Intelligent fake news detector and reasoner in medical domain using Description Logics

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Abstract: **This paper aims at investigating how Description Logics can be used to detect and reason inconsistencies arising between the myths spread online and the facts made available by the trusted sources. An algorithm has been presented for a procedural approach towards detecting inconsistencies and Fuzzy Logic was used to evaluate the truth rate of the myth if the considered myth is not completely false. The detected inconsistencies are presented to the human agents for specifying reasons behind the sentence being a myth**.

I. INTRODUCTION

A. Motivation

Human agents are too bad at detecting lies in the text and there are only 4% chances that humans will be able to detect lies correctly[1]. Such a low performance motivates the development of intelligent agents which could provide support to humans for detecting fake news. The major domain in which false information is spread is the health domain. On the web, fake news and misconceptions in the medical domain affect public health significantly. The truthfulness of information related to health has become a major issue that has been affecting mental and public health. The myths thus created hinder the true facts causing a huge mental rush among the common people.

B. Problem Definition

The problem can be technically formalized as a verification task. Intelligent fake news detectors are of utmost importance as past experiments have shown the human inability to differentiate between true and false news correctly and efficiently. These inconsistencies are detected using Description Logics and are observed to have certain patterns. Using these patterns new rules are designed to detect inconsistencies. The myths are verified against the facts collected from trusted sources. Texts present in natural language are converted to Description Logic formalizations. An abstract model of ontologies is created using which facts and myths will be identified and reasoning will be done. Since the main aim of this paper is to explain to a human agent why information might be wrong, no machine learning tool or method was employed. Instead, medical ontologies are used for reasoning.

II. LITERATURE REVIEW

The past methods for detecting frauds are classified in linguistic approaches that identify language patterns of deception and network approaches that use information from networks to measure deception [2]. A quantitative study was presented on the spread of medical fake news in social media[3]. In 2003, detailed work on description Logics and its implementation were presented by F. Baader [4]. In his research paper, Adrian Groza presented an intelligent tool developed using Description Logics to detect fake news in mental health and covid-19 [5]. Based on this past work, we extend the tool to another disease Dengue, and extract truth rates of the myths detected.

III. METHODOLOGY

This section discusses the methodology proposed to detect inconsistencies using Description Logics.

Table 1: Constructors and their syntax in DLs

CONSTRUCTOR	SYNTAX
Conjunction	$A \sqcap B$
Disjunction	$A \sqcup B$
Value Restriction	$\forall r.A$
Existential Restriction	$\exists r.A$
Individual Assertion	$a : A$
Role Assertion	$r(a , b)$

A. Description Logics

Description logics (DL) are a family of formal knowledge representation languages. It has concepts or sets, relations between these sets, and the instances of the concepts. Here the concepts are designed using the set of constructors formed by using conjunction, disjunction, value restriction, existential restriction, individual assertion, and role assertion (Table - 1).In this table A and B represent concept descriptions, r is the role name. A DL knowledge base is comprised of two components - “A Box” and “T Box”

T Box contains intensional knowledge in the form of terminology. It is designed by using declarations that describe the general properties of concepts. The axioms here are usually of the form $A \sqsubseteq B$ or $A \equiv B$.

Example: “ Dengue is an infectious disease caused by mosquitoes Aedes aegypti and Aedes albopictus” can be formalized with the TBox:

$$InfectiousDisease \sqsubseteq Disease$$

$$Aedesaegypti \sqsubseteq Mosquito$$

$$Aedesalbopictus \sqsubseteq Mosquito$$

$$Dengue \sqsubseteq InfectiousDisease \sqcap \forall causedby.(Aedesaegypti \sqcup Aedesalbopictus)$$

Here Infectious disease is a Disease, Aedes aegypti is a mosquito and Aedes albopictus is also a mosquito. Dengue is an infectious disease for which all its causes are of type Aedes aegypti and Aedes albopictus mosquitoes.

A Box contains existential knowledge about the domain of interest i.e. assertions about individuals (membership assertions) and derived assertions (role assertions). A concept A is satisfied if there exists an interpretation that does not result in null. A concept A subsumes B if there exists an interpretation of A which is a subset of any interpretation of D.

Example: hascause(Dengue , Aedesaegypti) formalizes the information that Dengue has a possible cause Aedes aegypti. In this case, the role hascause relates two individuals Dengue and Aedesaegypti.

B. Inconsistency Patterns

Inconsistencies can be detected using ABox and TBox.

Incoherent Ontology: The formalized ontology is incoherent iff there exists an unsatisfiable concept.

Example : $Dengue \sqsubseteq InfectiousDisease$ (1)

$$Dengue \sqsubseteq \sim Disease \quad (2)$$

$$InfectiousDisease \sqsubseteq Disease \sqcap Causedby.(Bacteria \sqcup Virus \sqcup Fungi \sqcup Parasites) \quad (3)$$

In this ontology, Dengue is included in the concept Disease as per axioms (1) and (3) taken form verified resources however the axiom (2) gives a contradiction stating Dengue is not a disease.

