Enhancing Cross-lingual Semantic Annotations using Deep Network Sentence Embeddings

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Abstract: Annotating documents using concepts of ontologies enhances data quality and interoperability. Such semantic annotations also facilitate the comparison of multiple studies and even cross-lingual results. The FDA therefore requires that all submitted medical forms have to be annotated. In this work we aim at annotating medical forms in German. These standardized forms are used in health care practice and biomedical research and are translated/adapted to various languages. We focus on annotations that cover the whole question in the form as required by the FDA. We need to map these non-English questions to English concepts as many of these concepts do not exist in other languages. Due to the process of translation and adaptation, the corresponding non-English forms deviate from the original forms syntactically. This causes the conventional string matching methods to produce low annotation quality results. Consequently, we propose a new approach that incorporates semantics into the mapping procedure. By utilizing sentence embeddings generated by deep networks in the cross-lingual annotation process, we achieve a recall of 84.62%. This is an improvement of 134% compared to conventional string matching. Likewise, we also achieve an improvement of 51% in precision and 65% in F-measure.

1 INTRODUCTION

Semantic annotation using ontology concepts plays an important role in data integration. The US Food and Drug Administration (FDA) and the Clinical Data Interchange Standards Consortium (CDISC) have jointly developed a series of study data standards. Since 2016, the submissions to FDA, such as new drug applications or biologics license applications have to comply with CDISC standards (FAD, 2017). Among them, the semantic annotation of any submitted medical form is also compulsory. These study data standards help the FDA to receive, process and review submissions more efficiently. Further, they also enable the FDA to explore many research questions by combining data from multiple studies. The submitted forms shall be annotated using concepts in the Study Data Tabulation Model Controlled Terminology (SDTM-CT). The SDTM-CT is part of the CDISC standards and is maintained and distributed as part of the NCI Thesaurus. This terminology covers a large set of medical forms used in clinical studies, for instance, the Epworth Sleepiness Scale (ESS) Questionnaire and the St. George's Respiratory Questionnaire (SGRQ). In SDTM-CT, a unique NCI concept is assigned to each question of these forms. We refer to this type of annotations as Question-as-Concept (QaC) annotations, i.e., the whole question is mapped to corresponding concepts in the ontology.

In this study, we are aiming at identifying QaC-annotations of medical forms but in a cross-lingual setting. We use the term *cross-lingual semantic annotation* to indicate the process of annotating non-English documents using English ontology concepts. This is especially a necessity for QaC-annotations as to the best of our knowledge, there exists no such concepts in other languages. Not only the submissions to the FDA but also clinical or epidemiological studies might use such medical forms in different languages. Annotating these forms using the same English concepts provides a stepping stone for cross-country comparisons. Figure 1 shows examples of such cross-lingual semantic annotations.

To ensure that multilingual versions of such standardized forms can obtain conceptually equivalent results, it is generally necessary to apply some cul-

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Question 1

OE	Poor appetite or overeating
DE	Verminderter Appetit oder übermäßiges Bedürfnis zu essen
GO	Decreased appetite or excessive need to eat

Associated UMLS concepts

CUI	Concept Name	Form
C2706943	Poor appetite or overeating in last 2W.presence:^Patient:Ord:Observed	PHQ-9
C2706945	Poor appetite or overeating in last 2W.frequency:Patient:Ord:Observed	PHQ-9
C2707461	Poor appetite or overeating in last 2W.presence:^Patient:Ord:Reported	PHQ-9
C2707462	Poor appetite or overeating in last 2W.frequency:^Patient:Ord:Reported	PHQ-9

Question 2

OE	Tension
DE	Anspannung
GO	Tension

CUI	Concept Name	Form
C3639361	Tension	BPRS-A
C4086709	Tension	PANSS
C3640479	Tension	HAMA

Figure 1: Cross-lingual annotation examples of two questions of medical forms. On the left, the original English questions (OE), their German version (DE) and their translations using Google Translate (GO) are listed. On the right, the mapped UMLS concepts are shown. In UMLS, each concept is assigned with a CUI (Concept Unique Identifier).

tural adaptation and validation for a certain language and/or a specific population. For instance, the Generalized Anxiety Disorder-7 (GAD-7) is a GAD screening form consisting of seven questions. Since the publishing of GAD-7 (Spitzer et al., 2006), it has been translated and adapted/validated into Portuguese (Sousa et al., 2015) for the European Portuguese population, into German for the German general population (Löwe et al., 2008), into Spanish for the people in Spain (García-Campayo et al., 2010) and into Chinese for people with epilepsy (Tong et al., 2016). The adaptation might result in further modifications on the translated versions that can complicate the cross-lingual annotation process.

Our previous study (Lin et al., 2020) shows that using conventional string matching approaches to find QaC-annotations for non-English medical forms is a challenging task. The unsatisfactory matching results can source from two factors. Firstly, due to the translation from English to target language and the cultural adaptation, the English and non-English versions can vary in formulation and wording. Secondly, to be able to annotate the German forms using concepts in English, we apply machine translators to translate these forms into English. This translation also increases the deviation from the original questions. As a result, the translated English questions were not identical but rather paraphrases of their original questions. This can lead to low annotation quality when using string matching methods such as N-grams, TF/IDF or LCS (longest common substring). One intuitive solution towards this problem is to use semantic matching instead of conventional string matching as either cultural adaptation of the forms or the translation between different language versions shall ideally still retain the semantics of the original question.

