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Report on Coupling Manual and Automatic Annotation

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Abstract

The Khresmoi project is building a multi-lingual search and access system for biomedical information and documents. The project is using automatic recognition of medical entities in text, such as Diseases and Drugs, to assist with that search. Automatic recognition of these entities is trained by manual correction of machine annotations. Manual correction proceeds iteratively. That is, an initial set of automatic annotations are corrected, these corrections are used to improve tha automatic application, this improved application used to generate further annotations for correction, and so on. Improvements are generated in two ways. In the first, an evaluation between the automatic annotations and the corrections is used to drive an error analysis, and thence improvements to application dictionaries, heuristics and grammars. In the second, manual corrections are used to provide entity features for a machine learned statistical model of the entities. Results show the approach to lead to a measurable increase in performance. Iterative improvement is ongoing, as further corrections are collected.

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1 Executive summary

- The Khresmoi project is using automatic recognition of medical entities in text, such as Diseases and Drugs, to assist with search of biomedical documents.
- Automatic recognition is trained iteratively using manually correction of automatic annotations in text.
- An initial set of automatically created annotations is presented to manual annotators for correction.
- Corrections are used to improve the performance of the automatic application.
- This improved application is then used to generate further automatic annotations for correction, and so on, iteratively.
- This report examines how manual and automatic annotation have been coupled in the Khresmoi project to improve annotation performance.
- It describes how feedback from manual annotation is used to modify automatic annotation through:
  - error analysis and the development of dictionary and heuristic based entity recognition
  - the machine learning of models of the text to assist with automatic annotation.
- A description of the process and its results are presented.

2 Introduction

The Khresmoi project is building a multi-lingual search and access system for biomedical information and documents [17]. Several technologies are used to improve search, including machine recognition of medical entities within text, and the linking of these to the Khresmoi Knowledge Base. Automatic entity recognition is coupled iteratively with manual improvement, in order to drive up performance. In summary, the process for coupling automatic and manual entity recognition is as follows:

1. an initial machine annotated corpus is created;
2. this is corrected by human annotators;
3. the machine entity recognition model is updated with these corrections;
4. the steps are repeated.

This report describes the system used for the above process, iteration of the process, and the results achieved in those iterations.

2.1 Background

Manual annotations are corrected according to a set of guidelines and management protocols, described in Khresmoi deliverable D1.1 “Manual Annotation Guidelines and Management Protocol”[5], which were themselves based on the project requirements, described in Khresmoi Deliverable D8.2 “Use case definition including concrete data requirements” [7]. An early version of the system used to create automatic annotations was described in D1.2 “Initial prototype for semantic

annotation of the Khresmoi literature" [2], and early results of the manual annotation described in D1.3 "Report on Results of the WP1 First Evaluation Phase" [1]. The final corpus of corrected annotations are collected into the Khresmoi Manually Annotated Reference Corpus, which is released as D1.4.1 with an accompanying report [6].

2.2 Summary of this report

This report starts with a description of the application used to generate automatic annotations, in the Section "Application description". This is followed by a description of the process in which manual and automatic annotation are coupled, in the Section "Iterative development process". Development iterations are then described in the remaining sections. "First iteration – improvement by error analysis" describes the initial iteration, and conclusions that were drawn and improvements made based on an error analysis of early manual corrections. "Second iteration – machine learned corrections" presents the first set of results from machine learned corrections. Finally, the Section "Ongoing iterations" describes the ongoing work to create further sets of automatic annotations for correction and feedback in to the development process.

3 Application description

The annotation software is written as a GATE application pipeline [8, 9]. The initial version of the software, as described in [6], was distributed and run on GATECloud.net [10] and equivalent systems. This initial version was developed into the version described here, in response to (a) analysis of dictionary lookup terms in the application and (b) analysis of initial manual corrections. The version described here may also be deployed via GATECloud.net, or within the Khresmoi crawling and indexing architecture. The application is still subject to development as improvements are suggested by the manual annotation. The final application will be reported by updates to this deliverable, and in future Khresmoi deliverables.

