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Connecting Question Answering and Conversational Agents

Contextualizing German Questions for Interactive Question Answering Systems

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Abstract Research results in the field of Question Answering (QA) have shown that the classification of natural language questions significantly contributes to the accuracy of the generated answers. In this paper we present an approach which extends the prevalent question classification techniques by additionally considering further contextual information provided by the questions. Thereby we focus on improving the conversational abilities of existing interactive interfaces by enhancing their underlying QA systems in terms of response time and correctness. As a result, we are able to introduce a method based on a tripartite contextualization. First, we present a comprehensive question classification experiment based on machine learning using two different datasets and various feature sets for the German language. Second, we propose a method for detecting the focus chunk of a given question, that is, for identifying which part of the question is fundamentally relevant to the answer and which part refers to a specification of it. Third, we investigate how to identify and label the topic of a given question by means of a human-judgement experiment. We show that the resulting contextualization method contributes to an improvement of existing question answering systems and enhances their application within interactive scenarios.

Keywords Interactive Question Answering · Question Classification · Topic Spotting · Machine Learning

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1 Introduction

Question Answering (QA) has become an important research topic in the field of Information Retrieval (IR) and Artificial Intelligence [Giampiccolo et al., 2007, Ferrucci et al., 2010]. Different to traditional IR approaches (e.g. search & browse) in which users need to wade through a large set of query-related documents, the domain of QA allows for the delivery of succinct answers to natural language questions as posed by a user. This is of relevance for all types of intelligent user interfaces as QA abilities significantly help to improve human-computer interaction. Question and answer-type classification, representing the tasks of identifying the expected question and answer categories of a user's query, can be regarded as the most fundamental tasks of most existing QA systems [Li and Roth, 2002, Ferrucci et al., 2010]. Generally speaking, these tasks aim at classifying any given input question with reference to a given set of output categories, that is, identifying the kind of answer formation, entity, or concept being asked. Examples are determining the question types as *factoid*, *list*, and *definition* (e.g. *How tall is ...*, *In which movies played ...*, *What is a ...*), or, in the context of answer types, the appropriate named entity class for the answer (e.g. *numeral, person, company, date, height, currency*).

Previous research [Suzuki et al., 2003, Zhang and Lee, 2003, Quarteroni et al., 2007, Blooma et al., 2009] has shown that question contextualization [Lin et al., 2003, Bradesko et al., 2010] contributes significantly to the accuracy of QA systems. With reference to the QA track at the TREC conferences [Voorhees, 2007, Peñas et al., 2010], current state-of-the-art QA systems show a reasonable performance (accuracy up to 0.80) when focusing

Table 1 Example question entry from the *CLEF-2007* monolingual QA task [Giampiccolo et al., 2007] with enhanced contextualization (*German: Wann wurde Pearl Harbor von den Japanern angegriffen?*)

Q: [*When was*]^q [*Pearl Harbor*]^s [*attacked*]^p *by the* [*Japanese*]^{spec}*?*
Question Type: *Factoid* **Answer Type:** *Num:Date*
Subject: *Pearl Harbor* **Predicate:** *attacked* **Object:** ⟨ *Num:Date* ⟩
Focus Node: *Pearl Harbor* **Focus Specification:** *Japanese*
Topic Hints: *Attack on Pearl Harbor* *Battle of the Pacific War* *World War II*

on factoid question types (e.g. *What is the height of Mount Everest?*). However, with reference to all question types, only mediocre results can be achieved (average accuracy of QA systems at *ResPubliQA* 2009 [Peñas et al., 2010]: German: 0.44; English: 0.61; Spanish: 0.44; French: 0.45;). Hence, despite the significant improvements of current QA systems, the field of QA still remains challenging [Giampiccolo et al., 2007, Voorhees, 2007,Peñas et al., 2010].

In this paper, we investigate an extended question contextualization method to improve the interpretation of German questions and, eventually, to enhance the performance of an *interactive* QA system. More precisely, we focus on a tripartite contextualization (see Table 1) to tackle the following questions:

1. **Question and Answer Type Classification:** What is the expected question type (e.g. list, fact, or definition) and what is the expected answer type (e.g. numeral, person name) being asked?
2. **Focus Detection:** Which part of the query is at the centre of attention (fundamentally relevant to the answer) and which part of the question refers to a specification of it?
3. **Topic Spotting:** What is the primary topic of the question? To which topic may the answer belong to? What is the question (or conversation) about?