In this study, we propose the use of deep network language models to encode the questions in the medical forms and use these sentence encodings to generate semantic annotations. The deep network extracts the semantic features of the input sequence and embeds it into a vector, a so-called sentence embedding. The current state-of-the-art deep network in natural language processing (NLP) is the language model BERT (Bidirectional Encoder Representations from Transformers, Devlin et al., 2018). Using the contextual embeddings generated by BERT and its variants such as RoBERTa (Liu et al., 2019) and ALBERT (Lan et al., 2019), many models have achieved best results in NLP tasks (examples see GLUE[1] and SuperGLUE[2] benchmarks). This includes the Semantic Textual Similarity benchmark (STSb, Cer et al., 2017) task, the most related task to this study. The goal of STSb is to assign scores for a pair of sentences based on their similarity. The training and fine-tuning of such models is computationally expensive and requires large dataset. For instance, Conneau et al. (2019) suggests that a few hundred MiB of text data is usually a minimum for learning a BERT model. Since our dataset size is limited, we selected existing pretrained and already fine-tuned models to apply to our task. This study has the following main contributions:

1) We manually build a parallel corpus in both English and German of medical forms.
2) We manually build a Gold Standard Corpus (GSC) to enable annotation quality evaluation.
3) We propose two workflows using deep network sentence embedding generation models for cross-lingual annotation.
4) We analyze the main factors in the proposed workflows and give recommendations on best practice.
5) We further improve the annotation quality by combining results using intersect and union.

[1] General Language Understanding Evaluation https://gluebenchmark.com

[2] SuperGLUE https://super.gluebenchmark.com/leaderboard

2 BACKGROUND AND RELATED WORK

Biomedical Cross-lingual Semantic Annotation. The Conference and Labs of the Evaluation Forum (CLEF) has hosted cross-lingual annotation challenges on biomedical named entities in 2013, 2015 and 2016. The CLEF-ER 2013 evaluation lab (Rebholz-Schuhmann et al., 2013) resulted in two multilingual gold standard corpora (GSC): the Mantra GSC (Kors et al., 2015) containing 5530 annotations in five languages and the QUAERO corpus (Névéol et al., 2014), a larger GSC with 26,281 annotations in French. However, since these corpora do not contain QaC-annotations, we have to build our own GSC in this study. The QUAERO corpus was used in the following two cross-lingual annotation challenges: the CLEF eHealth 2015 Task 1b (Névéol et al., 2015) and the 2016 Task 2 (Névéol et al., 2016). The winning team in 2015 (Afzal et al., 2015) uses the intersection of two translators to expand the UMLS terminology into French. They apply a rule-based dictionary lookup system to generate the annotation candidates that are further post-processed to reduce false positives. The best team in 2016 (Cabot et al., 2016) incorporates bag-of-words and pattern-matching to extract concepts. In 2018, Roller et al. (2018) propose a sequential concept normalization system which uses Solr to lookup French and English concepts sequentially and use the same post-processing as in (Afzal et al., 2015). Their system outperform the winning teams in the previous CLEF challenges. The above mentioned studies all focus on annotating biomedical name entities but not questions in the medical forms.

Lin et al. (2020) propose two workflows for cross-lingual annotation of non-English medical forms, in their case, in German. The first workflow annotates the German forms using all available German ontologies in the UMLS. The second workflow uses machine translators to translate the German forms into English and use three conventional string matching annotators: MetaMap (Aronson and Lang, 2010), cTAKES (Savova et al., 2010) and AnnoMap (Christen et al., 2015) to identify annotations. Compared to the second workflow, the first workflow produced very limited amount of annotations mainly due to the scarcity of German concepts in the UMLS compared to the English ones. By combining the three annotator results using union, they achieved a recall of 68.3% of their silver standard corpus. They also investigated the annotation quality of QaC-annotations using AnnoMap. On annotating original English forms, AnnoMap obtains 82.7% on precision, 82.3% on recall and 82.5% on F-measure. The annotation quality dropped significantly when annotating translated forms: 49.1%, 26% and 34% on precision, recall and F-measure, respectively. Hence, we seek to improve these results in this current study by incorporating deep networks such as BERT and its variants. In the following, we briefly describe the related models used in this study.

BERT and Its Variants. BERT is composed of multi-layer bidirectional Transformer encoders based on the Transformer implementation in Vaswani et al. (2017). It is pretrained using two methods: 1) masked language model (MLM) objective and 2) next sentence prediction (NSP). During MLM, some percentage of the input tokens are masked at random and the model learns to predict those masked tokens. The NSP task helps BERT to understand the relationship between sentences such as in Question Answering (QA) and Natural Language Inference (NLI) tasks. The corpora used for pretraining are the BooksCorpus (800M words) (Zhu et al., 2015) and the English Wikipedia (2,500M words). BERT was released as two sizes: the BERT$_{\text{base}}$ consists of 12 Transformer layers and the BERT$_{\text{large}}$ has 24 layers.

