A Python SDK for Authoring and using Computer-interpretable Guidelines

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Abstract: In this paper we describe a Python SDK that we developed and which we used to create a decision support system (DSS) for determining and presenting clinical practice guideline (CPG) recommendations for individual patients. Computer-interpretable guidelines (CIGs) are formalisms that represent CPG knowledge. Our Python SDK implements a model and an engine for a CIG formalism that can be easily integrated into any Python-based application. We describe important aspects of creating a guideline model with our CIG and present a web application that interacts with our guideline engine through a REST API. The web application implements generic components to manage and display the current input needs, recommendations, and statements. In comparison to PROforma, we added predicate components, which facilitate the reuse of logical expressions. Arguments refer to predicates instead of including expressions. This allows reusing the same expression in multiple arguments. We also allow the use of the predicates in other expressions, like in expressions of other predicates and task preconditions. To facilitate the integration of our CIG in decision support systems, we added properties to all PROforma components that represent a code from a terminology system.

1 INTRODUCTION

Clinical research aims at improving effectiveness and efficiency of patient health care. The increasing research generates a growing amount of evidence. Therefore, it is difficult for practitioners to keep up with the most recent knowledge about the best patient treatment. To overcome this, groups of clinical experts study and evaluate new evidence and formulate recommendations and statements for the patient treatment. They publish their results in form of clinical practice guidelines (CPGs) (?).

These written CPGs target a specific area of health care, for example, the treatment of a specific disease that occurs in a defined population. During a patient encounter, a practitioner must identify the parts of the guideline that apply to the patient, because guidelines refer generally to a population. For a single patient only specific parts of a CPG are of relevance. CPGs can be quite comprehensive documents, so this can be a tedious task. This is even more likely for patients with comorbidities, where multiple CPGs need to be consulted. Additionally, they might contradict each other, which would have to be recognized and resolved. As a solution to this, computer-interpretable guidelines (CIGs) have been invented. They are formalisms with concepts to represent the CPG knowledge (?; ?). By integrating CIG models into decision support systems, and allowing them to access information in patient health records (PHRs), the CIGs can identify CPG knowledge that is relevant for an individual patient. This happens in real-time and can be integrated into the practitioners daily routine. Decision support systems (DSS) could also include different CIGs and automatically manage contradictions to support the care of patients with multiple or comorbidities (?).

Although computer-interpretable guidelines have been researched for decades now, it has not been established that they are widely used in clinical routine. Instead, CPGs are still the common form for transferring evidence-based knowledge into the clinical routine. A reason for this might be that the transformation of a CPG into a CIG is often a time-consuming and coordination-intensive process, as expert knowledge is needed from two domains, the clinical and the technological area.

Another reason could be the low availability of standardized and user-friendly tools for creating

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CIGs. While several tools exist that support writing CPG text documents and publishing them as PDF documents (Microsoft Word, LibreOffice, Docbook, LaTeX), editors for CIGs are rare. The ontology editor Protégé (?) has been used as visual editor for models of different CIG formalisms (?, p. 751) and AsbruView is used to create models of the Asbru formalism (?). The PROforma formalism also has its own tools, which are Tallis and Alium from Deontics (?), and Arezzo from Elsevier InferMed (?). Arezzo and Alium are commercial tools, while Tallis (?) is available for research only.

Khodambashi et al. performed a review and analysis in the field of CIGs (?). They evaluated aspects of the following categories: "knowledge extraction performance, tool functionality, modelling perspective, user's effect on modelling, didactic support, usability, guideline verification and validation, integration, maintenance features and comparative analysis on encoding process". They concluded that "mainly technical and functional aspects of the technology" are addressed in the field of CIGs and postulated that it has "to move to a stronger focus on its users". We also believe that a strong focus on users is important, but the complexity of modelling a CIG cannot be avoided. Analytic and process oriented thinking is necessary, regardless of the tooling.

Furthermore, a CIG needs access to data from a PHR. Until today, accessing data from a PHR can impose a high effort, which can be an obstacle in the development of a CIG integrating DSS.

First, if digitally structured data is available, it is often not accessible through a standardized interface. This increases the effort to install a DSS with an integrated CIG in a clinical environment. However, the open HL7 FHIR standard (?) is being developed and increasingly used. It provides a standardized interface to access data from PHRs, reducing the effort to install decision support systems in different clinical environments.