Question type classification obviously refers to the most traditional task of contextualization. Focus phrase detection is to support the decoding of natural language questions into a triple representation (e.g. *subject, predicate, object*) as demanded and applied in most existing question answering systems that use RDF resources as a knowledge base. The purpose of the topic spotting component is again tripartite: First, it allows us to deduce a set of expected answer candidates from the identified topic by means of their thematical membership [Waltinger et al., 2011]. It enables confining the used knowledge base by topic. Second, it allows the incorporation of the (*interactive*) context information of the entire conversation within a certain timeframe. That is, the identified topic hints can be incorporated as an answer context for the next question (e.g. in the context of the Pearl Harbor example, the next question of the user might be: *What was the first ship to be sunk?*). Third, since this application is embedded within an existing conversational agent architecture, it allows us to summarize the entire conversation by means of its dialog topic (e.g. *We talked about World War II and the Attack on Pearl Harbor!*). Consequently, the proposed approach aims to enhance the conversational behaviour of a conversational agent by means of *knowledge awareness*, in terms of connecting question answering and conversational agents, and *subject awareness*, in terms of connecting topic detection and interactive user dialogues [Waltinger et al., 2011].

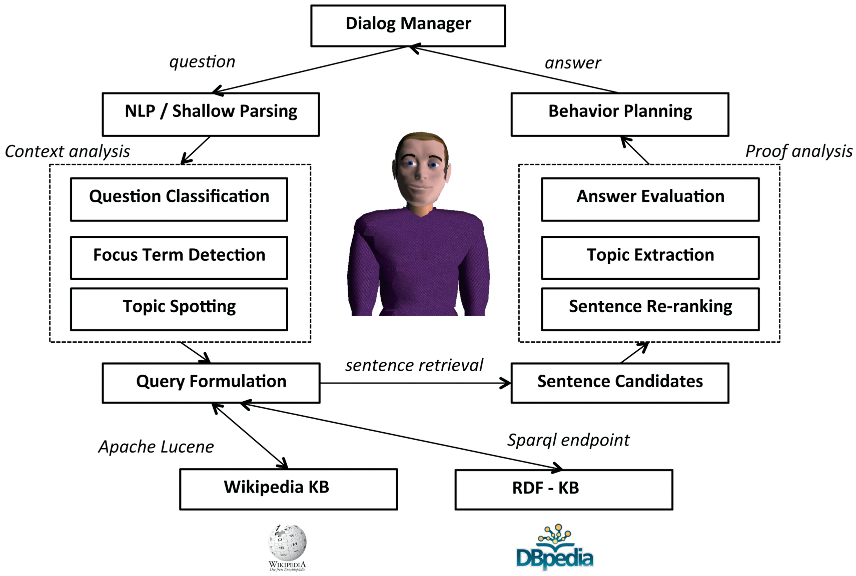
2 An Overview of WikiQA

In the *KnowCIT*[1] project, we extend the conversational abilities of the conversational agent *Max* [Kopp et al., 2005] by making the agent more context and topic aware in natural language interactions with humans. In this project, we connect two research areas which have moved closer to each other in recent years: Question Answering, here utilizing the Wikipedia-based question answering system *WikiQA*[2], and conversational agents, here: *Max*. Using information and answers drawn from the online encyclopaedia *Wikipedia*, *Max* is able to answer questions posed by his human dialogue partner as well as being able to identify the topic of an on-going dialogue [Breuing et al., 2011, Waltinger et al., 2011]. The overall architecture of the QA system employed in *Max* (see Fig. 1) can be subdivided into the classical processing pipelines for QA systems such as *context analysis* (e.g. question processing, shallow parsing, query formulation), *knowledge base retrieval* (e.g. semi-structured and/or RDF-based resources), and *proof analysis* (e.g. sentence candidate selection, re-ranking and answer evaluation). This specific system setup, however, also implicates several challenges: First and foremost, the response time. It is a mandatory precondition of our project setup that the QA system returns, out of millions of sentences, only

[1] Knowledge Enhanced Embodied Cognitive Interaction Technology (`www.cit-ec.de/research/knowcit`)

[2] The system is available at `www.wikiqa.de`

Fig. 1 Overview of the QA architecture within the dialog system of the conversational agent *Max*.



one single answer within a few seconds, in order to sustain the on-going conversation. Second, robustness is, in this context, of high priority. That is, the QA system must have a 'sense of confidence' about the answer, otherwise the interlocutor may not take the conversational agent's answers seriously in subsequent dialogues. In this regard, a contextualization of the users' questions, as proposed in this paper, additionally contributes to the accuracy, speed, and adequacy of the returned answers which in turn enables a more flexible, fluent, and coherent interaction between the artificial and the human interlocutors. Thus, we integrated our question contextualization approach into the agent's existing system architecture and evaluated a wide range of feature types and learning methods to exploit the applicability of our tripartite question contextualization in the context of interactive question answering.