The authors of RoBERTa (Robustly optimized BERT approach, Liu et al., 2019) propose an altered pretraining on BERT resulting in a better performing model. The new approach comprises modifications such as using dynamic masking, removing the NSP objective and using larger mini-batch size. However, the largest gain in performance of RoBERTa is due to an extensive training data expansion (use 160GB instead of 13GB) and training for more steps. RoBERTa achieves a Pearson-Spearman correlation of 92.4 on STSb, an improvement of 2.4 over BERT$_{\text{large}}$. Based on BERT, RoBERTa has also two model sizes: RoBERTa$_{\text{base}}$ and RoBERTa$_{\text{large}}$.

Opposite to RoBERTa that aims to gain better performance through more pretraining, DistilBERT (Sanh et al., 2019) focuses on producing a light-weighted version of BERT without losing too much performance. As in RoBERTa, DistilBERT also uses dynamic masking, a large batch size and removes the NSP task during the pretraining. The key feature of DistilBERT is a compression technique, the so-called *knowledge distillation* (Buciluǎ et al., 2006; Hinton et al., 2015), where a compact model - the student - is trained to reproduce the behavior of a more complex model - the teacher. The DistilBERT model comprises only 6 Transformer layers and 40% fewer parameters but is 60% faster and still retains roughly 97% of BERT's performance on the GLUE benchmark.

Sentence-BERT (SBERT). In this study we mainly utilize the pretrained SBERT models (Reimers and Gurevych, 2019). SBERT was developed to overcome the inefficiency of BERT for finding the most similar pair of sentences in a large dataset. Using BERT for the comparison, each pair has to be input into the network separately and consequently a comparison of 10,000 sentences takes 50 million inference computations ($\sim$65 hours). This is too expensive in terms of time and resources in our case as the ontologies we use contain over one million entries. SBERT uses different above-mentioned BERT variants as backbone and adds a pooling operation to generate a fixed sized sentence embedding. The authors applied siamese and triplet networks to fine-tune the models to generate better sentence embeddings for similarity comparison. The pretrained models of SBERT are fine-tuned either on the NLI datasets[3] with classification objective alone or additionally also on the STSb dataset with regression objective. The testing result on STSb (Spearman rank correlation coefficient = 79.23 using $\text{BERT}_{\text{large}}$ trained on NLI) outperforms the average BERT embeddings, InferSent (Conneau et al., 2017) and the Universal Sentence Encoder (Cer et al., 2018).

SBERT-WK. The SBERT-WK[4] (Wang and Kuo, 2020) aims to refine the sentence embeddings generated by SBERT. The word embeddings generated by SBERT are further modified based on how informative / important the word is. The word importance is derived from its neighboring words of the same layer and its cosine similarity changes through layers. The idea is if a word aligns well with its neighboring word vectors, it is less informative. Similarity, if a word evolves faster across layers (larger variance of the pair-wise cosine similarity), it is more important. Since it works on already generated embeddings, no further training is needed. Adding SBERT-WK can improve the SBERT results on STSb for approximately 5 scores on the Spearman rank correlation coefficient.

Multilingual Language Models. In addition to the English sentence encoders mentioned above, we also applied multilingual language models to generate sentence embeddings. Multilingual alignment of sentence embeddings aims to achieve that the different embeddings of different languages of a sentence shall be mapped to the same vector space. This is the basic hypothesis when using similarity or distances measures of the embeddings to estimate the closeness of the multilingual sentences.

The multilingual Universal Sentence Encoder (mUSE) is such a multilingual language model (Yang et al., 2019). It is pretrained on 16 different languages simultaneously. The term ”Multi-task Dual-Encoder Model” denotes mUSE’s framework, comprising a single encoder handling a variety of downstream task. The encoder consists of either Transformers, guaranteeing a better accuracy, or of Convolutional Neural Networks (CNN) that ensure an efficient computation. The mBERT [5], the multilingual version of BERT, is based on $\text{BERT}_{\text{base}}$ model and is trained on 104 languages using Wikipedia. Since mBERT was not trained on parallel corpus, the sentence embeddings do not align well.

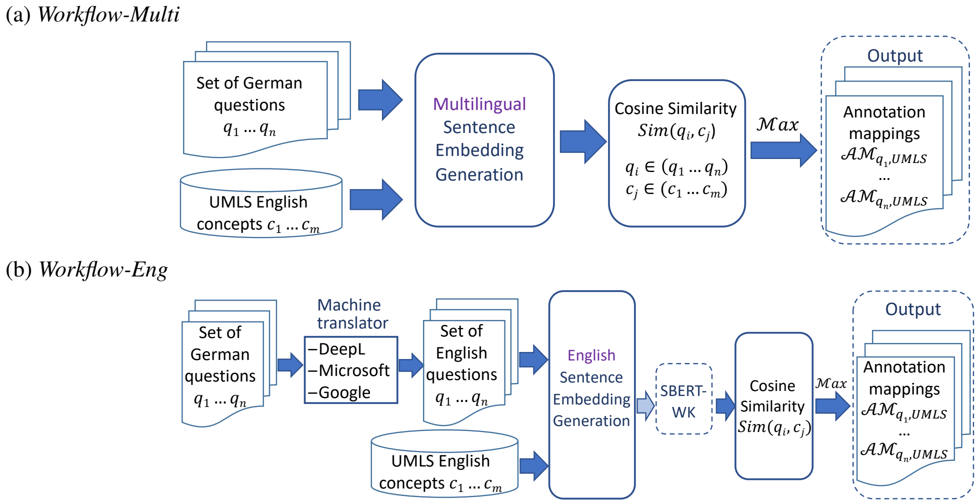
Lample and Conneau (2019) introduced the cross-lingual language models (XLMs) and utilise two methods to improve multilingual alignment. First, they use so-called translation language modeling (TLM) to learn XLM. Instead of using sentences of same language as in BERT MLM, TLM uses two parallel sentences of different languages as input sequence. The second method is using Byte Pair Encoding (BPE, Sennrich et al., 2015) on the same shared vocabulary instead of word or characters as input. Conneau et al. (2019) introduced a further cross-lingual pretrained model called XLM-R. R stands for RoBERTa as it is trained similar as RoBERTa. XLM-R uses only MLM as training objective as RoBERTa (i.e. no TLM) but with multilingual corpus. It is trained on even larger dataset (the CommonCrawl corpus (Wenzek et al., 2019), 2.5 TB) and in 100 languages. XLM-R sets a new stat of the art on XNLI of an 83.6% average accuracy.