Second, data is often stored unstructured and in natural language, which makes data processing difficult or even impossible. This means that a DSS using a CIG can not automatically access data, but requires a user to input it. This counteracts the time saving benefit of using a CIG over a CPG, especially with an increasing amount of data. We think that solutions to inquire digitally structured data need to be developed, because an automated processing of unstructured data in natural languange will not be generally possible.

We believe that more and more structured data will be available through a standardized interface in the near future, increasing the applicability of CIGs. This motivated us to find a way to apply clinical guidelines to patient data that is stored in a database. For the interpretation of patient data, medical terminologies like UMLS or SNOMED CT are important. We developed a software framework for authoring CIG models, into which we could integrate the support of such terminologies to facilitate semantically joining CIG components and patient data. In order to be able to reuse the technology, we decided to develop it as a Python SDK rather than a monolithic application.

2 METHODS

Several CIG formalisms have been introduced over the last two decades (?; ?; ?). M. Peleg (?) divides CIG formalisms into three categories: document models, decision trees and probabilistic models, and task-network models. Task-network models (TNMs) "provide modeling primitives specifically designed for representing complex, multistep clinical guidelines and for describing temporal and other relationships between component tasks. Unlike rulebased systems, TNMs can explicitly model alternative pathways or sequences of tasks (i.e., control flow), and they provide tools for visual representation of plans and the organization of tasks within them" (?, p. 53).

Especially GLIF (?) and PROforma (?; ?), two task-network model formalisms, have shown a high relevance. For our development, we selected PROforma as formalism as it is used in several research projects (?; ?; ?; ?; ?; ?; ?; ?; ?; ?) as well as in commercial solutions (?). From this we concluded that PROforma has the potential of being a universal CIG formalism and that it should fulfil our needs.

2.1 Implementation of PROforma Concepts

We implemented the PROforma concepts and guideline engine in the Python programming language. A detailed description of PROforma is given in (?). We chose Python, because it is an interpreted language that allows to evaluate expressions during runtime. This saved us the effort to implement an own expression evaluator. Python's popularity in the scientific community (?) additionally influenced our choice.

The PROforma components have been implemented as Python classes. They include the component data and parameterization. In our implementation the components have property objects that store values and changes locally. This is a difference to the original PROforma formalism, which has a global properties table that stores the component data and a global changes tables that stores value changes. Figure **??** shows the hierarchy of the most central classes.



Figure 1: This is the hierarchy of our Python classes that implement the PROforma components and properties. The base classes *Component*, *Task*, and *Property* are highlighted. One *Task* class contains multiple *Property* classes.

For each component we implemented a component controller class, which implements the engine logic and separates it from the component data. For example, the class *TaskController* can start or discard a task.

We do not parse and evaluate the original PROforma syntax. Our guideline models are persisted as RDF (?) documents using the turtle syntax (?). This saved us the effort to implement a parser for the PROforma syntax. The ontology of our guideline formalism is also available as an RDF document, which is automatically generated from the Python classes.

Logical expressions are written in Python syntax. They are allowed to use only a defined set of functions instead of the entire Python API to avoid adding arbitrary side effects and to reduce the risk of injecting malicious code through guideline models into a DSS.

In comparison to PROforma, we extended our CIG as follows:

• We added predicate components, which facilitate the reuse of logical expressions. Decision candidate arguments refer to a predicate instead of including an expression. This allows for reusing the same expression in multiple arguments by referring to the same predicate. We also support the use of predicates in other expressions, like the expressions of other predicates and task preconditions. Reusing expressions corresponds to the software development practice to prevent code duplication through modularization, which improves code maintainability. This makes expressions less complex and further corrections of a predicate will then automatically affect all expressions that use it. This saves the author time and prevents errors, because no manual search for and correction of the otherwise recurring pattern in expressions is necessary.