The rest of this paper is structured as follows: In Section 3 we review related work. Section 4 describes the methods for the tripartite question contextualization with reference to question classification, focus detection, and topic spotting. We present the results of the classification experiments and the unsupervised topic detection method, which is evaluated through a human-judgement experiment. Finally, Section 5 summarizes and concludes the paper.

3 Related Work

Question classification is an important step to narrow down the search space of question answering and dialog systems. In recent years, many approaches to this problem have been proposed. Most notably with reference to the primarily comprised category structure for question classification, [Li and Roth, 2002] presented a two-layered taxonomy (see Table 2), which consists of six coarse categories and a total of 50 finer categories. The authors used a hierarchical classifier (accuracy: 0.91) combining lexical and syntactic features (e.g. Part-of-Speech (PoS), Named Entity (NE), and head chunks) targeting the English language.

Table 2 Subset of the two-layered question classification taxonomy for typical answers in the *TREC* task by [Li and Roth, 2002] (six coarse and 50 fine named-entity types)

ABBR	abr.	exp.		
HUMAN	group	individual	title	...
NUM	date	money	distance	...
LOC	city	country	state	...
ENTITY	animal	body	term	...
DESC	definition	manner	reason	...

[Solorio et al., 2004] also used the two-layered question classification taxonomy within their language independent classification method. By combining word features and machine learning-based Support Vector Machines (*SVM*), they obtained an accuracy of 0.82 on English, 0.88 on Italian and 0.80 on Spanish. [Zhang and Lee, 2003] presented a comprehensive question classification evaluation using *SVM*, k-Nearest Neighbor (*k-NN*), *Naive Bayes*, the *Sparse Network of Winnows*, and *Decision Trees*. They found that the syntactic structures of questions support the question classification task. The proposed syntactic tree kernel *SVM* exhibits the best performance (accuracy 0.90). Similar results could be achieved by [Suzuki et al., 2003] using *HDAG Kernel* on Japanese questions and by [Blooma et al., 2009] employing the *Yahoo! Answers Dataset* (accuracy 0.75). Using head words and their hypernyms as features for an *SVM*-based question classification, [Huang et al., 2008] report an accuracy of 0.89. With reference to the German language, as targeted in this paper, [Davidescu et al., 2007] presented an extensive evaluation using various machine learning algorithms applied to the 50 hierarchically organized classes of the *SmartWeb* ontology [Sonntag and Romanelli, 2006]. Davidescu and collegues used shallow and syntactical features for the classification task and report an accuracy of about 0.45. Their comprehensive evaluation has clearly shown the complexity of the task of question classification for the German language. The German *LogAnswer* system [Furbach et al., 2008, Glöckner and Pelzer, 2010] uses 240 classification rules for the question classification task.

The system proposed by [Koehler et al., 2008] recognized the question type by primarily focusing on the identification of (fourteen different) question words (e.g. *Who, Where, What*). [Neumann and Sacaleanu, 2004] presented a cross–language QA system for German and English using the lexicalized tree substitution grammar (LTSG) for question classification and query construction.

In this paper, we utilize part of the question dataset and classification taxonomy as provided by [Davidescu et al., 2007] and [Li and Roth, 2002] for our experiments (as a baseline - accuracy of about 0.45 for the German language), although we additionally analyse different feature types (e.g. lexical word net, class labels of the hierarchical structure, syntactic chunks, bag-of-word) for the classification task using an SVM-based approach.

In the context of focus detection, [Damljanovic et al., 2010] presented an approach of identifying the question focus by combining syntactic analysis and an ontology-based lookup technique based on user interaction. In this regard, their approach is similar to the approach proposed in this paper, though, instead of predicting the answer type by combining the head of the focus with ontology-based lookup, we combine syntactic analysis with a topic model technique applied to the Wikipedia dataset.