The application can be considered as a number of GATE pipelines, each of which consists of GATE "Processing Resources" (PRs), with each document being run through the pipelines and their component PRs in order. The PRs and their function are described in the table below, after which two sections detail key parts of the application, term lookup and machine learning of entities.

Pipeline	Processing resource	Description
1. Lexico-syntactic pre-processing	Tokeniser	Standard GATE tokeniser,
	Sentence Splitter	GATE regular expression based sentence splitter
	POS Tagger	GATE port of the Brill PPOS tagger
	Morphological analyser	FLEX based morphological analyser
	Stemmer	Porter stemmer
2. Content demarcation	Check document type	Checks document to see if following content PRs need to be run
	BoilerPipe	GATE wrapper for BoilerPipe HML content detector
	Content grammars	Content heuristics
3. Stop-words	Gazetteer	Mark all stop-words from gazetteer
4. Term lookup	POS Tag selection grammar	Sets flags on tokens, based on their POS, specifying whether they may be at the start, end or middle of a term
	Gazetteer: abbreviations	Look up abbreviations
	Gazetteer: root forms	Look up root forms of words
	Gazetteer: stem forms	Look up stem form of words
	Gazetteer: string forms	Look up string form of words
	Merging grammar	Merges all looked up terms into a single annotation type, UmlsLookup

	Semantic type to name mapping grammar	Add human readable names for semantic types
5. Term disambiguation	Term selection grammars	Disambiguation heuristics: (1) retain only the longest UmlsLookup, (2) then among all the longest, first select all that come from UMLS preferred labels, (3) then choose among all of those the one with the highest CUI number (see reference [4])
6. Create annotations for correction	Gazetteer	Find all UmlsLookups with semantic types that match those used in the manual annotation guidelines
	Grammars	Post process UmlsLookup annotations into the schema used by Khresmoi
7. Machine Learning	Learning mode SVM, PAUM or other	Model learning only: learn model of Khresmoi entities from manual corrections to UmlsLookups, using UmlsLookups, other UMLS information and lexico-syntactic annotations as features.
	Application mode SVM, PAUM or other	Model application only: apply the above model, using UmlsLookups, other UMLS information and lexico-syntactic annotations as features, to predict Khresmoi entities.

3.1 Term lookup: creating the gazetteers

The main data source used for the automatic semantic annotation of text within Khresmoi is the Unified Medical Language System (UMLS) [3]. Gazetteers in step 4 above were created from UMLS terms and concepts as represented in the Khresmoi knowledge base. For each concept in UMLS, the UMLS provides a unique concept identifier, or CUI. Each concept is also assigned to one of a small

number of high level semantic types, from a semantic network. The identifier of this type is known as a TUI.

A preferred label is given to each concept by UMLS, and a number of alternative labels. We refer to these as "prefLabel" and "altLabel" respectively. These form the basis of the gazetteers. As the UMLS source vocabularies are not intended for natural language processing, however, there is much noise amongst these labels. We therefore carry out pre-processing to remove this noise, in line with the methods described by [11,16]. A full description of the gazetteer term processing follows:

1. A SPARQL query was used to retrieve, from the Khresmoi Knowledge Base:
    - all prefLabels and their associated CUI URIs (instance) and direct semantic type classes (TUI URIs) where the language tag of the label was "en". This resulted in 2 399 921 retrieved rows.
    - all altLabels in the same way: 2 447 977 rows
2. After filtering so that only the direct types corresponding to TUIs relevant to Khresmoi remain:
    - prefLabel: 454 127 rows
    - altLabel: 655 490 rows
3. The labels were then filtered as follows:
    - filter out labels that contain an at (@) sign
    - filter labels that contain "not otherwise specified", "unspecified" "[NOS]" and similar
    - filter labels that contain "NEC", "not elsewhere classified", "unclassified" and similar
    - filter very short labels
4. Also, labels were changed in the following ways:
    - remove angular brackets
    - remove multiple spaces
    - remove possessives
    - remove brackets at the end
    - remove parentheses at the end
    - invert labels that have a single comma: e.g. "pain, dorsal" → "dorsal pain"