- To facilitate the integration of our CIG in decision support systems, we added properties to all components that can represent a code from a terminology system. For example, the candidates of a decision can be labelled by codes from the "Unified Medical Language System" (UMLS) ontology. The properties, inspired by the Coding element of the FHIR standard (?), are: *code*, *code_system*, and *code_display*. This avoids ambiguities when implementing the interface to a PHR.
- We added an AbstractSourcesProvider class as an interface for retrieving data from patient health records. It defines two methods: one to check whether the data for a given source can be retrieved, and one for actually retrieving the data. Multiple derived classes (SourcesProvider) can be implemented, for example for accessing different databases. They are registered at an instance of a SourcesProviderManager class, which iterates over all SourcesProvider instances and queries whether they can provide a given source and retrieve its data. To facilitate the implementation of a specific SourcesProvider for a guideline model, a description of all data items is exported as a JSON file. This description includes the data item names, data types, and codes from terminology systems. It can be used by developers who implement the interface to a PHR as a reference, to prevent the need to use our graphical editor to lookup the data items.
- Furthermore, our implementation includes a concept for translations. In expressions like task captions and descriptions, a function *tr()* can be used to translate strings:

$$tr("text") \rightarrow "text"_{translated}$$
 (1)

The input string is looked up in a translation mapping and the translation is returned. It can be configured which translation mapping shall be used by the guideline engine, thus it is possible to translate the same guideline into multiple languages.

2.1.1 Graphical Editor

We developed a graphical editor to provide a userfriendly authoring environment. It follows a low-code approach to enable users with little programming expertise to develop CIG models. There are similar visual programming tools for PROforma in the Tallis and Alium software suites, but they use the PROforma syntax to store the guideline models, which we do not support in favor of RDF.

Our editor is based on the rapid prototyping platform MeVisLab (?), which has a graphical editor for developing networks of image processing and visualization modules. We adapted the graphical editor to allow for creating task networks of our CIG.

Guideline models are stored as MDL documents, a MeVisLab specific format, which includes information that is only needed by the editor, for example, the 2D positions of the tasks. For the use in our guideline engine, the guideline models are exported as RDF documents. Figure **??** and figure **??** show screenshots of our editor.



Figure 2: Chronic cough guideline model based on a Tallis example.



Figure 3: User interface with task parameterization, expression editor, and bookmark viewer.

Further features of the editor are:

- a. a bookmark system for storing URLs and PDF files for quickly viewing web pages and guideline documents in an integrated viewer,
- b. an integrated tester that uses the engine to execute the guideline models,
- c. a graphical user interfaces for task parameterization and for defining data items and predicates, and
- d. to collect all occurrences of the *tr()*-function and generate a Qt Linguist (?) translation source file (*.ts), which can be edited by translators using Qt Linguist to generate the translation mapping file that our engine can load.

3 RESULTS

With our guideline editor at hand, we authored a guideline model from our CIG. Then we developed a decision support system, which uses a web application to provide the user interface and a Python-based REST API service to control the guideline engine.

3.1 Authoring the Guideline Model

Our guideline model is based on the German CPG "S3-Leitlinie Colitis ulcerosa" (?). Authoring it required some practicing, because it is not only necessary to understand the PROforma components and tasks, but also how the execution of the engine works and how the guideline engine interacts with a DSS.

3.1.1 Transition of Task States

A CIG author needs to understand the transition logic of the task states, which are: *dormant, discarded, in_progress,* and *completed* (?, p. 438). In order to author a CIG model, tasks are connected in the graphical editor to define which tasks are antecedent tasks of others. This relation is relevant for the transition of task states.

When the execution is startet, the engine executes the guideline model in turns. Each turn, it reviews all tasks and it checks if the state of a task has to change. Initially, tasks are *dormant*. A task stays *dormant* unless it has no antecedent tasks or all of them are *completed* or *discarded*. If all antecedent tasks are *discarded*, the task is also *discarded*. If one or more antecedent tasks are *completed*, the tasks *wait condition* is evaluated. If the *wait condition* is false, then the task stays *dormant*. If it is true or if there is no *wait* *condition*, then the *precondition* of the task is evaluated. If it exists and evaluates to false, then the task is *discarded*, otherwise its state is set to *in_progress*.

After every engine turnaround our DSS checks which tasks are *in_progress*. If any of these tasks require user input, which can be either data that cannot be retrieved from a database or the confirmation of a task, then our DSS displays a user interface that allows entering data and confirming the task. If the user provided the input, the DSS forwards it to the engine, which then validates the input and completes the task, if the input is valid.

