

SKET X: A Visual Analytics Tool for Explaining Knowledge Extraction Results^{*}

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Abstract

In recent years, knowledge extraction approaches have been adopted to distill the medical knowledge included in clinical reports. In this regard, the Semantic Knowledge Extractor Tool (SKET) has been introduced for extracting knowledge from pathology reports, leveraging a hybrid approach that combines unsupervised rule-based techniques with pre-trained Machine Learning (ML) models. Since ML models are usually based on probabilistic/statistical approaches, their predictions cannot be easily understood, especially for what concerns their underlying decision mechanism. To explain the SKET's decision-making process, we propose SKET eXplained (SKET X), a web-based system providing visual explanations in terms of the models, rules, and parameters involved for each prediction. SKET X is designed for pathologists and experts to ease the comprehension of SKET predictions, increase awareness, and improve the effectiveness of the overall knowledge extraction process according to the pathologists' feedback. To assess the learnability and usability of SKET X, we conducted a user study designed to collect useful suggestions from pathologists and domain experts to further improve the system.

Keywords

Clinical Practice, Digital Pathology, Expert Systems, Explainable AI, Knowledge Extraction, Machine Learning, Visual Analytics

1. Introduction

In the last decades, eXplainable Artificial Intelligence (XAI) approaches have gained increasingly importance to face the lack of interpretability and explainability of AI models relying on Machine Learning (ML) and Deep Learning (DL) methods [2]. Indeed, in the medical domain, the transparency of models and their decision processes is essential to promote trustworthy AI [3, 4]. In this regard, the High-Level Expert Group on Artificial Intelligence (AI HLEG), set up by the European Commission, recently published a set of ethics guidelines for trustworthy AI, requiring that “*algorithmic processes need to be transparent and decisions explainable*” [5]. XAI approaches to support physicians and medical experts in the comprehension of algorithm predictions are urgently needed due to the increasing application of AI in the medical domain, especially for diagnostics [6]. In particular, explainability techniques can be useful in the Digital Pathology (DPATH) domain, where most of the approaches for image analysis are DL-based. Yet, they are effective but their comprehension can be challenging for humans


IIR2023: 13th Italian Information Retrieval Workshop, June 8th - 9th, 2023, Pisa, Italy


^{*}The full paper has been originally published in the Journal of Pathology Informatics [1]

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 CEUR Workshop Proceedings (CEUR-WS.org)

due to their black-box nature [7, 8, 9]. In this context, Pocevičiūtė et al. emphasizes the importance of understanding why a specific prediction has been made in order to trust machine predictions exploited for diagnostic purposes [10]. Moreover, from a recent interview presented by Evans et al., it emerges that pathologists clearly prefer visual explanations for XAI [11]. As a prominent example, HistoMaprTM is a proprietary explainability tool for DPATH designed to support pathologists during the annotation activities of histology images, by means of visual explanations [12].

In the DPATH domain the Semantic Knowledge Extractor Tool (SKET) has been introduced to extract meaningful information – i.e., concepts, entity mentions, and labels – from pathology reports provided in natural language [1]. SKET performs the knowledge extraction process and produces weak annotations (labels) that can be used to train image classification algorithms for supporting the decision-making process in the DPATH domain [13]. However, since SKET adopts a hybrid approach that combines unsupervised rule-based techniques with pre-trained ML models, understanding the rationale behind SKET’s predictions may not be obvious for humans, despite it is crucial in the medical domain to have transparent models in order to trust their results. To explain SKET’s results, we designed and developed SKET eXplained (SKET X) a web-based system that exploits Visual Analytics (VA) techniques to provide the pathologists and experts with visual analyses and explanations regarding the underlying SKET’s decision process.