With respect to the domain of topic spotting for question contextualization [Lin et al., 2003, Bradesko et al., 2010] in dialogue systems, [Gerber and Chai, 2006] presented a regression model to identify topic terms. [Myers et al., 2000] proposed an approach for topic spotting in conversational speech (ten topics of the Switchboard corpus [Godfrey et al., 1992]) using the machine-learning program *BoosTexter* [Schapire and Singer, 2000] (accuracy of up to 88.3%). [Gupta and Ratinov, 2007] also comprised ten categories of the Switchboard corpus using a feature-generation approach to knowledge transfer. Their Naive Bayes classification approach has shown an error reduction of 17% using external knowledge (e.g. *Yahoo Answer dataset*, 500 *Wikipedia* clusters, and *Google* 5-grams collection). [Liu and Chua, 2001] proposed a semantic perceptron net approach for topic spotting using the *Reuters* corpus. [Lagus and Kuusisto, 2002] presented an approach using neural networks for subject recognition of dialogues.

Different to the approaches above, the method proposed in the present paper uses the *Wikipedia* dataset as the primary knowledge base for both answer extraction and topic detection. That is, we are not focusing on term or phrase extraction from a given input text, but utilize an external knowledge base to derive topic labels for a given question-answer pair. More precisely, we make use of the topic identification systems proposed by [Breuing and Wachsmuth, 2012]. This approach is mainly based on the five main tasks determined in the context of the Topic Detection and Tracking (TDT) research program [Allan, 2002]. Moreover, the Wikipedia category system is accessed to realize a dynamic online topic identification enabling the topical specification of previously unknown dialog contributions. Further examples for interactive systems identifying conversational topics are *Conversation Clusters* which visually highlight topics discussed in conversations using Explicit Semantic Analysis (ESA [Gabrilovich and Markovitch, 2007]) [Bergstrom and Karahalios, 2009], an emergency interface tool displaying relevant information sources according to the described emergency, and an embodied conversational agent identifying out-of-domain topics on the basis of the Google's directory structure [Mehta and Corradini, 2008]. In general, the *Wikipedia* dataset has received much attention in the field of information retrieval [Gabrilovich and Markovitch, 2007] and topic detection [Schönhofen, 2009, Waltinger and Mehler, 2009, Breuing et al., 2011], but also most recently to the domain of question answering [Buscaldi and Rosso, 2006, Fissaha Adafre et al., 2007, Furbach et al., 2008, Waltinger et al., 2011]. In our approach, we use the *Wikipedia* dataset as our resource to structure the knowledge base and to derive article and category information for the topic labeling task. Our method is using the dataset also for the question classification and focus detection task.

4 Contextualizing German Questions

In this section, we present the methods applied to the task of question contextualization. In general, we make use of two different methods for the experiments. First, we utilize Support Vector Machines (SVM) [Vapnik, 1995] as the classical apparatus in the context of (text) classification. The current implementation of the classifier module is based on SVM^{light} [Joachims, 2002], where linear and radial basis kernel functions are evaluated in leave-one-out cross-validation. Second, we apply the *Open Topic Model* approach as proposed by [Waltinger and Mehler, 2009]. More precisely, we utilize the German *Wikipedia* dataset in combination with the *Apache Lucene* framework [Hatcher et al., 2010] to rank *Wikipedia* article and category entries according to their strength of association to a given natural language question [Waltinger et al., 2011]. See Table 3 for an example ranking for a given input question.

Table 3 Excerpt from the Wikipedia-ranking for input question: *'When was Pearl Harbor attacked by the Japanese?'*.

Rank	Wiki Article Set	Wiki Category Set
1	Attack on Pearl Harbor	Battle of the Pacific War
2	Pearl Harbor	1941
3	Pearl Harbor (movie)	Hawaii
4	USS Pearl Harbor (LSD-52)	Sea Battle (World War II)

4.1 Dataset

For the experiments, we used two different question collections. First, we utilized 200 questions (Definition: 28; Factoid: 164; List: 8) from the *CLEF-2007* (8th Workshop of the Cross-Language Evaluation Forum) monolingual QA task using German as the target language [Giampiccolo et al., 2007]. Additionally, we used a subset of 200 questions (Definition: 59; Factoid: 138; List 3;) from the *SmartWeb* corpus [Cramer et al., 2006]. Note that we annotated each question by means of its category and a subset of the two-level-based question taxonomy as provided by [Li and Roth, 2002] (see Table 2). That is, the first level refers to the three most coarse-grained *question type* (Q-Type) categories (e.g. Definition, Factoid, and List). At the second layer, we differentiate between six different *question index* (Q-Index) categories (Abbr, Human, Num, Loc, Entity and Description). The third layer, which we refer to as the *answer type* (A-Type), comprises ten named entity classes (e.g. Title, Date, State, Distance, ...). Consequently, we used both datasets in combination, resulting in 400 sentences and an *answer type* category set of 14 different classes. All natural language questions were linguistically analysed using the shallow processing tool *TreeTagger* [Schmid, 1994]. That is, we applied tokenization, Part-of-Speech tagging, and lemmatization on the evaluation dataset. In addition, we utilized the embedded chunk parser to determine the syntactic chunks (e.g. NC: noun chunks, PC: prepositional phrase chunks, VC: verb chunks) of each question. See Figure 2 for an example question representation used for the experiments.

