

# Semi-automatic Translations of Data Privacy Policies into Controlled Natural Languages

IRFAN KHAN TANOLI<sup>1</sup>, YASEEN KHAN TANOLI<sup>2</sup> AND ASIF KHALID QURESHI<sup>3</sup>

**ABSTRACT:** Natural languages (NLs) are a simple and understandable form for presenting knowledge. However, they are ambiguous and it turns out to be quite complex to process them with machines. Controlled Natural Languages (CNLs) are usually simpler versions of NLs that are obtained by restricting the grammar and vocabulary to reduce, or even eliminate, ambiguity and complexity. CNLs look informal like NLs and are easy to read and understand and can be easily be transformed into machine-readable forms. In this paper, we present NLPT for semi-automatic translation of privacy statements, from NL to a controlled natural one, to improve machine processing. To assess the performance, we experiment on a large set of

Twitter data policies. Here, we consider two main aspects i) the translation of social network data privacy policy and ii) the efficiency and efficacy of the proposed system. We also perform an empirical analysis of the results and conclude that our system can be used to translate input policies effectively and efficiently.

**INDEX TERMS:** Controlled Natural Languages, Data Modeling, Natural Language Processing, Social Networks Policies.

## I. INTRODUCTION

Social Networks (SNs) have a great impact on our everyday life. Users increasingly rely on SNs to share their opinions, plan activities, exchange information, and establish social relationships [1]. SNs interactions usually require the exchange of user's data for a variety of purposes, including the provisioning of services. The collection, usage, and sharing of user's data are usually regulated by SNs (e.g., Facebook data [2], Twitter privacy policies [3], Google privacy policies [4]). Usually, published in English NL, the policies [5] describe the terms and conditions under which the provider will manage the data in terms of e.g., authorised, obliged, or denied. Although the use of the English language enables end-users to read and understand the operations allowed (or obliged, or denied) on their data, a key issue relies on the fact that a plain NL cannot be used as the input language for a policy-based software infrastructure devoted to automatic policy management [6].

Previously in [6], we presented an approach to translate NL privacy policies, as they appear on social networks websites, into a CNL, namely CNL4DSA *Controlled Natural Language for Data Sharing Agreements* [7]. To assess the validity of our translator, we run the NLPT system on a small set of Facebook data policies. Initially, NLPT can translate only a few sets of data policies [6]. In this paper, we present the NLPT 2.0 with vast improvements from the previous version, equipped with a user-friendly GUI where non-expert users can input policies in NL sentences for translation purposes. Apart, the system is designed to assist researchers to evaluate policies specification of data privacy in social networks, also for other application domains (e.g., e-health, e-commerce, etc).

The rest of paper is structured as follows: Section II describes the overall system architecture. Section IV presents experimental setup. Section V discusses the results. The final section VI outlines directions for future work and draws the conclusions.

<sup>1</sup>Gran Sasso Science Institute, L'Aquila 67100, Italy (e-mail: irfankhan.tanoli@gssi.it)

<sup>2</sup>University of Beira Interior, Covilhã 6201-001, Portugal (e-mail:

yaseen.khan.tanoli@ubi.pt)

<sup>3</sup>Sir Syed University of Engineering and Technology, Karachi City, Sindh, Pakistan (e-mail: asif.khalid@ssuet.edu.pk)

Corresponding author: Irfan Khan Tanoli (e-mail: irfan.khan.tanoli@ubi.pt).

## II. ARCHITECTURE AND GRAPHICAL USER INTERFACE

In [6], we present the methodological approach including all necessary steps required for policy translation. We have illustrated our approach on Facebook Policies translations. In this section, we show the next prototypical version of the system so-called ‘Natural Language Policy Translator’ (NLPT) 2.0. The system enables generic social network NL data policies translation into CNL4DSA. Here, we highlight the overall architecture of NLPT 2.0, including its Graphical User Interface (GUI). In particular, we introduce the role of the Policy Writer, an end-user to input the original policy following the instructions available in the usermanual.

