Crowdsourcing Enabled Ontology Engineering

Abstract. Recent years have seen an increase in the use of crowdsourcing based methods at various stages of the ontology engineering lifecycle (e.g., verification of subsumption, assigning equivalences between concepts etc) thus laying the foundations of a novel approach to ontology engineering. Take up of this early research by the community at large, especially by practitioners, is however currently hampered by 1) a lack of understanding of which stages of the ontology engineering process can be crowdsourced and 2) tool support in ontology engineering platforms that would allow easy insertion of crowdsourcing into ontology engineering workflows. In this paper we perform an overview of recent works in the area and take a scenario-based approach to identifying those stages of the OE process where crowdsourcing makes sense. Then, we present the uComp Protege plugin, a plugin for the popular Protege ontology engineering platform that facilitates the integration of crowdsourcing stages into the OE process. TBD: clarify novelty (e.g., which new tasks we introduce?), sum up some important evaluation results.

Keywords: human computation, crowdsourcing, ontology engineering, ontology learning, Protege plugin

1 Introduction

[TBD - what is ontology engineering - and how it is always more distributed - WebProtege, GATE TEamWare - to create semantic annotations on text]

Crowdsourcing techniques allow outsourcing a task to "an undefined, generally large group of people in the form of an open call" [4] and are usually classified in three major genres depending on the motivation of the human contributors (e.g., payment vs. fun vs. altruism). Mechanised labour (MLab) is a type of paid-for crowdsourcing, where contributors choose to carry out small tasks (or micro-tasks) and are paid a small amount of money in return (often referred to as micro-payments). The most popular platform for mechanised labour is Amazon‘s Mechanical Turk (MTurk) which allows requesters to post their micro-tasks in the form of Human Intelligence Tasks (or HITs) to a large population of micro-workers (often referred to as turkers). Most projects use crowdsourcing marketplaces such as MTurk and CrowdFlower (CF), where contributors are extrinsically motivated through economic incentives. Games with a purpose (GWAPs) enable human contributors to carry out computation tasks as a side effect of playing online games [12]. Finally, altruistic crowdsourcing refers to cases where a task is carried out by a large number of volunteer contributors, such as in the case of the Galaxy Zoo (www.galaxyzoo.org) project where over 250K volunteers willing to help with scientific research classified Hubble Space Telescope galaxy images (150M galaxy classifications).

After concluding that micro-workers are a viable alternative for verifying subclass-superclass relations, Noy and colleagues [6] introduce a vision for a tool support that would facilitate the integration of crowdsourcing into OE workflows. [TBD: ZenCrowd and CrowdMap are already approaches that attempt to enable embedded human computation, by making crowdsourcing a part of computational workflow to solve Semantic Web specific tasks such as ontology matching and]. The GATE Crowdsourcing Plugin is a first example of a plugin in a popular toolkit that allows crowdsourcing from within the tool. [1]. We present such a tool in this paper, that not only allows the ontology engineer to crowdsource subsumption verification, but also a set of other tasks that often appear in ontology engineering scenarios.

RQ1: Which tasks can be crowdsourced? How do they fit in the OE workflow?

RQ2: How to provide tool support for crowdsourcing in OE?

The contributions of this paper are:

1. We distill a set of common crowdsourcing tasks that are likely to support a variety of ontology engineering tasks.
2. We present a tool, the uComp Protege plugin, which allows ontology engineers to crowdsource tasks directly from within the popular ontology engineering tool and as part of their ontology engineering workflows.
3. We evaluate some of the functionality of the plugin to estimate the improvements made possible over manually solving a set of tasks in terms of time and cost reductions, while maintaining a similar data quality.

2 Use of Crowdsourcing for Knowledge Acquisition

Crowdsourcing methods have been used to support several knowledge acquisition and, more specifically, ontology engineering tasks. To provide an overview of these methods we will group them along the three major stages of the Semantic Life-cycle as identified by Siorpaes in [10], where Stage 1 and 2 cover our notion of ontology engineering [TBD - clarify]. The main points of the following discussion are summed up in Table 1.