In this study we used pretrained multilingual language models developed by the authors of SBERT. They proposed a new approach called *multilingual knowledge distillation* that aims to reinforce better multilingual alignment of the generated embeddings (Reimers and Gurevych, 2020). The student model $\hat{M}$, generally (but not restricted to) a multilingual pretrained model, learns the behavior of the teacher model M, generally an intensively trained monolingual (English) model, so that the sentence embeddings of different languages shall be mapped to the same vector space. The training requires a set of parallel (translated) sentences $((s_1,t_1),\cdots,(s_n,t_n))$ where t_i is the translation of s_i. The objective is to minimize the mean squared loss so that $\hat{M}(s_i) \approx M(s_i)$ and $\hat{M}(t_i) \approx M(s_i)$. The training dataset in-

[3] Containing the Stanford Natural Language Inference dataset (Bowman et al., 2015) and the Multi-Genre NLI dataset (Williams et al., 2017)

[4] WK stands for the initials of the two authors

[5] Multilingual BERT https://github.com/google-research/bert/blob/master/multilingual.md



(a) *Workflow-Multi*

(b) *Workflow-Eng*

Figure 2: Two workflows to generate cross-lingual annotations using sentence embeddings.

cludes bilingual dictionaries and also several parallel corpora from the OPUS website (Tiedemann, 2012) such as translated subtitles of TED talks and parallel sentences extracted from the European Parliament website. The experiments on multilingual STS 2017 dataset (Cer et al., 2017) shows these multilingual SBERT models outperform mBERT and XLM-R significantly.

3 METHODS

3.1 Corpus and Ontology

We selected 21 German medical forms that contain in total 497 questions as our corpus. Since we need to build a Gold Standard Corpus (GSC) for evaluation, the selection criteria of our corpus include 1) the forms must have corresponding English forms and 2) the questions in the English forms must have corresponding QaC-annotations in the UMLS. Many of the forms included in our GSC were used in the LIFE[6]-Adult-Study (Loeffler et al., 2015). The study investigates prevalences, early onset markers, genetic predispositions, and the role of lifestyle factors of major civilization diseases, such as metabolic and vascular diseases, heart function, depression and allergies.

We choose the Unified Medical Language System (UMLS) Metathesaurus as our ontology source. The UMLS integrates a large set of biomedical ontologies so that we can maximize the semantic interoperability for our corpus. We use the 2019AB version which contains approximately 4.26 million concepts from 211 source vocabularies. Since using deep networks to generate sentence embeddings is a time consuming and resource intensive task, we conducted a selection process to reduce the number of ontologies. Henceforth, the resulting UMLS subset contains only 428,000 concepts (1,03 million entries) from three source ontologies (instead of 211) but still covers 99.1% of the GSC annotations. The subset consists of 1) NCI Thesaurus, 2) LOINC, and 3) Consumer Health Vocabulary. As mentioned in Section 1, the CDISC Controlled Terminology is included as part of the NCI Thesaurus.

Gold Standard Corpus (GSC). A manually built GSC enables us to compare the annotation quality of different sentence embedding models. The questions of the original English forms are entered into the UMLS UTS Metathesaurus Browser[7] and the concepts having exactly the same text are considered as a correct annotation in our GSC.

3.2 Annotation Workflows

We applied two workflows to annotate the German medical forms: the *Workflow-Multi* uses multilingual sentence encoders (Figure 2(a)) and the *Workflow-Eng* integrates machine translators and English sentence encoders (Figure 2(b)). For the *Workflow-Multi*, we input the German questions directly into the multilingual encoders. In *Workflow-Eng*, the German questions are firstly translated into English using ma-

[6] LIFE stands for Leipzig Research Center for Civilization Diseases https://life.uni-leipzig.de/en/life_health_study.html

[7] UMLS Terminology Services https://uts.nlm.nih.gov/metathesaurus.html

Table 1: Models and configurations used in *Workflow-Eng*. GO: Google Translate, DL: DeepL, MS: Microsoft Translator.

