Mixed-Initiative Active Learning for Generating Linguistic Insights in Question Classification

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Abstract

We propose a mixed-initiative active learning system to tackle the challenge of building descriptive models for under-studied linguistic phenomena. Our particular use case is the linguistic analysis of question types, in particular in understanding what characterizes information-seeking vs. non-information-seeking questions (i.e., whether the speaker wants to elicit an answer from the hearer or not) and how automated methods can assist with the linguistic analysis. Our approach is motivated by the need for an effective and efficient human-in-the-loop process in natural language processing that relies on example-based learning and provides immediate feedback to the user. In addition to the concrete implementation of a question classification system, we describe general paradigms of explainable mixed-initiative learning, allowing for the user to access the patterns identified automatically by the system, rather than being confronted by a machine learning black box. Our user study demonstrates the capability of our system in providing deep linguistic insight into this particular analysis problem. The results of our evaluation are competitive with the current state-of-the-art.

Index Terms: Mixed-Initiative Visual Analytics—Active Learning—Visual Text Analytics—Question Classification;

1 Introduction

Machine learning has taken center stage in automated language processing, particularly in areas where large corpora and curated datasets are available. While these methods have produced notable successes, they tendentially do not incorporate available deeper linguistic knowledge and understanding gained over decades of linguistic study. Furthermore, the models produced by automated learning often remain black boxes, not readily understood by linguists, who aim at deducing general linguistic insights from data, e.g., in the form of patterns and rules. Therefore, as with many other disciplines that rely more and more on machine learning, the need for explainable artificial intelligence systems is in high demand.$^1$

Going beyond the mere understanding of machine learning models, the demand for incorporating the users’ domain knowledge into the learning process has also increased. A common way in bringing the human into the algorithmic loop is through mixed-initiative systems. These are designed to allow for efficient and effective interactions between humans and machines, acknowledging the advantages (reasoning vs. computation) of each contributor, respectively. A fruitful technique to achieve such processes is through visual analytics, as surveyed by Hohman et al. [17].

Hence, contributing to a tighter integration of machine learning algorithms and expertise, we propose a paradigm for mixed-initiative active learning in the context of computational linguistic methodology. Our general model is applicable beyond the specific linguistic use case, however, to maintain the scope of this paper, we showcase the effectiveness of the proposed process on a concrete instantiation of a question classification model. Following the design guidelines proposed by Liu et al. [23], we define the main tasks of this explainable mixed-initiative active learning process as (1) understandability; (2) refinement; and (3) justification. Moreover, we aim for a high coverage of the search space for learning through ranking the instances shown to the user, to achieve maximum gain through minimal feedback.

Questions are abundant in everyday conversation (in a randomly sampled 2-million tweets corpus compiled by Efron and Winget [7], 13% of phrases are questions). The phenomenon has so far been understudied in computational linguistics, despite a recent aim on the development of question answering systems [39]. The focus of this paper lies in automatically determining whether questions are information-seeking or non-information-seeking, i.e., whether the speaker wants to elicit an answer from the hearer or not. Our approach generates linguistic insights that are representative for distinguishing different types of questions in natural language discourse.

In this paper our contribution is three-fold. (1) We introduce the general paradigm of mixed-initiative active learning in linguistics

and define the main steps required for such a technique. (2) We provide a concrete instantiation of an eXplainable Question Classifier (XQuC), discussing all relevant implementation details. (3) We evaluate our approach, confirming competitive classification accuracy with the current state-of-the-art and verifying the linguistic insight obtained through a set of learning cycles.

2 BACKGROUND

Visualizations for Text Analysis The significant growth of textual data and the development of text mining has led to the emergence of visual text analytics [22]. There, interactive visualizations are combined with text analysis techniques to enable effective data analysis and exploration. Classification is among many other text analysis tasks, such as information retrieval, natural language processing, topic analysis, and explanatory analysis [22]. To support an effective analysis, many visualization techniques have been studied and developed over the last decades. These visualizations facilitate data compression, summarization, and pattern recognition [5]. For the classification task, visualizations can be used to describe learned rules. Several visualizations have been developed, most frequently, in the field of bio-informatics [4, 31, 35]. Commonly, a graph representation is used to show the connections between different rule-components [31, 35].