Stage 1: Build and maintain Semantic Web vocabularies . Already in 2010, Eckert and colleagues [3] relied on MTurk micro-workers in the process of building a concept hierarchy in the philosophy domain. Judgements collected from micro-workers complemented the output of an automatic hierarchy learning method and focused on two main tasks: judging the relatedness of concept pairs (5-points scale between unrelated and related) and specifying the level of generality between two terms (more/less specific than). Noy and colleagues [6] focus on the task of verifying subclass-superclass relations that make up the ontology hierarchy as a critical task while building ontologies.

Games with a purpose, have also been used to support the process on ontology creation. OntoPronto game [10] aims to support the creation and extension of Semantic Web vocabularies. Players are presented with a Wikipedia page of an entity and they have to (1) judge whether this entity denotes a concept or an instance; and then (2) relate it to the most specific concept of the PROTON ontology, therefore extending PROTON with new classes and instances. Climate Quiz [9] is a Facebook game where players evaluate whether two concepts presented by the system are related (e.g. environmental activism, activism), and which label is the most appropriate to describe this relation (e.g. is a sub-category of). The possible relations set contains both generic (is a sub-category of, is identical to, is the opposite of) and domain-specific (opposes, supports, threatens, influences, works on/with) relations. Finally, Guess What?! [5] goes beyond eliciting or verifying relations between concepts and aims to create complex axioms to describe concepts in an ontology. The game explores instance data available as linked open data. Given a seed concept (e.g., banana), the game engine collects relevant instances from DBpedia, Freebase and OpenCyc and extracts the main features of the concept (e.g., fruit, yellowish) which are then verified through the collective process of game playing. The tasks performed by players are: (1) assigning a class name to a complex class description (e.g., assign *Banana* to *fruit&yellow&grows on trees*) and (2) verifying previously generated class definitions.

Stage 2: Align Semantic Web vocabularies The CrowdMap system enlists micro-workers to solve the ontology alignment task [8]. It relies on two types of atomic HITS: the first one, asks crowdworkers to verify whether a given relation is correct ("Is conceptA the same As conceptB? yes/no "); the second task, requests micro-workers to specify how two given terms are related, in particular by choosing between sameAs, isAKindOf and notRelated. CrowdMap is designed to allow sameAs, subsumption or generic mappings between classes, properties and axioms, but currently it only supports equivalence and subsumption mappings between classes. SpotTheLink is a GWAP that focuses on aligning Semantic Web vocabularies and has been instantiated to align the eCl@ss and UNSWPC [10] as well as the DBPedia and PROTON ontologies [11]. The final version of the game, solves ontology alignment through two atomic tasks (1) choosing a related concept: given a DBPedia concept they need to choose and agree upon a related PROTON concept; (2) specifying the type of relation between two concepts in terms of equivalence or subsumption.

[TBD if time and place] Community focused efforts in Noy2013

Stage 3: Annotate content and maintain annotations ZenCrowd [2] focuses on the entity linking problem, where crowd-workers are used to verify the output of automatic entity linking algorithms. Concretely, given a named entity, e.g., "Berlin", and a set of dbpedia URLs generated automatically, crowd-workers have to choose all the URLs that represent that entity or "None of the above" if no URL is suitable. In essence this is an annotation task. WhoKnows? [13] and RISQ! [15] are two games with a purpose which rely on similar mechanisms: they use LOD facts to generate questions and use the answers to (1) evaluate property ranking (which property of an instance is the most important/relevant); (2)

detect inconsistencies; (3) find doubtful facts. The obtained property rankings reflect the wisdom of the crowd and are an alternative to semantic rankings generated algorithmically based on statistical and linguistic techniques. The games differ in the gaming paradigm they adopt. While WhoKnows?! uses a classroom paradigm and aims towards being an educational game, RISQ! is a Jeopardy-style quiz game.

