









Evaluating Cross-lingual Semantic Annotation for Medical Forms

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Abstract: Annotating documents or datasets using concepts of biomedical ontologies has become increasingly important. Such ontology-based semantic annotations can improve the interoperability and the quality of data integration in health care practice and biomedical research. However, due to the restrictive coverage of non-English ontologies and the lack of comparably good annotators as for English language, annotating non-English documents is even more challenging. In this paper we aim to annotate medical forms in German language. We present a parallel corpus where all medical forms are in both German and English languages. We use three annotators to automatically generate annotations and these annotations are manually verified to construct an English Silver Standard Corpus (SSC). Based on the parallel corpus of German and English documents and the SSC, we evaluate the quality of different annotation approaches, mainly 1) direct annotation using German corpus and German ontologies and 2) integrating machine translators to translate German corpus and annotate the translated corpus with English ontologies. The results show that using German ontologies only produces very restricted results, whereas translation achieves better annotation quality and is able to retain almost 70% of the annotations.


1 INTRODUCTION


Ontologies are an established means to formally represent domain knowledge and they are used intensively in the life sciences, in particular to semantically describe or annotate biomedical documents. Such semantic annotations are helpful to improve interoperability and the quality of data integration, e.g., in health care practice and biomedical research (Hoehndorf et al., 2015). Biomedical annotations can


also enhance retrieval quality for semantic document search (Jovanović and Bagheri, 2017). For instance, PubMed¹, the search engine for MEDLINE database, uses MeSH (Medical Subject Headings) terms to retrieve more relevant results. The Text Information Extraction System (TIES)² of University of Pittsburgh utilizes concepts from the NCI Metathesaurus and their synonyms to obtain better recall of documents. Further, using the hierarchy information within the ontologies can further expand the potential matches. The TIES has been applied to retrieve clinical data of the Cancer Genome Atlas (TCGA) dataset and is able to find cases based on the semantic features of the pathology report.


Annotating data across multiple disconnected databases using concepts of the same ontologies sup-


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¹PubMed <https://www.ncbi.nlm.nih.gov/pubmed>

²TIES <http://ties.dbmi.pitt.edu>

ports improved data integration. One example is the German Biobank Alliance (GBA)³. The alliance consists of biobanks from 15 German university hospitals and two IT expert centres. The aim is to establish uniform quality standards and to make their biomaterials available for biomedical research throughout Europe. The information about the specimens, such as the diagnosis of the patients, are annotated with LOINC⁴ (McDonald et al., 2003) and ICD-10⁵ (World Health Organization, 2004) codes. A search interface that integrates these codes allows researchers to extract information across all biobanks.

We use the term cross-lingual semantic annotation task to denote the process of assigning concepts of English ontologies to text segments of non-English documents. This process is a necessity mainly because many biomedical ontologies are most well developed in English while ontologies in other languages are by far less comprehensive and do not cover as much knowledge (Schulz et al., 2013; Névéol et al., 2014b; Starlinger et al., 2017; Névéol et al., 2018 and as we will also show later in this paper). For instance, in the release version 2019AA of the Unified Medical Language System (UMLS) Metathesaurus, among the total of 14.6 million terms, 71% of them are in English, followed by 10% in Spanish. The other languages, such as French, Japanese or Portuguese, each covers less than 3% of the total term amounts. In addition, the tools for annotating non-English biomedical documents are not as well developed as tools for English documents (Jovanović and Bagheri, 2017), such as MetaMap (Aronson and Lang, 2010) or cTAKES (Savova et al., 2010). For instance, there have been efforts to adapt cTAKES for German corpora but further improvement is still needed (Becker and Böckmann, 2016). Overall, before UMLS has been adequately extended to cover its concepts in non-English and good quality annotators have been developed, cross-lingual annotation is the current way to overcome such deficiencies.

LIFE, stands for Leipzig Research Center for Civilization Diseases and conducts several epidemiological studies including LIFE Adult Study (Loeffler et al., 2015) and LIFE Heart Study (Beutner et al., 2011). The goal of LIFE Adult Study is to investigate the influence of genetic, environmental, social and lifestyle factors on the healthy state of the local population in the city of Leipzig, Germany. Since 2005, the project has recruited more than 10,000 participants. All participants took part at an extensive core assess-

ment program including structured interviews, questionnaires, physical examinations, and biospecimen collection. In this paper, we aim to annotate some of the medical forms used in the LIFE Adult Study. Since these LIFE forms are in German and we try to produce annotations as comprehensively and well-covered as possible, we decided to tackle the task as a cross-lingual semantic annotation problem.