Active Learning and Labeling in Visual Analytics Active learning is a subfield of machine learning that enables machines to choose the data from which they learn. Settles [32] writes that “Active learning systems attempt to overcome the labeling bottleneck by asking queries in the form of unlabeled instances to be labeled by an oracle (e.g., a human annotator).” These systems aim to achieve high accuracy using as few labeled instances as possible [32]. Bernard et al. [2] write that “Labeling data instances is an important task in machine learning and visual analytics.” Machine learning (in particular active learning) follows a model-centered approach which means that the system suggests new instances to be labeled based on the underlying model; visual analytics are specified on rather user-centered approaches where the user can select candidates for labeling based on her observations [2]. Similar to other existing approaches [16, 30], we combine active learning with visual interactive labeling techniques to combine the advantages of both techniques.

Different variants of active learning have been applied across a range of applications, in particular text classification [24, 33, 38], named-entity recognition [34], semantic parsing [38] and syntactic parsing [36, 37]. All these approaches require a gold-standard annotation of the seed set. Our approach employs linguistic rules in order to generate the initial seed set and integrates the human in the loop with a live annotation system that runs in parallel to the learning. The user receives immediate feedback on the performance of the model and the impact of individual rules, providing a level of explainability that was previously missing.

Questions in NLP Automatically distinguishing the different types of questions is complex: One type of question is posed to elicit information and get an answer from the hearer (canonical, information-seeking questions—ISQs), for the other type the speaker does not expect an answer but instead triggers a certain type of speech act [6] (non-canonical, non-information-seeking questions—NISQs). Examples of the latter are rhetorical questions or self-addressed questions. In English, the surface syntactic structure of both types is often identical, but they differ in terms of their communicational goals, i.e. their pragmatics.

Most of the existing work has dealt with factoid ISQs such as When was Alan Turing at Bletchley Park?, with the goal of building Question-Answering systems, e.g., see Wang and Chua [39]. Comparatively less research has focused on identifying and understanding NISQs, a class which features a number of different subtypes, for instance rhetorical questions (Have you ever even touched a computer?), echo questions (She said what?), ability/inclination questions (Can you pass the salt?), to name just a few. Among the few approaches that explicitly focus on NISQs, [14, 21, 26], only [19] take recent theoretical linguistic work on questions into account and attempt a linguistic interpretation. This lack of linguistic motivation has also been observed by Kübler et al. [20].

3 PARADIGMS OF MIXED-INITIATIVE ACTIVE LEARNING IN LINGUISTICS

We propose a mixed-initiative active learning technique to tackle the challenge of building descriptive models for under-analyzed linguistic phenomena. In this section, we describe these steps as general high-level components of a mixed-initiative active learning approach. A concrete instantiation of our proposed approach, tackling the challenge of question classification, is presented in §4.

Mixed-initiative systems [18] combine the intuition and knowledge of humans with the computational power of machines. In the context of machine learning and visual analytics, such systems have been proposed to refine and optimize models through achieving minimum user-feedback for maximum learning-gain, e.g., recently in the context of topic model optimization [10]. We propose a general paradigm of mixed-initiative active learning for computational linguistics as a method for effective utilization of the users’ knowledge, as well as the generation of explainable linguistic insight. We thus tackle three tasks, namely, (1) understandability of the effects of the users’ interaction on the learned model; (2) refinement of the model based on the users’ domain knowledge; and (3) justification of the linguistic insight obtained.

The process of active learning takes as input an unlabeled corpus and outputs an annotated corpus, in addition to linguistic insight (e.g., in the form of rules or deduced patterns). Before entering the active learning loop, the model can be primed through heuristics as optional seeds for the linguistic knowledge (e.g., a known set of rules or expected patterns). This step primes the active learning and avoids cold starts. Afterwards, the system enters the three-stage loop of active learning. The current state of the model, as well as the corpus annotations and linguistic patterns learned, are constantly updated and represented through visualizations or simple log files.