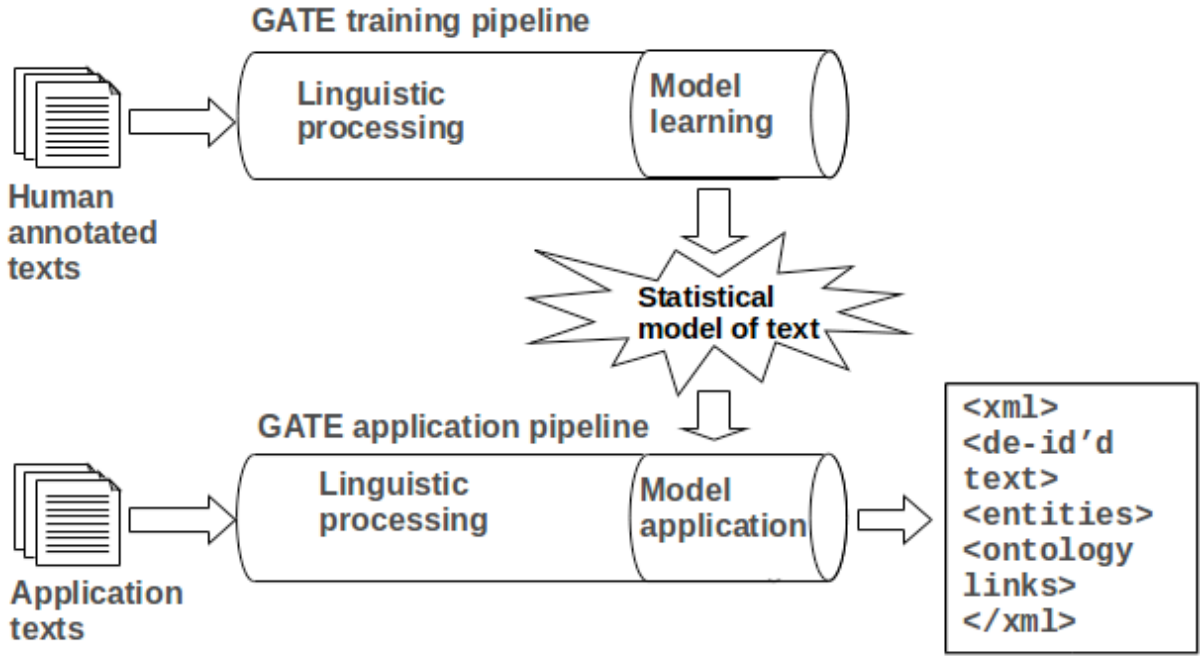
5. Then a final stage of filtering:
    - remove labels with 6 or more tokens
6. If filtered labels match a pattern for being an abbreviation, the label gets added to an abbreviation list, otherwise to a processed label (standard) list. After this we have:
    - prefLabel standard: 317 619
    - prefLabel abbreviations: 1 763
    - altLabel standard: 561 603
    - altLabel abbreviations: 12 225
7. All labels that match a list of stopwords are filtered out, after which we have:
    - prefLabel standard: 317 437
    - prefLabel abbreviations: 1 761
    - altLabel standard: 561 529
    - altLabel abbreviations: 12 172
8. After this, all labels that are not abbreviations are run through GATE, tokenised, POS tagged and stemmed and all word, number and symbol tokens are selected from the processed labels. For each original label, three new labels are created:
    - from all the original strings from the selected tokens
    - from all the roots from the selected tokens
    - from all the stems from the selected tokens
9. and from all of these, three gazetteer list files are created for each of the altLabel and prefLabel lists, giving a total of 8 gazetteer lists:
    - prefLabel, strings: 317 437
    - prefLabel, roots: 317 430
    - prefLabel, stems: 317 430
    - prefLabel, abbreviations: 1 761
    - altLabel, strings: 561 529
    - altLabel, roots: 561 512
    - altLabel, stems: 561 518
    - altLabel, abbreviations: 12 172

3.2 Machine learning of Khresmoi entities

The final stage of the Khresmoi application consists of a GATE machine learning processing resource. This operates in two modes.