4.2 Question Classification

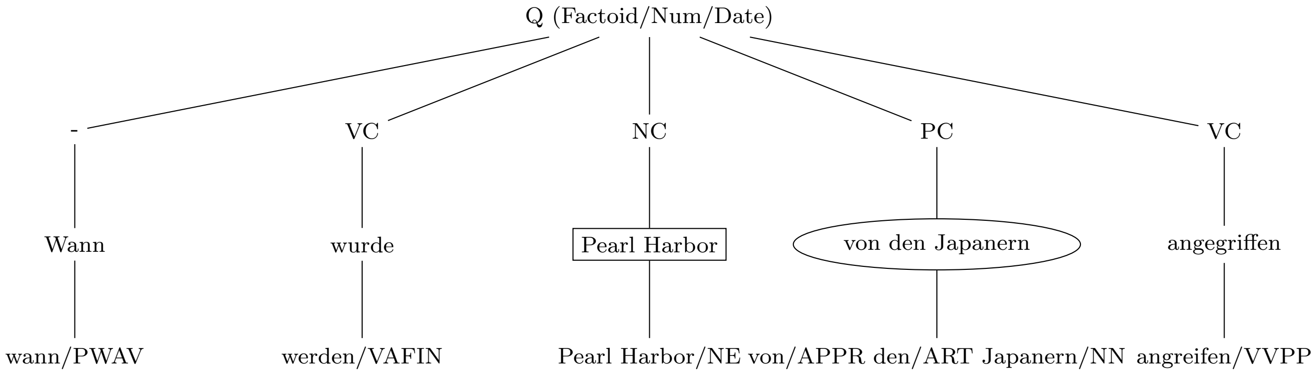
For the question classification task we employ an SVM-based approach. Previous research [Li and Roth, 2002, Davidescu et al., 2007] has already evaluated a wide range of machine learning classifiers, although, in the context of question classification, SVMs have not been extensively evaluated targeting the German language. In this work, we evaluated the following features to classify German questions by their question type:

- *Head words* refer to question words (e.g. *when was*, *what*, or *who is*) as the most obvious feature for question-type determination. Good performance for this feature has already been evaluated for the English language [Huang et al., 2008]. In our experiments, we used a quadgram-based approach to build the head word representation. More precisely, we focused on the first four words of each question by its lemmata and Part-of-Speech-tag (PoS) representation (e.g. feature set$f = \{wann, wann-werden, wann-werden-PearlHarbor, PWAV, PWAV-VAFIN, ...\}$).
- *Bag-of-words*, as the most traditional representation model in IR, represents each question as a set of words together with their frequency of occurrence, abstracting from its syntactic structure [Davidescu et al., 2007]. In our experiments, we built this representation by means of lemmata, PoS, and named entity class information using a trigram approach. That is, we allowed the incorporation of the syntactic structure to some extent, however, merging different feature categories (e.g. PoS, lemmata).

Table 4 German example questions from the *CLEF-2007* monolingual QA task [Giampiccolo et al., 2007] that are processed by the question contextualization pipeline.

Question	**Classification**	**Subject**	**Predicate**	**Focus Specification**
Wie hoch ist der Mount Everest?	Fac-Num-Dis	Mount Everest	hoch	
Wo lebt heute der Sohn von Audrey Hepburn?	Fac-Loc-Not	Audrey Hepburn	lebt	Sohn
Was ist Madame Tussaud?	Def-Def-Def	Madame Tussauds	ist	
Wo in Italien wurde die Villa Medici erbaut?	Fac-Loc-Not	Villa Medici	erbaut	Italien
Wie heißen die drei großen Wasserfälle im Canyon?	List-Ent-Pro	Canyon	heißen	drei großen Wasserfälle
Wie heißt das höchste Bergmassiv Afrikas?	Fac-Ent-Sub	Afrika	heißt	höchste Bergmassiv
Wie groß ist die Grundfläche des Pentagon?	Fac-Num-Size	Pentagon	groß	Grundfläche