[TBD: More: Celino; Sioarpaes ebay and video annotations]

SW Life-cycle Stage	**Approach**	**Genre**	**Solved Task**
Stage 1: Build and maintain Semantic Web vocabularies	InPho [3]	MLab	(T3) Specification of Relation Type (subs)
			(T1) Specification of Term Relatedness
	Noy [6]	MLab	(T2) Verification of Relation Correctness (subs)
	OntoPronto [10]	GWAP	Class vs. instance decisions
			(T3) Specification of Relation Type (subs/instOf)
	Climate Quiz [9]	GWAP	(T3) Specification of Relation Type (8 relations)
	Guess What?! [5]	GWAP	Verify complex class definitions
			Generate class names for complex defs
Satge 2: Align Semantic Web Vocabularies	CrowdMap [8]	MLab	(T2) Verification of Relation Correctness (subs/eqv)
			(T3) Specification of Relation Type (subs/eqv)
	SpotTheLink [11]	GWAP	(T1) Specification of Term Relatedness
			(T3) Specification of Relation Type (subs/eqv)
Stage 3: Annotate content and maintain Annotations	ZenCrowd [2]	MLab	Text to URL mapping (annotation)
	WhoKnows? [13]	GWAP	Answering quiz questions
	RISQ! [15]	GWAP	Answering quiz questions

Table 1. Overview of crowdsourcing approaches used to address tasks in various stages of the Semantic Web life-cycle [10], their genres and the type of crowdsourcing tasks that they employ.

2.1 Typical Crowdsourcing Task in Ontology Engineering

Based on the analysis of the crowdsourcing methods used to support ontology engineering tasks, it emerges that they often converge towards using a range of typical crowdsourcing tasks as follows.

T1. Specification of Term Relatedness. Crowd-workers need to judge whether two terms (typically representing ontology concepts) are related or not. In some cases they are presented with pairs of terms (InPho [3]) while in others they might need to choose a most related term from a set of given terms (SpotTheLink [11]). This type of crowdsourcing task is suitable to be used in diverse ontology engineering stages, for example, both in ontology creation scenarios (InPho [3]) and in ontology alignment ones (SpotTheLink [11]).

T2. Verification of Relation Correctness. Presented with a pair of terms (typically representing ontology concepts) and a relation between these terms, crowd-workers are required to judge whether the suggested relation holds or not. The majority of the works we reviewed report on verifying generic ontology relations such as equivalence [8] and subsumption [6, 8], which are relevant both in ontology evaluation [6] and ontology alignment scenarios [8].

T3. Specification of Relation Type. In these kinds of tasks, crowd-workers are presented with two terms (typically corresponding to ontology concepts) and can choose from a set of given relations the relation that best relates the terms. Most efforts focus on the specification of generic ontology relations such as equivalence (Climate Quiz [9], CrowdMap [8], SpotTheLink [11]), subsumption(Climate Quiz [9], InPho [3], OntoPronto [10], CrowdMap [8], SpotTheLink [11]), disjointness (Climate Quiz [9]) or instanceOf (OntoPronto [10], Climate Quiz [9]). The verification of domain-specific named relations such as performed by Climate Quiz [9] is less frequent.

T4. Verification of Domain Relevance. For this task, the crowd-workers confirm whether a given term is relevant for a domain of discourse. This task is mostly needed to support scenarios where ontologies are extracted using automatic methods, for example, through ontology learning.

The core crowdsourcing tasks we discuss above have been used by several approaches and across diverse stages of ontology (knowledge) engineering, therefore they are likely to be of interest in a wide range of ontology engineering scenarios. Therefore, they guided the development of our plugin, which currently supports tasks T2 and T4, as well as partially T3.

