

Where’s the Question? A Multi-channel Deep Convolutional Neural Network for Question Identification in Textual Data

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Abstract

In most clinical practice settings, there is no rigorous reviewing of the clinical documentation, resulting in inaccurate information captured in the patient medical records. The gold standard in clinical data capturing is achieved via “expert-review”, where clinicians can have a dialogue with a domain expert (reviewers) and ask them questions about data entry rules. Automatically identifying “real questions” in these dialogues could uncover ambiguities or common problems in data capturing in a given clinical setting.

In this study, we proposed a novel multi-channel deep convolutional neural network architecture, namely Quest-CNN, for the purpose of separating real questions that expect an answer (information or help) about an issue from sentences that are not questions, as well as from questions referring to an issue mentioned in a nearby sentence (e.g., *can you clarify this?*), which we will refer as “*c-questions*”. We conducted a comprehensive performance comparison analysis of the proposed multi-channel deep convolutional neural network against other deep neural networks. Furthermore, we evaluated the performance of traditional rule-based and learning-based methods for detecting question sentences. The proposed Quest-CNN achieved the best F1 score both on a dataset of data entry-review dialogue in a dialysis care setting, and on a general domain dataset.

1 Introduction

In healthcare, real-world data (RWD) refers to patient data routinely collected during clinic visits, hospitalization, as well as patient-reported results. In recent years, RWD’s volume has become enormous, and invaluable insights and real-world evidence can be generated from these datasets using the latest data processing and analytical techniques. However, RWD’s quality remains one of

the main challenges that prevent novel machine learning methods from being readily adopted in healthcare. Therefore, creating data quality tools is of great importance in health care and health data sciences. Erroneous data in healthcare systems could jeopardize a patient’s clinical outcomes and affect the care provider’s ability to optimize its performance.

Common data quality issues include missing critical information about medical history, wrong coding of a condition, and inconsistency in documentation across different care sites. Manual review by domain experts is the gold standard for achieving the highest data quality but is unattainable in regular care practices. Recent developments in the field of Natural Language Processing (NLP) has attracted great interest in the healthcare community since algorithms for identifying variables of interest and classification algorithm for diseases have been recently developed (Jiang et al., 2017).

In this paper, we presented a novel model for the extraction of queries (questions) in a corpus of dialogue between data entry clinicians and expert reviewers in a multi-site dialysis environment. The main contributions of this work are: (i) To the best of our knowledge, we are the first to benchmark the performance of different rule and learning-based methods for the extraction of question sentences from logs of real-world (medical) systems by providing specific misclassification cases that emphasize the limitation of each technique. (ii) We proposed a new deep neural network architecture, namely Quest-CNN which unifies syntactic, semantic and statistical features and is capable of identifying real questions that expect an answer, questions referring to an issue mentioned in a nearby sentence (*c-questions*) and sentences that are not questions. (iii) We examined the importance of the above mentioned features and we experimented extensively with different state of

the art deep learning models in order to determine the best architecture for this particular task. (iv) We investigated the effect of incorporating domain knowledge on the performance of a model by examining whether word embeddings and semantic features (that will be described in section 4.1) which are pre-trained in a domain-specific dataset rather than in a general dataset are more beneficial for the model. Finally, in addition to evaluating our model’s performance in a medical context, we also experimented in section 5 with a general-domain dataset (questions in the Twitter social platform) to show our model’s generalizability.

The rest of the paper is organized as follows. Related work is presented in section 2. The different question detection methods that will be examined, are described in section 3. Section 4 details the characteristics of the proposed multi-channel CNN model. Finally, the results of the experiments are reported in section 5 and a conclusion and a plan for future work are given in section 6.

2 Related Work

Different question-detection methods have mainly been focused on the extraction of questions in social online settings (e.g. emails, Twitter) (Li et al., 2011; Zhao and Mei, 2013). These methods can be classified into two categories: (i) Rule based methods that make use of rules like 5W1H words (What, Who, Where, When, Why, How) or question marks (QM) to identify questions (ii) Learning-based methods, which train a classifier based on the patterns of sentences.