In this study, we report different strategies to annotate German forms and also investigate the quality change of using machine translation in such annotation workflow. Our work has the following main contributions:

- 1) We manually build a parallel corpus in both English and German of medical forms used in a large epidemiological study.
- 2) We manually build a Silver Standard Corpus (SSC) that provides good quality annotations to evaluate cross-lingual semantic annotation tasks.
- 3) Based on 1) and 2), we are able to compare the annotation quality for using German ontologies on German forms versus the use of English ontologies.
- 4) We also investigate the annotation quality when using machine translation.
- 5) While questions in medical forms are typically annotated with several concepts we also consider the special case where questions correspond to a single concept. We determine a Gold Standard Corpus for such question-as-concept annotations and provide an initial evaluation for them.

In the following Section 2 we present related work on building our SSC and previous studies on cross-lingual semantic annotations. Section 3 describes firstly the parallel corpus and the ontologies we used for annotation. We then explain the methods used to build the Silver Standard and the various annotation tasks we applied to annotate non-English medical forms. In Section 4 we present the SSC. We further show the results of the various annotation tasks and compare them to the SSC. Finally, in Section 5 we summarize our findings and discuss directions for future research.

2 RELATED WORK

Silver Standard Corpus (SSC)

Building a manually annotated Gold Standard Corpus (GSC) is laborious, costly and needs human expertise. Hence, GSC can only cover a small number of semantic groups and is limited in the number of documents (Rebholz-Schuhmann et al., 2011). To overcome these shortcomings, the construction of Silver Standard Corpora (SSC) has been proposed. The term

³GBA <https://www.bbMRI.de>

⁴Logical Observation Identifier Names and Codes

⁵International Statistical Classification of Diseases: tenth revision

“Silver Standard” has been referred to corpora that are generated using several annotation tools and their outputs are then harmonized automatically (Rebholz-Schuhmann et al., 2010; Lewin et al., 2013; Oellrich et al., 2015).

The “Collaborative Annotation of a Large Scale Biomedical Corpus” (CALBC) is one of the first attempts to generate a large-scale automated annotated biomedical SSC (Rebholz-Schuhmann et al., 2010). The researchers applied four annotation tools on 150,000 MEDLINE abstracts and the resulting annotations are included in the final SSC based on their cosine similarity and at least two annotators agree on the same annotation (*2-vote-agreement*). In 2013, an English SSC was developed for the multilingual CLEF-ER named entity recognition challenge (Lewin et al., 2013). In total six annotation tools were used to generate the annotations. The annotations were chosen with a voting threshold of 3 tools and by applying a centroid algorithm (Lewin et al., 2012, 2013). Simpler methods were applied in (Oellrich et al., 2015) where *2-vote-agreement* was used as inclusion criterion by using four annotators and the annotations have to be exact or partially matched. To be able to determine the annotation quality of the cross-lingual annotation tasks, we also built an English SSC. As in previous works, we use automatic annotation tools to generate a set of annotations first. But differently, we then manually verified the generated annotations. In this way we can avoid the problem that using voting agreement for inclusion might only reveal the closeness of the tools but not necessarily the correctness of the annotations (Oellrich et al., 2015).

Biomedical Cross-lingual Semantic Annotation

The CLEF (Conference and Labs of the Evaluation Forum) has hosted several challenges on cross-lingual annotation of biomedical named entities. The CLEF-ER 2013 evaluation lab (Rebholz-Schuhmann et al., 2013) was organized as part of the EU project “Multilingual Annotation of Named Entities and Terminology Resources Acquisition” (MANTRA). The organizers provided parallel corpora including MEDLINE titles, EMEA (European Medicines Agency) drug labels and patent claims in English, German, French, Spanish and Dutch. These documents were annotated using terms from ten UMLS Semantic Groups, in both English and non-English concepts. An English SSC was also prepared by the organizers (Lewin et al., 2013). The seven systems submitted to the challenge showed high heterogeneity (Hellrich et al., 2014).