3 The uComp Protege Plugin

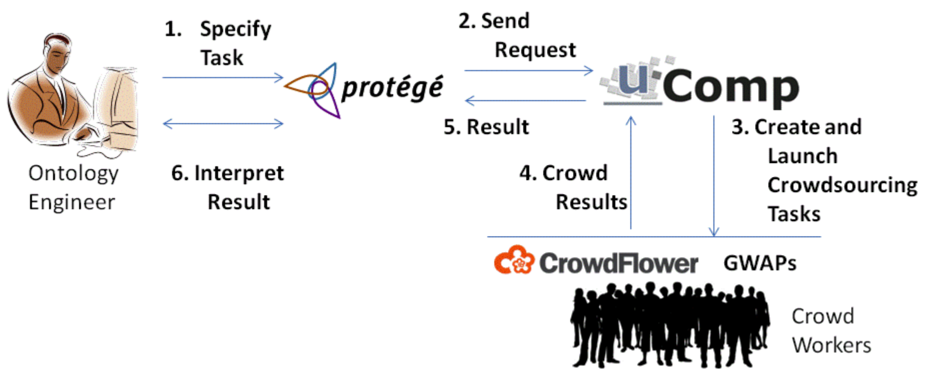


Fig. 1. Main stages in using the uComp plugin.

In order to support ontology engineers to easily and flexibly integrate crowdsourcing tasks within their ontology engineering workflows, we implemented a crowdsourcing plugin in Protege, one of the most widely used ontology editors.

The typical workflow of using the plugin involves the following main stages (as also depicted in Figure 1.

1. **Task Specification.** An ontology engineer using Protege can invoke the functionalities of the plugin from within the ontology editor at any time within his current work. The plugin allows specifying some well defined ontology engineering tasks, such as those discussed in Section 2.1 above. The view of the plugin that is appropriate for the task at hand is added to the editor's user interface via the *Window* → *Views* menu. The ontology engineer then specifies the part of the ontology to verify (eg. a specific class or all classes in the ontology), provides additional information and options in the plugin view and then starts the evaluation. The user can always cancel (pause) the validation process.
2. **Task Request**[? .] The plugin uses the uComp API[1] to request the processing of the task by the crowd.
3. **Creation of Crowdsourcing Tasks.** The crowdsourcing itself happens through the uComp platform[2], a hybrid-genre crowdsourcing platform which facilitates various knowledge acquisition tasks by flexibly crowdsourcing the received tasks to games with a purpose and mechanised labour platforms alike (in particular, CrowdFlower) [7]. Depending on user settings, the uComp API delegates the job to a GWAP, to CrowdFlower or to a combination of these two genres.

4&5 Collection of Crowd Results. The uComp platform collects and combines crowd-work harvested through various genres and sends the data to the plugin.

6. **Result Presentation and Interpretation.** As soon as available, the plugin presents the results to the user and saves them in the ontology. Depending on the result, the user will perform further actions such as deleting parts of the ontology which have been validated as non-relevant.

