Adding Temporal Dimension to Ontology Learning Models for Depression Signs Detection from Social Media Texts

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Abstract: Approaches to early detection of depression based on individual's language are receiving increasing attention, with detection software systems based on lexical, grammatical or discursive components applied to medical corpus or social media texts. However, these first detection systems are defragmented, each attending to a specific feature or linguistic level, and not addressing a more conceptual level. Existing ontology learning (OL) methods extract the ontology referred in the text. In addition, existing systems perform language analysis for the detection of depression as a snapshot of each individual, regardless of their temporal dimension. Is it possible that suitable linguistic features to detect early signs of depression vary over time? And the underlying ontology? This paper presents a model that adds the temporal component to current ontology learning models to perform evolutionary analysis of both linguistic and ontological features to texts from social networks. The model has been applied to an external corpus of depression from social media texts, with a two-fold goal: 1) validating the model by contrasting it with OL models without temporal component 2) producing a corpus of evolutionary OL results applied to the depression detection from social media texts.

1 INTRODUCTION

Depression is considered one of the most common mental illness and one of the main diseases in recent decades. Due to its complex diagnosis and variability of presentations in different people, interdisciplinary research approaches have become the most successful methods for early risk prediction (Losada et al., 2018a) and depression detection, combining information about patient's profile, doctor's experience, well-tested medical questionnaires and semiautomatic analysis for assisting doctors to analyze indicators. Within this last category, patient language is a powerful indicator of personality traits and emotions, and provides valuable clues about mental health, presenting good results as auxiliary indicators for helping doctors in an early risk prediction of depression (Al-Mosaiwi & Johnstone, 2018, 2019; Pennebaker, Mehl, & Niederhoffer, 2003).

This connection between depression and distinctive linguistic patterns have serve to create promising software systems for assisting depression early prediction. These systems have been tested using textual corpus from clinical sessions or from social networks, and classified them (Brewster, 2006; Hazman, El-Beltagy, & Rafea, 2011; Wimalasuriya & Dejing, 2010) regarding the linguistic parameters analyzed for each system. Most of them are focused on lexical or grammatical features (propositions or pronouns) or ontological, discursive or topic-based features. The ontological level, relating the underlined ontology with the language patterns used by the patient, offers important information about the universe of discourse of the patient (Gruber, 1995), as well as how the patient refers to its discourse universe.

However, as far as we know, the temporal component of this language pattern analysis, especially at ontological or discursive levels, is not considering as a feature in the current software systems. This means that the information corresponding to changes in patient language patterns is not tracked or analyzed. The historical information of the patients is one of the most valuable inputs for doctors in the detection, diagnosis and evaluation of mental illnesses. In addition, temporal dimension is crucial in order to reveal early signs of psychological

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disorders trying to detect some indicators of appearance of initial signs of depression and understanding the evolution of an individual from the early stages (e.g. mood changes, lack of sleep) to severe stages (e.g. suicidal thoughts).

Focusing only in the ontological component of the language patterns, this paper proposes a model that adds the temporal component to current ontology learning models, allowing us to perform evolutionary analysis of both linguistic and ontological features to texts from social networks. The model has been applied to an external corpus of depression from social media texts. The application shows how we can add the temporal dimension to existing ontology learning models in a real case, as well as produces a valuable corpus of ontological and linguistic pattern results over time in depression contexts.

2 BACKGROUND

Two main areas are related with our proposal: 1) ontology learning methods from English unstructured text from social networks, and 2) existing works specifically focused on depression detection software, contextualizing the application of our proposal to this field.

2.1 Ontology Learning

Ontology Learning is defined as the discovering of the underlined ontology from textual sources (Hazman et al., 2011). As an ontology, we understand here "an explicit, formal specification of a shared conceptualization of a domain of interest" (Gruber, 1995). Thus, the underlined ontology of a given text allow us to extract information about a) concepts and relations referred in the source texts and b) linguistic patterns used for referring to these concepts and relations. This information conforms a relevant input in the language studies, including applications of ontology learning in biomedical or legal domain (Morales, Scherer, & Levitan, 2017).