The first step of the active learning loop is the instance sampling. Here, the selection of the instances which require user-feedback defines the search space considered by the algorithm. We aim at fulfilling two criteria in this step, namely, high coverage, i.e., considering a wide range of the search space through, for example, pool-based
We use JavaScript and the D3.js library for interactive visualization of the intermediate rules.

The second step is the labeling. This is the main interaction step between the users and the algorithm. A labeling interface can be designed through a dialog system, a visualization, or other interface design mediums. Such a labeling interface might also incorporate different levels of user feedback and domain expertise. The primary tasks that such an interface should provide are to label an unannotated data instance, verify a given annotation, resolve conflicts, and estimate the users’ confidence and confidence. As well as enable users to provide a justification for their decisions (which can be used in the model training).

Lastly, the third step of the active learning process is the model training and update. This step incorporates the newly obtained knowledge in the current model, updating its current state and monitoring its quality. This step largely depends on the underlying model and thus varies in each concrete instance of this process. However, due to the modularity and abstraction of our active learning approach, multiple models with varying parameters and learning approaches could be trained side-by-side (within the same system) and treated as an ensemble or as competing models.

4 XQuC: Explainable Question Classifier

Using XQuC, we train a rule-based classifier to distinguish TSQs from NISQs. The system’s workflow is shown in Figure 2: We first create training data by extracting questions and their context (two sentences before and after the question) from the CNN corpus, a large corpus of transcribed natural language dialog. Based on the information in the context, the type of question is later disambiguated by the human. We then use linguistic heuristics to generate a seed set from that training corpus (§4.1). In this step, the classification model is initialized (expressed by Algorithm 1). Afterwards, the active learning process is started: In each step, we use a certainty-based sampling in order to choose one to three questions that are then annotated by the user (§4.2). XQuC uses a visual user interface for the annotation task and, additionally, shows the intermediate classification results (§4.3). The visual representation helps to understand and justify how users’ decisions influence the model’s performance. The user can interactively refine the model, by interactively manipulating its visual representation. In each learning step, the model is updated, and new questions are sampled for the next iteration step.

The system has a server and client architecture. In the server (programmed in Java), the classification model is generated and the instance sampling for active learning is performed. In the client, we use JavaScript and the D3.js library to create a visual interface for question labeling and for visualization of the intermediate rules.

Algorithm 1 Question Classifier

```plaintext
1: procedure CREATEMODEL
2:    for i = 0 to initialRules.length do
3:        initialRule ← initialRules[i]
4:        addRuleUpdateWeight(initialRule)
5:    waitingQueue ← all instances
6:    toWeight(waitingQueue)
7:    toAnnotate ← waitingQueue[0]
8:    annotated ← annotate(toAnnotate, ø, ø)
9:    updateModel(annotated)
```

Algorithm 2 Model Update

```plaintext
1: procedure UPDATEMODEL(annotatedInst)
2:    annotated ← annotatedInst[0]
3:    verified ← annotatedInst[1]
4:    resolved ← annotatedInst[2]
5:    addRuleUpdateWeight(annotated)
6:    if verified ≠ ø then
7:        addRuleUpdateWeight(verified)
8:    if resolved ≠ ø then
9:        addRuleUpdateWeight(resolved)
10:   annotateInstances()
11:   sortToWeight(waitingQueue)
12:   toAnnotate ← waitingQueue[0]
13:   toVerify ← getSimilar(labeled)
14:   toResolve ← getConflicting()
15:   annotated ← annotate(toAnnotate, toVerify, toResolve)
16:   if annotated!= ø then return updateModel(annotated)
```

4.1 Seed Set Generation

For generating the seed set, we capitalize on recent theoretical linguistic insights on questions plus our own observations. The resulting heuristics are possible indicators of NISQs and fall broadly into four categories: The first category consists of fixed lexical expressions such as ‘give a damn’ [3], ‘on earth’ [1], ‘after all’ [28]. The second category encompasses structural patterns such as modals at the beginning of the question followed by negation (‘Wouldn’t you say that...? ’) [12] or the interrogative ‘why’ followed by the adverb ‘so’ or ‘that’ and some adjective (‘Why are you so angry?’). A third category subsumes discourse-structural patterns between the question and its context, e.g., if the same speaker utters a sequence of questions right after one another [1], or simply continues talking after posing a question, this is indicative of an NISQ. The same happens if the speaker consecutively repeats the same question or parts of it. The fourth category represents various other “markers” found in the data, such as questions within quotation marks and within a speaker’s dialogue turn: Those indicate that a speaker is only quoting someone else’s question. In the context of our work, we understand heuristics as deduced patterns from datasets that can be further generalized if verified over multiple resources. From such heuristics, we generate seed rules which are added to the initial rule-based model, described in §4.3.