### A. ARCHITECTURE OF NLPT

Natural Language Policy Translator (NLPT) 2.0 is composed of different components. Figure 1 reports the NLPT high level architecture. The details of each component are as follows: Policy Writer is an entity that

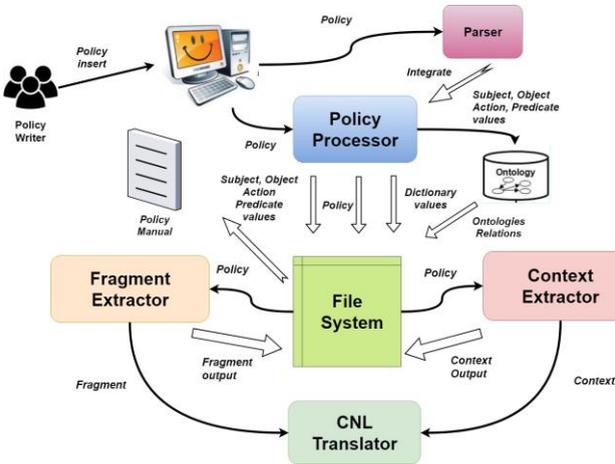


FIGURE 1: System Architecture NLPT 2.0

appropriately writes the policy. The major need for the presence of a Policy Writer is to avoid the possible incorrect tagging operated by the dependency parser. There are different styles of writing the policies, according to the different online service providers: if a privacy statement is long and complex, quite naturally it contains several different predicates. In this case, it may happen that the parser does not parse the statement properly, or it wrongly tags few terms. This issue has a direct impact on the policy translation, particularly for the extraction of actions and predicates.

As an example, let the reader consider the following policy: (<https://twitter.com/en/privacy>)

**M1:** ‘We also collect contact information if you choose to upload, sync, or import it from a device’.

Processing M1 using the Dependency parser, we obtain the output shown in Figure 2.

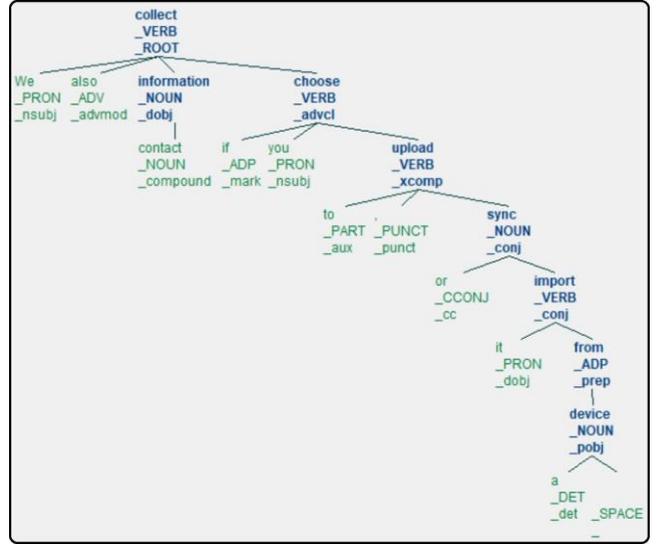


FIGURE 2: M1 upon dependency parser processing-1

The Policy Parser (PP) labels ‘sync’ as a noun, while this should be tagged as a verb. However, if we simply edit the policy to specify it properly, i.e., with the right combination of Subject Verb and Object (SVO), then the parser works fine. An adequate rephrasing is:

Rephrase M1: ‘We also collect data if you choose\_to\_upload data or you sync data or you import data from a device’.

The resulting output in Figure 3. It is also worth noting that terms like ‘information’, ‘content’, ‘contact information’, ‘content and information, and so on, need to be replaced with the generic word ‘data’, for a more accurate tagging. Also, we introduce ( ) in an infinitive form verb i.e., ‘choose\_to\_upload’ which makes the translator recognize as a single word.