Model	Size	Training	SBERT-WK	Corpus	Result size
BERT	large / base	NLI NLI + STSb	with w/o (only on base-models)	GO DL MS	$k \in \{1,2,3,5\}$
DistilBERT	base				
RoBERTa	large / base				

Table 2: The three multilingual embedding generation models used in *Workflow-Multi*. To simplify the description in the text, we introduce codes in the first column to refer to these models.

Code	Teacher model	Student model
M1	mUSE	DistilmBERT
M2	SBERT (BERT$_{\text{base}}$-NLI)	XLM-R
M3	SBERT (BERT$_{\text{base}}$-NLI+STSb)	XLM-R

chine translators before input into English encoders. We use three machine translators, namely DeepL[8], Microsoft Translator[9] and Google Translate[10] and hence obtained three translated corpora. The optional SBERT-WK is applied on the embeddings generated by English encoders (i.e. in *Workflow-Eng*).

A preliminary experiment concludes that using cosine similarity produced better results than using Euclidean or Manhattan distances (data not shown). Hence, for both workflows, the cosine similarities are calculated between the generated sentence embeddings of each question and that of each UMLS concept. The resulting mappings of each question are ranked based on their cosine similarities. We then retain various Top k results for evaluation where $k \in \{1,2,3,5\}$. For instance, a Top3 result set contains mappings having the highest three cosine similarities of that question. We use precision, recall and F-measure to present our results. We also use *Workflow-Eng* to annotate the original English corpus as the reference comparison.

3.3 Baseline: AnnoMap

Our baseline annotator is AnnoMap (Christen et al., 2015, 2016). AnnoMap generates annotation candidates based on three string similarity functions: TF/IDF, Trigram and LCS. After candidate generation, an optional group-based selection can be applied to improve precision (Christen et al., 2015). AnnoMap retains only candidates whose similarity scores are above a given threshold δ. For our experiment, we set two thresholds $\delta \in \{0.6, 0.7\}$ and set the same result sizes as in approaches using deep networks, i.e. $k \in \{1,2,3,5\}$. We do not use group-based selection so that we can expand the result to meet the larger result set size setting. We annotate the three translated corpora used in the *Workflow-Eng* and also the original English corpus as reference.

3.4 Deep Network Language Models

Multilingual Embedding Generation Models. We selected three pretrained models of Reimers and Gurevych (2020) for the multilingual sentence embedding generation in *Workflow-Multi*. These pretrained models are obtained from the SBERT repository[11]. Table 2 lists their corresponding teacher and student models. The first model (M1) uses multilingual models as teacher and student models. The models M2 and M3 both use English models as the teacher models (two SBERT models trained on different pretraining dataset) and the same multilingual model (XLM-R) as the student model. These models are introduced in Section 2.

English Embedding Generation Models. Table 1 details the SBERT models we used in this study with their further configurations for the *Workflow-Eng*. There are three pooling strategies used in SBERT: 1) use the CLS token 2) max pooling and 3) mean pooling. We choose the models using mean pooling as they are the best performing models proven by a preliminary test using our dataset. In contrast to BERT and RoBERTa, DistilBERT has only the base-model. These models are fine-tuned using two labeled training datasets: 1) NLI only or 2) NLI + STSb. We utilize the implementation of SBERT-WK in the SBERT repository on the base-models. Since the SBERT-WK is computationally expensive and primary results of large-models with SBERT-WK show no significant benefit, we do not apply SBERT-WK on large-models. We used three translated corpora and at the end retain result sets of 4 different sizes. Consequently, we have 192 configuration settings (`configs`): 144 `configs` for the base-models [12] and 48 `configs` for the large-models.

[8] https://www.deepl.com/translator

[9] https://www.microsoft.com/en-us/translator/

[10] https://translate.google.com

[11] https://public.ukp.informatik.tu-darmstadt.de/reimers/sentence-transformers/v0.2/

[12] 3 models × 2 training datasets × 2 SBERT-WK-setting × 3 corpora × 4 result sizes = 144 `configs`

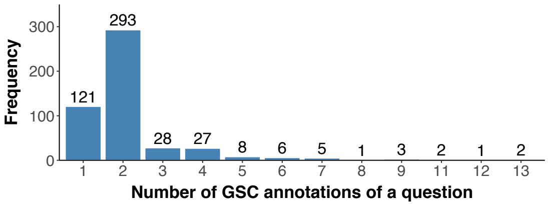


Figure 3: Frequency distribution of number of annotations of a question in the GSC.

4 EVALUATION

4.1 Gold Standard Corpus

We manually identified 1105 GSC annotations for the 497 questions. Figure 3 shows the frequency distribution of number of annotations of a question. Most of the questions have 1 or 2 GSC annotations and about 10% of the questions have 3 or 4 annotations. There are only few questions having more than 5 mapped UMLS concepts. From our observations, this is mainly due to 1) same question of a form might be given multiple CUIs in the UMLS or 2) the same question occurs in different forms and hence has different CUIs. Figure 1 shows such examples.

4.2 Cross-lingual Annotation

Baseline. When annotating the original English corpus, our baseline, AnnoMap, achieves the best precision of 93.61%, the best recall of 86.52% and the best F-measure of 80.08% using different settings (Table 3). The best results on the translated corpora, however, drop significantly. The best precision on the Google Translate corpus decreases to 61.69% and best recall is rather low (36.20%). Overall, the best F-measure AnnoMap achieves on the translated corpora is 38.47%. The results using the DeepL and Microsoft Translator corpora are slightly worse than Google Translate results. This confirms our previous study (Lin et al., 2020), concluding that conventional string matching methods deliver unsatisfactory results for such a cross-lingual annotation problem.

