a graph is in Figure 4. The entities in the graph can be duplicated, as an entity can occur in more mentions. The clusters of the same entities are clearly visible as well as the connections between similar entities. We point out that the Nokia_E72 is not linked to Nokia, because there is no link on Nokia_E72 page to Nokia and they do not occur in a paragraph together. On the other hand, it is linked to S60_(software_platform) and Symbian, which are linked to Nokia. The sizes of the nodes correspond to the score the entity got. Different sizes for the same entity can happen as the entity may be in different mentions, therefore in a different context.

For disambiguation we use PageRank [2] on the graph of pairs entity-mention. The inspiration for using Pagerank for disambiguation comes from [1]. We tried several alternatives of how big the graph can be:

1. The nodes of the graph were the entities-mention found in the text.
2. Same as 1 and we add entities that are linked to at least k nodes in the graph.
3. We use the graph of all entities from knowledge base, but only the found entities emit the pagerank.

The first and the smallest version is used in our system. The other ones were much slower and provided no increase in precision.

The PageRank algorithm is modified in the following way. We want entities that are more probable candidates to emit more rank than the less probable entities, so instead of emitting a constant, entities emit their MentionProbability. In this scenario, the entity 19 would emit only 0.0002, but entity GSM would emit 0.41.

The weight of the link between the entities is omitted and we use constant damping factor. Only exception is a link between two entities with same URI, where the damping factor is halved. This weakens the “self-promotion” of the entity.

Next heuristic is to use “curvature”, proposed in [4]. The curvature is defined as follows:

$$curvature(e) = \frac{\#\text{ triangles } e \text{ participates in}}{\#\text{ triangles } e \text{ could participate in}}$$

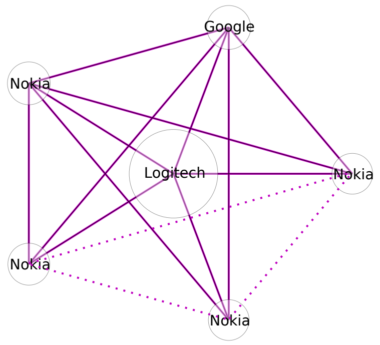

Figure 5: Graph of neighbours of Logitech with missing links dotted.

In Figure 5 is a graph of neighbours of *Logitech*. The number of triangles *Logitech* participates in is 7 and number of possible triangles is 10, so $curvature(Logitech) = 0.7$.

After the PageRank algorithm, entities has a score assigned. This score is then weighted by EntityProbability (a probability that the anchor of the mention leads to the given entity). This corresponds to "commonness" defined in [8].

There were again several dead-ends we followed:

- We tried to use some degree of the linkage between two entities, such as the relatedness [8], but the results were worse. The most probable reason behind this is that the number of entities co-occurrences is small and the weight of the link is not significant.
- The first approach we used was to create a textual context of an entity and match that context to the text around a mention. From tf-idf, through okapi, mutual information, entropy, information gain and to compression distance, none of these approaches contributed to performance of the system and they were computationally heavy.
- Another approach is to use Viterbi algorithm [11], used for named entity disambiguation in [5]. This approach performs worse than the PageRank, probably because the training data is not big enough. Viterbi algorithm finds the most probable entities in the sequence of mentions, but with a lot of mention overlaps it is not performing well.
- Apart from EntityProbability, we computed the inverse probability $P(a|e)$ as well, using it along with MentionProbability in a Naïve Bayes classifier. It did not result in any performance increase.

3.3 Mapping to Freebase entities

Entities found have to be mapped to Freebase and the results have to be limited to the entity snapshot provided by the organizers. During the steps described above we use all entities from DBpedia and we include overlapping entities. Now we need to filter out those that are not in the snapshot and leave only the longest mentions. Though it first seemed straightforward, it turned out to be a complex problem.

We often find an entity which is not in the snapshot that overlaps a mention of an entity in the snapshot. E.g. for a query "obama family tree", we find "obama", "obama family", "family tree" and "tree" as entity mentions. But entity Family_of_Barack_Obama, which is mapped to the mention "obama family", is not in the snapshot. If we discard the whole mention, we would loose the mention about Barack_Obama as well.