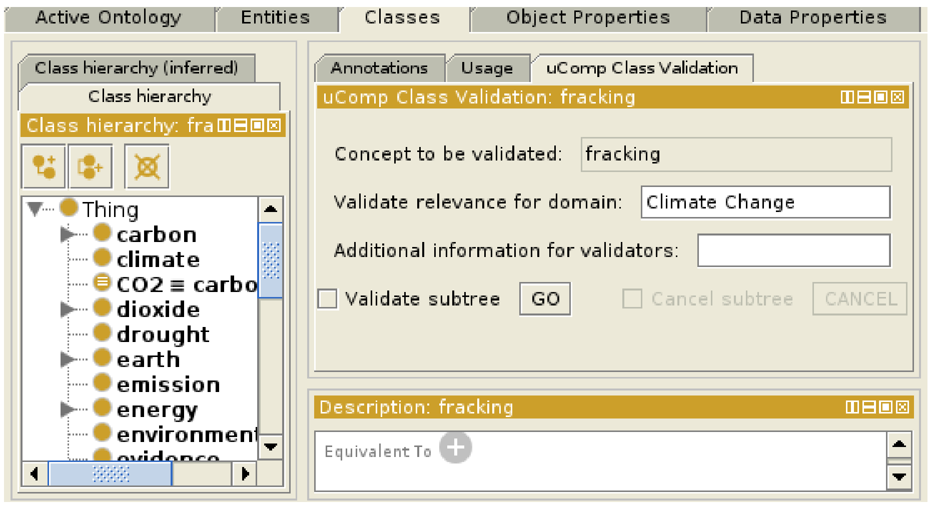
3.1 Plugin Functionality

Figure 2 shows the basic interface for the domain relevance task, the other tasks have similar interface. Initially, the user adds the new view in the Protege window. The plugin interface contains task specific information (eg. the concept selected by the user for validation), generic information such as the *domain* of the ontology and *additional information* (see below), and a `GO` button to start the validation process.

All data collected by the plugin which should be persistent is stored in the ontology in `rdfs:comment` fields, for example information about the domain, the job ID, and results from the game.

[1] TBD: is there an URL for this

[2] The platform is currently being developed as part of the uComp project, `http://www.ucomp.eu/`



uComp Class Validation: fracking

Concept to be validated: fracking

Validate relevance for domain: Climate Change

Additional information for validators:

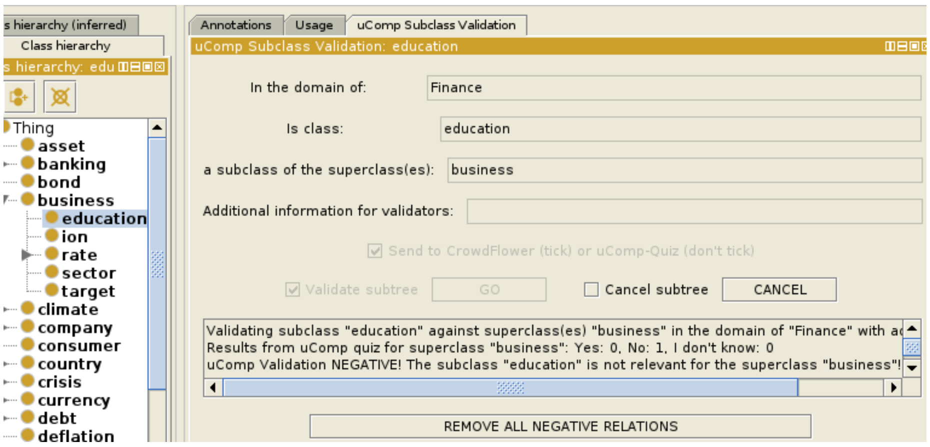
Validate subtree GO Cancel subtree CANCEL

Fig. 2. Screenshot showing the interface for validating a concept.

The User Interface What is common among all tasks handled by the plugin, is the selection of a *domain* and that the user can provide additional information about the task. The domain is simply the field of knowledge which the ontology covers. If entered once, the domain will be stored in the ontology (as `rdfs:comment`) and be pre-filled subsequently, but it can also be changed at any time. For every task, the plugin contains a predefined task description (typically including examples) which is presented to the crowd-worker. If the ontology engineer wants to extend this task description, (s)he can provide more guidelines in the *additional information* field. In many cases the user of the plugin wants to verify not only a single class, but a part of the ontology, or even the whole ontology. This can be achieved with the *Validate subtree* option. If the option is selected, the current concept and all its subconcepts are verified (recursively). To verify the entire ontology, the user invokes the plugin from the uppermost class, i.e., (*Thing*). In the remainder of the section we give some details about the parts of the plugin used in the evaluation (see Section 4), ie. verification of domain relevance and of relation correctness.