Therefore, to mitigate such issues, we introduce the role of the Policy Writer, who does not need to be a CNL expert or a domain expert, just an end-user who should know the correct way to write and enter the policy in the system. To train the Policy Writer, a Policy Manual is provided with all the instructions.

The next component Policy Processor ((PR) 1 processes the policy by applying sentence and words tokenization, stop-words removal, and the definition and creation of the dictionary for the uni-gram training for tagging object(s) and subject(s) in the policy. PR also lists the number of subject(s), object(s), action(s) and predicate(s). The Policy Processor is entirely developed with the combination of NLTK [8], and Spacy [9]. The output of this processing is then stored in a file using the Python OS.System function.

The identified subject(s), object(s), action(s) and predicate(s) is/are given in input to the Ontology Builder, already equipped with some predefined predicates, e.g., hasRole, hasID, hasOwner, for subjects,

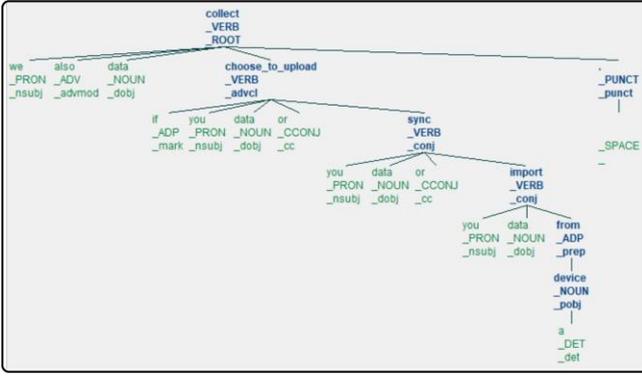


FIGURE 3: Policy upon dependency parser processing-3

hasCategory for objects and object/subject isRelatedto, isPartof object/subject. We also define the classes: subject, object, action, category, predicate, id, owner, and role.

The Ontology Builder is implemented using Owl ontologies [10] and Owl ready [11], a Python module to load them. The ontologies vocabulary is updated manually, whenever any new term is required to process the policy. The result is stored in a file, later used by the Context Extractor (CE).

Next, the Fragment Extractor (FE) extracts the fragment ‘subject action object’. This component is implemented using logic programming for fragment recognition in a policy, i.e., it maps subject, action, and object with the identified values and shows the output. For example, Fragment Extractor efficiently extracts the fragment, i.e., ‘we collect data’: ‘subject action object’ (See Figure 10). The output is again stored in a separate file, saved in the file system, and later used by the CNL Translator (CNLT).

The Context Extractor (CE) extracts the CNL4DSA contexts. This component is developed using logic programming, and it also recalls the output of the Ontology Builder, to retrieve the contexts with predicates hasRole and hasCategory, if any. If we consider M1, the expected context is:

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subject hasRole: ‘we’ AND subject hasRole: ‘you’
AND object hasCategory: ‘data’ AND subject (you)
predicate (choose_to_upload) object (data) AND
subject (you) predicate (sync) object (data) AND
subject (you) predicate (import) object (data) is a
composite context.

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The output is again stored in a separate file for the CNL Translator usage. CNL Translator (CNLT) recalls the outputs of FE and CE from the file-system and shows the policy translation into CNL4DSA. CNLT has been designed to discriminate between authorization, obligation, and prohibition fragments.

The component *Complete Translation into CNL (CTCNL)* orchestrates the previously introduced components, by calling Policy Parser first, following Policy Processor, next Ontology Builder, afterwards Fragment Extractor, following Context Extractor and, finally CNL Translator. Figure 4 shows the complete process flow of translation as a single iteration.