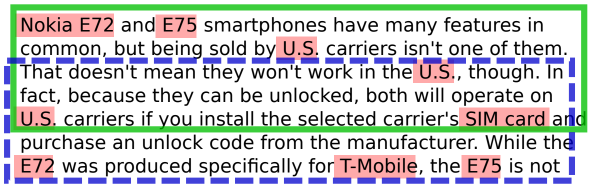
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Figure 6: Two overlapping windows of size 6.

We also encountered cases such as this: "cherry tomato seed kit". We mapped "tomato" to the entity Tomato. But Tomato is not in the snapshot, so we take the next best entity from the snapshot, which happens to be Tomato_(musician). Regarding the score, Tomato got 2.91 and Tomato_(musician) only 0.002. Therefore if the best entity from the snapshot has a score much lower than the best winning entity, we discard this mention.

Finally, the last case to solve is the following: "Symbian 9.3 series 60". Among others there are two overlapping mentions "3 series" as BMW_3_Series and "Series 60" as S60_(software_platform), but one is not a submention of the other. In this case, we take the mention longer by word count. If the number of words of mentions is equal, then we take the mention, whose winning entity has higher score. In this case, the S60_(software_platform) has a score of 2.96 and BMW_3_Series has 0.64, so the S60_(software_platform) wins.

4. PERFORMANCE ON ERDC DATA

4.1 Specifics of the Long Track system

The Long Track texts were taken from web pages, the length of the documents ranged from 100 words to over 1500. For large texts, creating the whole graph is intractable, because all pairs of entities has to be processed and the construction of such a big graph is computationally expensive. Therefore a sliding window on mentions is used—the graph is created from candidate entities of 20 mentions at a time. The overlap is 10 mentions and the score is averaged from the two windows which used the same mention. The example of the window is in Figure 6.

4.2 Our performance on the Long Track

The organizers provided us with a set of 51 documents annotated with entities. These annotations were not final, but it was a guidance to quickly estimate the performance of the system. The performance estimates from our evaluation were different from a case when we run the proper evaluation on the ERDC website. Usually, if the system improved offline, it improved online as well. The online test set used 101 documents. We use our offline metric in the following text and compare it to the online testing at the end of the section.

We started with a simple mention detection based on Wikipedia and then focused on improving the disambiguation. When the performance of disambiguation was good enough, we got back to mention detection and tried to improve its

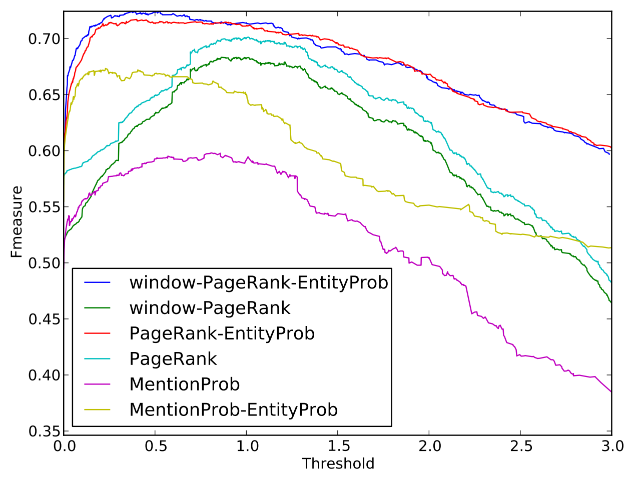

Figure 7: F-measure based on threshold for different configurations.

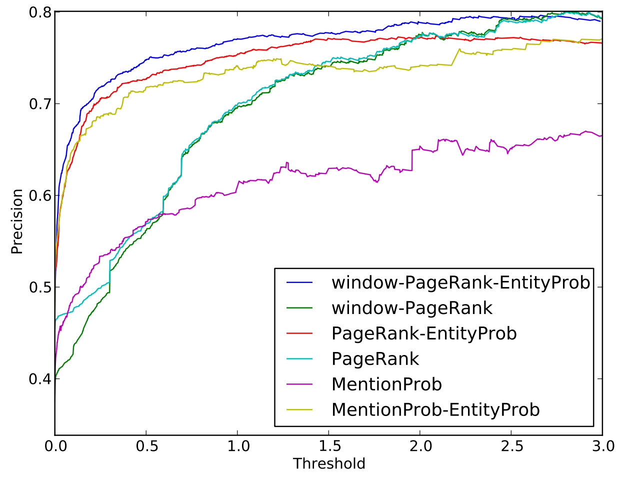

Figure 8: Precision based on threshold for different configurations.

recall by introducing the tracing entities mentions by a word from title or its abbreviation. In the following text we discuss disambiguator tuning using the mention detection we used in our final system.