4.2 Certainty-based Sampling

After generating the seed set and during each active learning step, we sample instances to be annotated by the user. There are two main approaches to instance sampling for active learning: pool-based sampling [24] and query-by-committee algorithm [11]. The former selects the best examples from the entire pool of unannotated documents, the latter measures the variance indirectly, by examining the disagreement among class labels assigned by a set of classifier variants, sampled from the probability distribution of classifiers that results from the annotated training examples.

In our approach, we use the certainty-based sampling. This technique is similar to pool-based sampling: The system selects one random instance which does not satisfy any existing heuristic of the model. If all instances satisfy at least one heuristic, the next sample is an instance of low certainty (described in §4.4). Here, the distance between the sum of the rule weights of the two classes is the smallest among all training instances.

4.3 Annotation

In the first iteration of the active learning, the user annotates only one uncertain instance. In the following steps, at most three instances...
A minimum and maximum threshold of the nodes’ support is used to specify its significance for the learning process. We search for an instance which satisfies the heuristic(s) defined by the user, she can change the rule or remove it from the model, and extracts heuristics based on the sequential combination of these features. If no text is selected, the system extracts a heuristic based on how users’ decisions influence the model’s quality, we visually represent the hierarchical graph structure utilizing a force-directed layout. Two example rule instances are shown in Figure 3. After each iteration step, the visualization is updated. If an erroneous rule is detected by the user, she can change the rule or remove it from the model, to exclude too general or specific rules from the final model.

Figure 3: Each rule consists of three parts: features describing the context before, question, and context after. Color coding is used to highlight whether two parts have different speakers. The opacity of rule borders shows its level of certainty.

For each instance, the user can specify the part of the question or its context which is assumed to be relevant for the classification task and also whether meta information about the speakers (questioner and answerer) is relevant. This information is sent to the server, where a new rule is created or the weight of an existing rule is updated accordingly. In order to create a rule, we integrate information that can be accessed via off-the-shelf tools, such as the Stanford CoreNLP software. For example, we use these to provide information on part-of-speech (POS) tags and named-entities (NE). Our system analyzes the underlying features of the selected text-regions and extracts heuristics based on the sequential combination of these features. If no text is selected, the system extracts a heuristic based on the feature distribution in this particular instance. We take into account that in some situations the user can be unsure about the correct label. Therefore, it is possible to specify the user’s confidence level for each instance separately, i.e. confident vs. not confident, or add a label NONE.

We create the rule-based model by applying a hierarchical graph structure. Two graphs (one for each class) in a combination build up the final classification model. Each seed and user-generated rule is added as a node to the directed graph; the child and parent nodes are sorted according to their certainty. They can then be interactively selected for a repeated annotation, if needed, which is another way to refine the model.

4.4 Question Classification

After the generation of seeds and during each active learning iteration step, we classify instances using the temporal model and show the classification results in the visual user interface. We calculate the certainty of each instance having one of the two classes (ISQ vs. NISQ). The certainty of an instance is calculated as follows: 

certainty := \sum_{i} \text{weight}(i),

where \text{weight}(i) is the number of rules which satisfy the particular instance for the particular class.

If the difference between certainty values for the two classes (ISQ and NISQ) is \(< 0.2\) (a heuristic chosen after the first evaluation of the system), then the instance is labeled as NONE. Otherwise, the instance has the label of its most certain class.

The classified instances are visually displayed in three groups, as shown in Figure 5: ISQ, NONE, NISQ, respectively. The instances are sorted according to their certainty. They can then be interactively selected for a repeated annotation, if needed, which is another way to refine the model.