Firstly, we can find in literature initial approaches trying to extract in a semiautomatic or automatic way some ontological information from linguistic patterns, such as processes relations or event mining (Reuter & Cimiano, 2012). Regarding these studies, most of them present high scores on recognition in a limited functional environment or limited to a specific domain or tasks.

Secondly, there are existing attempts for enriching ontology learning with text mining techniques from 2000, e.g. some workshops in ECAI conference (Staab, Maedche, Nedellec, & Wiemer-Hastings, 2000), to present. Main concerns here includes topical concepts and concept definitions agreement within the corresponding community, learning associations from texts, Named Entity and Terminology extraction, Acquisition of selected restrictions from texts, Word Sense disambiguation or computation of concept lattices from texts. We can also classify all these text mining works in function of the kind of technological technique employed: supervised (based on previous annotations) vs. unsupervised. Wimalasuriya survey (Wimalasuriya & Dejing, 2010) presents the most common software architecture for this kind of techniques, as well as some examples of classical applications domains. In addition, some authors (Asim, Wasim, Khan, Mahmood, & Abbasi, 2018; Brewster, 2006; Hazman et al., 2011; Shamsfard & Barforoush, 2003; Somodevilla, Ayala, & Pineda, 2018; Wimalasuriya & Dejing, 2010) recently perform exhaustive reviews of the current software methods for ontology learning. All these methods have been successfully applied to a wide variety of domains, which makes ontology learning a solid area to consider when we want to extract complex information (linguistically and conceptually based) from unstructured sources.

Regarding ontology learning in social media contexts, most of the approaches focused on extracting parts of the ontology (Asim et al., 2018; Breslin, 2012; Reuter & Cimiano, 2012), such as concepts or events, particularizing approaches for texts with shorter length and interaction characteristics similar to dialogue (posts-based interactions).

In summary, ontology learning is a promising area with successful applications both at the level of manual analysis and semi-automation. However, none of the current methods recently reviewed (Asim et al., 2018; Wimalasuriya & Dejing, 2010), even in social media contexts, have specific temporality support. This means that current methods extract the underlying ontology as a snapshot of the text at a specific time. In reported applications, this snapshot condenses enough information. However, it does not allow the study of the evolution in the underlying ontology of the text or its linguistic patterns over time. Because of our needs in the domain of mental illness, we think that the inclusion of a temporary layer to the ontology learning methods will facilitate this evolutionary analysis and allow us a better investigation of the connection and evolution of linguistic and ontological patterns in depression contexts.

2.2 Depression Signals and Early Risk Prediction from Social Media

Language and depression studies are recently gaining importance in research (Al-Mosaiwi & Johnstone, 2018; Kiss & Vicsi, 2017; Kokanovic et al., 2013; Morales et al., 2017). Until recently, it was very difficult to obtain reliable data on depression from any source (from medical reports, due to their classified character; from social networks, due to their confidentiality, reliability and true diagnosis problems). From 2016, The Early Risk Prediction on the Internet (eRisk) (D. Losada, Crestani, & Parapar, 2017; David E. Losada et al., 2018) workshop explores the interaction between language and mental disorders in online social media. In particular, the workshop proposed to address the early detection of depression in an automatic way and released a corpus of social media users who suffered from depression. The results of the workshop showed that there is a large spectrum of techniques that can be used to detect this mental illness. In this paper, we use the eRisk corpus to validate our model.

Specific works on depression detection from social media texts are a field relatively new, with promising approaches. Most of them works with depression lexicons from Twitter (De Choudhury, Gamon, Counts, & Horvitz, 2013), or for Reddit and micro-blogs platforms (Coppersmith, Dredze, & Harman, 2014; David E Losada & Gamallo, 2018). It is also necessary to highlight that the Computational Linguistics and Clinical Psychology Workshop (clpsych.org) has recently organized "shared tasks" of depression and post-traumatic disorders, performing content analysis in support forums for people with disorders (Resnik, Resnik, & Mitchell, 2014). These tasks were oriented to automatic classification (do not focus on early prediction or temporal analysis) but, still, they will be valuable references for our research. In addition, there are a few initiatives related to them, such as personality and health mining competitions as CLEF eHealth (http://sites.google.com/view/clef-ehealth-2018/home) or PAN (http://pan.webis.de).