The CLEF-ER 2013 resulted in a small multilingual gold standard corpus (the Mantra GSC) that con-

tains 5530 annotations in the above mentioned five languages (Kors et al., 2015) and the QUAERO corpus, a larger GSC with 26,281 annotations in French (Névéol et al., 2014a). The QUAERO corpus was used in CLEF eHealth 2015 Task 1b (Névéol et al., 2015) and 2016 Task 2 (Névéol et al., 2016), the further cross-lingual annotation challenges. The best solution in 2015 (Afzal et al., 2015) used the *intersection* of two translators, i.e. Google Translator and Bing Translate, to expand the UMLS terminology into French. The annotations were generated by a rule based dictionary lookup system, Peregrine (Schuemie et al., 2007). The generated annotations went through several post-processing steps to reduce false positives. The challenge in 2016 used the same training set as in 2015 but took the test set provided in 2015 as the development set. The test set in 2016 was a new one, hence, the results between the two years cannot be compared directly. The winning team in 2016 (Cabot et al., 2016) used ECMT (Extracting Concepts with Multiple Terminologies) that relies on bag-of-words and pattern-matching to extract concept. The system integrates up to 13 terminologies that were translated into French.

In 2018, Roller et al. (2018) proposed a sequential concept normalization system that outperformed the winning teams in the CLEF challenges in 2015 and 2016 in most of the corpora. They use Solr to lookup concepts sequentially, i.e. the French term to be annotated is firstly searched in the French UMLS, then the English version of the UMLS and finally the term is translated into English using a self-developed neural translation model for further searching in the English UMLS. Similar post-processing procedures as in (Afzal et al., 2015) were also applied.

Most recently, Perez et al. (2019) evaluated two approaches to annotate Spanish biomedical documents with concepts in the Spanish UMLS. The first approach integrates a NLP pipeline in the pre-processing, Apache Lucene for concept indexing and a word-sense disambiguation component. The second approach uses machine translation to obtain English documents and these documents are annotated using MetaMap with the same Spanish UMLS subset but the English version. Finally, the generated English annotations are transferred back to Spanish. The combination of the results using *union* of these two approaches performed best (F-measure of 67.1%) on the MEDLINE sub-corpus in the Spanish Mantra GSC. On the other hand, Roller et al. (2018) achieved 69.1% in F-measure on the same sub-corpus.

As mentioned above, machine translators have been mostly applied to translate the ontologies into the corresponding language in the cross-lingual anno-

	Question	Associated UMLS concepts	
English	Feeling nervous, anxious, or on edge	1	C0027769 nervous
		2	C0003467 anxious
		3	C3812214 Feeling nervous, anxious or on edge
German	Nervosität, Ängstlichkeit oder Anspannung	1	C0027769 Nervosität
		2	C0087092 Ängstlichkeit
DeepL	nervousness, anxiety or tension	1	C0027769 nervous
		2	C0003467 anxious

Figure 1: An example question from the form "Generalized Anxiety Disorder" in original English, German and after DeepL translation. The associated UMLS concepts to each version of the question are also presented.

tation tasks (e.g. Hellrich and Hahn, 2013; van Muligen et al., 2013; Afzal et al., 2015). In contrast to previous work, we choose to translate the corpus but not the ontologies. This is mainly because with our parallel corpus and the advantage of having manually verified SSC, we are able to examine the impact on annotation quality of utilizing machine translators.

3 METHODS

3.1 Corpus and Ontology

The corpus used in this study includes 37 forms and 728 questions in German. These forms were used in the LIFE Adult Study (see Section 1). We selected the assessment forms that are available in multiple languages including English and German or are originally in English and have been translated into German. Hence, we can build a parallel corpus consisting of forms in both English and German. Some examples of these forms are the standardized instruments used in clinical studies such as the Patient Health Questionnaire (PHQ, Kroenke et al., 2002) and the form "Generalized Anxiety Disorder" (GAD-7, Löwe et al., 2008). Figure 1 shows an example question from GAD-7 in three different versions: English, German and the German-translated version using the machine translator DeepL (see Section 3.3 for further detail). It also presents the associated UMLS concepts for each version of the question.

The goal of the annotation task is to find as many annotations as possible per question of a form so that we can maximize semantic interoperability for our corpus. We choose UMLS Metathesaurus as ontology source and use three annotation tools, namely MetaMap (Aronson and Lang, 2010), cTAKES (Becker and Böckmann, 2016) and AnnoMap (Christen et al., 2015, 2016), to annotate the forms. UMLS integrates many biomedical ontologies. We use its version 2017AA which contains 201 source vocabularies with approximately 3.47 million concepts. For different annotation tasks we utilize dif-

ferent subsets of UMLS as explained in Section 3.3 below.