2. SKET X

SKET X is a web-based tool that aims to visually explain SKET predictions in order to ease their comprehension and support pathologists and domain experts in understanding the underlying machine decision mechanism [1]. SKET X is available at <http://w3id.org/sketx>¹ and provides a visual interface to interact with an online instance of SKET; it can be used to continuously refine SKET parameters and rules in a human-in-the-loop interaction so that to improve SKET’s effectiveness progressively. SKET X allows the users to explain the rationale employed to determine the Named Entity Recognition and Linking (NER+L) pipeline’s outputs, including the concepts and the corresponding mentions identified by SKET in the provided clinical reports. Through SKET X, users can get useful insights about SKET’s knowledge extraction process and the resulting outputs. Specifically, users can visually identify the different components (e.g., models, rules, and parameters) activated during the knowledge extraction process. Thereby, users can easily understand why a certain output has been generated for the given clinical reports. SKET X exploits VA techniques to make SKET’s outputs visually intuitive via interactive interfaces. SKET X allows the users to execute SKET several times as independent pipelines considering different models, parameters, and data. Thereby, users can easily compare SKET’s results using the dedicated interface tab *Compare* which displays the results of two pipelines considered in the comparison in two vertical panels arranged side-by-side. Moreover, users can compare variations of the same pipeline which is executed with different configuration parameters to assess their impact on the overall effectiveness of the knowledge extraction process. As a result, pathologists’ feedback can be exploited to refine the rules considered in

¹Access provided with credentials demo/demo

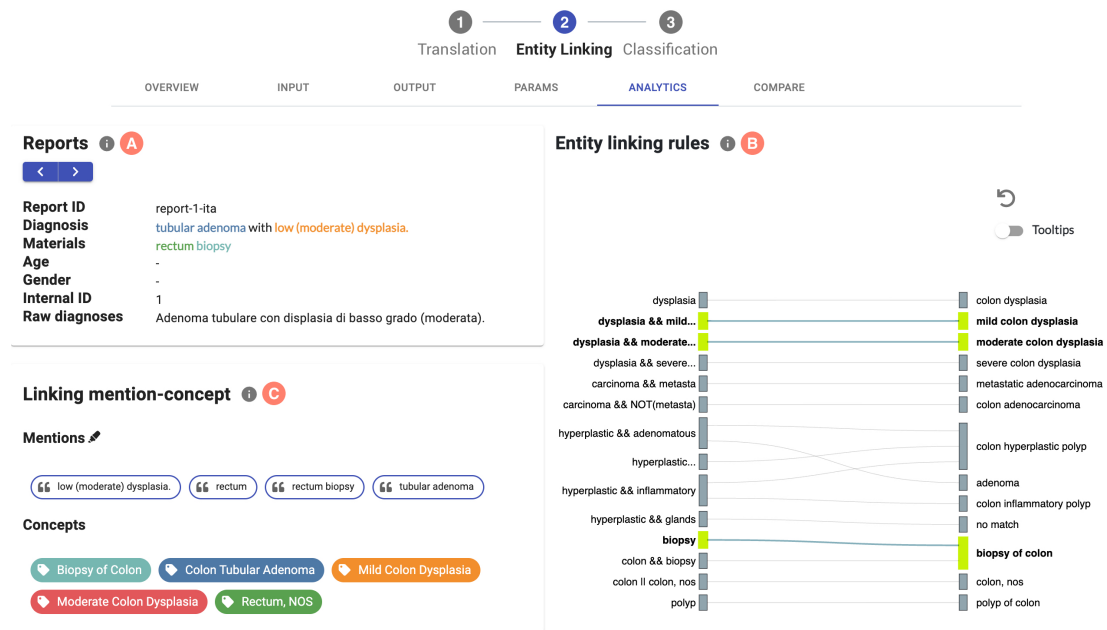


Figure 1: Analytics tab of the SKET X interface for the Entity Linking (EL) phase: (A) report information and left/right controls to change the current report displayed; (B) Sankey diagram reporting the rules used by SKET for the Named Entity Recognition (NER) task; and, (C) list of mentions and concepts extracted by SKET. Each concept and the corresponding mentions are highlighted consistently (same color) in (A) and (C). Users can click on a specific concept to highlight the relevant rules in the Sankey diagram involved in the prediction as well as the corresponding mentions in the report text. The Sankey diagram consists of two columns: (i) the left column reports the rules triggers, which are boolean expressions designed to test the presence/absence of specific sentinel terms on each entity mention identified. In case one or more mentions satisfy a rule trigger, then the related concepts are highlighted accordingly on the Sankey diagram (right side) and reported also in (C).