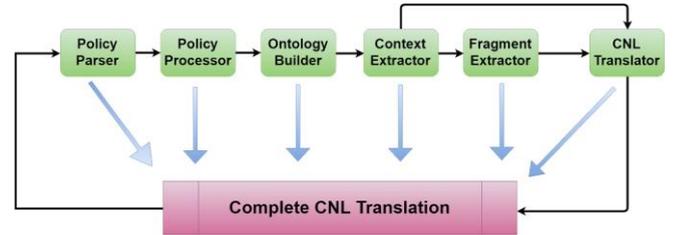


FIGURE 4: Complete CNL Translation Process

### III. GRAPHICAL USER INTERFACE

The Graphical User Interface GUI of NLPT is developed with the Python Automatic GUI Generator (PAGE) [12]. Figure III shows the main screen. The right side and bottom side of the window show the components (under the form of buttons). The user inputs the policy in the text area. If the text area field is empty, an empty field error is prompted, Figure 5.



FIGURE 5: Empty Field Error

Consider the following example Twitter policy P1:

P1: We collect the content, communications, and other information you provide when you use our Products, including when you sign up for an account, create or share content, and message or communicate with others (<https://twitter.com/en/privacy>).

First, the Policy Writer needs to check whether the policy is accurately parsed by the parser. Otherwise, the Policy Writer should rephrase the policy taking as guide the policy manual:

Rephrase P1: we collect the data that data you provide when you use our products including when you sign up for an account, when you create the data, when you share the data when you message with others, and when you communicate with others.

The policy is not entirely rephrased, however, there is the need to add punctuation and remove some parts, to make the constructs of the sentence easily recognizable

by the parser. As anticipated above, words like ‘content, communication, other information are rephrased into the generic word ‘data’.

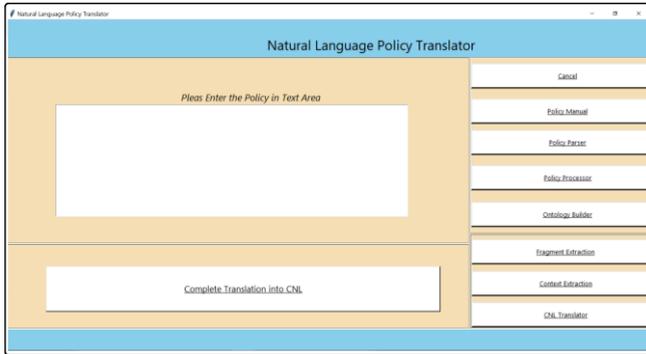


FIGURE 6: NLPT Graphical User Interface

When a policy is enter in NLPT, Figure 7 and 8 show the outputs of Policy Processor. The output of Ontology Builder, i.e., ontologies with the values of subject and object is shown in Figure 9. The output generated using Fragment and Context extractor show in Figure 10.



FIGURE 7: Output of Policy Processor.a

The CNLT displays the input policy and the CNL4DSA output, hiding the internal process. It also discriminates between authorizations, prohibitions, and obligations. Referring to P1 and its output in Figure 11 shows the result. Moreover, it is also possible to view the outputs of each component altogether by using Complete Translation button and the order of operation is as follows: Policy Parser -> Policy Processor -> Ontology Builder -> CE -> FE -> CNLT as presented in Figure 4.

#### IV. EXPERIMENTAL SETUP

In this section, we run the experiments on a quantitative basis, to assess the NLPT performances. We select a subset of Twitter data policies [3]. The main goal of



FIGURE 8: Output of Policy Processor.b



FIGURE 9: Output of Ontology Builder

the experiment is to assess whether NLPT is capable of translating any social network data policies. To analyze the performances of the different components, we define some evaluation criteria:

#### Evaluation Criteria:

- 1) How many policies are accurately parsed by Policy Parser (PP), correctly labeling action(s) and predicate(s) in a policy?
- 2) How many times is there the need of updating the dictionary, in terms of subject(s) and object(s), while processing the policy with Policy Processor (PR), until no update is needed?
- 3) How many times is there the need of updating an existing ontology, or creating a new one until no update is needed?
- 4) From how many input policies does Fragment Extractor (FE) correctly extract the fragments?
- 5) From how many input policies does Context Extractor (CE) correctly extract the contexts?
- 6) From how many input policies is CNLT able to correctly recognize as authorisations, obligations, and prohibitions?
- 7) What is the Success Rate of PP, FE, CE and CNLT, over the total number of policies?