Recently, different deep-neural networks have achieved a state-of-the-art results in text classification. In the **KIM-CNN** model (Kim, 2014) t filters are applied to the concatenated word embeddings of each document in order to produce t feature maps, which are fed to a max pooling layer, in order to create a t -dimensional representation of the document. In addition, in (Liu et al., 2017) the **XML-CNN** network was introduced, where a dynamic max-pooling scheme and a hidden bottleneck layer were used to achieve a better representation of documents. Another state-of-the art deep model is **Seq-CNN** (Johnson and Zhang, 2015) where each word is represented as a $\|V\|$ -dimensional one-hot vector where V is the vocabulary of the dataset and the concatenation of the word vectors are passed through a convolutional layer, followed by a special dynamic pooling layer. Furthermore, in **FastText**

(Joulin et al., 2017) the embedding of the words that appear in a document were averaged to create a document representation. Finally, a comprehensive analysis of clinical-domain embedding methods is presented in (Khattak et al., 2019).

3 Question detection

As mentioned above, the task of identifying sentences that contain questions and *c-questions* can be broken into two sub-problems: (i) Detecting question sentences from unstructured data (logs) (ii) Correctly identifying the *c-questions* and the real questions that require an answer.

In order to create the corpus of candidate questions, we explored both rule and learning based approaches. We also compared the performance of each method on the task of identifying questions on (medical) unstructured text and analyzed the most common misclassification cases.

Rule-based Approach: In particular, we employed the following rules: (i) The last character of a sentence is a question mark (ii) The rules that were introduced in (Efron and Winget, 2010) (e.g I* [try*,like, need] to [find, know]) (iii) The sentence contains a 5W1H word (iv) The refined 5W1H rules from (Li et al., 2011): The sentence contains a 5W1H word at its beginning or it contains auxiliary words (e.g. “what is” instead of what or “how does” instead of how)

Learning-based Approach: These approaches learn specific patterns that can be used to identify sentences that are questions. In this study, we evaluated the following methods: (i) A Naive Bayes Classifier which was trained on the NPS Chat Corpus that consists of over 10,000 posts from instant messaging sessions (Bird et al., 2009). As these posts have been labeled with dialogue act types, such as “*Statement*”, “*ynQuestion*”, we used the classifier without any further training. (ii) The syntactic parser from the Stanford CoreNLP Natural Language Processing Toolkit (Manning et al., 2014) which provides a full syntactic analysis of an input sentence. The question-sentences were identified, by examining the syntactic structure of each sentence in the dataset.

4 Quest-CNN Architecture

In this section, we describe our proposed model which has as input all the sentences that the above question extraction method identified as questions and it distinguished between the sentences that are

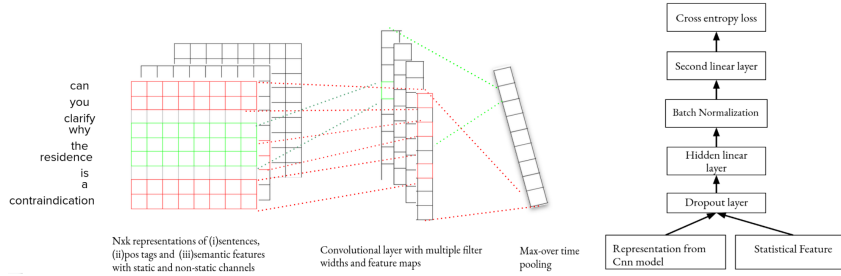


Figure 1: Proposed architecture of Quest-CNN with the (three) feature channels for an example sentence

actual questions and *c-questions*.

The architecture of our model is depicted in Figure 1. The key characteristic of our model is its capability of unifying the syntactic properties of questions, the semantic features of words by incorporating domain knowledge and statistical features (section 4.1) in a multi-channel CNN scenario.