In the first mode, training, the machine learning PR uses manual annotations to learn a classifier for the Khresmoi entities. The features for learning instances are provided by the prior steps of the application. In the second mode, application, the machine learning PR applies the classifier to unseen documents, constructing instances for classification from the same features used for learning the classifier.

This is shown in the following diagram, adapted from [12]:



The GATE machine learning PR provides an abstraction layer over multiple machine learning algorithms. The PR defines how instances should be constructed from text, and what should be used to define features for those instances. It also deals with mapping multi-class problems (such as the one faced with the Khresmoi entities) into a series of binary classification problems. The PR is configured by providing an XML description of the class and of instances, and a definition of the machine learning library to be used.

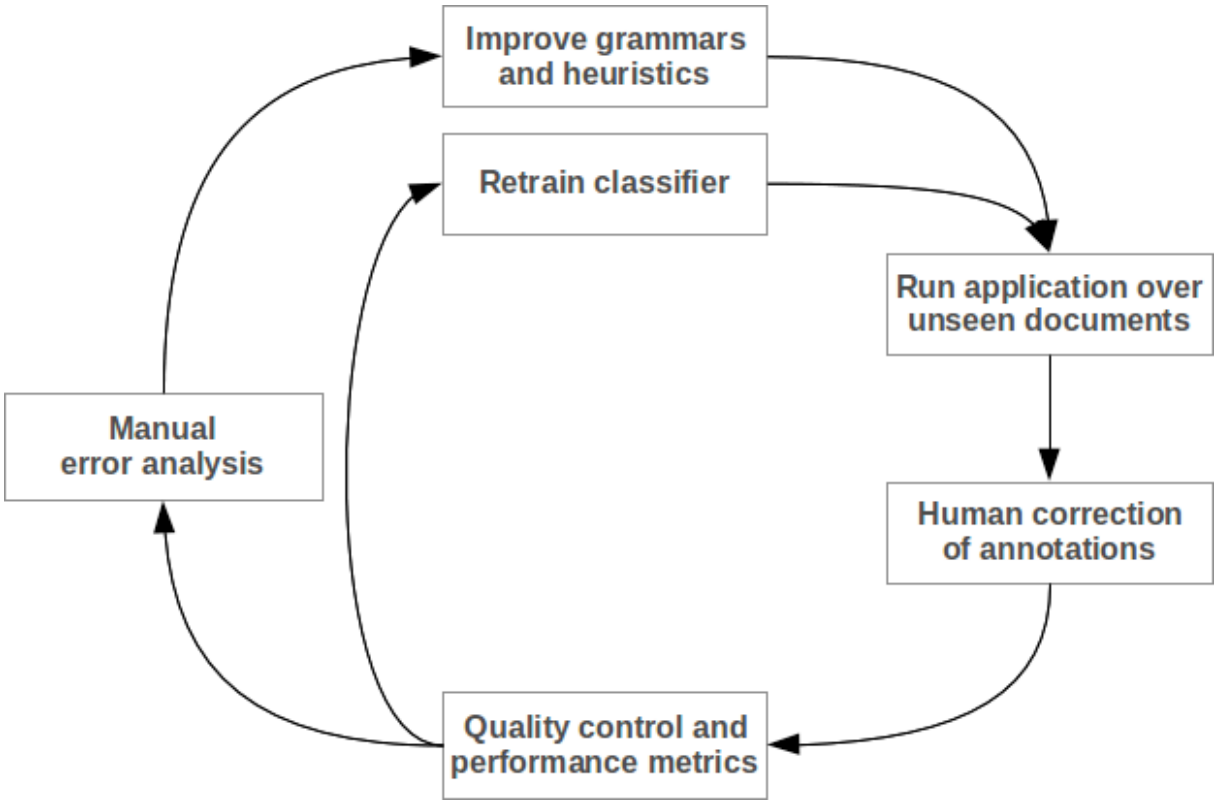
The machine learning algorithms used for experiments are the Support Vector Machine (SVM) and Perceptron implementations shipped with GATE. The precise algorithm used will be described with each set of results. Both of these algorithms may suffer from imbalanced training data, i.e. the case where tokens comprising entities are less frequent than tokens comprising non-entities. The GATE implementations allow this unevenness to be taken into account, by adjusting the margins between classes in the classifier hyperspace [13].