Table 3: The best precisions, recalls and F-measures obtained by AnnoMap with thresholds $\delta \in \{0.6, 0.7\}$ and result sizes $k \in \{1,2,3,5\}$. The last row of each metric in grey is the best corresponding result obtained using the original English corpus (OE). GO: Google Translate.

Corpus	δ	Result size	Precision	Recall	F-measure
Precision					
GO	0.7	Top1	61.69	13.85	22.62
OE	0.7	Top1	93.61	41.09	57.11
Recall					
GO	0.6	Top5	35.65	36.20	35.92
OE	0.6	Top5	51.43	86.52	64.51
F-measure					
GO	0.6	Top2	53.19	30.14	38.47
OE	0.7	Top2	89.31	72.58	80.08

Table 4: Averaged annotation quality using multilingual encoders. For the model codes refer to Table 2.

Model code	$M_{Precision}$	M_{Recall}	$M_{F-measure}$
M1	43.66	46.38	41.61
M3	39.48	42.02	37.63
M2	38.90	41.06	36.96

Workflow-multi. In this part we compare the annotation quality of the three multilingual models in *Workflow-Multi*. Table 4 shows the mean precision, recall and F-measure, averaged over different result sizes. The best performing model is M1. It also obtained the best precision (57.14% with Top1), best recall (61% with Top5) and best F-measure (48.69% with Top2). The sole difference between M2 and M3 is that the teacher models are fine-tuned on different datasets (NLI and NLI + STSb, respectively). However, this does not affect much on the annotation quality as the results from M2 and M3 are very similar.

Workflow-eng. We took the means of the precision, recall and F-measure values across different `configs` to see how various factors such as model type or corpus influence annotation quality. Tables 5 and 6 show the results. Firstly, we compare the annotation quality produced by the three models BERT, RoBERTa and DistilBERT. Since DistilBERT has only base-model, we excluded the results of the large-models of BERT and RoBERTa from comparison. The averaged performance of BERT and RoBERTa are almost identical with BERT producing slightly better results (Table 5(a)). Considering that DistilBERT is significantly smaller in size, the annotation quality is only marginally worse than the other two models. In terms of fine-tuning data used to train the SBERT models, the `configs` fine-tuned on both NLI and STSB perform slightly better than the models solely tuned on NLI (Table 5(b)). This result consents to the findings of the original paper (Reimers and Gurevych, 2019). Among the corpora generated by three machine translators, using Google Translate results in the best performance with a 1% lead over DeepL in all metrics and outperforms Microsoft Translator by more than 2.5% (Table 5(c)). Table 5(d) confirms that the best precision is achieved when taking only Top1 results, while, as expected, the Top5 result sets obtain the best recalls. However, the highest F-measure scores are generated by the Top2 result sets. This is conceivable as most of the questions have two or less GSC annotations (see Figure 3).

Table 5: Averaged annotation quality based on different factors. n denotes the number of configs used for averaging. Note that large-models are excluded from Model comparison as DistilBERT has only base-models. GO: Google Translate, DL: DeepL, MS: Microsoft Translator.

	$M_{Precision}$	M_{Recall}	$M_{F-measure}$
(a) Model ($n = 48$)			
BERT	48.04	50.75	45.68
RoBERTa	47.64	50.53	45.39
DistilBERT	46.41	49.09	44.15
(b) Training data ($n = 96$)			
NLI + STSb	47.83	50.60	45.51
NLI	47.34	50.10	45.06
(c) Corpus ($n = 64$)			
GO	48.78	51.72	46.47
DL	47.68	50.40	45.36
MS	46.28	48.93	44.03
(d) Result size ($n = 48$)			
Top1	62.36	28.05	38.69
Top2	56.50	50.83	53.52
Top3	42.44	57.26	48.75
Top5	29.02	65.26	40.18

Large-models generate better results but not always. Among the 48 comparisons between configs, in 12 cases the large-models do not perform better than base-models. The refinement of SBERT-WK on the SBERT-generated embeddings improves the annotation quality on base-models and even exceeds the large-models (Table 6). All 72 comparisons between configs of base-models show that the application of SBERT-WK yields better results than without using SBERT-WK. The largest improvement of using SBERT-WK on base-models is 6.84% in precision, 6.42% in recall and 5.62% in F-measure.

Table 6: Averaged annotation quality of configs using different SBERT-WK settings and model sizes. The results of DistilBERT are excluded because it does not have large-models. Hence, the results of each row are averaged over $n = 48$ configs.