Let $x_i \in \mathbb{R}^k$ be the k -dimensional word vector corresponding to the i -word of each sentence. Each sentence can be presented as the concatenation of the word embeddings of its words. By using multiple t convolutional filters the model can capture multiple features for each sentence, as each filter $u \in \mathbb{R}^{hk}$ will create one feature c_i for each word region $x_{i:i+h-1}$ (of size h):

$$c_i = f(u^T \cdot x_{i:i+h-1} + b)$$

where $b \in \mathbb{R}$ is a bias term and f is a nonlinear activation function such as the rectified linear unit (ReLU). By padding the end of the sentence, the model can produce a feature map $c_u = [c_1, c_2, \dots, c_{n-h+1}]$ that is associated to a filter u ,

where n is the number of words of the largest sentence. In addition, by using t filters (with different window sizes) the model can create t feature maps that are passed through a max pooling operation in order to obtain one value c_{max} for each filter. The output of the pooling layer is then concatenated with the vector of the statistical features of each sentence thus creating a richer representation of each sentence. Finally, the representation of the sentences are passed through two fully connected layers and a softmax layer that outputs the probability distribution over the labels of the sentences.

Finally, our model consists of multiple channels that represent different features. Each filter i is applied to all the channels and the feature map c_i is calculated by adding the results in each channel. In the ablation study (section 5.2.3), we presented the

performance of different variations of the model which consist of one to three channels and use (or not) the information of the statistical features.

4.1 Feature description

Since the classification of the sentences is challenging due to their short length, we tried to utilize not only lexical features but also syntactical features, statistical features and semantic features using domain knowledge. In particular, we investigated the influence of the above mentioned features by creating multiple feature-channels for each sentence.

Word representation: The first channel consists of the k -dimensional word embeddings of the words of a sentence where $x_i \in \mathbb{R}^k$ corresponds to the i -th word in the current sentence. For the initialization of the word embeddings, we examine multiple options. We can either randomly initialize the vectors and then allow their modification during training or use pre-trained word embeddings that were trained in a much bigger corpus.

In the second case, we also investigated the effect of two popular pre-trained word embedding datasets. The first one is a general domain dataset, the Google News dataset that contains **300**-dimension word2vec embeddings that were trained on 100 billions words (Mikolov et al., 2013). The second one is the Multiparameter Intelligent Monitoring in Intensive Care (MIMIC) III dataset which is a publicly available ICU dataset (Johnson et al., 2016) that consists of medical data (e.g. laboratory tests, medical notes) collected between 2001 and 2012. Since a training course is mandatory in order to access it, there are no available word embeddings. Thus we trained our own embedding model that produced **300**-dimension word2vec embeddings based on the **NOTEVENTS** table which consists of 2,083,180 rows of patients notes. We believed that the comparison of the effectiveness of our model when it is provided with a large general

domain dataset or a smaller specific domain dataset can be a useful guide not only to our work-case but for other NLP problems as well. Words that do not appear in the pre-trained vocabulary are randomly initialize using a uniform distribution in the range $[-\sqrt{\frac{3}{dim}}, +\sqrt{\frac{3}{dim}}]$ (where *dim* is the dimension of word vector)(Aguilar et al., 2017).

POS-tagging word representation: Questions usually have specific syntactic structures and by including this channel we hoped to capture these meaningful syntactic features. By obtaining the POS tags of the words in each sentence, we produced embeddings of each POS tag which has the same dimension as the word embeddings. The vectors of POS tags in the model can either be initialized randomly using a uniform distribution in the range $[-\sqrt{\frac{3}{dim}}, +\sqrt{\frac{3}{dim}}]$ and allow their modification during training or they can be created as one-hot vectors (vectors with all 0s and one 1 which indicates the existence of a specific POS tag word). By comparing these two representations we aimed to understand whether a richer representation of POS-tagging word can significantly improve the performance of the model.