The features used for constructing classification instances are taken from those described in the following table, precise features will be given with each set of results. Other features may be added in the future.

Annotation providing classification instance feature	**Windowing**	**Attribute of annotation used**
Token	From -n to n tokens on each side of the entity, n reported with each set of results	String
		Part of Speech
		Root
		Orthography
UMLS gazetteer lookup	From -n to n tokens on each side of the entity, n reported with each set of results	TUI (semantic type identifier)
		CUI (concept identifier)

4 Iterative development process

Manual and automatic annotation are coupled through an iterative process. This is illustrated in the diagram below, with each step described in the text following the diagram.



Run application over unseen documents

An iteration starts by running the full application over unseen documents. Documents are selected to:

- Be representative of the full Khresmoi document set.
- Be within parameters that make them straightforward for human annotators (e.g. within certain length limits, and having contentful text).
- Reflect problems that need addressing, given the outcome of previous iterations.

Human correction of annotations

Automatically annotated documents are uploaded up to GATE Teamware [14], an annotation workflow web server. GATE Teamware allows complex annotation workflows to be executed online. These workflows may include distributed manual annotation steps, with human annotators being assigned a GATE Teamware account. In the case of Khresmoi, a workflow has three criteria:

- Which documents need annotating
- How many manual annotators should annotate each document – allowing double, treble, or greater levels of annotation.
- Which human annotators should be used for this workflow
- Whether an addition "consensus" step is required.

As annotators login, Teamware assigns documents to them, in order to meet these criteria. If a consensus step is required, then the results from individual annotators will be passed to a further annotator for reconciliation of differences.

Quality control and performance metrics

Once a batch of documents has been completed, an initial analysis is carried out to ascertain the quality of the batch. This includes measurement of inter annotator agreement, and measurement of automatic / manual agreement (i.e. precision and recall). At this stage, some documents or annotators may be rejected as outliers. If no consensus set of annotations has been created in the previous step, annotations may be combined by majority voting – i.e. an annotation will be accepted if it has been accepted by the majority of annotators.

Manual error analysis

The quality controlled batch is then analysed for differences between the automatic and manual sets, using tools from the GATE quality control suite. These include a variety of quality control measurements, together with difference viewers.

Improve grammars and heuristics

The error analysis is used to inform manual improvements to the application's grammars and heuristics. For example, quality control may show that a particular kind of UMLS term is leading to false positives. The heuristics for gazetteer filtering could be amended in response to this. As another example, quality control may show that a only the head word of particular kind of term is annotated automatically, and so grammar rules could be added to improve recognition of the whole term.

Retrain classifier

In addition to the above grammar improvement step, the corrected documents are used to retrain the entity classifier.

5 First iteration – improvement by error analysis

5.1 Description

The first iteration involved no machine learning of corrected annotations. While the application used was analogous to the non-machine learning parts of the application described above, the definition of annotations created differed, as described in D1.4.1 [6].

During this iteration, issues concerning the use of UMLS arose from an error analysis of manually corrected documents. Although UMLS is a rich source of biomedical terms, its source vocabularies were never created with natural language processing in mind. The use of UMLS for NLP is therefore problematic, and within the first iteration, this was characterised by three overlapping issues:

- High degree of term ambiguity – many terms in UMLS correspond to multiple concepts.
- Low signal to noise ratio – many terms in UMLS can only be understood in the context of their source vocabulary ("heart" for example, may refer to the concept for "mouse heart"). Many others are also ambiguous with words in general language.
- Large numbers of "non-content" terms, such as HTML menus, disclaimers etc., were annotated leading to a large number of irrelevant and false positive annotations.