predictions, leading to improved effectiveness of the knowledge extraction process.

Figure 1 shows the main interface of SKET X which is organized in six tabs: *Overview*, *Input*, *Output*, *Params*, *Analytics*, and *Compare*. The current active tab in figure is *Analytics* which allows the user to analyze the outputs for the current phase (e.g., Entity Linking (EL)) of the knowledge extraction process. The interface is divided in three major parts: (A) report section displaying information for the current report as well as controls to navigate among the reports; (B) Sankey diagram presenting the SKET's rules for the current phase and highlighting the subset of rules activated for determining the current outputs; (C) section presenting the SKET's outputs. We can observe that SKET identifies several concepts including *Biopsy of Colon*, *Mild Colon Dysplasia*, and *Moderate Colon Dysplasia* that have been identified using the SKET's rules highlighted in the Sankey diagram on the right side.

User study

To evaluate SKET X in terms of learnability, usability, and user satisfaction we conducted a user study to collect feedback from pathologists and experts to improve SKET X accordingly. We

provided the participants anonymized credentials to access SKET X and a private link to an online form where they could answer predefined questions and provide feedback. The user study was organized into two parts, designed to measure the learnability and usability of SKET X, respectively. The learnability part focused on assessing the users' confidence and awareness with accomplishing the following predefined tasks with SKET X: (i) analyzing the mentions/concepts identified by SKET; (ii) analyzing the labels (weak annotations) produced by SKET and (iii) answer questions about the results produced by SKET. To guide and support the users in the analysis process, we provided two explanatory videos. Then, the collected answers of each user were compared with the correct ones to assess the user proficiency with SKET X in the analysis and interpretation of SKET's results. Secondly, we evaluated SKET X in terms of usability and user satisfaction using the System Usability Scale (SUS), that is considered an industry standard for assessing systems' usability [14]. Finally, we collected useful suggestions from pathologists and other experts to identify the key necessities and foster further advancements in the design of transparent and explainable models/algorithms for DPATH.

3. Conclusions

We introduced SKET X, a web-based system designed to explain the outputs generated by SKET through visual interactive interfaces. SKET X aims at simplifying the comprehension of SKET outputs as well as supporting pathologists and domain experts in their analysis, thus increasing awareness and understanding of the machine decision process. SKET X exploits VA techniques to explain why a specific prediction of SKET has been made and which are the roles of its different components - e.g., models, rules, and parameters - involved in the knowledge extraction process. Hence, SKET X allows expert users to not only comprehend SKET results but also get valuable insights concerning the knowledge extraction process. Moreover, we assessed SKET X in terms of usability and learnability, by conducting a user study with digital/computational pathology experts. For what concerns measuring the SKET X's learnability, we asked the participants to complete a sequence of analysis tasks by employing SKET X and then we asked them to answer a multiple-choice questionnaire. Thereby, we evaluated the number of tasks completed correctly by each user and thus the degree of understanding. From the answers and the explanations collected, we observed that almost all the participants correctly understood how to use SKET X to explain SKET results. Moreover, we asked the participants to answer a set of multiple choice questions to appraise user satisfaction and system usability according to the SUS scale. In this regard, we computed the average SUS score and it emerges that the usability of SKET X is quite good with a score equal to 66.7.

Acknowledgments

The work was supported by the ExaMode project as part of the EU H2020 program under Grant Agreement no. 825292.

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