Semantic Features: Semantic features were also introduced in order to boost the model’s performance by connecting different words that share a semantic meaning. In order to extract relevant clinical entities, we used the UMLS Metathesaurus, a large biomedical thesaurus, which organizes words by (medical) groups and links similar words (Humphreys et al., 1998). The identification of the medical words and their UMLS groups was accomplished using the open-source Apache clinical Text Analysis and Knowledge Extraction System (cTakes)(Savova et al., 2010). We examined two different strategies for incorporating semantic features: (i) Replacing the words that appear in the database with their respective medical group name or (ii) Creating a new channel where, for each group, a new vector is created which was initialized either randomly or by using the pre-trained word2vec vectors as described above.

As our final goal for the model is to work in any domain, in the experiment section, we also presented our model’s accuracy by extracting concepts from WordNet, which is an extensive lexical database where words are grouped into sets of synonyms (synsets).

Finally, four statistical features were included in the model namely the length of the sentence, the

number of words, the number of capitalized words and the coverage of the vocabulary. These features were introduced in (Zhao and Mei, 2013) for the identification of questions in the Twitter platform.

4.2 Regularization

For regularization, we used “embedding dropout”, an idea that was introduced in language modeling in (Merity et al., 2018), and performed dropout on entire word embeddings, thus removing some words in each training phrase. Although the “embedding dropout” technique was used for the purpose of regularization RNN-based models, we observed that it can work equally well in a CNN-based model as its main purpose is to make a model rely less on a small set of input words.

In addition, we applied dropout on the last two fully connected linear layers. The Dropout mechanism randomly sets a portion of hidden units to zero during training, thus preventing the co-adaptation of neurons (Srivastava et al., 2014).

5 Experiments

In this section, we presented the result of an empirical evaluation on the question-detection methods that were described in section 3 and our proposed model in section 4. In particular, we analyzed the performance of the rule and learning based methods and we provided specific examples that highlighted their limitations. We also provided a comparison between different deep learning text classification methods that were described in section 2 in order to show the efficiency of our proposed model. Finally, we conducted an ablation study that demonstrated the importance of the features (channels) for achieving high-accuracy results.

Datasets. The main dataset used in this study is a review log consists of the query-answer dialogue in the Dialysis Measurement, Analysis and Reporting System (DMAR[®]). DMAR[®] is a web-based application that collects patient-level, clinical data within a renal program (Blake et al., 2013; Oliver et al., 2010) and its review module facilitates the “query-answer” style of communication between the reviewer (Neurologist) and users (renal coordinators) during routine care process. A user would post a question to the reviewer only when she/he was unsure about the correctness of patient data (for example *why the hernia was considered absolute contraindications?*). Therefore, the questions in this dialogue dataset provided a good indicator

of data quality issues. The dataset used in this study was extracted from DMAR[®] between 2013-2019. ¹ This dataset offered a rare (in terms of quantity) opportunity to examine a vast array of different questions types during medical data review processes over a fairly long period of time in a multi-sites real-world clinical setting. The annotations of the sentences were created by manually checking each sentence, as a ground truth was non-existent. Unfortunately, due to the sensitive nature of the dataset (contains medical information of patients), we cannot provide a link to a downloadable version of the data without the approval of the research ethics boards.

In addition, in order to test our model in a general setting, we experiment with the Twitter dataset which was created and analyzed in (Zhao and Mei, 2013). This dataset contains 2462 tweets which were annotated by two human annotators as questions (conveying an information need) or non-questions. This dataset was used to evaluate the models in the binary classification task to separate actual questions from sentences that do not require an answer. Table 1 lists the statistics of both datasets.