5 Evaluation

In order to evaluate our model, we train multiple classifiers: SVM [15]; Decision Tree [29]; Naïve Bayes [25]) to compare our rule-based model against. We train the rule-based model with two different settings. The results are provided below.

5.1 Data

To evaluate our system, we use the CNN corpus\(^4\). We employ punctuation-based question extraction and additionally extract their context (two sentences before and after the question). We create a gold standard for which three linguistic experts each annotate 400 questions as ISQ or NISQ and we then take the result of the majority vote as the ground truth. They additionally record a confidence score (not confident vs. confident) for each question. Regarding the ISQ vs. NISQ classification, Fleiss’ \(\kappa\) is 0.554.

5.2 Machine Learning Models

Machine learning algorithms have been used in previous work to train question classifiers, mainly for social media data [14,21,27,40]. Although such data is complex and noisy (e.g., because of the length of the turn, ungrammaticality of sentences and spelling mistakes), the

We conduct two experiments in order to evaluate our active learning system. One expert from linguistics participate in each experiment. In the first experiment (Setting 1), the rules for the rule-based model are generated only from the questions themselves and the speaker information. In the second experiment (Setting 2), the context before and after are taken into account.

In both settings, the users are asked to perform 30 annotation iterations. They are allowed to refine the model manually by deleting false rules from the model’s visual representation.

We train three commonly used classification models (SVM, Decision Tree, and Naïve Bayes) to classify questions as ISQs vs. NISQs and compare their performance with our rule-based model. For the evaluation, we generate a bag-of-word representation of the questions and their context before and after. To reduce the chance that rules are more specific and thus capture less instances.

Dataset is enriched with information like usernames, hashtags and urls, which are used as additional features for the training and improve the performance. This can be seen in the best-performing classifier to have been evaluated in a comparable way to ours. [21] have trained a Random Forest classifier and report 0.76 precision, 0.87 recall and 0.77 accuracy in correctly classifying ISQs, using the question, its context and the Retweet feature. The work does not provide performance details for NISQs.

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In both settings, the users are asked to perform 30 annotation iterations. They are allowed to refine the model manually by deleting false rules from the model’s visual representation.

In both settings, the results show how context information influences the classification in that rules are more specific and thus capture less instances.

**Setting 1** In the first experiment, the rules are from the question itself and the speaker information. Figure 6 shows the model’s performance for ISQs and NISQs. The precision for both classes is relatively stable during the whole learning process. The recall constantly increases for ISQs (from 0.20 in the third iteration to 0.58 in the last iteration), causing a slight decrease of the model’s precision (from 0.82 in the third iteration to 0.70 in the last iteration). After 30 iterations, less instances are classified as NISQs (recall is 0.41) than ISQs. However, the heuristics which are learned are more descriptive. The precision for this class stays above 0.8 during the whole learning process.

**Setting 2** In the second experiment, the heuristics are generated from the question, the context before and after, and the speaker information. Figure 7 shows the performance of ISQs and NISQs. In comparison to the first experiment, the final recall of ISQs is reduced (from 0.58 to 0.29). However, the precision in the second experiment rises higher (0.70 in the first experiment and 0.81 in the second). The reason might be that the generated rules, when the contextual information is taken into account, are more specific; thus less instances are classified as ISQ. A similar observation can be made for NISQs. Due to the context information, the rules created are more specific. Thus, less instances are labeled as NISQs. In iteration 28 the recall of the model for ISQs is lower and in the next iteration increases again. The increase is influenced by a manual refinement of the model; the user detected a falsely generated rule (PROPER NOUN) which was then manually removed from the graph representation. This observation shows the importance of a visual feedback during the learning process which enables the user to improve the model’s quality when it is needed. The final results of the model after 30 iterations for both settings are shown in Table 1.