3.2 The Silver Standard Corpus

The SSC is constructed using the English corpus and the English version of UMLS. Since UMLS is very large and not all contained ontologies are relevant, we select a subset of it to optimize efficiency. In a previous study, Lin et al. (2017) compared the three annotators that we also use in this work. The results showed that cTAKES generates the best recall. Consequently, we use cTAKES to determine a subset of the UMLS that covers approximately 99% of the annotations that were found by using the entire UMLS. The subset includes 1.03 million concepts from six ontologies: 1) UMLS Metathesaurus⁶, 2) MeSH, 3) NCI Thesaurus, 4) LOINC, 5) SNOMED CT_US, and 6) Consumer Health Vocabulary. We call this subset selected UMLS subset.

We use three tools: MetaMap, cTAKES and AnnoMap to annotate the English forms with the selected UMLS subset. A detailed description and tests of the parameters of these three tools can be found in our previous publication (Lin et al., 2017). Since we will manually verify the pre-annotations produced by the automatic annotators, we set up the tools in a way that they can produce good recall but not extremely bad precision. For each annotation candidate, MetaMap computes a score considering linguistic metrics and the scores range between 0 and 1000. We use a filtering score of 700 for MetaMap, i.e. only candidates having scores of more than 700 will be included in the result set. Based on our initial study, the annotation results using a filtering score 700 also gained better F-measure than those using filtering scores 800 and 900 (which are subsets of 700). Because cTAKES tends to return many false positives, we use *longestMatch* and without *overlap* to get the best precision. With *longestMatch* setting, we allow cTAKES to return only the concept with the longest

⁶This is a subset of the UMLS Metathesaurus with the Root Source Abbreviation (RSAB) as "MTH"

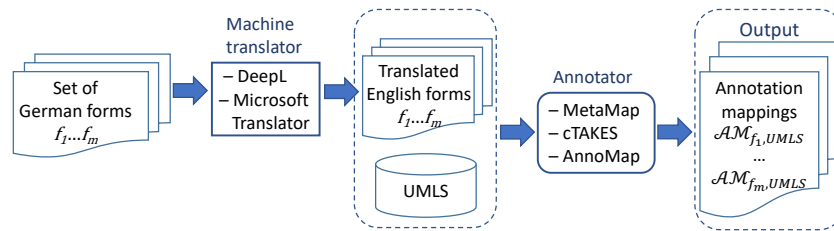


Figure 2: Workflow for cross-lingual semantic annotation using machine translators.

matched span and without *overlap* avoids the matches on discontinuous spans.

For AnnoMap, we investigate two configurations: 1) AnnoMapQuestion that uses whole questions to find matching concepts for annotation and 2) AnnoMapWindow that matches fragments of questions within a defined window size. AnnoMapQuestion constructs a similarity score from three string similarity functions: TF/IDF, Trigram and LCS (longest common substring) similarity. It retains all annotation candidates with a score above a given threshold δ . For this work we set three filtering thresholds (δ) of 0.5, 0.6, and 0.7 for the AnnoMapQuestion. AnnoMapWindow uses Soft TF/IDF to match words/phrases within a defined window size. We consider three window sizes of 2, 3, and 5 words. An annotation is kept if its Soft TF/IDF similarity is larger than 0.7. A further filtering mechanism in AnnoMap called group-based selection is also applied to improve precision (Christen et al., 2015).

The annotated results are verified manually to build the SSC. The manual verification is done by two human annotators with assistance of a GUI application for annotation selection (Geistert, 2018). An annotation is included in the SSC if both human annotators consented. For the manual selection of the annotations, we use the following principles:

1. Use the context to select the most appropriate concept: if there are several concepts assigned to the same segment of text, choose the one with the most precise description based on definition, synonym and semantic types.
2. If more than one concept fits perfectly to the same mention, keep all of those concepts: this is the case when concepts are of different but suitable semantic types. For instance, for the question "Shortness of breath" in the form PHQ, the UMLS concept with CUI (Concept Unique Identifier) C0013404 of semantic type "Sign or Symptom" and C3274920 of semantic type "Intellectual Product" are both correct and are both retained as annotations.
3. If the whole question matches to a UMLS concept, we also include concepts that match and thus annotate fragments of the question. For example, UMLS

concept C3812214 is named "Feeling nervous, anxious or on edge" and corresponds to a whole question in form GAD-7 (see Figure 1). We call such concepts questionAsConcept-type annotations (QaC-annotations) in this paper. In the manual verification process, we not only keep such concepts, but also the concepts which covers fragments of the question, e.g. the concepts C0027769 for "nervous" and C0003467 for "anxious".

We calculate the Inter-Annotator Agreement between the two human annotators using Cohen's Kappa (Cohen, 1960).