For the evaluation of the question detection methods, the accuracy, recall and F1 score (the harmonic mean between recall and precision) were reported. For the evaluation of the deep-learning models, we reported the micro-averaged F1 score and the F1 score for the multi-class and binary-class dataset respectively on the testing and the validation set. ²

	DMAR	Twitter
Comments	22125	2462
Questions-Sentences	4486	2462
Actual questions	2575	1262
C-questions	136	-
Comments with ?	2722	2462
Comments with 5W1H	1780	836
A.N. of words	15.0020	11.4130
A.N. coverage of words	0.0006	0.0011
A.N. of capitalize words	2.3148	2.1397
A.N. lengths	85.4490	66.3850

Table 1: Statistics of the datasets; we use the acronym A.N for average number

¹REB# 18-1604 approved by the Conjoint Health Research Ethics Board (CHREB), University of Calgary.

²https://scikit-learn.org/stable/modules/generated/sklearn.metrics.f1_score.html

5.1 Question Extraction

The performance of different question extraction methods on the DMAR dataset was presented in Table 2. The results showed that simple rules method, i.e. identifying question marks, had a medium performance. The reason for the misclassification cases may be due to the language patterns in casual conversational log, where people sometimes forgot to add a question mark (?) in a question (*what symptoms did the patient present.*) or they used a question mark to show irony (*the procedure has already begun so maybe an update next time?*), or tried to be polite when they encouraged a person to take action (*please see comments?*).

By adding the 5H1W rule, the recall could be boosted but the precision dropped significantly, due to the fact that many sentences could contain 5W1H but are not questions (e.g. *just wait and see what happens*). Furthermore, we observed that by applying the refined rules introduced in (Li et al., 2011), the model could maintain almost the same recall, while achieving a significant improvement in precision. Finally, the results revealed that the rules in (Efron and Winget, 2010) had the overall best (F1) performance. This indicated that even if these rules were made for a different context (twitter), they could be applied to other domains (e.g. medical).

Methods	Prec. (%)	Recall (%)	F1 (%)
Naive Bayes	77.2	55.8	64.8
Parsing algorithm	93.0	38.7	54.7
QM	86.2	91.1	88.6
QM & 5W1H	59.3	94.9	73.0
Rule 1 Li et al.(2011)	83.9	91.6	87.6
Rule 2 Li et al.(2011)	82.6	91.6	86.9
Rule 1,2 Li et al.(2011)	86.1	91.2	88.6
Rule Efron et al.(2010)	86.2	91.8	88.9

Table 2: Precision, Recall and F1 scores for question identification methods; best results are **bolded**

By investigating the performance of the learning-based approaches, we observed that the parsing algorithm could significantly improve the precision of question-detection but with low recall performance as it missed a large number of questions. This is largely caused by the irregular syntax patterns used in real-life casual conversation (e.g. *he is still sitting in my baseline?*). Finally, the Naive Bayes Classifier identified half of the questions

with low precision which indicates that using transfer learning (it is trained on the NPS Chat Corpus) cannot achieve a good performance especially in cases where the conversation is domain-specific, such as in a clinical setting or a electronic medical record system. Thus, methods of this type would need to be trained with domain-specific examples, which are usually resource-intensive.

It should be noted that we did not evaluate the different question extraction methods on the Twitter dataset as it was constructed by tweets that were all “potential” questions (they all contain a question mark) and thus it cannot provide a fair comparison of the methods. To evaluate the QUEST-CNN model’s ability to identify the actual question and the *c-questions*, we used the Twitter dataset and the dataset that contains all the sentences extracted by all the question extraction methods from the DMAR dataset.

5.2 Multichannel-CNN experiments

In this section, we reported the evaluation of our proposed model in identifying questions and *c-questions*. Firstly, we presented a comparison of our model with the other deep-learning models that were described in section 2. In addition, we also tested the performance of a bi-directional LSTM (BI-LSTM) model that used as input all the features that we described in section 4.1 where the last hidden state is fed to a fully-connected softmax layer. Finally, we compared our model to logistic regression (LR) using an one-vs-rest multi-class objective and a support vector machine (SVM) model using a linear kernel. For the last two methods, we used the tf-idf measure of the words as features.