3.1.2 Types of Tasks

PROforma defines different task types: *Enquiry*, *Action*, *Decision*, *Plan* (?; ?). The purpose of these tasks needs to be understood, as well as a how a DSS that integrates the guideline engine handles them.

Enquiries are used to access data at a certain engine state. They request *sources* when they are started to trigger the retrieval of data for their *data items*. Either the source data is queried automatically through our *SourcesProviderManager* instance, or it needs to be provided by the DSS that integrates the CIG, for example by asking the user with a dialog. For such an interactive usage of the CIG, it is relevant where and when an *enquiry* is started in the guideline model. For example, the interactive usability depends on

- how often a user is asked to input data and
- how much data a user has to provide.

The design of the guideline model defines at which time of execution which data is required. A DSS that integrates the CIG cannot even this out to improve the usability. For example, defining a single *enquiry* that requests all *sources* in the beginning of the execution is possible, but the user might have to input many data items that will not be used along the executed guideline path.

Actions are tasks with the intent to invoke a procedure, which can be an automatic function of the DSS or an instruction that is displayed to the user. While authoring a CIG, the connections in the task network, preconditions, and procedure description are the most important sub components of actions that need to be defined. The effect of an action task has to be implemented in the DSS that integrates the guideline engine.

Decisions are tasks that can get complex. They contain an arbitrary number of decision *candidates*, where each *candidate* can have an arbitrary number of *arguments*. Arguments are either in favor of or against the candidate. They refer to *predicates*, which

are expressions that can access *data items*. If the predicate expression evaluates to true, then the argument applies and it is considered when arguments of the candidate are weighed up. If the predicate is false, then the argument does not apply and it is ignored. For example, an argument against a candidate for a specific drug therapy might be the allergy to an active ingredient. If the patient does not have this allergy, the predicate will evaluate to false and the argument does not apply.

Arguments in favor of a candidate inrease its *net-support* value, arguments against it decrease the netsupport value. In other words: a candidate with a higher netsupport value than another candidate has a stronger support based on their arguments. This information can be either displayed to a user of the DSS when the *decision* must be made manually, or the guideline engine will automatically choose the candidate with the highest netsupport value. In addition to the netsupport value, a candidate can also include an expression that evaluates to a truth value to specify if it is recommended.

Plans are tasks that act as structural elements and are a kind of modularization. They contain an inner task network. In early authoring stages of a CIG model, when the model often changes, it may help to omit plans. Otherwise it may be frequently necessary to move tasks in and out of inner task networks. *Generic tasks*, which only include common task properties like the precondition, can be used as an antecedent task to serve to some degree as a replacement for plan features like sharing a precondition for a task network.

3.1.3 Data Items

A work intensive area is the management of *data items*. A complex CIG model can require hundreds of them. For each data item, a type, value range, caption, description, and code from a terminology system need to be provided. During authoring it can happen that certain already modelled data items need to be discarded or that they have to be replaced by multiple data items.

3.1.4 CIG Model Tests

As our CIG model grew, we found that we could break parts of it while continuing with its development. Similar to complex software, a complex CIG model cannot be entirely overlooked. We started to develop Python unit tests that execute the CIG model with the CIG engine. The tests provide specific input data and verify that expected execution paths were encountered. These tests helped us to detect and fix problems early, which is more efficient and effective than discovering and fixing the problems at a later stage of the guideline model development.

3.2 Our Decision Support System

The decision support system that we developed includes a Python based REST API service. It embeds and runs our guideline engine and allows for loading externally provided guideline models and translation mapping files. It also includes a *SourcesProvider* class that implements the *AbstractSourcesProvider* interface and supports querying our database that contains the patient data. An instance of this class is registered at the *SourcesProviderManager* instance.

The user interface of our DSS is implemented as a web application using the Angular framework (?). It includes our guideline model and sends it to the REST API service, which then initializes our guideline engine. It further communicates with our REST API service to execute the guideline.

After each engine turnaround, the REST API service queries the engine for all tasks with the state *in_progress*. If any of these tasks have *sources* with requested *data items* where the data could not be retrieved from our database, or if the task needs to be confirmed by a user, then it returns a JSON object to the web application. This JSON response contains the description of the task and its *sources*. If no task needs data or requires confirmation, then the next engine turnaround is automatically triggered. This procedure is repeated until all tasks are either *completed* or *discarded*.