3.3 Annotating German Medical Forms

We investigate two approaches to annotate German forms. Firstly, we explore the feasibility of annotating the corpus of German forms with the German UMLS. Secondly, we investigate the annotation of machine-translated corpora with English UMLS versions. Using the SSC as the reference mapping, we are able to comparatively evaluate the annotation quality of both approaches. We note that the annotation quality is also influenced by the translation from the original English corpus to the German version. However, it is difficult to quantify this quality change due to the lack of corresponding subset of German UMLS.

Annotating German Corpus: To annotate the German corpus, we use all available German ontologies in UMLS (German UMLS). They include 1) DMDICD10 (ICD-10), 2) ICPCGER (ICPC), 3) LNC-DE (LOINC), 4) MDRGER (MedDRA), 5) MSHGER (MeSH), 6) DMDUMD (UMDNS) and 7) WHOGER (WHOART). Since cTAKES and MetaMap are designed to annotate English corpora, we use AnnoMapQuestion to annotate the German corpus. The annotations found by AnnoMapQuestion are verified manually to obtain only correct annotations. Further, we use the same method and the same seven ontologies but in English (German UMLS in English) to annotate the parallel English corpus to produce comparable results as to the German corpus.

These annotations are also manually verified.

Annotation using Machine Translated Corpora:

Figure 2 shows our workflow for cross-lingual annotation using machine translators. We translate the German forms using machine translators and annotate the translated forms using the English UMLS. To be comparable, we use the same method to annotate the translated corpora as for the SSC, i.e. use selected UMLS subset as ontologies and the three annotation tools with the same parameter settings.

For the selection of suitable machine translators, we first randomly selected 50 questions from our German corpus and translated them into English using five machine translators: DeepL⁷, Microsoft Translator⁸, Google Translate⁹, Yandex¹⁰ and Moses¹¹. We manually checked the translated results. The translators that produced the best translations of a question (most similar to the original English text) was graded with one point. Finally, we selected the best two translators with the highest number of points for further experiments. They are DeepL and Microsoft Translator.

Lin et al. (2017) showed that combining annotations generated by three annotators using *2-vote-agreement* (at least found by two of the three annotators) can obtain better F-measure than using single tools. Hence, we combine the results from MetaMap, cTAKES, AnnoMapQuestion and AnnoMapWindow using this method. Further, combining annotation results using *union* can improve recall. Hence, we further combine the results from the annotators using *union* to see how many correct annotations are retained after translation. In addition to combining the results from the tools, the results from using different translators can also be combined. For example, Afzal et al. (2015) took the *union* of concepts translated by both Google Translate and Microsoft Bing to achieve good recall for annotating the QUAERO corpus. Similarly, we will consider the combination of DeepL and Microsoft Translator results using *union*.

3.4 QuestionAsConcept-type Annotations

QaC-annotations can be very useful for data integration applications. For example, to compare the results of the same question/questionnaire from different research studies, the annotations can be applied in the

⁷<https://www.deepl.com/translator>

⁸<https://www.microsoft.com/en-us/translator/>

⁹<https://translate.google.com>

¹⁰<https://translate.yandex.com>

¹¹<http://www.statmt.org/moses/>

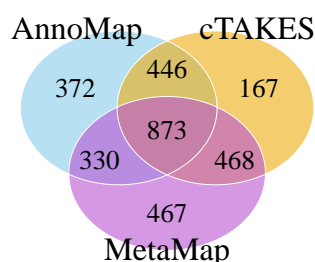


Figure 3: Number of annotations generated by each annotator in the Silver Standard Corpus. The result of AnnoMap is the *union* of the results of AnnoMapQuestion and AnnoMapWindow.

item matching process. Furthermore, cross-country comparisons can also be possible if questions of different languages can be mapped to the same UMLS concept. Therefore, we manually built a Gold Standard Corpus consisting of questionAsConcept-type of annotations. We first identified the forms that have such concepts in UMLS based on the AnnoMap results in the SSC. We then used keywords of the questions to search the correct QaC-annotations in the UMLS UTS Metathesaurus Browser¹². The questions with QaC-annotations were included in the GSC. We then evaluate how the annotators perform on finding such QaC-annotations. We again use the same way we pre-annotate the SSC to annotate these questions and only the QaC-annotations are counted as true positive. Further, we also investigate the annotation quality with machine translators using the same methods mentioned in Section 3.3.