These issues led to two problems with early batches used for manual correction:

1. The more annotations there are the harder it is for manual annotators to correct the annotations
2. The number of resulting annotation types makes it difficult to construct meaningful semantic search queries
3. Contentful text was sometimes swamped by non-content, making it hard for annotators to deal with.

As discussed in [1] the approach we adopted to deal with the first two problems during manual annotation is based upon work reported in [4]. Essentially whenever more than one UMLS annotation is created for the same document span only the annotation with the lowest CUI is retained. The reasoning behind this approach is that the lower the CUI, the more general the concept. Keeping only the most general concept should result in fewer annotations which still encode the same information.

The third problem was dealt with by demarcating contentful sections of text. In the application described in previous sections, this task is carried out by a GATE BoilerPipe processing resource.

5.2 Results

Corpora and results for this iteration are given in Khresmoi Deliverable D1.3 [1].

6 Second iteration – manual and machine learned corrections

6.1 Description

The application used for the second iteration resulted from changes made in response to the error analysis of the first iteration, as described in the previous section, and from changes to the gazetteers, after an analysis of gazetteer term lists and of annotated documents from earlier iterations. The application also incorporated machine learning of entities, as a way to take further corrections and feed them forward to further application improvements. These two changes resulted in the application described in the earlier Section "Application description" .

The corpus used for this evaluation consisted of the Initial Corpus described in the accompanying deliverable, D1.4.1 "Manually Annotated Reference Corpus", comprising 625 documents. As there was some change in the definitions of semantic types between this Initial Corpus, and those created by the application, the initial corpus was amended to map the manual annotations to the annotations created by the application, as follows:

1. "Content" annotations were created from "Section" annotations: the Section annotation was used from within the consensus set but if none is found there, one was used from the manual annotation sets;
2. A new annotation type UmlsLookup was created wherever there was a Problem (i.e. Diseases) or Anatomy annotation. This was carried out for manual annotation sets, consensus sets and for the original automatic pre-annotation set.

The UmlsLookup annotations (combined Problem, i.e. Diseases, and Anatomy) could then be compared to the results from the original automatic annotation, and to results from the latest automatic annotation.

For comparisons, the current application was also amended to only create semantic annotations of the same UMLS type as in the manual corpus.

6.2 Results

Results given in this section use standard definitions of Precision (P), Recall (R), and F1 measure. Two variants of each are given:

- Strict, where for two annotations to match, they must cover exactly the same document span;
- Lenient, where for two annotations to match, they must have overlapping document spans.

The Lenient measure allows us to determine how much error is due not to a failure to find an entity, but to a failure to find the correct extent of the entity (e.g. an application might miss adjectives that are commonly part of the entity label).

The first set of results compares the manual annotations from the Initial Corpus to two non-machine learning applications:

- Initial Prototype: the initial prototype application, from which manual corrections were made
- Second Prototype: the application reported in this document

The results of these evaluations are given in the following table:

Experiment	Key annotations	Response annotations	Strict			Lenient		
			P	R	F1	P	R	F1
First prototype	Manual corrections from first prototype	Automatic annotations from first prototype	0.56	0.60	0.58	0.67	0.72	0.70
Second Prototype	Manual corrections from first prototype	Automatic annotations from second prototype	0.58	0.64	0.61	0.71	0.78	0.74

The second prototype shows small gains in both precision and recall, for the UMLS semantic types present in the initial corpus. This is presumably due to the improvements in term lookup, through improved gazetteers.