Al these works indicate the possibilities of depression prediction from social media. However, ontology learning applications with temporal component to this field are still barely unexplored. The method proposed here tries to solve some of these shortcomings, contributing with ontological information and their temporal evolutionary analysis to all this set of technologies, methods and approaches.

3 PROPOSAL: A TEMPORAL-BASED ONTOLOGY LEARNING METHOD

As we previously detailed, ontological information extracted from texts can be a very valuable input in the early detection of signs of depression from social networks. However, the application of any of the current ontology learning methods lacks the necessary temporal approach that allows an evolutionary analysis.

Employing the current methods of ontology learning it is possible to make two approaches: 1) treat the entire corpus as a large text, so we would obtain an aggregated underlined ontology (result of evaluating all the texts at once) or 2) treat each corpus document as a separate text, so we would obtain an underlined ontology for each of the analysed texts. Note here two important aspects of both approaches: neither deals with a temporary component, so, in the first case, we only have one ontology at a given time (without evolutionary analysis), and in the second case, we have several ontologies but no connection between them, so we cannot perform evolutionary analysis either. This absence of a temporary component also severely penalizes applications to short and disconnected texts such as those derived from social networks and, as we have explained before, temporal analysis is a crucial analysis in mental illness application domains.

In order to fill this gap, we present a proposal to add a temporary layer to existing ontology learning methods. Using ontology learning principles as a basis, we developed the proposal from scratch but in highly modular schema, as the pipeline shows in Figure 1.

The initial input is a corpus or collection of free-style textual documents. Following the ontology methods existing methods, we decide to apply the second approach studied above for the discovery of ontological information: extract an ontology for each existing text in the corpus or collection. Thus, each corpus analysed produced a set of underlined ontologies (not only one) that allow us to perform evolutionary analysis of the information. Phase I of the pipeline runs the ontology learning (OL) model chosen for extracting candidates for concepts and their relationships for each existing text. The result of Phase I is a ranked set of candidates for concepts and relationships for each document. Then, the pipeline consults the temporal information available in the collection. Phase II is responsible for resolving, stor-

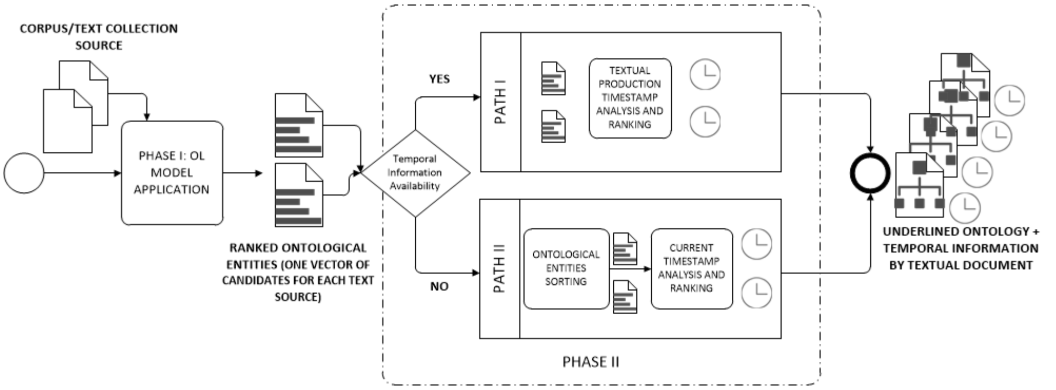

Figure 1: BPMN model (OMG, 2011) of the proposal pipeline, adding temporal dimension to OL methods.

ing and keeping the temporary information of the ontological extraction process updated. In the phase II the pipeline evaluates the given corpus regarding temporal information available:

If the corpus has temporary information about the production of texts (that is, when a due text is written and / or added to the corpus), the pipeline creates the necessary entities to maintain that information in each of the candidates for concepts and relationships, as a label of them (PATH I).