4 EVALUATION

4.1 The Silver Standard Corpus

In total 12,551 unique annotations are found by three annotators and eight different settings, i.e. same annotation found by several annotators or with different settings are counted as a unique annotation. From those, we identified 3,123 manually verified annotations as the Silver Standard. The Inter-Annotator Agreement (IAA) between the two human annotators is 93.9 Kappa. Since the annotation principles are concise and the human annotators only have to decide if an annotation is correct or not (dichotomous), the IAA is relatively high. Figure 3 presents the contribution of each annotator in the SSC where the result of AnnoMap is the union of AnnoMapQuestion and

¹²UMLS Terminology Services <https://uts.nlm.nih.gov/metathesaurus.html>

Table 1: Annotating German corpus and the original English forms using different UMLS subsets. The annotations are generated by AnnoMapQuestion with $\delta = \{0.5, 0.6, 0.7\}$ and then manually verified. German UMLS contains all available German ontologies in 2017AA UMLS. German UMLS in English are the same ontologies as in German UMLS but the English version. The selected UMLS subset is the subset of UMLS that used to build SSC. Hence, the results in the last row equates to the results of SSC.

Corpus	UMLS subset	No. of concepts in ontologies	No. of annotations
German	German UMLS	111,079	81
Original English	German UMLS in English	604,452	249
Original English	selected UMLS subset	1,031,097	395

AnnoMapWindow. In total, MetaMap contributes the most (2,138 annotations) while cTAKES the fewest (1,954 annotations) to the SSC. More than one-fourth of the annotations in SSC are found by all three tools (873 annotations, 28.0%). Importantly, approximately one-third of the annotations are only found by single tools (1,006 annotations, 32.2%). These annotations would have been missed out if a *2-vote-agreement* was applied for the inclusion in the SSC. Notably, MetaMap, which is designed for annotation tasks using UMLS, is able to find 467 annotations that are not found by the other two tools.

Figure 4 shows the number of annotations found by each annotator in the SSC with respect to the number of words of the found annotations. The number of words of an annotation is calculated by averaging the number of words of its concept name and all its synonyms. The annotations found by MetaMap are mostly consisting of less than 2 or 3 words and it can not find any annotations that are longer than 5 words. The reason of not finding longer annotations is because MetaMap splits the input text into phrases first and these phrases are the basic units for the annotation generation. cTAKES is able to find annotations longer than 5 words but relatively few. The results of AnnoMapWindow on the distribution of number of annotations against annotation length is similar to those of cTAKES but AnnoMapWindow is able to find more annotations longer than 5 words. In contrast, AnnoMapQuestion generates few short annotations but contributes the most for the annotations with 5 or more words due to its focus to annotate entire questions.

4.2 Annotating German Corpus

In this section we investigate the annotation results of the German corpus using German UMLS and compare them to the results from the parallel English corpus. Table 1 shows the number of concepts in the different UMLS subsets and the number of manually verified annotations. In total, 81 correct annotations are obtained when the 37 German forms are anno-

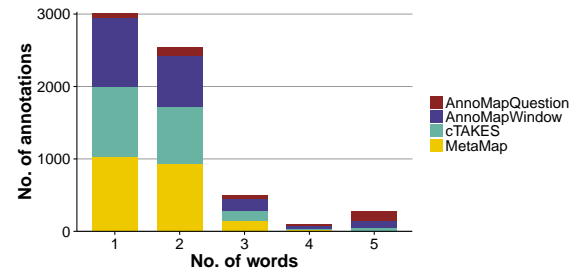


Figure 4: Number of annotations generated by each annotator for different number of words of the annotations in the SSC. Note that no. of words = 1 in x-axis represents the average word number less than 2 and no. of words = 2 represents the average word number larger than 2 but less than 3 and so on. No. of words = 5 includes all annotations with average word number larger than 5.

tated using all UMLS ontologies that are available in German (German UMLS). Using the same UMLS ontologies but in English (German UMLS in English) to annotate the English corpus produces 249 correct annotations, i.e., about three times as many as for the German corpus. This is because the German UMLS version contains much fewer concepts (111,079) than those in English version (604,452) despite the restriction to the same set of seven ontologies. Similarly, German version has only 1/7 number of entries as in the English version (217,171 vs. 1,463,453). For instance, the German version of MeSH is translated from the English version. The main keyword of each concept is 1:1 translated but the number of synonyms differ in two languages. Further, many of the descriptions, references and definitions are not translated from the original version (DIMDI, 2019). A further observation is that the German annotations are mostly short concepts with one or two words and do not include any QaC-annotations. It indicates that such concepts do not exist in the German UMLS, as opposed to the results we see from the respective English UMLS.