In addition, we conducted an ablation analysis of our model. In summary, the baseline was a **CNN-rand** model where the word embeddings were randomly initialized but could be modified during training. We also provided the performance of our model when the word2vec embeddings were used (Google News or MIMIC) and we examined whether allowing further training of the embeddings (**CNN-non static**) can achieve better results than keeping them static(**CNN-static**). Finally, we examined whether the statistical, the POS-tag and the semantic features were meaningful features and which form of the features (as they were described in section 4.1) could achieve a better performance (**multi-channel** scenario).

All the experiments were performed with Py-

Torch 0.4.1. Scikit-learn 0.22.2 was used to implement the SVM, the LR model and the computation of the tf-idf vectors. All experiments were executed on a Intel(R) Core(TM) i7-8665U CPU @ 1.90GHz with 15 GB RAM running Ubuntu 18.04.3 LTS.

5.2.1 Hyperparameter Tuning

In order to address the concerns of reproducibility of the NLP community (Dodge et al., 2019), we provided the search strategy and the bound for each hyperparameter as follows: the batch size was set between 32 and 64; the dropout embedding and the learning rate were from a uniform distribution on the interval $[0, 0.5]$, $[0, 0.2]$ and $[1e-6, 1e-1]$ respectively; the filter sizes of the models were between (2,3,4), (3,4,5) and (2,4,8); the feature map, the dynamic pool, hidden linear layer and the hidden size of the BI-LSTM were from a discrete uniform distribution on the interval $[100, 200]$, $[2, 6]$, $[40, 100]$, $[25, 75]$ respectively; the SEQ-CNN filter size was between the values 2,3,4 and feature map from a discrete uniform distribution on the interval $[800, 1200]$. The best assignment was chosen based on the F1 value achieved on the DMAR validation set after 50 search trials. We did not perform any other dataset-specific tuning. An implementation of all the models is downloadable in our github repository³.

In the interest of providing a fair comparison we tuned the hyperparameters of each model. To train XML-CNN, we selected a dynamic pooling window of length 3, a learning rate $5e-5$, a batch size of 32, feature map 128, hidden linear layer of size 77, filter sizes of (3,4,5) and dropout of 0.338. For Kim-CNN, we used batch size 64, filter sizes of (2,4,8), feature map of 164, learning rate 0.003 and dropout 0.077. For FastText, we used a batch size of 64 with learning rate 0.051. For training the Bi-LSTM, we chose a batch size of 64, learning rate 0.004, dropout of 0.056 and hidden size of 50. For SEQ-CNN, we used a batch size of 32, learning rate 0.084, filter size of 4, feature map 1033 and dropout 0.215. Finally, for the SVM and the LR model, we chose the default hyperparameters of the scikit-learn library.

For the QuestCNN, we used a batch size of 32, a learning rate 0.012, a feature map of 160, filter sizes of (3,4,5), a hidden linear layer of size 96, a dropout rate of 0.164 and an embedding dropout of 0.016. In addition, we applied spatial batch normal-

³https://github.com/gmichalo/question_identification_on_medical_logs

Model	DMAR				TWITTER			
	Test F1 %	Val. F1 %	R.T sec.	param.	Test F1 %	Val. F1 %	R.T sec.	param.
LR	64.3±0.2	65.0±0.4	0.5	4091	53.2±0.3	57.4±0.5	0.3	7133
SVM	76.8±0.4	77.2±0.2	0.7	4091	61.2±0.3	61.6±0.4	0.4	7133
KimCNN	83.9±0.3	84.4±0.2	536	2578371	61.7±0.4	62.7±0.5	180	4171778
BILSTM	82.9±0.2	83.3±0.2	168	1593715	58.9±0.4	59.3±0.4	100	5706010
XMLCNN	85.5±0.2	86.0±0.3	319	2209953	61.1±0.5	61.6±0.5	158	3803775
SeqCNN	84.2±0.1	84.4±0.1	3191	1243735	64.7±0.2	65.1±0.2	3142	1242701
FastText	77.8±0.1	79.9±0.1	45	1200003	63.0±0.3	63.6±0.4	36	2793602
QuestCNN	86.9±0.2	87.4±0.3	594	2988183	65.5±0.2	66.7±0.3	399	7100486