Inconsistent Ontology: The formalized ontology is inconsistent if the corresponding Abox formalization consists of an individual that belongs to an unsatisfiable concept.

Example : Low platelet count : Dengue (4)

Dengue : Disease (5)

Low platelet count $\sqsubseteq \sim$ Disease (6)

From axiom (6) it can be inferred that *Low platelet count* and *Disease* are two disjoint concepts.

However *Dengue* can be inferred from both the concepts. Thus the system interprets an empty set i.e. Low platelet count : $\perp$.

Several Antipatterns can be used to indicate inconsistency or incoherency in an ontology.

A few of those are:

1. ***Universal Existence :*** $UE1 : A \sqsubseteq \forall\, r.C$

   $UE2 : A \sqsubseteq \exists\, r.B$

   $UE3 : B \sqsubseteq \sim C$

UE2 adds an existential restriction for concept A that conflicts with the existence of an universal restriction for same concept A in UE1.

Example : *UE1 : Oxygen Therapy* $\sqsubseteq \forall$ *treats. Deadlydisease* (7)

UE2 : Oxygen Therapy $\sqsubseteq \exists$ *treats.Dengue* (8)

UE3 : Dengue $\sqsubseteq \sim$*Deadlydisease* (9)

Assume axioms (8) and (9) have been taken from trusted sources. The concept in axiom (7) conflicts with the other two due to the for all quantifier.

2. ***Onlyness is Loneliness:*** $OIL1 : A \sqsubseteq \forall\, r.C$ (10)

   $OIL2 : A \sqsubseteq \forall\, r.B$ (11)

   $OIL3 : B \sqsubseteq \sim C$ (12)

In OIL1, concept A can only be linked with role r to B. However in OIL2, concept A can only be linked with role r to C. But OIL3 states that B and C are disjoint.

$$Example : OIL1 : Antibiotics \sqsubseteq \forall\ kills.Virus \tag{13}$$

$$OIL2 : Antibiotics \sqsubseteq \forall\ kills.Bacteria \tag{14}$$

$$OIL3 : Virus \sqsubseteq \sim Bacteria \tag{15}$$

Assume axioms (13) and (14) have been taken from trusted sources and axiom (15) which has been taken from online news causes a contradiction wth above two as it states that Virus and Bacteria are disjoint concepts.

C. Detecting inconsistencies present in myths against the true facts.

For designing reasoner and myth detector a dataset of 10 myths and 10 facts was collected from online sources. For facts some trusted official sources were chosen and myths were collected from online news sources etc.

Table(2) shows the dataset used.

Myths	Corresponding Facts
Any mosquito can cause Dengue	Mosquito aedes aegypti and mosquito aedes albopictus causes dengue
Low platelet count ensures dengue	A low platelet count can be an indication of dengue
Papaya leaves can cure dengue	Papaya leaves cannot cure dengue
Dengue fever cannot do any harm	Severe Dengue can cause organ impairment and plasma leakage
Dengue only affects children and old individuals	Dengue can affect anyone irrespective of age
Clean house prevents dengue	Cleanliness doesnot gurantee prevention from dengue
Dengue can be cured by drinking goat's milk	No evidence exist which can prove that goat's milk cures dengue
Dark clothes attract mosquitos	Any type of clothes cannot attract mosquitos
If you suffer from dengue once , you will never get it again	People can suffer from dengue again and again

People should always be vigilant	Mosquitos bite only at a temperature less than 20 degrees

Example1: The following sentence was collected from an online news source '***Papaya leaves can cure dengue***' whereas a true fact '***Papaya leaves cannot cure dengue***' was collected from a trusted source. An ontology was designed to convert these sentences into DLs. When thesse two sentences are given as input to the same ontology , the designed reasoner will detect incoherence and signal direct negation. Papaya leaves as a result become an unsatisfiable concept.

$$Dengue \sqsubseteq \exists\ haspossiblecure\ .\ Papayaleaves \qquad \text{-}myth$$

$$Dengue \sqsubseteq \sim\exists\ haspossiblecure\ .\ Papayaleaves \qquad \text{-}fact$$

Example2: Consider the myth ***'Dengue only affects children and old individuals'*** which is formalized as -

$$Dengue \sqsubseteq \forall\ affects.(Children \sqcup Old\ Individuals)$$

However true knowledge from trusted source is :

$$Dengue \sqsubseteq \forall\ affects.(anyone)$$

The inconsistency will be identified in ABox such that if anyone who is not a child or Old individual can still be affected by Dengue.

This method for detecting fake news relies on the existence of trusted medical sources that are available on the Internet, with medical domain considered the most successful for the Semantic Web. The available medical knowledge can be reused in different domain ontologies.

D. Fuzzy logic to evaluate truth rate

It was observed from the facts and myths that there are certain myths that cannot have a truth value of complete zero as there is a certain overlap between the true value of the mth and the fact. So, fuzzy logic was used to evaluate the truth rate of the myth.