To facilitate user interactions, our web application implements generic input components for each task type. All of them display the task caption and description.

The input component for *Actions* additionally displays the *procedure* text. We have not implemented any automated triggers for actions.

Another input component exists for tasks that include *sources*, which can be *enquiries* and *decisions*. This input component displays the *data item* values of the *sources* and allows entering values for *data items* that do not have a value.

For the more complex *decisions*, there is an additional input component to display their *candidates* in a vertical list. The *candidates* are ordered by *netsupport* value and priority, and information about the *arguments* for and against them is added to an expandable section, which is collapsed by default. The *candidates* are selectable by the user, and the task will not complete until a *candidate* was selected. *Plans* have no input component. Instead their inner tasks will be handled when they are *in_progress*.

4 DISCUSSION AND CONCLUSIONS

The presented decision support system is based on our Python SDK and allows for determining and presenting clinical practice guideline recommendations for individual patients. We authored a CIG model of the "S3-Leitlinie Colitis ulcerosa" (?) guideline. We did not evaluate it clinically, because the focus of our work was the realization of the technical concepts. The model and the engine for CIGs can easily be integrated into any Python-compatible application such as decision support systems that will become more and more relevant when digitization of hospitals increases. In combination with the graphical editor for the transformation of CPGs to CIGs, arbitrary guidelines could be modeled and integrated in decision support systems.

Besides this we also implemented new functionality compared to existing methods. For example, we added predicates to the PROforma concepts that allow for a modular use of expressions, so that they can be reused in other expressions and decision candidate arguments. This avoids the necessity of duplicating expressions, which also improves the maintainability when expressions need to be adapted throughout the modelling phase of the CIG.

Learnings regarding the development of such systems are as follows:

- The transformation of a CPG into a CIG requires the mental work of mapping statements and recommendations to tasks and decision-making based concepts. This can be challenging and requires practice, if CPGs do not focus on decisionmaking or do not describe a process. Some CPGs rather provide an enumeration of statements and recommendations.
- Other difficulties are that CPGs are sometimes ambiguous, vague (?), and target clinical practitioners, who can resolve ambiguities and fill in missing knowledge using their expert background. For computer scientists, this means that they cannot author a CIG on their own, they must be counseled by clinical experts.
- New CIG authors may be unsure about when to use an *enquiry* or a *decision*. For example, if a DSS shall allow a user to select a therapy with a specific drug. It is possible to ask if this drug

should be used for the treatment using an *enquiry* and a boolean *data item*. But clinical evidence may describe conditions under which a drug can be applied as well as alternative drugs. Instead of an *enquiry*, a *decision* should be used. The drug and its alternatives are modelled as *candidates* and the conditions are represented by *arguments*. An argument in favor of a drug could be a certain indicator, an argument against it could be an allergy.

- Trustworthiness of CIGs: CPGs need to be trustworthy in order to be accepted by clinicians (?). For example, conflicts of interest of the authors or different expert opinions about clinical evidence can impact the CPG trustworthiness, which needs to be addressed. CIGs that are created on top of the CPG knowledge inherit these issues. They may add deviations and errors that occur during their modelling. This could make it more difficult to trust CIGs, because digital models are exact, so they have to be correct, otherwise they could present false information. But as with other software, it is impossible to prove that they are correct, so testing and reviewing will be necessary measures to make them trustworthy.
- The recommendations of the guideline "S3-Leitlinie Colitis ulcerosa" include evidence grades, recommendation grades, and consensus grades. PROforma has no direct representation concepts for these classifications. There could be situations where they can be mapped to decision candidate priorities or netsupport values, but that can also be wrong. For example, prioritizing a drug therapy because of higher grades can be clinically wrong. A problem is also that a CPG recommendation may be represented through multiple CIG components. And CIG Components can also be part of the representation of multiple CPG recommendations. This makes it difficult to define the entities in the CIG that should represent the grades.

In the future, we would like to combine CIGs with local decision trees of specific hospitals or sites, maybe enhanced by deep learning results, to allow for integrative clinical decision support. The integration of multiple local decision trees into CIGs and the modelling of uncertainty from CPGs into CIGs are important steps for future developments.

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