Task 1 - Verification of Domain Relevance. Verification of domain relevance of a class (called “uComp Class Validation” in the plugin) helps to decide if a concept (class) is relevant for a domain. First, the ontology engineer adds the corresponding view (*Window* → *Views* → *Class Views* → *uComp Class Validation*) to the UI. This is the simplest type of validation task, so the process is very much in line with the *usage* described above. Figure 2 shows the UI for the class “fracking” before initiating the verification. [TBD - how does the returned result look like? Do we have a screenshot?]

Task 2 - Verification of Relation Correctness. The second task is the verification of relation correctness, more precisely the verfication of IS-A



In the domain of: Finance

Is class: education

a subclass of the superclass(es): business

Additional information for validators:

```
Validating subclass "education" against superclass(es) "business" in the domain of "Finance" with a
Results from uComp quiz for superclass "business": Yes: 0, No: 1, I don't know: 0
uComp Validation NEGATIVE! The subclass "education" is not relevant for the superclass "business"!
```

Fig. 3. Screenshot showing the interface for subClassOf relation validation, including the display of results

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(subClassOf) relations between classes. The corresponding view is named *Class Views* → *uComp SubClass Validation*. When selecting a class in Protege, the plugin automatically detects its superclasses (if any) and fills the boxes in the plugin UI. As soon as results are available these are presented in the UI, as shown in Figure 3. The screenshot gives an example with one evaluator, who rated the *IS-A* relation between "education" and "business" as invalid. As the majority of ratings is negative, a button to remove the relation is displayed.

Task 3 - 5. The uComp Protege plugin also supports 3 other tasks, which we will cover only briefly, as they are not part of the user evaluation in Section 4. Task 3 is the verfication of *instanceOf* relations between an individual and a class, i.e. the crowd helps to verify if a given *instanceOf* is valid. Task 4 is concerned with validating *domain* and *range* of properties, which results in two separate sub-tasks (domain, range). And finally, we implemented a Protege view component that collects suggestions for labelling unlabeled relations from a set of given properties (relations).

3.2 Crowdsourcing Task Interfaces

Screenshot, instructions, pre-loaded gold, pre-set verification question, contributor and job settings

3.3 Implementation and Installation Details

Protege was developed in Java, it can easily be extended in the form of *plugins* which are typically Java Archive (.jar) files stored in the Protege `plugin` directory. The most common form of a Protege plugin is a *view plugin*, which implements a single view for a specific area of an ontology (e.g. classes, individuals, object properties, . . .).

Installation and setup. The plugin is available at `TODO--addlinkonceuploadedtoProtege`, includes detailed documentation about the tasks and the usage of the plugin. TODO (if necessary) documentation is accessible at .. To use the plugin you need to your uComp-API key[3] in a file named `ucomp_api_key.txt` in folder `.Protege`.

4 Evaluation

4.1 Evaluation Scenario - Ontology Engineering using Ontology Learning

Eckert has a similar scenario and Noy

Ontology construction from scratch is cumbersome and expensive (add citation?). Ontology learning supports the ontology building process by providing an automatically generated starting point. As automatically generated ontologies typically contain questionable or wrong ontological elements, a phase of redesign (especially pruning) is necessary.

In the ontology engineering scenario in this paper we aim to simplify the phase of pruning an ontology of concepts (classes) not relevant to the domain, as well as of *isA* relations that are not valid. The uComp Protege plugin also supports other tasks, such as validating *instanceOf* relations or checking *domain/range* restrictions (see below), but these are not part of the evaluation in this publication.