Table 3: Results of mean \pm standard deviation of five runs from each model on the test and the validation test; average running time (R.T.) and number of trainable parameters (param.) are also provided for each model. The number of parameters is different between datasets as we included the embeddings vectors that are fine-tuned for each dataset; all models used the same (MIMIC) embedding; best values are **bolded**

ization to the output of each channel of our model and batch normalization to the output of the hidden linear layer which is a technique for normalizing layer inputs. This technique has been shown to accelerate the training of different deep learning models (Ioffe and Szegedy, 2015). The Adam optimizer (Kingma and Ba, 2015) was chosen, with cross-entropy loss, as our optimization objective. Finally, each model was trained for 30 epochs.

Furthermore, in Figure 2, we provided the validation performance of the models based on the technique in (Dodge et al., 2019) that measures the mean and variance of the performance of a model as a function of the number of hyperparameter trials. Finally, as the datasets do not have a standard dev set, we split the dataset to 80% training, 10% validation and 10% testing. In order to present more robust results, we ran our model on five different seeds and we provided the average scores for the testing and the validation set.

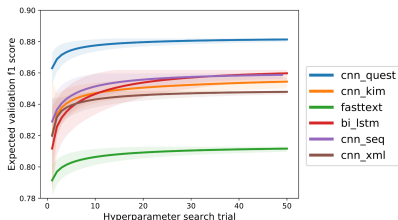


Figure 2: Expected validation performance of all the deep learning models over 50 hyperparameter trials. The standard deviation of the expected performance is represented as the shaded area in the graph

5.2.2 Deep Learning Model comparison

The mean and standard deviation (SD) of the scores for our model and the other competing models on the task of identifying questions are reported in Table 3. QUEST-CNN was shown to have achieved the best F1 score for both datasets (86.9% and 65.5%). This is due to the fact that the model utilizes information from all the features (syntactic, semantic, statistical) and uses regularization and normalization techniques. In section 5.2.3, we analyzed in detail the effect of each feature. The FastText model performed the poorest on DMAR (77.8%) as this model didn't consider the word order of the sentence but it required the least amount of running time. In addition, Kim-CNN, XML-CNN and Seq-CNN architectures had similar performances on the DMAR dataset (83.9%, 85.5% 84.2%) but on the twitter dataset Seq-CNN had the second best performance (after Quest-CNN) with 64.2%. However, the running time of the Seq-CNN is the largest by a considerable margin. Furthermore, the Bi-LSTM model which utilized all the features, achieved a non-optimal performance, which confirmed our hypothesis that a CNN-architecture is more suitable for the task of question identification. Also, it should be noted that SVM and LR achieved a decent performance. SVM in particular, achieved a similar performance to the FastText model on the DMAR dataset and even surpassed the BI-LSTM on the Twitter dataset.

5.2.3 Ablation Study

The comparison of the performance of different variants of our model is presented in Figure 3. Firstly, even our baseline model (CNN-rand) per-

6 Conclusion and Future work

In this paper, we have provided an analysis of the performance of existing methods for question extraction with real-world misclassification examples that showed the weak point of each method. Furthermore, we have proposed a novel approach for the automatic identification of real questions and *c-questions*. We have also shown empirically that the proposed architecture of unifying syntactic, semantic and statistical features achieved a state-of-the-art F1 score for this particular task. Finally, we have presented the relevance of exploiting domain knowledge in the overall performance of a model.

We are in the process of obtaining access to datasets from different application contexts in order to examine the generalizability of our model. As for future work, we plan to extend our work by calculating the similarity of questions in order to create groups of questions that represent the most impactful “problems” of a given application environment. Finally, we plan to compare our model with recent language representation models like the BERT model in (Devlin et al., 2019) both for the task of question identification and for the task of creating the above mentioned “problem” groups.