Case Study	Total Policies	Correct Parsing	Incorrect Parsing	Dictionary Update	Ontology Update
Twitter	100	77	23	18	18

TABLE 1: Policy parser results for Twitter

Case Study	Total Policies	Accurate F.E	Inaccurate F.E	Accurate C.E	Inaccurate C.E
Twitter	100	84	16	72	28

TABLE 2: FE and CE results for Twitter

$$\text{PP Success Rate} = (77/100) * 100 = 77\%$$

$$\text{FE Success Rate} = (84/100) * 100 = 84\%$$

$$\text{CE Success Rate} = (72/100) * 100 = 72\%$$

$$\text{CNLT Success Rate} = (90/100) * 100 = 90\%$$

The complete results are shown in Table 1, Table 2 and Table 3

The success rate for each component is shown in Table 4. The PP and FE success rates are above 75%. While CE success rates lay between 55% and 75%. The CNLT performance obtains approximately the 90% success rate. The categorised performance of each component is shown in Table 5.

## VI. CONCLUSION

In this paper, we presented the NLPT 2.0 an extended version of our work [6] having new functionalities for translating data privacy policies with their descriptions in NL into phrases of a CNL. The work aims to provide an effective and efficient technique for the formal analysis of privacy policies. Social media sites use natural language (NL) when posting the data policies about the handling of user’s data. But these policies are often unclear and ambiguous and as stressed before, are not machine check-able. This is why we resorted to controlled natural languages (CNLTs). These languages are engineered languages with a strict lexicon, vocabulary, syntaxes, grammatical construction, and pragmatics and are more amenable to machine processing. The target language is for translation is CNL4DSA. This language is closer to a purely natural language and thus eases readability and usability by non-experts.

Case Study	Total Policies	Accurate Distinction by CNLT	Inaccurate Distinction by CNLT
Twitter	100	90	10

TABLE 3: Overall results of Twitter

Case Study	P.P Success Rate	F.E Success Rate	C.E Success Rate	CNLT Success Rate
Twitter	77%	84%	72%	90%

TABLE 4: P.P, F.E, C.E and CNLT Success Rates

Case Study	P.P	F.E	C.E	CNLT
Twitter	Excellent	Excellent	Above Average	Excellent

TABLE 5: F.E, C.E and CNLT performance evaluation against Success Rate

The experiment on Twitter data policies demonstrated the overall performance of NLPT 2.0 is quite good. Overall results of different system components are encouraging and satisfactory. We identified certain limitations with our system during experimentation, and we are considering improvements in the future. We are investigating the capability of automatically creating/updating the ontologies. We cannot simply input a policy in its original form. The Spacy dependency parser [9] may not be able to correctly parse too complex sentences, Quite obviously, an incorrect parsing also has a direct impact on FE and CE performances. We introduced the role of a Policy Writer, whose job is to rephrase the policy following the instructions available in the policy manual.

For now, the whole process is semi-automatic since it requires human intervention at different stages. For future work, we want to experiment with our approach on other social network data policies e.g., Facebook, Google, etc, and also for other domains, e.g., ‘e-health privacy policies’, e-commerce policies’, ‘cloud computing privacy policies’. Initially, we only experimented our approach with Twitter policies, but with our understanding, our approach is sufficiently flexible to be used in other domains by just creating/updating the vocabulary in terms of subject and object relevant for the considered social network sites.

Moreover, we have not dealt with policies with more than one fragment. If a verb followed by an infinitive form appears, such as ‘choose to upload’, we preprocess that form by introducing an underscore (‘\_’), i.e., ‘choose\_to\_upload’, and let the translator consider it as a single word. We do not consider automatic co-reference detection. This is a limitation of the approach and we intend to solve the issue, possibly using existing tools for automatic co-reference detection.

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