First, we used a simple heuristic—using MentionProbability as disambiguation score. We got f-measure 0.5850, precision 0.5778 and recall 0.5924.

Then we weighted the score by EntityProbability and the scores improved to f-measure 0.6605, precision 0.6708 and recall 0.6505. Up to here, the time to process the 50 texts was 11ms.

The PageRank on the graph of entities was introduced, achieving f-measure 0.7235, precision 0.7538 and recall 0.6956. Using PageRank required some parameter tuning. E.g. the number of iterations is 10. If we increase it to 20, the performance is f-measure 0.7182, precision 0.7415 and recall 0.6964.

Unfortunately, the construction of the graph was too demanding and the time for processing the dataset increased to 150ms. Hence we used the sliding window described in

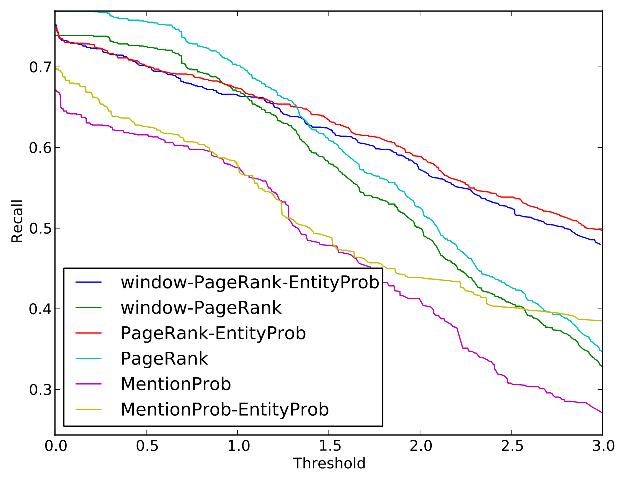

Figure 9: Recall based on threshold for different configurations.

Section 4.1. After that, the time dropped to 72ms and we did not get any timeouts from the online testing. Using the sliding window, the performance changed to f-measure 0.7272, precision 0.7671 and recall 0.6912.

Final heuristic was to use the curvature, which did not increase the processing time significantly and improved the performance to final f-measure 0.7305, precision 0.7659 and recall 0.6982.

This system configuration had f-measure 0.7509, precision 0.7796 and recall 0.7242 on the train set using online evaluation. Both the precision and the recall were considerably higher than using offline evaluation. This may be due to the fact that the rules stated that the correct annotation is when the right mention and the mention provided by the system "overlap", without further specification, but our offline evaluation required precise match.

The performance on the final testing set of was f-measure 0.7193, precision 0.7928 and recall 0.6583. Despite being much worse than the training set, it took us to third position by a hair's breadth (the fourth team had f-measure 0.7137).

There are three graphs showing f-measure, precision and recall on the vertical axis and threshold on the x axis in Figures 7, 8 and 9. Each line corresponds to a variant of our system. The threshold is used to discard all entities with lower score than the threshold. High threshold results in low recall and high precision and vice versa.

4.3 Specifics of the Short Track system

Web search queries are characteristic by its specific language and type of writing. The queries are often unformatted, it is common that they do not contain punctuation and/or diacritics and one could not expect even the right usage of capital letters. This last fact is quite important for our task, because most named entities begin with a capital letter that could simplify the mention searching.

Misspells are common as well. Resulting problems could be solved by using query correction system but for our purpose we were satisfied with expected common errors contained in mention detection data from Wikipedia.