The remainder of this section gives a brief introduction to the ontology learning system used. The very first version of the system was published in 2005 ([**?**]), with improvements presented for example in Weichselbraun et al. [**?**] or Wohlgenannt et al. [14]. The system is geared towards learning lightweight domain ontologies from heterogeneous sources (text, social media, structured data). As we are learning domain ontologies in periodic intervals (monthly) from scratch, there is a focus on ontology evolution experiments, too. In a nutshell, the process is as follows: The ontology learning framework starts from a small seed ontology (typically just a few concepts and relations), and extends this seed ontology with additional concepts and relations. Evidence for new concepts and relations is collected from heterogeneous evidence sources with methods such as co-occurrence analysis or Hearst patterns. The neural network technique of spreading activation is the main algorithm used to determine the most important new concepts from the plethora of evidence. After positioning the new concepts in the ontology, the extended ontology serves as new seed ontology, and another round of extension is initiated. The system currently stops after three extension iterations.

[3] Request a key from the uComp team, see `http://soc.ecoresearch.net/facebook/election2008/ucomp-quiz-beta/api/v1/documentation/`

4.2 Evaluation Goal

The goal of the evaluation is to assess the improvements that the uComp Plugin could enable in a typical ontology engineering scenario in terms of typical project completion aspects such as time, cost and quality of output. The usability of the plugin is an additional criteria that should be evaluated. Concretely, our evaluation goals can be summarised into the following questions:

Time *How does the use of the plugin affect the time needed to perform ontology engineering tasks?* - We distinguish here the total task time (Ttt) as the time taken from the start of the ontology engineering task until its finalisation; and the time of the ontology engineer spent actively in the task (Toe). In a crowdsourced scenario, Toe ¡ Ttt, because the ontology engineer is only actively working during the outsourcing of the task and the review of the result. In contrast, in a traditional scenario Toe = Ttt. What is of interest to us is the time reduction ratio, that is (Ttt-Toe)/Ttt. (this will be computed as an average over multiple measurements, and over various ontology engineering tasks).

Cost *Are there cost benefits associated with the use of the plugin?* We compute costs related to payments for the involved work-force, that is payments to ontology experts and payments to crowd-workers. Costs of ontology experts are computed by multiplying the time they spend on the task (Toe) with an average salary. In order to allow comparison to other similar cost-focused studies [1], the wage of a research scientist was assumed to be $54,000 per annum.

Quality *What are the implications on the quality of the resulting output when using the Plugin?* Several earlier studies [e.g., Thalhammer13, Sabou13, Noy?, Sabou13] have shown that the quality of the semantic tasks performed by crowd-workers is in general similar to (or even better than) the quality of tasks performed by ontology engineers. While the quality of the obtained data is not the core focus of our evaluation, we expect to obtain results similar to those already published [TBD: note however, that unlike earlier studies which focus on simple, atomic tasks, we focus on more complex engineering tasks - is this really true?]

Usability *Is the plugin usable?* As any end-user tools, the plugin should be easy to understand and use by the average ontology engineer already familiar with the Protege environment.

4.3 Evaluation Setup

The setup involves working with two groups of ontology engineers, which will perform the same OE tasks.

Evaluators

Group 1 This group used the traditional (that is manual) approach to perform the ontology engineering tasks. It consisted of 8 ontology engineers

Group 2 This group, consisting of 2 ontology engineers, used the Plugin to perform the ontology engineering tasks. Group 2 was given a short tutorial about the plugin (30 minutes) and filled in a short usability questionnaire about using the plugin.

Evaluation Data The input to all evaluation tasks are ontologies generated by an ontology learning algorithm (primarily) from textual sources.

For every ontology snapshot, ie. every result of an ontology learning stage, as well as the resulting ontology the system exports an OWL file (using the Turtle seralization format, which can be converted to RDF/XML easily). The conversion of our internal format for lightweight ontologies is straightforward for concepts (which resemble to OWL classes). WordNet hyper- and hyponym relations are mapped to the OWL subClassOf property. The only challenging aspect is the representation of unlabeled relations in OWL. Our system creates ObjectProperties named "relation_n", where "n" is an auto-incrementing number, as it is not possible to use the same ObjectProperty more than once. The label for those relations is plainly "relation". The periodically created versions of the domain ontology can be uploaded to a triple store and are thereby accessible via the SPARQL.