**5.4 Use Case: Explainable Linguistic Insight**

One of the core merits of our system lies in its explainability: We can understand and justify how decisions of the user lead to a model...
This pattern is a counterexample to the observation that con-

The evaluation exposes the benefits and limitations of our approach:

Table 1: Performance of off-the-shelf classifiers trained with a bag-

<table>
<thead>
<tr>
<th>ISQ</th>
<th>Precision</th>
<th>Recall</th>
<th>F-Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM</td>
<td>0.729</td>
<td>0.701</td>
<td>0.715</td>
</tr>
<tr>
<td>Decision Tree</td>
<td>1.000</td>
<td>0.185</td>
<td>0.312</td>
</tr>
<tr>
<td>Naive Bayes</td>
<td>0.734</td>
<td>0.692</td>
<td>0.712</td>
</tr>
<tr>
<td>Setting 1</td>
<td>0.70</td>
<td>0.58</td>
<td>0.64</td>
</tr>
<tr>
<td>Setting 2</td>
<td>0.81</td>
<td>0.29</td>
<td>0.42</td>
</tr>
<tr>
<td>NISQ</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SVM</td>
<td>0.673</td>
<td>0.706</td>
<td>0.689</td>
</tr>
<tr>
<td>Decision Tree</td>
<td>0.519</td>
<td>1.000</td>
<td>0.684</td>
</tr>
<tr>
<td>Naive Bayes</td>
<td>0.670</td>
<td>0.717</td>
<td>0.693</td>
</tr>
<tr>
<td>Setting 1</td>
<td>0.82</td>
<td>0.41</td>
<td>0.55</td>
</tr>
<tr>
<td>Setting 2</td>
<td>0.50</td>
<td>0.21</td>
<td>0.30</td>
</tr>
</tbody>
</table>

Table 1: Performance of off-the-shelf classifiers trained with a bag-of-word model of frequent n-grams and overall results for Settings 1 and 2. ISQ are better classified when context is taken into account (Setting 2), while NISQ seem to benefit more from the speaker information (Setting 1).

and also gain linguistic insights into the phenomenon. Figure 8 shows examples of rules learned for ISQs.

For instance we can elicit patterns such as the following, where a speaker is asking trivia questions (this can be ascertained by clicking on the pattern in the graph): a question ending with a PREPOSI-

Figure 8: Continuously updated graph visualizing the linguistic patterns that have been learned for the ISQ class. A pattern can be modified or removed in real-time by the user, using the functionality of its context menu.

In our future work, we aim at further refining the descriptor features used in the classification. Moreover, we are currently investigating different approaches with which users can provide and define their own features, based on their understanding of the domain problem. Lastly, for the task of question classification, we intend to expand our interface to include prosodic information, either provided by the dataset or by the users. The prototype will be made publicly accessible in the VisArgue framework (http://visargue.inf.uni.kn/).

6 Conclusion

In this paper we have presented a mixed-initiative active-learning system for question classification that generates explainable linguistic insights in the form of classification rules. The results highlight the complexity of the problem and prove the usefulness of the implemented visual user interface, which, in turn, provides real-time feedback on the quality of the model and the generated heuristics to aid in constantly improving the model’s performance.

Our observations show that, currently, the performance of the system might be limited due to the features used for the learning process. In order to improve the performance, we plan to integrate additional features such as the similarity between the question and its context, and prosodic features.

Another limitation of the system is the sensitivity of the rule-based model: Setting 2 shows that a rule which is too general can negatively influence the final model. If it is not detected and removed by the user, it can have a negative influence on the model’s performance. In order to make the model more stable, we could combine an ensemble of models created by multiple users in a single classifier.

5.5 Limitations and Lessons Learned

The evaluation exposes the benefits and limitations of our approach: First of all, the real-time feedback after each iteration step showing the influence of the decisions made by the user is important for detecting automatically-generated errors and resolving them (as shown in Setting 2). In comparison to the trained machine learning models, our active learning system reaches a relatively high precision, but a limited recall. The system can learn descriptive rules, but those rules only cover a subspace of our training corpus.

During the experiments, we observed that even linguistic experts had a challenge to label the data with a high confidence, as frequently the instances were highly ambiguous. It confirms the need for an iterative learning process which integrates the human in a feedback loop. Only permanent feedback from the expert (e.g., manual adaption of the model by wrongly learned information) can help to generate a stable classifier.

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