If the corpus does not have this information, the pipeline creates the necessary entities to maintain temporary information in real time of the analysis performed, that is, it will assign a timestamp to each of the candidates for concepts and relationships, as a label of them (PATH II). This will allow us to perform ontology learning evolutionary analysis also in collections of texts or corpus without prior temporal information. Thus, we can order our texts and perform an evolutionary analysis as well, but with temporal labels relative to the analysis itself and not to the date of production of the texts.

Each of the paths of the pipeline produces the ontological information with the temporal layer completed, one result by each analysed text presented in the original corpus/collection.

As a result, we can maintain the temporal traceability of the production of the texts in the corpus analysed in the case of the PATH I, performing evolutionary analysis of the ontological information and the linguistic patterns contained on it. For example, we could now know what concepts appear and disappear from the ontology over time or in a range of dates, or if a linguistic pattern (the use of a term for a concept, or the use of a particular verb for a relationship between concepts) is maintained or varies over time. In our specific case in depression detection, this is especially useful given the studies that relate this type of linguistic-ontological patterns and specific disease states, allowing its analysis as a differential factor in much greater depth. In the case of PATH II, in corpus that do not have temporary information on the production of the texts, the module for ordering the documents by the user is necessary to perform a relative evolutionary analysis.

This prior arrangement serves as a reference timestamp for the evolutionary analysis (the first document will be analysed before and its associated ontology and information will carry a timestamp prior to the last document) so that an analysis similar to that of PATH I can be performed but only relative in the corpus itself. Thus, we can also analyse what concepts appear and disappear from the ontology over time or if a linguistic pattern (the use of a term for a concept, or the use of a particular verb for a relationship between concepts) is maintained or varies, but we cannot place it in its real time of production. Next paragraphs detail the proposed definitions and calculus for the PHASE II paths.

Taking C_n as the input collection of n documents written in free style that we want to analyse, we formalized for PATH I the following results:

V_d, Vector of ontology learning candidates extracted: for one document d, p pieces of text (posts in social media) and k ontological entities extracted:

$$V_d = \binom{p}{k} \quad (1)$$

$$CValue_d = \binom{cvalue}{k} \quad (2)$$

$CValue_d$, Vector of ontology learning score values (c-value): for one document d and k ontological entities extracted and C-value score calculated for these k entities.

$(O)^n$, Set of ranked aggregated vectors of candidates for the C_n collection, with k ontological entities extracted and their C-values scores. For each d document in C_n, PATH I searches, temporal information available in the corpus (although this aspect of the pipeline does not correspond to the scope of the paper, it possible to see a possible temporal information search implementations here (Rust, 2018).

$$(O)^n = \sum_{n=0}^{n} \binom{cvalue}{k} \binom{p}{k} \qquad (3)$$

For each d document in C_n with temporal information, PATH I calculates:

$$\mathrm{T}\,(\mathrm{O}^n) = \sum_{n=0}^{n} \binom{cvalue}{k}\ \text{tprod} \qquad (4a)$$

T (O^n): Set of resultant values of assigning to each ontological entity (extracted from the n document) their corresponding timestamp referred to the input corpus information t_{prod}.

Regarding PATH II, we define $D_{u,d}$ as the set of d documents of the collection ordered by the user. Then, using this order as a temporal reference, PATH II calculates V_d, $CValue_d$ and $(O)^n$ applying same PATH I formulae. Then, for each d document in C_n, PATH II stamps current temporal information of the system. For each d document in C_n with temporal information, PATH I calculates:

$$\mathrm{T'}\,(\mathrm{O}^n) = \sum_{n=0}^{n} \binom{cvalue}{k}\ \text{tcurrent} \qquad (4b)$$

T' (O^n): Set of resultant values of assigning to each ontological entity (extracted from the n document) their corresponding current relative timestamp $t_{current}$.