We evaluate the plugin over two ontologies covering two diverse domains. Some details of the input ontologies are:

	Climate Change Ontology	**Finance Ontology**
Nr. of Classes	101	77
Nr. of Relations	62	50
Nr. of IsA Relations	43	20
Nr. of Un-named Relations	18	30

Table 2. Overview of the ontologies used in the experiments.

Evaluation Tasks We perform the evaluation of the plugin over two different ontology engineering tasks in order to 1) test different functionalities of the plugin; 2) obtain evaluation result over a range of tasks.

Both user groups will perform the following tasks:

Task 1: Check concept relevance for a domain For each concept of the ontology decide whether it is relevant for the domain in question (in our case, climate change and finance). Input: concept (class) and domain name; Output: true/false ratings – we use a uComp_class_relevance annotation in Protege to save the results – domain experts use true/false

Task 2: Check the correctness of isA relations For all isA relations in the ontology verify whether they are correct. Manual experts set the value for a certain annotation uComp_subclassof_check

Evaluation Metrics For time: For each participant measure Toe, and Ttt, for each task. Compute averages per participant Compute group averages and differences

For costs: Compute avg costs per participant and per group and differences

For quality: Since we do not have a baseline, we will proceed as follows: Task 1: compute pair-wise inter-expert agreement for both groups; and between groups this will measure how different the output is between the plugin and non-plugin group. If it is small then the results are similar; Compute also Cohens Kappa Task 2: same approach as with Task 1 Task 3: Here I think we should evaluate the quality of labels ourselves (em and Gerhard) for each produced ontology; and then compute a precision value

python time_analysis.py 27.375 avg vari 25.234375 stddev 5.02338282435

23.0 avg vari 38.75 stddev 6.22494979899

21.2857142857 avg vari 50.4897959184 stddev 7.10561720883

15.0 avg vari 31.4285714286 stddev 5.60611910581

	Climate Change Ontology		**Finance Ontology**	
	Task 1	Task 2	Task 1	Task 2
Manual validation - AVG time	27.375 (8)	23.0 (8)	21.28 (7)	15.0 (7)
Manual validation - STDDEV	5.023 (8)	6.225 (8)	7.106 (7)	5.610 (7)
CF validation - time				
Time reduction / ratio				

Table 3. Time measures .. TODO.

	Climate Change Ontology		**Finance Ontology**	
	Task 1	Task 2	Task 1	Task 2
Manual validation	0.338 (8)	0.502 (8)	0.500 (7)	0.388 (7)
Percentage valid – Manual	0.71	0.5	0.72	0.15
Manual + CF (Kappa)		0.527 (9)	0.504 (8)	0.429 (8)
TODO				

Table 4. Quality measures .. TODO.

We have measured inter-rater agreement using the statistical measure of Fleiss' Kappa. Fleiss' Kappa assesses reliability of agreement with a fixed number of raters and categorical ratings assigned to a number of items.

Table 4 presents quality measures .. bla TODO. Inter-rater agreement rates measured with Fleiss' Kappa are consistent and rather high, except for the class relevance verification task for the *Climate Change* ontology. The number of raters per task is given in parantheses. TODO refine *Percentage valid* reflects the ratio of unit where the majority of raters confirm the validity.

```
Usability -- OLGA:
Although I didn’t succeed to run the plug-in, i think, i could already answer the questi

1)The documentation was easy to understand.
-> 4, th part about installing plug-in was a bit of mixture with general info about prot
2) The plugin functionality was easy to use.
-> 5 , it is especially good that one can choose to make the check for all ontology at o
3) I would prefer to use the plugin as opposed to doing these tasks manually.
-> 5
4) The use of the plugin saves a lot of time to the ontology engineer.
-> 5
```

5 Conclusions and Future Work

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