Example: The sentence (myth) '***Clean house prevents dengue'*** will be assigned a modality ***sure*** when given input to the ontology whereas the fact ***'Cleanliness does not guarantee prevention from dengue'*** will be assigned a modality ***unsure*** when given input to the same ontology. The modality sure indicates definiteness whereas unsure indicates may or may not be.

Using triangular and trapezoidal functions the overlap (intersection) was evaluated to calculate the truth rate of the sentence with respect to the fact.

IV. PROPOSED MODEL

Algorithm1 presents the formalized method proposed to detect and reason the fake news in the medical domain. Input to the algorithmic model is a set of sentences collected from online resources and a set of facts collected from trusted sources. The output comprises of the explanations corresponding to the generated inconsistencies and truth rate corresponding to the myth.

Algorithm 1: Event flow of the system proposed

Input A: Set of myths
Input B: Set of facts
Output: An explanation regarding the inconsistencies and truth rate
For s in sentences:

1. Map *s* to the corresponding fact
2. Generate corresponding DLs
3. If ((detected inconsistency using ABox) or
4. (detected inconsistency using TBox)) :
5. Apply reasoning on the inconsistency detected
6. Apply fuzzy logic to evaluate truth rate

So a generalized stepwise approach for any other domain can be as follows:
Step1: Identify myths related to the scenario. These myths are easily available on the web on some online news portals.

Step2: Convert myths in natural language to description logics (DLs)

Step3: Identify or create medical ontologies for scenario

Step4: Identify inconsistencies between medical ontologies in DL (trusted sources) and online medical texts which are converted in DL in Step 1.

Step5: Generate explanations to provide reasoning for the inconsistencies signaled.

Step6: Apply fuzzy logic to evaluate the truth rate of the myth.

V. EXPERIMENTATION

The model proposed was given an input sentence. This sentence is assumed to be one of the myths mentioned in Table(2). Further, it is mapped to the corresponding fact which is also assumed to be considered from the facts mentioned in the same table. The model will generate corresponding DLs and then the same ontology designed will take these formalizations as inputs.

This will signal inconsistencies and the inconsistencies signaled will be used to generate reasoning to present the user with a clear concept of why the myth is being considered as a myth.

Furthermore, a mapping of the myth and the fact onto a fuzzification will generate the truth rate of the sentence selected by the user for verification.

VI. INNOVATIVE CONTENT AND RESULTS

The past work has been restricted to detecting myths in mental health and covid-19 and providing appropriate reasoning. This paper successfully provided a model that would generate reasons and detect myths on a disease named “Dengue”. However, a generalized algorithm and stepwise formalization have been presented for any domain. Previous works would detect myth however most of the myths have a certain rate of falsehood and truth in them. So we contributed to the existing work by providing a truth rate to the myth. For this fuzzy logic was used.

The model behaved quite well on the knowledge base considered. It was able to identify myths, provide reasonings successfully, and gave an expected truth rate 90% of the time. The model can be successfully deployed as an agent to break myths and provide true facts to the people.

VII. CONCLUSIONS AND FUTURE WORK

We successfully built an end-to-end system by using Description Logics to explain inconsistencies and evaluate the truth rate associated with a myth. We developed an ontology to support the reasoning process for Dengue. We focused on the conversions from NL to Description Logics.

The future work shall be focused on developing an interactive query system for considering all kinds of the myths and doubts of the users related to a certain domain. For this purpose, usage of Fuzzy description logics shall be used to cover more amount of myths.[6]

VIII. REFERENCES

[1] C. F. Bond Jr and B. M. DePaulo, “Accuracy of deception judgments,” P*ersonality and social psychology* Review, vol. 10, no. 3, pp. 214–234, 2006.

[2] N. K. Conroy, V. L. Rubin, and Y. Chen, “Automatic deception detection: Methods for finding fake news,” *Proceedings of the Association for Information Science and Technology*, vol. 52, no. 1, pp. 1–4, 2015.

[3] P. M. Waszak, W. Kasprzycka-Waszak, and A. Kubanek, “The spread of medical fake news in social media–the pilot quantitative study,” *Health Policy and Technology*, 2018.

[4] F. Baader, D. Calvanese, D. McGuinness, P. Patel-Schneider, D. Nardi et al., The description logic handbook: Theory, implementation and applications. Cambridge university press, 2003.

[5] A. Groza and A. -D. Pop, "Fake news detector in the medical domain by reasoning with description logics," *2020 IEEE 16th International Conference on Intelligent Computer Communication and Processing (ICCP)*, 2020, pp. 145-152, doi: 10.1109/ICCP51029.2020.9266270.

[6] I. A. Letia and A. Groza, “Modelling imprecise arguments in description logic,” Advances in Electrical and Computer Engineering, vol. 9, no. 3, pp. 94–99, 2009.