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Appendices

A UMLS Metathesaurus

As we described in the paper, for the creation of the semantic features of our model, relevant medical group names from the UMLS Metathesaurus were extracted. An example of mapping words to medical group names can be observed in Figure 4 where different words that have a medical significance can be categorized as a medical procedure, a disorder or an anatomy term.

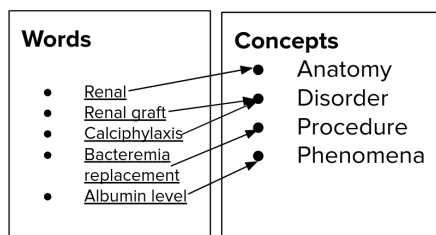


Figure 4: Example of mapping words to medical group

We also provide a complete list of all the Semantic Group Names and Semantic Type Names in Table 4 that our semantic feature model can choose from. In our experiment, we chose to only use the more general Semantic Group Names, since sentences are generally short in length, so we wanted to have a dense connection between different words that are semantically similar as possible. Finally, it should be noted that UMLS also contained additional Semantic groups (like Occupations, Organizations), which we decided to remove from the process of creation of semantic features, as these groups are irrelevant to the domain of the testing dataset. However, these medical groups did not influence the general performance of our model.

B C-question Format

In this paper, we introduced the notion of *c-question*, which is a question referring to an issue mentioned in a nearby sentence. The annotations of the sentences were created by manually checking each sentence and we adhered to the following rules:

A sentence can be classified as a *c-question* if:

- It can be classified as a real question i.e it expects an answer (information or help) about an issue.

Group Name	Semantic Type Name
Anatomy	Anatomical Structure
Anatomy	Body Location or Region
Anatomy	Body Part, Organ, or Organ Component
Anatomy	Body Space or Junction
Anatomy	Body Substance
Anatomy	Body System
Anatomy	Cell
Anatomy	Cell Component
Anatomy	Embryonic Structure
Anatomy	Fully Formed
Anatomy	Anatomical Structure
Anatomy	Tissue
Disorders	Anatomical Abnormality
Disorders	Cell or
Disorders	Molecular Dysfunction
Disorders	Congenital Abnormality
Disorders	Disease or Syndrome
Disorders	Experimental Model of Disease
Disorders	Finding
Disorders	Injury or Poisoning
Disorders	Mental or
Disorders	Behavioral Dysfunction
Disorders	Neoplastic Process
Disorders	Pathologic Function
Disorders	Sign or Symptom
Phenomena	Biologic Function
Phenomena	Environmental Effect of Humans
Phenomena	Human-caused
Phenomena	Phenomenon or Process
Phenomena	Laboratory or Test Result
Phenomena	Natural Phenomenon or Process
Phenomena	Phenomenon or Process
Procedures	Diagnostic Procedure
Procedures	Educational Activity
Procedures	Health Care Activity
Procedures	Laboratory Procedure
Procedures	Molecular Biology
Procedures	Research Technique
Procedures	Research Activity
Procedures	Therapeutic or Preventive Procedure

Table 4: The Semantic Group Names and the Semantic Type Names from UMLS library that were used for the semantic features.

- The issue of the question should not be recognizable from the sentence of the question. Usually the question would use a demonstrative pronoun (can you clarify this?).
- The issue of the question should only be identified in a nearby sentence.

	question	c-question
A.N. of coverage	6.10^{-4}	2.10^{-4}
A.N. of length	83.1	24.8
A.N. of words	14.4	4.9
A.N. of dem. pronoun	0.3	0.3

Table 5: Statistics of questions and c-questions; we use the acronym A.N for average number and dem. for demonstrative pronoun.

Finally, in Table 5, we list the statistics of the sentences that were classified as question-sentences and the *c-questions* in order to make the distinction between these categories more understandable. For example, we can observe that even if the average number of words of questions is 2.9 higher than the average number of words in *c-questions*, the average number of demonstrative pronouns is the same for both categories.