We also annotated the English corpus using the selected UMLS subset that was used to build the SSC. Using this subset, we obtained 395 correct annotations. This number reveals that the respective

Table 2: Annotation quality by using the translated corpora, DeepL and Microsoft Translator (MT). The results of MetaMap are obtained using filtering score of 700. The AnnoMapWindow (AnnoMapW) results are from three window sizes 2, 3 and 5 and the AnnoMapQuestion (AnnoMapQ) results are from three similarity thresholds, i.e. $\delta = \{0.5, 0.6, 0.7\}$. The results of SSC (in gray) are also presented for comparison. In addition, the annotation quality of the combination of tools using 2-vote-agreement (2VoteAgree) and *union* are shown as rows and that of the combination of both translators (*union*) are shown in column.

Annotator	Precision				Recall				F-Measure			
	SSC	DeepL	MT	<i>union</i>	SSC	DeepL	MT	<i>union</i>	SSC	DeepL	MT	<i>union</i>
MetaMap	57.2	26.3	24.9	22.7	68.5	40.5	38.9	45.1	62.3	31.9	30.4	30.2
cTAKES	41.5	18.3	16.9	15.9	62.6	36.9	35.7	42.7	49.9	24.5	23.0	23.1
AnnoMapW	23.9	9.5	9.3	8.0	62.6	35.2	32.6	41.5	34.6	15.0	14.4	13.4
AnnoMapQ	36.8	14.3	12.0	11.8	12.6	6.1	4.8	7.5	18.8	8.5	6.9	9.2
2VoteAgree	59.3	25.6	23.7	22.7	71.1	40.0	38.2	46.6	64.7	31.3	29.3	30.6
<i>union</i>	24.9	10.6	10.1	9.3	100.0	58.0	54.1	68.3	39.8	17.9	17.0	16.4

German UMLS subset in English (German UMLS in English) lacks many of the most relevant ontologies, such as NCI Thesaurus or SNOMED CT_US. Therefore, it is crucial to include all ontologies in UMLS that are relevant for a given annotation task.

4.3 Using Machine Translators

In this section we report the annotation results of using the two selected machine translators, DeepL and Microsoft Translator. DeepL, which produced the best translation result in the machine translator selection process, also performs better than Microsoft Translator (Table 2). Annotating using DeepL translated corpus results in better precision and recall and consequently also the F-measure is better. This indicates that using only a small amount of translated samples (in our case, 50 questions) can already determine the suitability of a translator. (Methods described in Section 3.3).

By translating the German corpus into English and annotate them using the English UMLS, we are able to find more correct annotations than by annotating the German forms directly using the German UMLS. In contrast to the 81 annotations found using German corpus by AnnoMapQuestion (reported in Section 4.2), translating the German forms using DeepL and Microsoft Translator, AnnoMapQuestion obtained 190 and 150 correct annotations, respectively (data not shown). Combining the results from different tools using 2-vote-agreement on the results from original English corpus (SSC in Table 2) improves precision, recall and F-measure of single tools. The best single tool result is generated by MetaMap with F-measure of 62.3% while 2-vote-agreement is able to achieve 64.7%. Interestingly, this is different for the translated corpora where MetaMap alone produces slightly better results than the combina-

tion 2-vote-agreement. The best F-measure for translated corpora is obtained by MetaMap using DeepL (31.9%) and that of the 2-vote-agreement is 31.3%.

The recall results of the row *union* in Table 2 shows how many annotations are retained from all tools after translation. In total, 58.0% of the annotations in SSC are retained using DeepL and 54.1% by using Microsoft Translator and even 68.3% if we take the union for the two translators. This is a very promising result and substantially better than using only one of the annotators or only one of the translator tools (e.g. MetaMap using DeepL is restricted to a recall of 40.5%).

The precision results (and as a consequence the F-measure results) in Table 2 are relatively low when using the translated forms. However, this is of less importance if we apply a manual selection and verification of the automatically found annotation candidates as we did in building the SSC. With such a manual verification, we can ideally achieve a precision for the translated corpora of 100%. In combination with the recall of 68.3% this would result in a F-measure of as good as 81.2%.

4.4 QuestionAsConcept-type Annotations

Finding questionAsConcept-type of annotations is of highest priority in terms of meta-analysis or data integration across multiple databases. We built a Gold Standard Corpus that contains 205 questions and 214 QaC-annotations. Since QaC-annotations are defined to map a whole question, there is deviation in the number of questions and the number of annotations in the GSC. The main reason is that there are multiple QaC-annotations that are of different but suitable semantic types mapped to the same questions.