Fig. 2 German example question from the *CLEF-2007* monolingual QA task [Giampiccolo et al., 2007] utilizing chunk, PoS-Tag and lemma representation after preprocessing. The expression marked with the rectangle highlights the focus term/phrase, the ellipse marks the specification of the question (English: *When was Pearl Harbor attacked by the Japanese?*)



– *Chunk* refers to the syntactic chunk representation of the respective question (see Figure 2). That is, we added a *bag-of-chunks* to the *bag-of-words* representation [Zhang and Lee, 2003] (e.g. feature set $f = \{VC, VC - NC, VC - NC - PC, ..\}$).
– *GermaNet* terms refer to hypernyms and hyponyms of the German lexical semantic wordnet *GermaNet* [Lemnitzer and Kunze, 2002]. That is, we enhanced any given input question by means of semantic relation information as identified by its labeled synset structure (e.g. angreifen $\mapsto$ beschädigen)
– *Wikipedia* articles and categories are used to enhance the question representation by its topical context [Waltinger and Mehler, 2009].
– *Taxonomy structure* features refer to categories of the used question taxonomy [Li and Roth, 2002]. More precisely, we enhance the question representation (*bag-of-words*) by its superordinate category label (e.g. factoid or definition) (e.g. Number $\mapsto$ Factoid). The rationale behind this approach is that since we are not aiming at a multi-label classification, the hierarchical structure allows us to narrow down the set of possible target categories.

As the *SVM* classifier expects questions represented as data vectors, each input was transformed to a weighted feature vector. Here we made use of the well-known TF-IDF [Salton and Buckley, 1988] weighting scheme.

The results of the question classification experiments on the *CLEF* corpus are shown in Table 5. The results of the *SmartWeb* and the combined dataset are shown in Table 6 and Table 7. Our baseline consists of the performance published by [Davidescu et al., 2007], who used 500 questions from the SmartWeb corpus. Their best results have shown an accuracy of 0.65 when using the Naive Bayes approach. In this context, our results (average 0.74 over all three layers of the SmartWeb; 0.77 using the combined dataset) can be regarded as a good performance. Interestingly, the feature enhancement approaches (in terms of *GermaNet* and *Wikipedia*

Table 5 Results of the question classification using *CLEF* dataset. We report F1-Measure by means of the *SVM*-based leave-one-out cross-validation using bag-of-words (bow), headwords (head), *Wikipedia* categories (wiki) and *GermaNet* terms (germ) representation. +Q-Type and +Q-Index refer to the enhancement by means of their taxonomy features. We leave out the chunk feature as it did not improve the classification performance.

Label	bow	head	wiki	germ
Q-Type	0.916	**0.930**	0.734	0.848
Q-Index	0.824	0.849	0.413	0.697
Q-Index (+Q-Type)	0.830	**0.856**	0.413	0.707
A-Type	0.682	0.681	0.374	0.586
A-Type (+Q-Index)	0.724	**0.781**	0.383	0.586

Table 6 Results of the question classification using SmartWeb corpus. We report F1-Measure by means of the *SVM*-based leave-one-out cross-validation using bag-of-words (bow) and headwords (head) representation.

Label	bow	head
Q-Type	0.850	**0.860**
Q-Index	0.742	0.732
Q-Index (+Q-Type)	0.776	**0.788**
A-Type	0.634	0.637
A-Type (+Q-Index)	0.721	**0.766**

Table 7 Results of the question classification on combined (co) dataset using *CLEF* and *SmartWeb* corpus. We report F1-Measure by means of the *SVM*-based leave-one-out cross-validation using bag-of-words (bow) and headwords (head) representation.

Label	bow	head
Q-Type	0.813	**0.823**
Q-Index	0.812	0.790
Q-Index (+Q-Type)	0.838	**0.820**
A-Type	0.695	0.724
A-Type (+Q-Index)	0.757	**0.762**

categories) did not improve the classification accuracy. In addition, utilizing the syntactic chunk information of a question also did not improve the performance (average accuracy of 0.72 on combined dataset). Moreover, it can be identified that using head words only (represented as quad-gram) exhibits the best performance on all three datasets (up to 0.82 at the *CLEF* dataset). That is, the first words opening a natural language question already indicate the type of the question as well as the type of the expected answer. As only a small amount of different wh-words exist, their particular range in terms of correct answers are clearly separated which significantly helps to narrow down the search space. Moreover, the enhancement of the hierarchical structure by means of superordinated categories obviously contributes, in addition, significantly to classification accuracy (up to 0.85 at the *CLEF*).