SBERT-WK	Size	$M_{Precision}$	M_{Recall}	$M_{F-measure}$
with	base	49.36	52.21	46.97
w/o	large	48.23	51.04	45.91
w/o	base	46.33	49.06	44.11

Best Performing configs. Table 7 presents the best performing configs in precision, recall and F-measure using *Workflow-Eng*. The best performing configs using the original English corpus (listed as the last column of each metric) indicates the best achievable results. The best performing configs in each metric all applied SBERT-WK and Google Translate in their workflows. The highest precision, 66.6%, is attained by DistilBERT$_{\text{base}}$ trained on NLI + STSb. The best three recalls are generated by RoBERTa. The best recall achieved is 70.86% by RoBERTa$_{\text{base}}$. Interestingly, the best F-measure (57.17%) is yield by RoBERTa$_{\text{base}}$ which is only trained on the NLI corpus. As the table shows, the differences in performance between models trained on NLI + STSb or NLI only are marginal. Notably, the best DistilBERT model (trained on NLI + STSb and with SBERT-WK) accomplished the best precision, rank 6 in recall (c.a. 2% less than the best recall) and rank 3 in F-measure (0.38% less).

Computation Efficiency. Table 8 shows the computing time per embedding for different model settings. While BERT and RoBERTa have similar efficiency, DistilBERT is almost 2 times faster. Adding SBERT-WK on the base models of BERT and RoBERTa prolongs the embedding generation by a factor of 2.6. In our case with a dataset of more than 1,000,000 concepts, the total run time increases from approximately 4 hours to 10.5 hours. Interestingly, the time increase of adding SBERT-WK on DistilBERT is ”only” doubled. This is probably due to DistilBERT’s architecture, as it only has half the amount of Transformer layers as BERT or RoBERTa, resulting in reduced computation steps of SBERT-WK. Using the large-models requires on average another 17ms per embedding than using base-models with SBERT-WK.

Combination of Results. In our previous studies (Lin et al., 2017, 2020) we showed that combining using union or intersect on the result sets generated by different annotation tools and corpora can further improve annotation quality. Therefore, we apply two combinations in this study. In *Combi-1*, we combine the results generated from SBERT with those from AnnoMap. The combinations are carried out on results having same result size and same corpora. With *Combi-2*, we combine the results of SBERT configs that are generated using all three different translated corpora. With respect to *Combi-1*, Table 9 shows that the best precision of combined result sets reaches 85.63%. This is a significant improvement of the precision of the best AnnoMap and SBERT results (61.69% and 66.6%, respectively). Using *Combi-2* we accomplish a precision of 93.27%, a further improvement of 7.64%. The best recall generated by *Combi-1* is 73.94%, that is an increase of 37.64% on AnnoMap (36.20%) and merely 3.08% on SBERT

Table 7: The `configs` of the best precisions, recalls and F-measures. The last row of each metric in grey is the best corresponding result obtained using the original English corpus (OE). Equally performing `configs` are either presented in the same row or with the same ranking number. For example, with respect to precision, three `configs` rank third, two with the same model setting (RoBERTa) but different corpora (presented as the same row) and one `config` (BERT) is noted as rank 3. GO: Google Translate, DL: DeepL, MS: Microsoft Translator.

Ranking	Model	Size	Training	SBERT-WK	Corpus	Result size	Precision	Recall	F-measure
Precision									
1	DistilBERT	base	NLI + STSb	with	GO	Top1	66.60	29.95	41.32
2	BERT	large	NLI + STSb	w/o	GO	Top1	66.40	29.86	41.20
3	RoBERTa	large	NLI + STSb	w/o	GO/DL	Top1	66.20	29.77	41.07
3	BERT	base	NLI	with	GO	Top1	66.20	29.77	41.07
4	RoBERTa	base	NLI	with	GO	Top1	66.00	29.68	40.95
5	BERT	base	NLI	with	MS	Top1	65.39	29.41	40.57
	BERT	large	NLI + STSb	w/o	OE	Top1	96.18	43.26	59.68
Recall									
1	RoBERTa	base	NLI + STSb	with	GO	Top5	31.51	70.86	43.62
2	RoBERTa	large	NLI + STSb	w/o	GO	Top5	31.43	70.68	43.51
3	RoBERTa	base	NLI	with	GO	Top5	31.11	69.95	43.06
4	BERT	base	NLI	with	GO	Top5	30.95	69.59	42.84
5	RoBERTa	large	NLI + STSb	w/o	DL	Top5	30.74	69.14	42.56
6	DistilBERT	base	NLI + STSb	with	GO	Top5	30.58	68.78	42.34
	BERT	base	NLI + STSb	with	OE	Top5	40.97	92.13	56.71
F-measure									
1	RoBERTa	base	NLI	with	GO	Top2	60.36	54.30	57.17
2	BERT	base	NLI	with	GO	Top2	60.16	54.12	56.98
2	RoBERTa	base	NLI + STSb	with	GO	Top2	60.16	54.12	56.98
3	DistilBERT	base	NLI + STSb	with	GO	Top2	59.96	53.94	56.79
3	RoBERTa	large	NLI + STSb	w/o	GO/DL	Top2	59.96	53.94	56.79
4	RoBERTa	large	NLI	w/o	DL	Top2	59.66	53.67	56.50
5	BERT	base	NLI	with	MS	Top2	59.56	53.57	56.41
	RoBERTa	base	NLI + STSb	with	OE	Top2	85.31	76.74	80.80

Table 8: Averaged computation time per embedding of different models, sizes and with or w/o SBERT-WK.