We then examine the three annotators for their

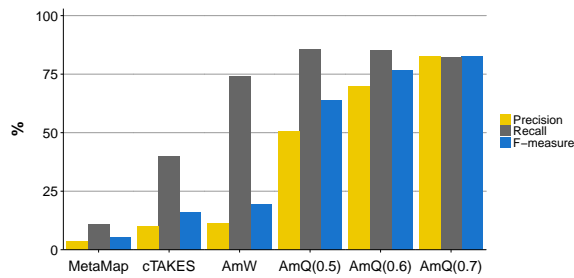


Figure 5: Annotation quality of three annotators for QaC-annotations using original English corpus. MetaMap is with filtering score of 700. AmQ denotes the annotator AnnoMapQuestion and the numbers in the parentheses indicate the threshold δ used in post-processing. AmW refers to AnnoMapWindow.

ability to find such annotations. Figure 5 shows the results. AnnoMapQuestion is the most suitable tool to find annotations that have longer text. With the increase of the threshold δ from 0.5 to 0.7, the precision improves significantly (from 50.8% to 82.7%). On the other hand, the recall results do not vary much, with 85.6% using $\delta = 0.5$ and 82.3% using $\delta = 0.7$. As a consequence, the best F-measure, 82.5%, is achieved using $\delta = 0.7$. AnnoMapWindow is able to find 159 QaC-annotations (74.0% recall) while cTAKES only found 86 (40.0% recall). Since MetaMap can only annotate short phrases, it only found 23 QaC-annotations (10.7% recall).

We also investigate the annotation quality on QaC-annotations if machine translators are involved. Since AnnoMapQuestion is the most suitable tool, we report only the best results from it, i.e. with $\delta = 0.7$ (Figure 6). Again, the results using DeepL are better than those of Microsoft Translator. Translation has more impact on recall than on precision. This might be explained by the fact that even with AnnoMapQuestion that already considers similarity measures such as trigram, TF/IDF and a LCS (Longest Common Substring) (Christen et al., 2015), the change of the wording and the sequence of the words after translation hinder the annotator to find the correct match. Many true positives have become false negatives. Using DeepL alone, we are able to retain only 26.5% recall. Even by combining the Microsoft Translator results, the recall of the *union* can only reach 30.7%.

4.5 Result Summary

The presented evaluation showed that the three considered annotator tools are able to find both concepts for short phrases (i.e. using MetaMap, cTAKES and AnnoMapWindow) and also concepts that annotate

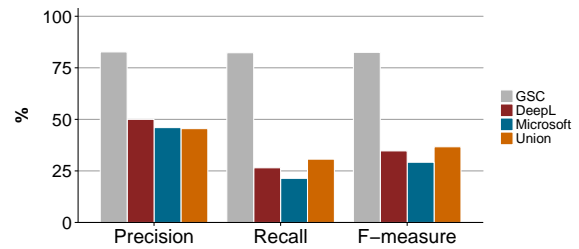


Figure 6: Annotation quality of QaC-annotations using translated corpora from DeepL, Microsoft Translator and the *union* of them. The results of using original English corpus (GSC) is also shown for reference. Used annotator is AnnoMapQuestion with $\delta = 0.7$.

whole questions (using AnnoMapQuestion). Based on a parallel corpus and the determined SSC, we could evaluate the annotation quality of different annotation approaches. We investigated two possible ways to annotate the German forms, i.e. 1) direct annotation using German UMLS ontologies and 2) integrating machine translators into annotation workflow. Due to the current restriction on the coverage of UMLS in other languages than English, direct annotations using the original non-English corpus can only produce very restricted results. The cross-lingual annotation approach provides two advantages. Firstly, it gives the possibility to use the English version of the UMLS, which is much more comprehensive than in other languages. Secondly, one is able to apply many annotators as most of them are designed to annotate English corpora. This is a better option than using just the non-English UMLS, as we have shown in this study. With translation, we are able to obtain a recall of 68.3%. This indicates an F-measure of 81.2% is possible using machine translators.

5 CONCLUSIONS

In this study we present a parallel corpus of medical forms used in epidemiological study or clinical investigations. We use three annotators to automatically generate annotations first and then manually verified them to build an English SSC. The obtained annotations in the SSC have been integrated into the LIFE Datenportal¹³ and will be used to enhance the search function in the future. For future work, we seek to develop further methods to improve the annotation quality on such cross-lingual annotation tasks. As we have shown in this study, due to translation the paraphrase of the questions significantly decreases the chance of annotators to find the correct concepts. We will there-

¹³<https://ldp.life.uni-leipzig.de>

fore include additional semantic matching mechanism to enhance matching probability and hence to obtain even better recall and good precision.

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