The most important difference from the ERD for texts lies in the possible ambiguity of detected queries. It is due

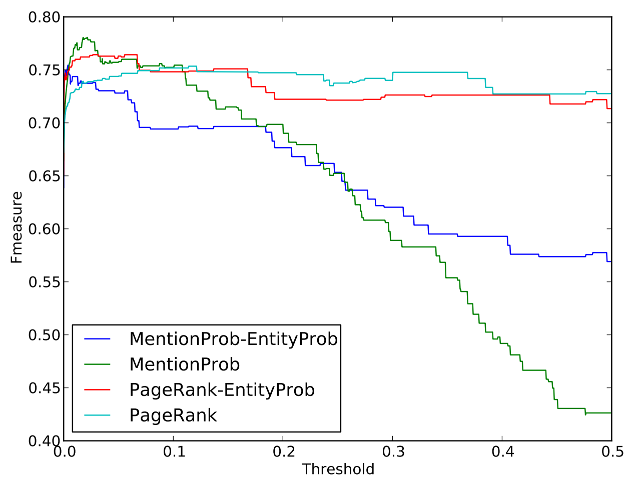

Figure 10: F-measure based on threshold for different configurations on provided test set.

to smaller extent of the given context. In these cases it is necessary to provide all possible correct disambiguations. The threshold for Short Track had to be set according this need. Apart from the threshold, we punish low score disambiguations in cases when another candidate with much higher score is present. This feature helps in cases when the context provides enough support for one of the candidates correctly striking-out the others.

We made experiments with numbers of different set ups similarly to Long Track task. However we did not encounter any problems with time complexity as the texts analysed were much shorter. The main problem during the learning process was the amount of testing examples. The organizators provided us with a set of 90 annotated queries, and similar amount (100) was used to determine quality of contending systems. This was a bit harsh, because the improvements of the system was hardly observable (e.g the number of all annotated entities for 90 queries was only 61). Similarly an improvement that was able to fix one annotation gave us almost 1% boost on f-measure (0.01). However similar improvement was not expected on bigger amount of data. Luckily the testing set used was later extended to 500 queries, which gave us another possibility to systematically improve the settings of our system without being worried about possible overfitting.

We can observe those issues (on provided small test set) in Figure 10 where even the substantial drops represents a change in only two or three queries. Another interesting case is the big difference between the absolute values of f-measure on these data and on the final test set. The change was slightly over 0.1.

The final setup we used was the same as for the Long Track, except without the sliding window, as there was not any speed issues. We were able to reach 0.6260 f-measure on regular test set and in the finals the number has improved to 0.6693.

5. CONCLUSIONS

The ERD Challenge gave us a great opportunity to enhance our work on entity recognition and disambiguation we were currently developing at Seznam.cz. A challenge of this kind always pushes the state-of-the-art performance further—let us mention the Netflix prize which accelerated research in the collaborative filtering movement.

Although this paper has not introduced any ground-breaking theoretical results, we believe that the actual performance of the system motivated by simple, logical heuristics, may inspire researchers in ERD. This contrasts with the Netflix prize, which was won by a heavy, black-box, machine learning and ensembles of classifiers. Actually, we were surprised that our system without heavy parameter tuning and machine learning performed so well.

The system described has a modular architecture that permits easy trials of different configurations and methods. There is a few dozens of options from which we chose the best combination for the challenge. This configuration was thoroughly described in the paper as well as the information how each of the component increased the performance of the system. We omitted detailed description of other components we did not use in the best model.

The lack of machine learning represents also a room for improvement. Using of large data sets like ClueWeb [6] with deep learning and statistical processing, creates a potential to bring the ERD to another level. For example, having more entities co-occurences, we may be able to use the weight of the link in the PageRank.

Also using more than one disambiguator and learning a classifier on the scores from disambiguators output is an interesting way to go. We did many attempts to make use of the textual contexts, but with no results. Using this information as a feature for a classifier should provide new information. Our preliminary trial was not successful, but we still think there is a potential.

6. ACKNOWLEDGMENTS

We would like to thank our colleagues Jiří Materna, Jiří Hroza, Václav Němčík, and Lukáš Nalezenec for their support of our work and for their help with presenting it. We would also like to thank the organizers of the ERD Challenge for a great opportunity and great organization.

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