Model	Size	SBERT-WK	Time (ms)
BERT	base	w/o	25.1
BERT	base	with	65.3
BERT	large	w/o	81.5
RoBERTa	base	w/o	23.5
RoBERTa	base	with	62.4
RoBERTa	large	w/o	80.0
DistilBERT	base	w/o	13.6
DistilBERT	base	with	27.3

(70.86%). This indicates that combining AnnoMap and SBERT does not add many more correct annotations to the SBERT result sets. Encouragingly, with *Combi-2* we achieve the best recall of 84.62%, that is another gain of 10.68% compared to *Combi-1*. The best F-measure using *Combi-1* (56.96%) is slightly lower than SBERT's best F-measure (57.17%) but *Combi-2* achieves 63.45% by 2-vote-agreement (an annotation is considered as correct by at least two of the three `configs`).

4.3 Result Summary

In this section we summarize our findings. Considering the settings in *Workflow-Eng*, the differences in annotation quality between different models and training data are neglectable. However, since DistilBERT is much more efficient, it would be a better choice if computational resources are restricted and/or the annotation task is time-critical. The best performing machine translator for our dataset is Google Translate. Instead of using the large-models, adding SBERT-WK to the base-models can improve the results more significantly whilst being more efficient. In order to find such QaC-annotations using the UMLS as concept source, we recommend at least to retain the Top2 results.

Figure 4 presents the best results of all approaches we investigated in this study. Notably, if the task is not cross-lingual but to annotate the original English forms, the performance of the newly proposed system and the baseline is rather similar (80.80% using SBERT and 80.08% using AnnoMap in F-

Table 9: The best combination results. The rows in gray are the best corresponding results obtained using the original English corpus (OE). GO: Google Translate, DL: DeepL, MS: Microsoft Translator. The threshold (δ) of AnnoMap used in the combination is indicated in the Corpus column.

Method	Model	Size	Training	SBERT-WK	Corpus (δ)	result size	Precision	Recall	F-measure
SBERT + AnnoMap									
Precision									
intersect	BERT	base	NLI	w/o	GO (0.6)	Top2	85.63	25.34	39.11
intersect	RoBERTa	large	NLI	w/o	OE (0.6)	Top1	99.62	23.89	38.54
Recall									
union	RoBERTa	large	NLI + STSb	w/o	GO (0.6)	Top5	27.35	73.94	39.93
union	RoBERTa	large	NLI	w/o	OE (0.6)	Top5	34.12	95.75	50.31
F-measure									
union	RoBERTa	base	NLI + STSb	with	GO (0.7)	Top2	56.38	57.56	56.96
union	BERT	base	NLI + STSb	with	OE (0.7)	Top2	83.11	83.26	83.18
3 Corpora									
Precision									
intersect	BERT	large	NLI	w/o	GO	Top2	**93.27**	36.38	52.34
	RoBERTa	base	NLI + STSb	w/o	DL				
	BERT	base	NLI	with	MS				
Recall									
union	RoBERTa	base	NLI + STSb	with	GO	Top5	20.10	**84.62**	32.49
	RoBERTa	large	NLI + STSb	w/o	DL				
	RoBERTa	large	NLI	w/o	MS				
F-measure									
2-vote-agreement	DistilBERT	base	NLI + STSb	with	GO	Top2	77.79	53.57	**63.45**
	RoBERTa	large	NLI	w/o	DL				
	BERT	base	NLI	with	MS				

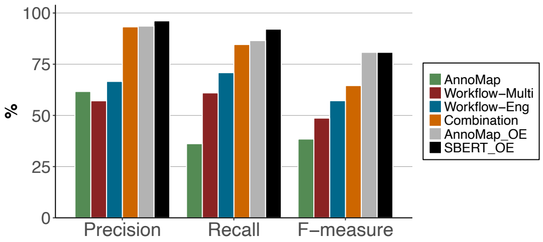


Figure 4: The best results of each approach. GO: Google Translate, OE: original English corpus.

measure). However, in the cross-lingual scenario, the newly proposed deep network annotation system exceeds conventional string matching methods significantly in all three measures. We achieved an improvement of 134% in recall (from 36.20% of AnnoMap to 84.62% of combination), 51% in precision (AnnoMap: 61.69%, combination: 93.27%) and 65% improvement in F-measure (AnnoMap: 38.47%, combination: 63.45%). Secondly, the best performing `configs` using *Workflow-Eng* outperform the best model in *Workflow-Multi*. This indicates that it is still inevitable to apply the more complex workflow (i.e. *Workflow-Eng*) as long as the multilingual encoders do not generate better aligned sentence embeddings. Instead of using a single SBERT model, our study conveys that combining SBERT result sets of all three language corpora can further improve the annotation quality. Hence, having different translated versions of the questions is beneficial. Overall, if we can apply manual verification on the Top5 results (semi-automatic annotation) and achieve a precision of 100%, with the best recall of 84.62%, a F-measure of 91.67% is feasible.

5 CONCLUSIONS

In this study we propose to use deep network generated sentence embeddings to tackle the cross-lingual annotation task. The results are very promising for questions of medical forms. For future work, we seek to investigate the application of such semantic annotation technique on other type of annotations (e.g. biomedical name entities) or in other domains.

We used current state of the art models for the embedding generation in this study. Our result shows that the annotation quality using multilingual encoders still fall behind that of using English encoders. A further improvement of the multilingual encoders to produce better aligned sentence embeddings is beneficial for our task. As this simplifies the annotation procedure significantly by excluding the machine translation.

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