Note that the proposed pipeline has been defined independently of the ontology learning method selected, the domain of application or the corpus used as a source. Thus, our proposal could serve as a general solution for the need of a temporal layer in current ontology learning methods. In the next section, we particularize the application by selecting all these aspects to illustrate the entire pipeline proposal.

4 VALIDATION: APPLICATION TO A SOCIAL MEDIA DEPRESSION CORPUS

Within the scope of our proposal, it was necessary to apply and evaluate the proposed pipeline with respect to its ability to resolve, store and keep updated the temporary information in a real corpus. Performing a specific application of the pipeline requires defining a) the ontology learning method chosen b) the application domain and c) the corpus or collection used as a source (the pipeline input).

Regarding the ontology method employed, the review detailed in section 2 offer us a relevant pool of methods and their current reliability, strengths and weaknesses. Very few methods reviewed above presents open-source implementations that allow us to use them as initial method for our pipeline implementation. From them, the C-value (Frantzi, Ananiadou, & Mima, 2000) method presents better behaviour in ontology learning, especially in concepts extraction (Asim et al., 2018). C-value domain-independent method is a well-known ontology learning method that calculates a C-value score for each text analysed, in function of linguistic and statistical parameters, and giving as a result a vector of ontological entities candidates ranked by the C-value score. It presents especially good behaviour in the semi-automatic extraction of multi-word and nested ontological concepts from English corpora (Asim et al., 2018). In addition, C-value have been previously used in the medical domain with good results (Lossio-Ventura, Jonquet, Roche, & Teisseire, 2013). C-value have been tested and previously implemented in several platforms. We have used an updated open source implementation of the algorithm for English language (Conde, 2018) as a base for adding the temporal dimension and implementing our pipeline. All these reasons made us choose C-value as a starting learning ontology method to illustrate our pipeline and apply it to a real corpus.

The application domain (mental illness) and the corpus chosen is due to our interest on depression detection based on language patterns through software systems. The original eRisk corpus (D. Losada & F. Crestani, 2016; D. E. Losada & F. Crestani, 2016) contains 2-year textual interactions on Reddit from 892 users, divided into two groups: 137 subjects have explicitly declared that they have been diagnosed with depression by medical professionals, and the remaining 755 subjects are a control group. All details regarding data acquisition, initial annotations, depression diagnosis criteria, data cleaning and legal treatment etc. are reported by the original authors (D. E. Losada & F. Crestani, 2016). We have applied the proposed pipeline to the depression corpus:

1. Each eRisk document presents Reddit posts from a subject (that it could be in the depression group or in the control group) in JSON format. In Phase I, the pipeline implements C-value algorithm, obtaining a ranked vector of candidates to

ontological entities with their corresponding ontological C-value score.

2. Then, the pipeline checks again the eRisk corpus, searching for temporal information (Rust, 2018). Due to eRisk corpus contains temporal information of each post of the Reddit production timestamp, the pipeline decides executing PATH I algorithm (see Figure 1).
3. In PATH I, the pipeline storages the timestamp of each Reddit post for each JSON document (corresponding to each subject in the collection). This information is aligned to their corresponding vector of ontological entities candidates for each post. As a result, the pipeline obtains a vector of ontological concepts aligned with their timestamp of production. This allow us to perform evolutionary analysis on the ontology, answering questions regarding the ontological evolution over the 2 years of data for each subject.

The execution of the pipeline would be similar in case of the pipeline would execute PATH II but ordering the corpus documents (See Figure 1). The proposed method in form of a pipeline have allowed us to track and maintain temporal information for each ontological vector of the C-value algorithm output vector. Figure 2 shows a screenshot of the final output of the pipeline (PATH I) for our depression corpus application. We selected a few *p* posts of the one subject, showing the original texts and their corresponding ontological entities extracted, including temporal information of the production of the texts.

5 DISCUSSION

The proposed method represents the first known approach to the combination of ontology learning methods with temporal analysis to allow ontological evolutionary analysis. Due to the innovative nature of the proposal, it is not possible to evaluate the results obtained with existing benchmarks, beyond the good results already reported (Asim et al., 2018) of the ontology learning methods from unstructured sources.