4.3 Focus Chunk Detection

The focus detection task locates the actual question object in front. That is, we need to identify which part (e.g. person name, company) of the question is at the centre of attention, and which part of the question refers to a specification of it, in order to identify the sequence of words which defines and disambiguates a given question [Moldovan et al., 1999]. Consider the following example: *'Name the 8 districts of Hiroshima'*. As shown in Figure 3, the PC chunk element (*Hiroshima*) can be identified as the question focus. The NC chunk, *the 8 districts*, serves as the specification of the object. Since *Hiroshima* is the only named entity in the question, this example is obviously of very basic nature. But what about the following questions: *'When did Audrey Hepburn marry Mel Ferrer?'* (focus on *Audrey Hepburn* or *Mel Ferrer*?), *'Who was the first African American who played for the Brooklyn Dodgers?'*, or to use the running example *'When was Pearl Harbor attacked by the Japanese?'* (NC is at the focus). Therefore, the task of focus chunk detection refers to identifying that part of the syntactic chunks which serves as the primary object of the question. In the current QA system, we need this information as a hint in which *Wikipedia* article we might find the desired information. To use the running example, we most probably find the information on the Pearl Harbor site instead of the *Wikipedia* Japan website. In addition, we need to extract the main object to query the RDF-based *DBpedia* dataset.

For the experiments, we manually annotated 200 questions of the *CLEF* question collection by means of their syntactic chunk representation and individually marked the focus and specification part in each question. Finally, we used the *bag-of-words* and the *bag-of-chunks* representations (as described in the previous section) for an SVM-based classification, using again leave-one-out cross-validation. In a second experiment, we applied the *Wikipedia*-based *Topic Model* approach. That is, for each input question we extracted a set of article and category titles from the *Wikipedia* dataset and ranked the respective chunk parts of the question with reference to the ranked *Wikipedia* results. More precisely, we focused on term overlap between each *Wikipedia* entry and each chunk part of the question. If the *Wikipedia* entry contains parts of the observed syntactic chunk, the latter will be labeled by the rank number of the respective *Wikipedia* rank score. Finally, we chose that part of the chunk set as our focus chunk which has the highest rank number. As shown in Table 8, the *Pearl Harbor* chunk is ranked higher than the *Japanese* chunk part (at rank 12). Therefore, the algorithm would detect *Pearl Harbor* as the focus chunk for the given input question.

The results of both experiments are shown in Table 9. The *SVM* results show that the incorporation of the syntactic chunk representation of questions let the performance only be mediocre (F1-measure[3] of 0.53). Interestingly, using only chunk and part-of-speech (including named entities) information, and therefore abstracting from the word (lemma) information, let us slightly increase the performance for this task. With respect to the (simple) un-supervised ranking approach

[3] F1-measure refers to the weighted harmonic mean of precision and recall.

Fig. 3 Parsed question representation of *"Name the 8 districts of Hiroshima"* used for focus chunk detection.

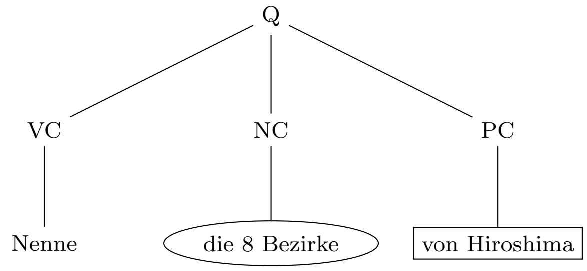


Table 8 Example *Wikipedia*-ranking of input question: *'When was **Pearl Harbor** (NC^{rank1}) attacked by the **Japan**ese (PC^{rank12})?'* for focus chunk detection task.

Rank	Wikipedia Topic Model
1	Attack on **Pearl Harbor**
2	Pearl Harbor
3	Pearl Harbor (movie)
4	USS Pearl Harbor (LDS-52)
5	1941
..	..
12	Naval battles involving **Japan**

Table 9 Results of the focus chunk detection experiment on *CLEF* corpus using *SVM* and leave-one-out cross-validation (F1-measure) and results of the *Wikipedia* topic model (accuracy).