The second prototype was augmented with machine learning as described in the section "Machine Learning of Khresmoi Entities" above, using the GATE Perceptron with Uneven margins algorithm (PAUM). This application was used to predict chunks where a UMLS term should be found, again training and comparing against manual corrections where all annotation types had been merged into a single type. As an initial test of the effectiveness of manual annotations in improving annotation quality, the application was evaluated over two folds with a 75% holdout. Several feature sets were evaluated, as described in the following table:

	Feature set				
	1 TOK	2 +TUI	3 +CUI	4 +THR	5 -SUR
Algorithm and options (see GATE manual for option descriptions)	PAUM -p 1 -n 10 -optB 0.3	PAUM -p 1 -n 10 -optB 0.3	PAUM -p 1 -n 10 -optB 0.3	PAUM -p 1 -n 10 -optB 0.3	PAUM -p 1 -n 10 -optB 0.3
POS, window -3 to +3	Yes	Yes	Yes	Yes	Yes
Root, window -3 to +3	Yes	Yes	Yes	Yes	Yes
Kind, -3 to +3	Yes	Yes	Yes	Yes	Yes
TUI, -8 to +8	No	Yes	No	Yes	No
TUI -3 to +3	No	No	Yes	No	Yes
CUI -3 to +3	No	No	Yes	No	Yes
Thresholds	Default	Default	Default	Changed	Default
Surround mode	True	True	True	True	False

The results of evaluations of these feature sets are given below:

Experiment	Key annotations	Response annotations	Strict			Lenient		
			P	R	F1	P	R	F1
1 TOK	Manual corrections from first prototype	Automatic annotations from second prototype with PAUM	0.89	0.59	0.71	0.98	0.65	0.78
2 +TUI			0.90	0.65	0.76	0.98	0.70	0.82
3 +CUI			0.91	0.65	0.75	0.98	0.70	0.81
4 +THR			0.91	0.63	0.75	0.98	0.68	0.80
5 -SUR			0.30	0.45	0.36	0.60	0.91	0.72

Token level features alone give greater precision and worse recall than in the non-PAUM gazetteer applications reported in the previous table. This is to be expected: the PAUM is able to generalise the context of terms, giving precision in detecting them, without the noise present in a dictionary. It does not, however, have the recall possible with a dictionary. These results are broadly similar to those reported in [15], and the literature referenced there.

Additional UMLS lookup features (experiments 2 and 3) make use of the term dictionaries in UMLS, and show some improvement in recall over token features alone, without loss in precision. The approach in these experiments has successfully combined the precision of the PAUM, with at least some of the recall of a dictionary. In general, performance is greater when combining the PAUM with dictionary lookup. Changing thresholds and algorithm surround mode makes little difference.

7 Ongoing iterations

At the time of writing, a further phase of manual annotation correction is ongoing. As batches of this correction become available, they will be handled in line with the procedures described in the Section "Iterative Development Process" described above. Given the results presented so far, and given that significant corrections have already been made to the grammars and heuristics used in the application, it is possible (and even likely), that most of the future improvements will be made by retraining the application's classifier model on the corrected documents. This improved model can then in turn be run on further documents, and these corrected in their turn.

It is expected that further iterations will lead to additional layers of complexity and granularity being added to existing annotations. For example, annotators could be asked to repeat previous tasks, but this time judge a more fine-grained semantic type assigned to annotations.

Results of applying this to the annotation application will be provided when available.

8 Conclusion

This report has described methods for coupling manual and automatic annotation of Khresmoi entities, in an iterative process, in an attempt to drive improvement in the automatic annotation. Improvements are made in two ways: manual changes to grammars and heuristics; and re-training of a classifier.

Both approaches have shown some success. Manual changes to grammars and heuristics resulted in a small improvement in both precision and recall when measured against corrected annotations. A single iteration of classifier re-training has shown that precision can be improved with no loss in recall, again when tested against the manually corrected annotations. It is our expectation that as further manual correction iterations are performed, we will continue to be able to make improvements to the application.

As further manually corrected annotations become available, it will be possible to carry out further experiments with classifier feature sets, and with greater levels of semantic detail being added to annotations.

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