Said that, evaluating at a qualitative level, the results obtained add value compared to traditional methods of ontology learning: we will have, in addition to the underlying ontology, evolutionary information, as seen in our case of depression corpus application. In the case of relative evolutionary analysis (PATH II), the pipeline presents an alternative solution to have a chronological reference in form of timestamp for the ontological information extracted during the analysis itself. More work is needed to validate its usefulness in specific application contexts.

Other known restrictions are 1) results dependence on the original language of the texts from corpus or collection and 2) results dependence on the performance of the chosen ontology learning method. In the first case, because most of them only support English, we value as future work exploring the possibilities of ontology learning methods for other languages and studying the possibilities of language generalization of the method.

In the second case, ontology learning (as emergent research area) present some needs in terms of methods and tools for evaluating and comparing results. This means that the evaluation of the information extracted is based mainly on a principle of utility, satisfaction and quality perceived by the user who will use the information extracted to make decisions. In fact, “not so much consensus about a delimit task of automatic extraction of ontologies” (Buitelaar, Cimiano, & Magnini, 2005). Said that, this lack of evaluation possibilities difficult the comparison between approaches and the evaluation of the results, with very few raw results published and in non-standard formats, that could serve as a gold standard for improving the approaches. For this reason, we make available both the pipeline implementation as an adaptation of the selected ontology learning method to our pipeline in a public repository (Martin-Rodilla, 2019). In addition, we offer our results of extracted ontology for depression with temporal component with the source corpus (D. Losada & F. Crestani, 2016; D. E. Losada & F. Crestani, 2016) under petition for research purposes, producing a corpus of evolutionary OL results applied to the depression detection from social media texts. These contributions try to collaborate to the proliferation of research resources for comparison, dissemination and evaluation in this area.

6 CONCLUSIONS

This paper presents a double contribution:

1) a pipeline model that adds the temporal component to current ontology learning models, performing evolutionary analysis of both linguistic and ontological features extracted form unstructured texts and 2) an application case of the method to an external corpus on depression prediction from social media texts.

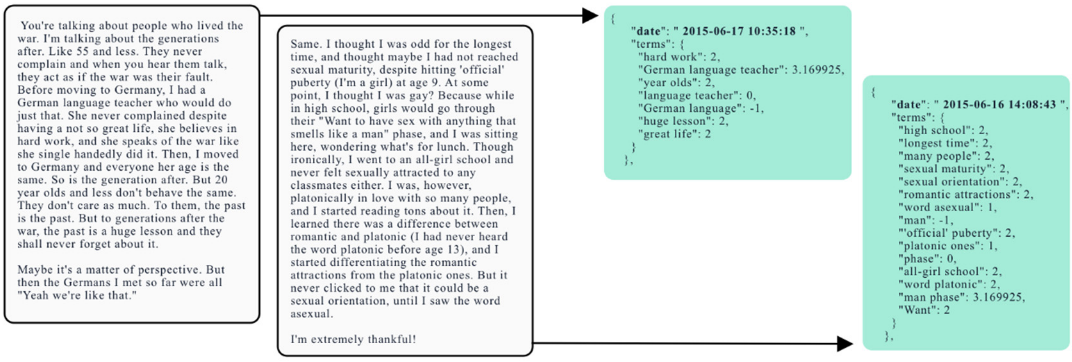

Figure 2: Original texts for a depressed subject from the depression corpus and the corresponding pipeline output: ontological entities vector and their temporal information results.

We are at a favourable time to investigate depression signs, due to the existence of validated collections of reliable diagnosis's data.

In the first case, the method adds value to the existing ontology learning method and approaches, allowing the evolutionary analysis of their current outputs. However, more work is needed in order to test the pipeline method in different application scenarios and input corpus. In the second case, the application showed here constitutes a valuable dataset itself for continuing researching on the software prediction and detection of first signs of the depression phenomenon, with complex and varied features that requires interdisciplinary perspectives.

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