Method	F1/Acc
SVM - with lemmata	0.529
SVM - without lemmata	0.533
Wikipedia - exact match	0.695
Wikipedia - substring match	**0.934**

by means of the *Wikipedia* topic model, we can identify that by using an exact match strategy for focus term detection, we clearly outperform the *SVM* approach (accuracy of 0.69). When allowing the incorporation of the substring strategy for the ranking, we achieve a quite reasonable accuracy of 0.93 for this task. That is, the proposed approach of ranking *Wikipedia* articles enables us to extract the main object of a user question (see Table 4). This information can be incorporated in a question answering system (unstructured or RDF-based) as a hint in which *Wikipedia* article the desired answer information might be located.

4.4 Topic Spotting

In the last experiment, we focus on the task of topic spotting in natural language questions. That is, we aim at labeling any given question by its thematic affiliation. Since the *question answering* system is embedded within a conversational agent architecture, which aims to detect and track the topic during the user-agent interaction, it is possible to not only return the answer but also the conversational topic. Thus, the agent is able to demonstrate his topic awareness by additionally presenting utterances such as "Hey, we speak about Pearl Harbor!" or "Hey, we speak about World War II!". Different to existing approaches, we thereby do not focus on term extraction or a clustering of a given dialogue dataset, but on labeling the questions as posed by the user individually (online) and by means of external topic labels using the *Wikipedia* dataset. More precisely, for each question we determine three different topic labels: First, we use the title of the best ranked article of the *Wikipedia* topic model as a topic label (e.g. Pearl Harbor). Second, we use the title of the most highly ranked category (e.g. 1941). Third, we utilize the title of the most highly ranked category, that is at least one link distant from the best ranked article in its category taxonomy structure (e.g. World War II). The rationale behind this approach is that an article title consists prevalently of terms that also occur in the question (e.g. as a substring), and can thereby be regarded as very 'close' to the input question representation (similar to the related clustering approaches). Predicted categories mainly refer to an abstract concept representation of the question and do not necessarily share features with the input question. Using categories which are at least one link distant from the respective article aims to label the input question by its broader topic (e.g. Pearl Harbor $\mapsto$ World War II; Helmut Kohl $\mapsto$ politics).

In the experimental setup, we were interested in which kind of label should be used for the interactive question answering system and which is regarded as an appropriate (human-like) response to the current topic by the user. Focusing on this aspect, we conducted a human-judgement experiment. We asked five volunteers to rate the different predicted topic labels by means of their thematical appropriateness for the given question embedded within the considered dialogue. Overall we used 200 questions from the *CLEF* task, each having three different topic labels given, where each label could be rated by three categories (a: fits well; b: mediocre; c: not appropriate). Finally, we calculated the inter-annotator agreement using Fleiss' Kappa [Fleiss, 1973] and the average pairwise percent agreement. The re-

Table 10 Results of the topic spotting experiment reporting Fleiss Kappa for inter-annotator agreement and average pairwise percent agreement on CLEF dataset.

Label	Fleiss' Kappa	Average pairwise
Article	0.43	**78,4%**
Category	0.33	60.6%
General	0.24	50.3%

sults are shown in Table 10.

We can identify that when using articles as a topic reference, a moderate agreement within all annotators can be achieved (average pairwise agreement of 78%). Using category information to label the given question, only a fair agreement can be achieved. What does that mean? Obviously, apart from the fact that some of the examples were not appropriate at all, the volunteers tend to rather expect terms that already occur in the question than labels within a certain scale of generalization. As, for example, to the question: "*Who is the singer of U2?*", they rather expect the label "We talk about *U2*" than "*Alternative rock-band*". Since we only used one single question as an input for the topic labeling task instead of providing an entire conversational sequence, the predicted topic labels rather refer to so-called *sentence topics* than *discourse topics* [Bublitz, 1989]. Embedded within an interactive, conversational system, the results may differ according to the topical context given by the present conversation. Evaluation on this aspect will be part of future work.

5 Conclusions

This work described a question contextualization approach for a German interactive question answering system employed within the architecture of the conversational agent *Max*. We thereby focused on a tripartite contextualization. *First*, as the most basic task, question type classification: We could identify that using headwords only as an input representation with *SVM*, a good performance with an overall accuracy of up to 0.85 can be achieved. *Second*, we proposed a method for detecting the focus chunk part of a given question. With an accuracy of 0.93, the results show a strong performance in this task. *Third*, we investigated how to label and directly display the topic of a given question using a large set of community-generated article and category labels from the *Wikipedia* dataset. The conducted user-judgement experiment suggested, with an average pairwise agreement of 78%, to use the *Wikipedia* article rather than category information to label single questions topically. Altogether, we have described three different approaches to the task of contextualizing German questions. The proposed approaches can be applied to improve existing unstructured and RDF-based question answering systems.

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